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A FRAMEWORK FOR ENGINEERED COMPLEX ADAPTIVE SYSTEMS OF SYSTEMS

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DISSERTATION

A FRAMEWORK FOR ENGINEERED COMPLEX ADAPTIVE SYSTEMS OF SYSTEMS

by

Bonnie W. Johnson

September 2019

Dissertation Supervisor: Alejandro S. Hernandez

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13. ABSTRACT (maximum 200 words)

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A FRAMEWORK FOR ENGINEERED COMPLEX ADAPTIVE SYSTEMS OF SYSTEMS

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Submitted in partial fulfillment of the
requirements for the degree of

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LIST OF ACRONYMS AND ABBREVIATIONS

A2/AD	anti-access/area denial
AI	artificial intelligence
AMRAAM	advanced medium-range air-to-air missiles
BMA	battle management aids
BMC2	battle management and command and control
BOAR	between order and randomness
CAS	complex adaptive systems
CASoS	complex adaptive systems of systems
CG	cruiser
CLT	central limit theorem
COA	course of action
CSE	complex systems engineering
CVN	aircraft carrier
DDG	destroyer
DIME	diplomatic, information, military, economic
DL	Distributed Lethality
DMO	Distributed Maritime Operations
DoD	Department of Defense
DRM	distributed resource management
EMCON	emissions control
FCQ	fire control quality
GST	General Systems Theory
HMI	human machine interface
HSCC	health, status, capability, and configuration
HVU	high value unit
IFC	integrated fire control
IFF	interrogation friend or foe
ISR	intelligence, surveillance, and reconnaissance
ISS	International Space Station
JDAM	joint direct attack munitions

JDL	Joint Directors of Laboratories
KD	knowledge discovery
MOE	measures of effectiveness
NCW	network centric warfare
PA	predictive analytics
RM	resource management
SA	situational awareness
SE	systems engineering
SOC	self-organized criticality
SoS	systems of systems
SoSE	systems of systems engineering
TSE	traditional systems engineering
TTP	tactics, techniques, and procedures
UAS	U.S. National Airspace System
UAV	unmanned aerial vehicle

EXECUTIVE SUMMARY

This dissertation presents a grounded theory for complex adaptive systems of systems (CASoS) as engineered solutions to highly complex problems. The CASoS theory provides a definition of this new class of system solutions and describes their characteristics and principles. This grounded theory emerges from three disciplines: systems theory, systems of systems theory, and complex systems theory. The research follows the classic grounded theory methodology of gathering and coding data and allowing theory to emerge. This exploratory research derives a CASoS conceptualization and engineering approach as implications of the theory.

The rise of technology, computers, information systems, automation, and global networks has led to an Age of Interactions that has introduced multi-faceted problems unlike any before seen (Alberts 2011). These highly complex problems are unpredictable and present dire consequences if not addressed. They consist of distributed and heterogeneous entities and events that are dynamic—changing states rapidly and unexpectedly. This presents a non-linear problem space, in which awareness is limited (often incomplete or erroneous), and numerous decisions and actions must be made quickly and in an adaptive manner. According to Calvano and Johns (2004), such complex problems overwhelm traditional systems that cannot adapt quickly enough, cannot address numerous missions, and cannot process information quickly enough to make the required rapid decisions.

CASoS is a new class of theoretical system solutions intended to address highly complex problems. This research defines CASoS characteristics and principles based on a classic grounded theory research methodology. CASoS adapt to their environment through complex interactions among their self-organizing constituent systems that give rise to purposeful, emergent, meta-level, and multi-minded behavior. As shown in Figure ES-1, they are composed of numerous heterogeneous, distributed constituent systems that can self-organize and, behave independently and collaboratively in a purposeful manner. This gives rise to the adaptive, intentional, emergent, and evolving behaviors that can address a complex, dynamically changing, and unpredictable environment. CASoS combine complex adaptive systems behavior with systems of systems. The theoretical characteristics of CASoS are openness, changing boundaries, constituent system variety, architecture (adaptive, highly connected, collaborative, and distributed), behavior (multi-level, purposeful, emergent, multi-minded, self-organizing, adaptive, and evolving), and complexity (detailed, dynamic, non-linear, and resilient). The theoretical principles of CASoS are holism, contextual, goal-oriented, operational viability, requisite variety, high flux, and information.

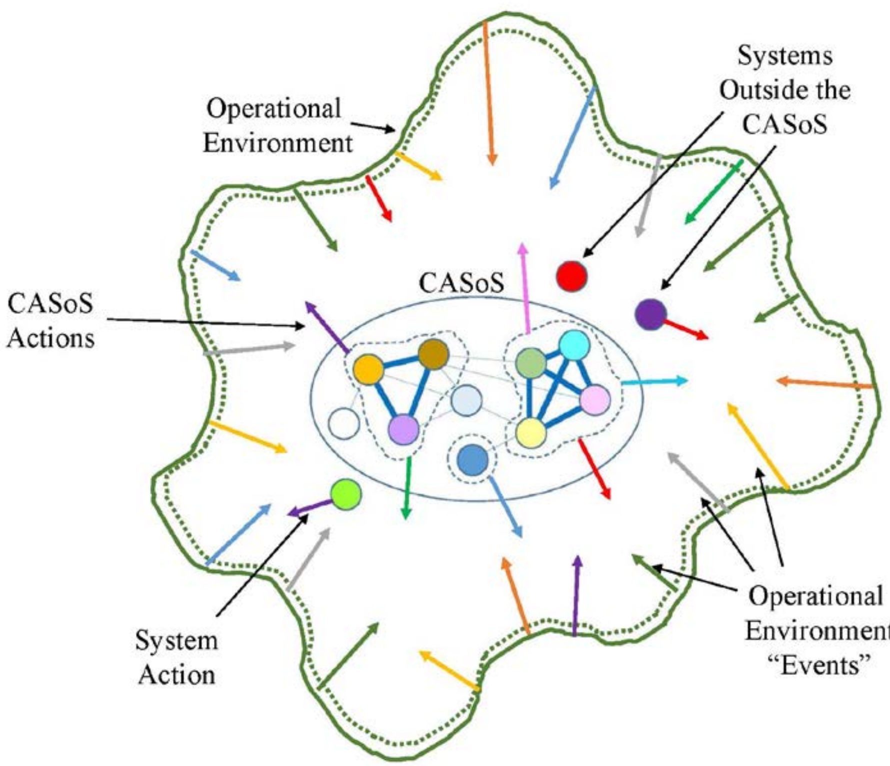

Figure ES-1. A CASoS Interacting with a Complex Environment

The research explored the engineering implications of the CASoS theory. This resulted in a conceptualization of an engineered CASoS and a definition of the required engineered capabilities. An engineered CASoS must possess the ability to make purposeful, intentional decisions. It must have an adaptive architecture that enables agile interactions and relationships among the constituent systems. The architecture will rely on interaction mechanisms that control information sharing and interaction among constituent systems. The architecture is in effect, a resource of the CASoS, that is managed through the interaction mechanisms to ultimately enable collaboration and emergent and adaptive behavior. An engineered CASoS must be comprised of a system of intelligent constituent systems that can act independently and collaboratively and can make decisions to control behavior at the multiple levels. It is a system of decision systems that is collectively managing resources to best address the problem space. Engineering aspects of this intelligent decision-making include the role of appropriate human-machine interaction and the synchronization of decisions among distributed systems to effectively collaborate and self-organize. Knowledge discovery and predictive analytics are two other capabilities required to engineer a CASoS. A CASoS must be able to discover knowledge or gain and maintain situational awareness of its environment. This requires sensors for gathering data, and analytics to make sense of the data and develop knowledge. A CASoS must also have predictive analytics to hypothesize possible effects of different actions. The CASoS uses these predictions to influence its decisions to control its adaptive behavior.

A final aspect of the CASoS theoretical framework was the implication of the theory on the systems engineering approach required to develop a conceptual design of a CASoS. This part of the advanced coding phase produced guidance for a CASoS engineering approach as well as a high-level systems engineering approach for CASoS design and development. Three overarching CASoS systems engineering goals were identified: (1) to engineer a solution that can address a given highly complex problem, (2) to ensure that CASoS emergent behavior is desired and that undesired and unpredicted emergence does not occur, and (3) to engineer a solution that can evolve over time as the problem domain changes. Guidance included the necessity of a top-down approach, an intelligent distributed peer architecture intelligent distributed peer architecture approach, considerations concerning constituent systems, and a process of continuous design throughout the system life cycle to enable adaptation and evolution. The CASoS systems engineering approach is a top-down design and development of the CASoS architecture and intelligent agents; the embedding of intelligent agents into legacy and new constituent systems, and a continuous process of operational design-on-the-fly and design-for-updates throughout the remainder of the CASoS life cycle.

Theory validation was accomplished through a modeling and simulation analysis. The CASoS solution approach was applied to the naval tactical problem domain. This domain was shown to contain the characteristics of a highly complex operational environment. A naval tactical scenario was modeled based on a highly complex Anti-Access/Area Denial (A2/AD) littoral threat environment with a red force consisting of sea-launched anti-ship missiles and ground-launched anti-aircraft missiles. A blue force strike group of destroyers and airborne early warning aircraft accompanied a high value unit ship. This strike group was modeled in two ways: first as a baseline non-CASoS variant to represent an abstraction of the current tactical approach, and second as a CASoS variant employing the CASoS collaborative, connected, and adaptive solution approach. The modeling and simulation analysis provided a statistical comparison of tactical operational effectiveness of the two variants according to their ability to defend blue forces (prevent casualties), defend quickly (destroy red forces in less time), and maximize the use of a diverse set of weapons. The analysis demonstrated that the CASoS solution approach was superior to the baseline approach—decreasing blue casualties, decreasing the time required to kill red forces, and implementing an improved layered defense. The analysis demonstrated that the CASoS solution was superior to the baseline approach, even as the threat environment increased in complexity. The modeling and simulation analysis demonstrated the value of the CASoS characteristics and principles as enablers of the improved solution for the naval tactical problem domain. The naval tactical application and modeling and simulation results demonstrated the four validation criteria of grounded theories: fit, relevance, workability, and modifiability.

This dissertation applied a grounded theory research approach to study CASoS, as a new class of system solutions to highly complex problems. The grounded CASoS theory that emerged produced a new class of systems that can be engineered to address complex problems. The theory provides the definition, characteristics, and principles of CASoS solutions. The theoretical implications provide a conceptualization of an engineered CASoS, and a CASoS systems engineering approach. This dissertation contributes to the bodies of systems theory knowledge and systems engineering knowledge and it provides a conceptualization and approach to engineering solutions to highly complex problems.

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Calvano, Charles, and Philip John. 2004. “Systems Engineering in an Age of Complexity.” *IEEE Engineering Management Review* 32 (4): 29–38.

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I. INTRODUCTION

A. THE PROBLEM[1]

> Most people would agree that the world is becoming more complex. Much of this is driven by two phenomena that have started to dominate our lives in recent years. First, we face an unprecedented level of integration and are immersed in a "complex" web of interacting technologies and processes, dominated by the developments in information and communication technologies. Second, rapid change has become the norm with technologies, practices, and organizations being introduced continuously into this highly integrated web. (Calvano and John 2004, 29)

This dissertation develops theory, explores concepts, and presents a unifying framework for engineering complex adaptive systems of systems (CASoS) as solutions to highly complex problems. The research builds on developing bodies of knowledge in systems theory and complexity theory. It focuses on the application of engineered CASoS to address challenging multi-dimensional problems such as the emerging naval concepts for Distributed Maritime Operations (DMO) (King and Friedman 2017), Distributed Lethality (DL) (Rowden 2016b), and Integrated Fire Control (IFC) (Yoshihara 2012). A comprehensive study for engineering CASoS solutions, as well as a method for identifying and developing effective responses to naturally occurring, human-modified, and human-made complex problem spaces, represents a new body of knowledge in systems engineering (Johnson 2018a).

The rise of automation in many systems—and technology ubiquity in general—present complex problems that require a solution that can continually adapt to meet the changing demands of the operational situation. The interaction of heterogeneous and increased technologies introduces multi-faceted problems that are unlike any before seen.

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Bonnie Johnson. 2018. "Towards a Theory of Engineering Complex Adaptive Systems of Systems." Paper published in *IEEE Xplore Proceedings of the 18th Annual IEEE International Systems Conference,* Vancouver, BC, 23–26 April 2018.

Alberts (2011) states that we have entered the Age of Interactions in which events and decisions are linked to many outcomes that affect many other events. Bar-Yam (2004a) cites many examples of complex problem spaces including military conflict, health care, education, international development, large-scale natural disasters, ethnic violence, and terrorism. National strategies often invoke the diplomatic, information, military, and economic (DIME) elements, as is the case when countries apply economic sanctions, or use diplomatic negotiations. Hillson (2009) writes that the DIME elements constitute actions and consequential effects that can be highly interactive, complex, and unpredictable. He explains that as nations implement the DIME elements, the effects can be highly interrelated and can have unpredictable consequences. Technology advances in global information and communication infrastructures increase these complex interactions and the tempo of cause and effect. Complexity scientists are studying the causes and effects of seemingly unrelated events that have significant repercussions. Lagi, Bertrand, and Bar-Yam (2011) performed a study found that agricultural price increases in North America due to droughts were inadvertently linked as a causal factor in violent protests in North Africa and the Middle East.

Technological advances in computers, Big Data, artificial intelligence, global information and communication networks have contributed to complex problem spaces. Figure 1 illustrates these technological contributors. Big Data refers to the current paradigm of enormous amounts of data and information that exist because of commercial, government and military enterprises, as well as individual communication and participation in social media (Zhao, MacKinnon, and Gallup 2015). Big Data fosters the Age of Interactions through the new technologies that enable rapid capture, processing, and storing of vast amounts of data, which result in heightened awareness, information overload, and unlimited access to information systems, individuals, and enterprises. The network of interconnected nodes and links in the upper right quadrant of Figure 1 graphically portrays complex interactions among distributed entities. The lower left quadrant illustrates a vastly more complex interaction that increases in scale according to the number and types of nodes and interconnecting links. The graphic of satellite communications is a reminder of the global nature of today's Age of Interactions.

Figure 1. Complex Problem Space Contributors. Adapted from Bryant (2017), Berman (2017), Mullins (2011), and Vulpani (2015).

Complexity is the state of having many different elements intricately interconnected and intricately related to their environment. Highly complex problems are unpredictable and present dire consequences if not handled properly. They change over time, are unique from moment to moment, and often present shortened reaction times for decision-makers involved in addressing them (Young 2012). Complex problems, resulting from numerous non-linear interactions, can overwhelm traditional systems that cannot adapt quickly enough; cannot address multiple mission occurring simultaneously; and cannot process information quickly enough to make effective decisions. Calvano and John (2004) studied systems engineering methods aimed at handling complex problems. They called the current age, the Age of Complexity. They found that traditional methods of engineering systems to meet well-defined static requirements are not sufficient to meet the adaptable and complex behavior required of engineered solutions for highly complex problem spaces.

This dissertation studied a new class of engineered systems with the potential to address highly complex problem spaces. These complex decision spaces require a new approach: one that enables intelligent adaptive systemic behavioral responses and courses of action to tackle the complexity. The CASoS approach designs a system of systems solution with behaviors of complex adaptive systems to enable them to produce intentionally designed and desired emergent behavior through the self-organization of their intelligent and purposeful constituent systems.

B. THE MOTIVATION

Complex adaptive behavior emerges from a set of distributed constituent systems that have the ability to communicate, attain knowledge of the environment, and act in a self-organized, yet cooperative manner to address a challenging problem. Figure 2 illustrates this emergent behavior. Two prominent features of this approach are the ability of the constituent systems to attain situational awareness of the operational environment and the ability for emergent behavior to arise. These features provide an adaptive behavioral feedback process.

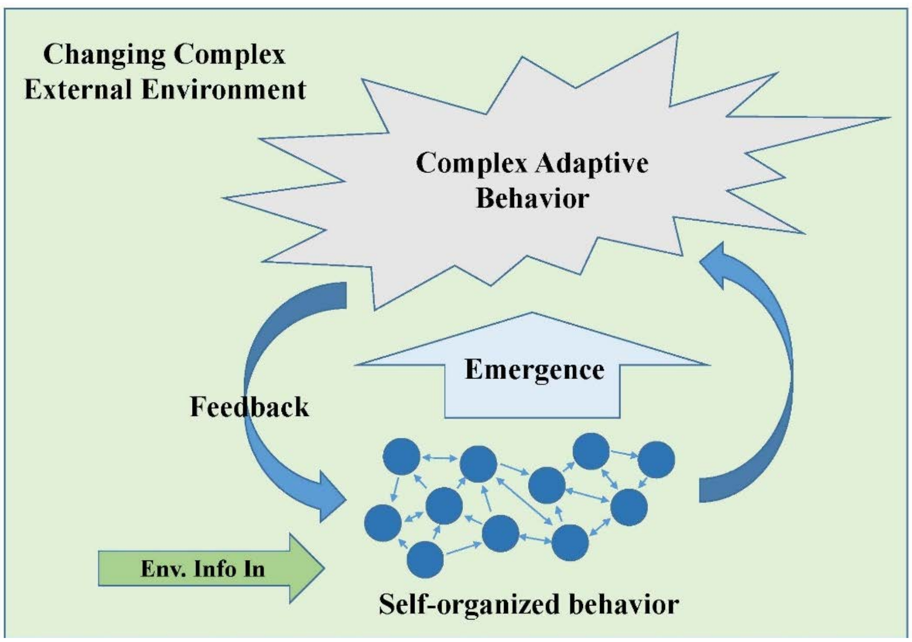

Figure 2. The CASoS Solution Opportunity.
Adapted from Holland (1995).

Theoretical advancements in systems thinking, systems of systems engineering, complexity, and complex systems engineering present new ways of contemplating complex problems that validate the need for a new class of engineered systems. Further, technological advancements in decision aids, data fusion, advanced processing, communication, data architectures, and predictive analytics form the basis for developing a conceptual design and architecture for engineering new solutions.

C. METHODOLOGY

This dissertation addressed the following research question: What are the characteristics and principles of a new class of systems that can address highly complex problems that overwhelm current systems and engineering approaches? The goal of this dissertation research was to clearly define and articulate a new class of engineered system solutions to highly complex problems.

A grounded theory approach enabled the discovery, development, refinement, and validation of a theory for complex adaptive systems of systems (CASoS) using empirical and abstractive data collected through observation, artifacts, and case study. CASoS constitute a new class of engineered system solutions to highly complex problems through an adaptive architecture and system of intelligent constituent systems that can learn, self-organize, and collaborate to achieve desired adaptive emergent behavior. The research followed a grounded theory approach with three predominant steps, which are described in detail in Chapter III:

1. The gathering of data through literature review and discourse with subject matter experts.

2. Data coding and synthesis arising in a theory for the characteristics of CASoS.

3. Advanced coding and theoretical integration producing a CASoS conceptualization and a CASoS engineering design approach.

Using the results of the grounded theory approach, the validity of the theory was demonstrated through modeling and simulation analysis using the Map Aware Non-Uniform Automata (MANA) tool. In this software, a highly complex naval tactical scenario was simulated to compare an engineered CASoS solution approach to a traditional baseline approach. The results of this analysis are described in detail in Chapter VI.

D. CONTRIBUTIONS TO SYSTEMS ENGINEERING

This dissertation provides several contributions to the body of systems engineering knowledge. Through the process of answering the research question, this dissertation provides a theory defining and describing the characteristics and principles of a new class of systems: CASoS. The dissertation explains how the class of CASoS fits within existing systems theory. It develops a theoretical explanation of what constitutes a highly complex problem. It studies the implications of the CASoS theory for engineering a CASoS solution—describing what engineered capabilities are required and what systems engineering approach is needed. Finally, it demonstrates grounded theory validity through an analysis of the theory's application to the naval tactical problem domain.

II. LITERATURE REVIEW

A. INTRODUCTION[2]

The motivation to conduct this dissertation research was threefold: (1) the emergence of complex problems that are unexplained/undefined in terms of the current lexicon of complex systems; (2) new approaches to complex problems have been directed by national and strategic leaders; and (3) new theoretical approaches and technology advancements offer a novel approach for engineering complex systems.

A number of problem spaces have been observed that are becoming increasingly complex in the Age of Interactions. Figure 3 describes four examples. The first example, tactical warfare, presents highly unpredictable threat environments requiring time-critical decisions and potentially dire consequences (Young 2012). Modern warfare continues to grow in complexity due to the proliferation and evolution of technology (McBride 2000). Threats may arise from the land, air, sea, underwater, cyberspace, or even space itself. Threats may take the form of missiles, swarms of drones or small ships, directed energy, information warfare, cyber-attacks, or complex combinations of these. This dissertation generalizes the CASoS approach but implements it to address tactical warfare fusing distributed assets that act collaboratively and adapt to threat environments. Engineering a complex solution enables desired emergent behavior by utilizing distributed assets for collaborative operation.

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[2] Parts of this chapter were previously published by:

Procedia Computer Science (Bonnie Johnson and Alejandro Hernandez. 2016. "Exploring Engineered Complex Adaptive Systems of Systems." *Procedia Computer Science* 95 (2016): 58–65).

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Proceedings of the 18th Annual International Command and Control Research and Technology Symposium (ICCRTS) (Bonnie Young [now publishing as Bonnie Johnson]. 2013. "Complex Systems Engineering Applications for Future Battle Management and Command and Control." In *Proceedings of the 18th Annual ICCRTS,* Alexandria, VA, 19–21 June 2013).

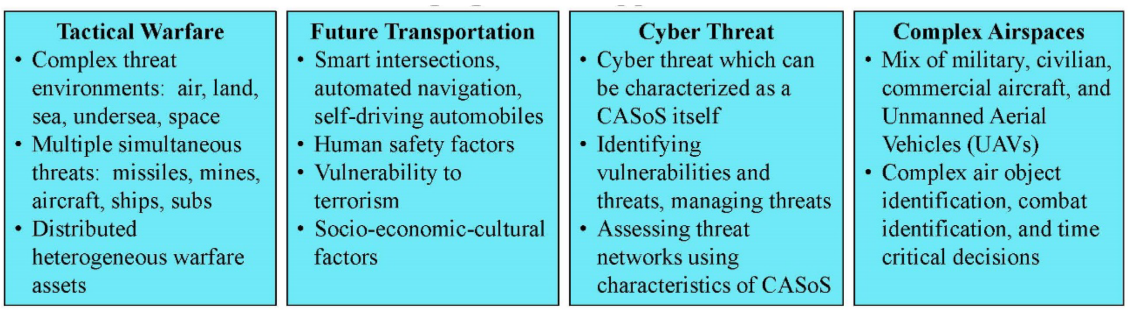

Figure 3. Emerging CASoS Applications

Some other examples of complex challenges include are future transportation, the cyber threat, and future airspaces. As more automation and sensors become commonplace in cars, society enters an era of self-driving vehicles as a mainstay of daily transportation (Hanebrink et al. 2016). Adopting a CASoS approach to this transition offers opportunities to streamline traffic—decreasing or even eliminating traffic jams (Walter 2017), achieving greater energy efficiency (Wadud 2016), and improving road safety (Laris 2017). The cyber threat is a complex problem space with computer hacking arising from nation-states, terrorist groups, and individual actors (Genge, Kiss, and, Haller 2015). As more systems become automated and networked, there are more possibilities for cyber-attacks. A holistic CASoS approach would take advantage of the cyber space's natural environment of a networked architecture of distributed systems. An adaptive distributed SoS approach will be required to address this ever-changing problem. The complex airspace, as described by NASA, the U.S. National Airspace System (UAS) includes more than 87,000 flights per day, about 5,000 flights in the air at any given moment, and more than 14,000 air traffic controllers managing these flights (National Air Traffic Controllers Association 2019). The U.S. Federal Aviation Administration reports that "our current air traffic control system is not equipped to handle the predicted volume or variety of aircraft predicted for 2035 and beyond" (Atkinson 2015, 1). Resulting problems will include crowded skies, corresponding safety issues, longer delays, more congestion at airports, and less response time for air traffic controllers (Katina and Keating 2013). Presenting a CASoS approach to managing the future UAS offers required adaptability and the ability to develop holistic solutions that account for a highly interconnected problem space.

The Navy has identified a number of existing and emerging complex challenges. Anti-access/area denial (A2/AD) threats at sea may contain massive swarms (Kazianis 2016) of missiles, fast attack craft, or drones. Yoshihara (2012) describes a possible adversarial strategy in which they launch ballistic missiles at ships and only need to reach the fleet's defensive area for the Aegis system to automatically respond with expensive defensive engagement missiles. This causes the Navy ships to expend valuable weapons that are costly and difficult to resupply during maritime operations. Proliferation of weapons and increasing access to technology increases the number, type, and destructive power of possible adversaries.

The Navy has proposed a Distributed Lethality (DL) approach using naval warfare assets in an adaptive force package to operate independently in offensive roles while also being capable of operating collaboratively within a strike group to support a variety of defensive, offensive, passive, and active roles (Rowden, Guamtaotao, and Fanta 2015). The Navy has described a future concept of operations called Distributed Maritime Operations (DMO) that "distributes both lethality and platforms throughout an area of operations while retaining the ability to concentrate the effects of weapon systems and maneuver forces" (King and Friedman 2017). Naval forces must be capable of flexibly adapting to unpredictable and changing threat environments with varying levels of system of systems (SoS) collaboration. Additionally, the Navy has been working on Integrated Fire Control (IFC) concepts in which distributed ships, aircraft, sensors, and weapon systems can achieve shared situational awareness and perform collaborative engagements to extend the defended area and response time against a variety of air, surface, and underwater threats (Young 2012). Figure 4 illustrates naval warfare examples of highly complex problem spaces where a new approach is necessary.

Figure 4. A New Approach Is Directed.
Adapted from Hill (2016) and Rowden (2016b).

Gady (2016) reports on a successful Joint Navy-Marine Corps exercise at White Sands Missile Range in September 2016 that integrated a Marine Corps F-35B acting as an elevated sensor with a ground station connected to the Aegis Combat System simulating a ship at sea. This exercise is a step towards demonstrating the Navy's desire to achieve both IFC and DL. Gady (2016, 1) writes, "The live fire drill was designed to test the U.S. Navy's new air warfare concept, Naval Integrated Fire Control-Counter Air (NIFC-CA), and is focused on improving situational awareness and extended-range cooperative targeting. NIFC-CA is part of the U.S. Navy's new distributed lethality naval surface warfare concept." The exercise demonstrated the ability for two weapon systems to work collaboratively: the F-35B acting as a broad area sensor, and the Aegis Combat System detecting, tracking, and destroying targets. Figure 5 provides a conceptual illustration of this IFC and DL exercise.

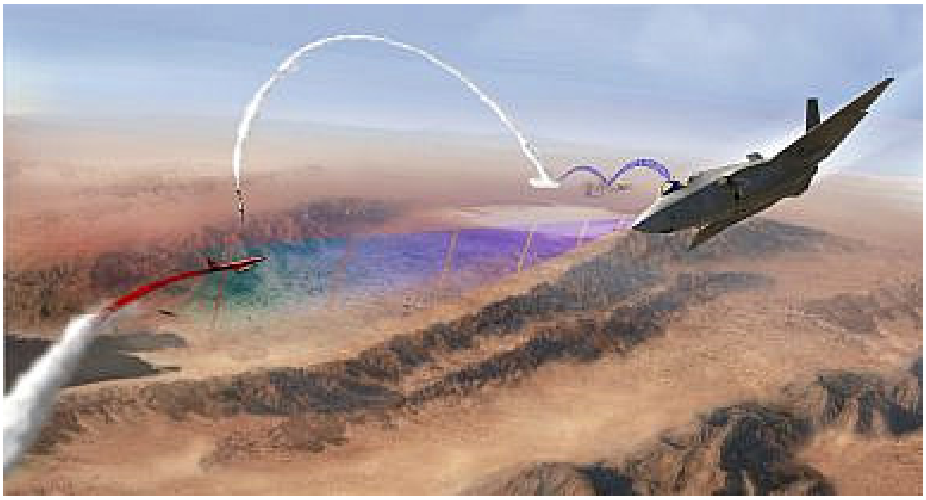

Figure 5. IFC/DL Exercise. Source: Rowden (2016a).

Finally, an opportunity exists: the same information, computer, and network technologies that are causing complex problem spaces can also be enablers for engineering solutions in the form of CASoS. Complex operational environments require engineered solutions that can adapt in response to changing environments; self-organize and determine effective courses of action; and respond and act in purposeful and intentional ways. These computational and communication technologies can embed distributed systems with intelligence and the architectural means to perform collaboratively to achieve emergent behaviors as well as performing independently. Thus, a CASoS solution can provide behaviors at multiple system levels and can greatly increase the numbers and types of possible behavioral responses to complex problem spaces. For Naval DMO, DL and IFC, a CASoS approach will allow distributed warfare assets to self-organize and act independently or to collaborate in an adaptive manner. This will enhance the ability of distributed warfare assets to respond effectively to unpredictable threat environments that are in constant flux and span multiple mission areas, as illustrated in Figure 6.

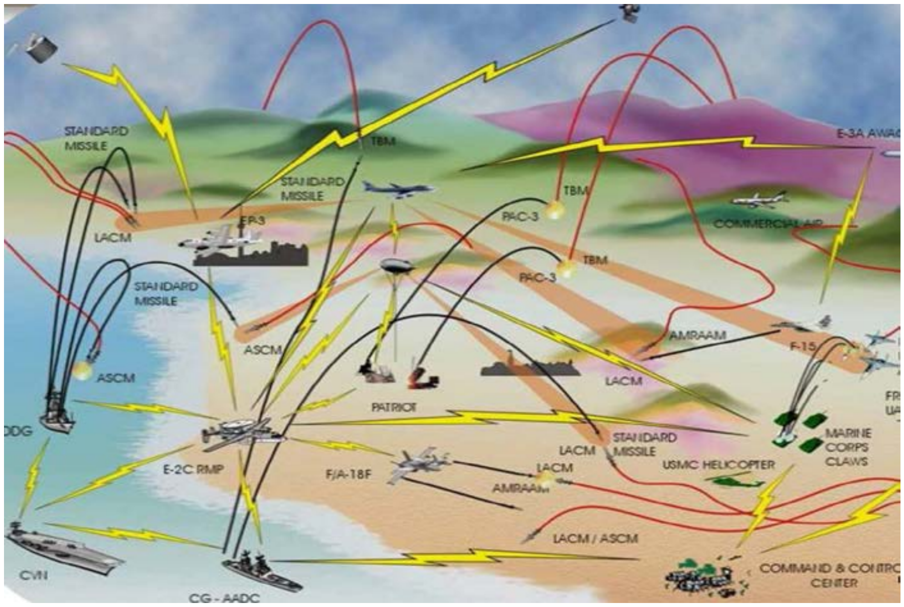

Figure 6. Complex Tactical Environment. Source: Young (2012).

Many defense studies and programs have the objective of improving tactical warfighters' abilities to conduct missions in highly and increasingly complex tactical environments. The following concepts have led to the idea that the effective coordination of distributed warfare assets on ships, aircraft, underwater, and even space-based platforms could lead to significant tactical improvements in complex tactical environments.

- Network Centric Warfare (NCW) (Cebrowski and Garstka 1998)
- Navy's Common Command and Decision (CC&D) system
- Joint Single Integrated Air Picture (Karoly et al. 2003)
- Navy's FORCEnet (Clark and Hagee 2005)
- Dave Albert's books: *Network Centric Warfare* (Alberts 1999), *Information Age Warfare* (Alberts 2001), *Power to the Edge—Command and Control in the Information Age* (Alberts 2003), and *Agility* (Alberts 2011)

As illustrated in Figure 6, the desired improvements include increased and shared knowledge of the battlespace, faster reaction times within highly compressed decision cycles, layered defense strategies with improved probabilities of kill and less weapon attrition, and new configurations of engagement strategies involving cooperation among distributed weapons and sensors.

Studying the complex tactical environment led to three observations:

- There is value in taking a systems approach to address these types of complex problems;
- The collaboration and resulting emergence from the cooperation of distributed systems offers significant performance gains and possibilities for addressing these types of complex problems; and
- These types of problems are complex, and therefore, complex and adaptive system solutions are required to address them.

These observations led to three fields of research for the dissertation literature review: (1) systems, (2) systems of systems, and (3) complex systems. Figure 7 provides a mapping of the literature review to orient the three fields and illustrate how they are interrelated. Systems is the all-encompassing field, including systems theory, systems thinking and an extensively large base of literature on the topics of system definitions, principles, characteristics, axioms, examples, and applications. Systems of systems (SoS) is a subclass with the set of systems. This discipline focuses on SoS definitions, characterizations, categorizations, examples, and applications. Similarly, complex systems is another subclass of systems with an extensive body of work describing its definitions, characterizations, and applications.

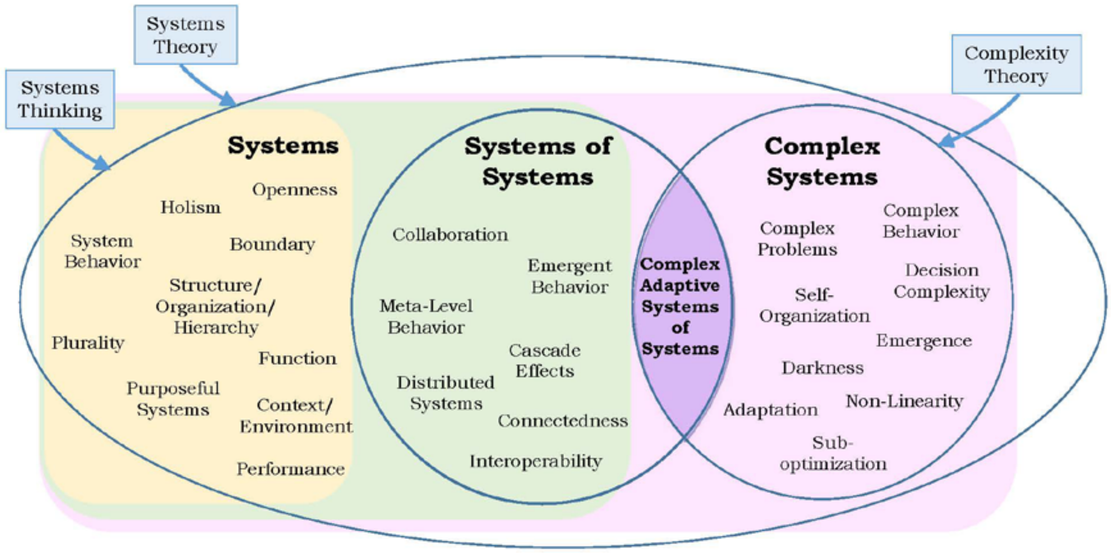

Figure 7. Literature Review Mapping

The remainder of this chapter defines the niche that CASoS holds in the domains of systems, SoS, and complex systems. It explains how the systems movement led to systems theory and systems thinking, providing a foundation for a systems solution to highly complex problems. It describes SoS characteristics which are necessary for understanding collaboration of distributed constituents and emergent behavior. It explains the current understanding of complexity as it pertains to adaptation, non-linearity, self-organization, and other characteristics of complex systems. This dissertation asserts that the class of CASoS lies within the system domain, in the intersection of SoS and complex systems—benefiting from the characteristics of each of these domains and enabling a solution to highly complex problems.

B. SYSTEMS

> The 21st Century has been described as "The Systems Century." The phenomena [of interacting technologies and processes, dominated by the developments in information and communication technologies] certainly reinforce the systemic nature of the world, and since this trend is human-made, we must ensure that we are "engineering" it in an appropriate and acceptable way. (Calvano and John 2004, 29)

For the purposes of this dissertation, we use Hitchins' (2005, 1) definition of a system as "an open set of complementary, interacting parts with properties, capabilities and behaviors of the whole set emerging both from the parts and from their interactions." This section explores what it means to view the world in a systemic way—identifying entities in the real world as systems and identifying desired systems to be engineered— all in an attempt to better understand problems and address them. Understanding systems theory and systems thinking provides a background, context, and theoretical basis for developing theories for CASoS solutions.

Scientists seek to understand phenomena. Historically they have reduced objects into parts to determine what each part does in an attempt to better understand the whole. Douglas Hofstadter (1979, 312) jokes that "reductionism is the most natural thing in the world to grasp. It is simply the belief that 'a whole can be understood completely if you understand its parts, and the nature of their sum.'" Scientists have continued this reductionist approach, discovering that each part is comprised of smaller parts and so on (Bar Yam 2004b). What is left out of this approach are the relationships that exist internally between the parts of objects and externally with their environment. Systems science recognizes the limitations of reductionism and takes a holistic and expansionist approach to understanding phenomena, viewing the world in terms of systems, and studying system behaviors and interactions with their environments.

Systems theory had its beginnings in the late 1920s as the need for a systems approach arose when the biologist, Von Bertalanffy, realized that the reductionist and mechanistic approach of physicists and other scientists had failed to provide a complete understanding of physical phenomenon. Specifically, he argued that a mechanistic approach (in which the behavior of systems is determined strictly by the internal interactions of the parts from which they are composed) could not fully explain the biological phenomena of life. Von Bertalanffy advocated an approach to biology that considered the organism as a whole or a system. He based this approach on the fact that organisms are open systems. He developed the General Systems Theory (GST) that focused on system structure instead of functionality. GST included physical systems and models from different scientific fields that needed to address system concepts such as order, organization, wholeness, and teleology (purposeful phenomena or behavior); all of which had been neglected by mechanistic science (Bertalanffy 1950, 1951, 1968, 1972).

Von Bertalanffy saw organismic and systems theory as representing what Kuhn (1962) called paradigm shifts, or revolutions in scientific thought and theory. He saw this as a departure from classical analytical (reductionist) science that was dependent on the isolation of component parts and the linear behavior of the parts themselves. He cited Rapoport (1966) who asserted that systems represent organized complexity with interactions that are non-linear.

In the late 1940s, further theoretic advancements were made that contributed to the rethinking and broader applications of system science. Norbert Wiener published his theory of cybernetics in 1948, based upon emerging developments in computer technology, self-regulating machines, and information theory. Cybernetics focused on the servo-mechanisms that provide for negative feedback behavior in teleological (self-regulating, goal-seeking) systems. Von Bertalanffy viewed cybernetics as a special case of GST, focusing on control systems that use communication and information transfer between systems and their environments for feedback. Cybernetics developed concurrently with Shannon's information theory (1948) and Von Neumann and Morgenstern's game theory (1944). Information theory was based on the concept that information could be defined as entropy and the meaning of a message (in a human sense) could be considered irrelevant. This allowed a focus on the efficient transmission of data and how to identify and reduce transmission errors. Game theory developed decision-making methods for handling situations in which competition and conflict exist. It focused on developing strategic thinking and making decisions in situations involving uncertainty. Wiener (1961) suggested the application of cybernetics, information theory, and game theory went far beyond engineering to the fields of biology and the social sciences. The mathematics and principles developed by Wiener, Rosenblueth, Bigelow, Ashby, and others—informed by social scientists Lewin, Bateson, Mead, and Deutsch—were promoted as having equal weight in mechanical, biological, and social systems (Porter 2016). Hitchins (1992) reminds us that classical science and engineering concentrate on closed systems. He points out that according to the second law of thermodynamics, entropy (disorder) increases in a closed system, this "knowledge is not very useful since the systems we see and interact with daily are open systems" (Hitchins 1992, ix).

Ackoff and Emery (1972) explain this revolution in thought as a methodological key to open doors previously closed to science. Before the Systems Revolution, scientists derived their understanding of how things function using reductionist methods to study the parts and their structure. Now scientists tend to derive an understanding of the parts and their relationships by first understanding the functioning of the whole. The advent and evolution of computers has supported this revolution. Computers have enabled scientists to study systems that are far more complex by using non-linear computational models. Computer simulation has replaced some laboratory and field experimentation to expedite an understanding of complex systems. Systems theory provides a basis for multidisciplinary understanding (Adams et al. 2014). The multi-disciplinary and systemic perspectives of this 20th century paradigm shift in scientific inquiry established an ideological foundation for the current focus of systems science on nonlinearity and uncertainty in the behavior of complex systems.

Systems thinking is a way of understanding problems and developing solutions using a systemic approach. Modern system theorists are concerned with system thinking and its many applications. A number of recent books and articles discuss the use of systems thinking for business applications as well as for addressing complex problems. Systems thinking is a process of understanding situations or entities by focusing on relationships and interdependencies.

Systems thinking fits alongside science and engineering as a method of inquiry for gaining knowledge and truth (Zandi 2000). Employing expansionism over reductionism enables the inclusion of context and environment into inquiries. Systems thinking necessarily includes more real world considerations than classical science inquiries. These real world inquiries include irreversibility, complexity, emergent properties, indeterminism, complementarity, and open systems. Zandi (2000, 12) writes that "the most important implication of system thinking is that almost every problem that is perceived to be well-structured is at best really an approximation of an ill-structured one, and it depends on the purpose of inquiry whether or not the approximation is acceptable."

The systems thinking method begins with a description of the real world in terms of systems. The method identifies and represents real world entities as systems and defines their boundaries, components, structure, and relationships. It elicits system principles and characteristics from the systems relationships and behavior. Finally, it describes system behavior in terms of inputs, outputs and state descriptions (Checkland 1993). Hitchins (1992) developed a cyclical model of a systems thinking process based on Checkland's soft systems methodology. Figure 8 illustrates Hitchins' cyclical model, showing a series of steps that begin and in end in the real world. The real-world problem is mapped into the systems thinking world in steps 3 and 4 where the problem is viewed and modeled systemically. Finally, the process compares the system model of the world with the real world problem to ascertain desirable changes (step 6) and determine improvements and actions (step 7).

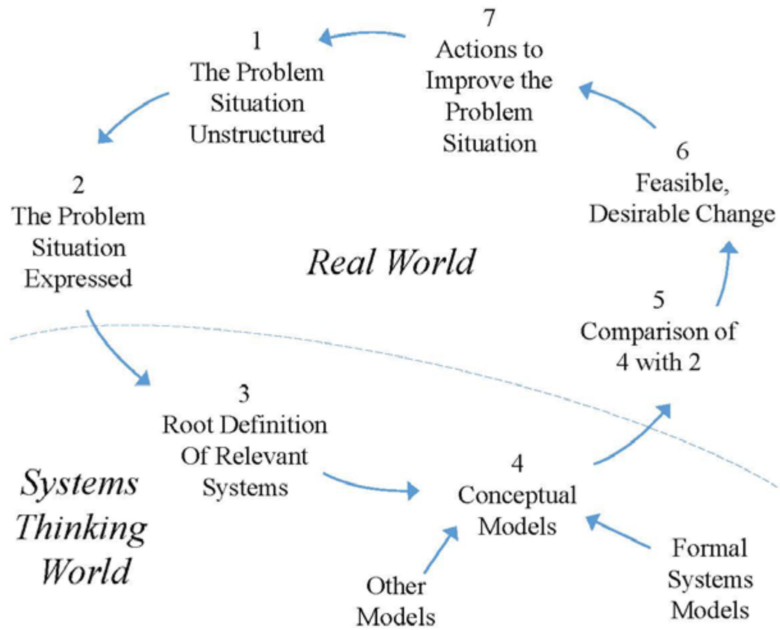

Figure 8. Systems Thinking Process. Source: Hitchins (1992).

There are a number of benefits to approaching a problem using system thinking. Systems thinking includes a focus on connectedness, relationships, and context, thereby enabling a better understanding of complex system structures and behaviors. Systems thinking enables an understanding of systems in their context, resulting in a holistic understanding (Capra 1996).

Gharajedaghi (2011) identifies three categories of systems thinking—holistic thinking, operational thinking, and design thinking—which he contends are all necessary for understanding how to deal with emerging chaotic problems. Holistic thinking is concurrently acquiring and iteratively expanding one's understanding of the structure, function, and process of a system. Operational thinking is a "mapping of relationships—capturing interactions, interconnections, the sequence and flow of activities, and the rules of the game" (Gharajedaghi 2011, 109). It describes the dynamic process of using a structure's parts to create desired functions. It unlocks the black box, or unknown set of functions, that exists between a system's input and output. Design thinking selects a desired outcome and invents the ways to bring it about. The design process creates solutions to deal with "real world, ill-defined, ill-structured, or wicked problems" (Gharajedaghi 2011, 137). All three types of thinking are important aspects of systems thinking and provide a foundation for engineering CASoS.

C. SYSTEMS OF SYSTEMS

The concepts, systems within systems, and the more well known, system of systems, were first introduced by Berry (1964) and Ackoff (1971). These new types of systems came into popularity in the 1990s as a number of systems engineers began to study them with regard to "joint warfighting" (Manthorpe 1996), "large-scale concurrent and distributed systems" (Kotov 1997), and "large networks of systems" (Shenhar 1994). The SoS concept has continued to gain interest and assert itself as a sub-discipline of systems engineering, referred to as SoS engineering (SoSE) (Dahmann and Baldwin 2008).

A SoS is the meta-level system structure resulting from the collaboration of independent systems. Hitchins' (2005, 8) defines a SoS as "an open set of complementary, interacting systems with properties, capabilities and behaviors of the whole SoS emerging both from the systems and from their interactions." His definition highlights the interaction of the systems to achieve emerging capabilities and behaviors. He goes on to explain that a SoS is the same as a system except with a simple hierarchy twist inherent in the meta-level structure. The SoS exhibits increased functionality and performance capabilities, referred to as emergent behavior. Emergent behavior arises from the interactive behavior of the constituent systems. Dagli and Kilicay-Ergin (2009) noted that if any part of the SoS is lost or degraded, this will degrade the performance of the whole. This mirrors the system concept that all subsystems are required elements of the primary system. The concepts of collaboration and meta-level structure within the SoS are important features for addressing complex problems. Both offer potentially significant advantages for engineered SoS, with the ability to provide behavior at multiple levels and exhibit emergent behavior. Coupling these advantages with the feature of purposefulness enables intentional purpose-driven emergent functionality at multiple levels. This capability is the basis for seeking a SoS solution to certain highly complex problems.

Examples of engineered solutions that benefit from a SoS approach include: Navy ships, commercial aircraft, the International Space Shuttle (ISS), and UAV surveillance aircraft such as the Global Hawk. All of these examples involve the integration of high-tech constituent systems such as sensors, communication, propulsion, power, and aeronautical or buoyancy systems. Navy ships also include weapon systems and in the case of aircraft carriers, they contain an entire air wing of aircraft and aircraft support systems. Commercial aircraft coordinate within a larger system of air traffic control systems. The ISS and many UAV's include offboard systems such as ground control operations and launch and recovery systems. All of these SoS examples are dependent on the integration and collaboration of constituent systems for the higher level functionality that emerges from the combination of constituent system actions. For some SoS, (such as ships and aircraft), the constituent systems are largely collocated, however other SoS consist of geographically distributed systems (such as the ISS and UAV examples).

SoSE has been evolving to address the unique challenges presented by the characteristics of a SoS, namely the parallel development of multiple systems and the difficulties in making them interoperable. Much of the focus of SoSE has been on integrating existing systems with the prospect of purposefully gaining emergent capabilities through their interactions (Maier 1998, Dahmann, Lane, Rebovich, and Baldwin 2008). Hitchins (2005, 5) criticizes this bottom-up SoSE integration method of joining or networking existing systems together, writing that such efforts are “very likely to inadvertently couple functions that were previously not coupled which may unwittingly be creating a complex mesh of unforeseen unwanted couplings, the behavior of which can be both unexpected and counter-intuitive.” He notes the crucial importance of viewing an engineered SoS with a top-down holistic approach in each phase of the life cycle to avoid unwanted emergent behavior.

D. COMPLEXITY

> The complexity and diversity of the world is the hope for the future. (Palin 2003, 1)

Complexity is a result of open systems and their nonlinear interactions with each other and their environment. The ever-advancing progression of computers and analytic computational methods has enabled a better understanding of complex behavior. These methods of identifying and understanding complex behavioral dynamics have spread to many disciplines that span the understanding of complexity in natural systems (e.g., weather, climate effects, group animal behavior [such as swarms, colonies, migrations, and epidemics]) and socio-technical systems (e.g., financial networks, social media interaction, communication systems, information systems, power systems, military conflicts, transportation, urban studies). Many universities and institutes are applying complexity theories and approaches to study a variety of natural and human-generated phenomena. They seek to understand complexity and its causes and to prevent or lessen the damaging results of financial crises, natural disasters, and epidemics, to name a few. They hope that by studying complexity, they can better identify and predict complex behavior.

A simple way to introduce complexity is with the **BOAR** principle: “complexity lies **B**etween **O**rder **A**nd **R**andomness” (Page 2011, 32). Complexity theory has arisen from observed phenomena that produces surprisingly unpredictable results from simple structures (Honour 2006). Waldrop (1992) explains that complexity is operating at the edge of chaos. Complexity occurring in systems may exhibit chaotic behavior while also resulting in recognizable patterns (Honour 2006). Figure 9 is an example of complexity with organized swarm behavior emerging from relatively simple structures—in this case a large flock of birds. Theorists explain that because structural order produces stability, complex systems persist in chaotic environments even as their components change and adapt. Complex systems often survive by changing their behavior. Complex systems, therefore, provide useful solutions to complex environments through their dynamic characteristics (Honour 2006). These characteristics of adaptation, dynamic change, and resilience are critically desired features of engineered CASoS solutions.

Figure 9. An Example of Naturally Occurring Complex Behavior.
Source: Dibenski (1986).

Complexity theory provides an approach to understand and define a system. It contributes to an understanding of the effect of environments on complex systems and how systems can learn by selecting alternative courses of action for improvement (Dagli and Kilicay-Ergin 2009). Combining the disciplines of system science and biology to understand system dynamics from the principles of thermodynamics has contributed new theories of complexity and chaos based on the non-linear behavior found in organic and inorganic systems (Ackoff 1971, Prigogine and Stengers 1984, Simon 1996). Complex systems science studies how systems interact with their environments and each other to give rise to collective emergent behaviors (Bar-Yam 1997, 2004a). Capra (1996) explains that complexity science deals with non-linear interactions among systems that often result in non-intuitive, unpredictable behavioral outcomes, or patterns.

Complex systems are defined as large combinations of interacting elements (or components) that have no central control and whose interactive behavior produces emergent level behavior (Mitchell 2009). They require the ability to sense their environment and are able to process this information. They adapt to their environment through learning and evolution. They produce emergent and self-organizing behavior. Hitchins (1996) defines three components of complexity: variety, connectedness, and disorder. He explains that a system is more complex when there is a large amount of variety in the components; a large number of interconnections between components; and when the variety and interconnections are tangled and disorderly, rather than orderly. Figure 10 shows examples of three categories of systems: ordinary, systems of systems, and complex systems.

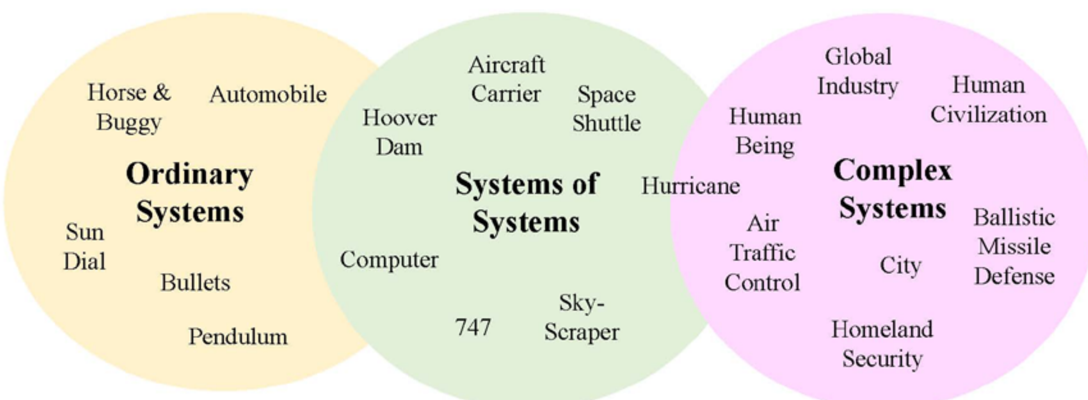

Figure 10. Systems According to Degree of Complexity. Adapted from White (2005).

Sandia National Laboratories began studying complex systems in 2002 and introduced the Phoenix initiative in 2008 to study CASoS. They defined CASoS as "vastly complex eco-socio-economical-technical systems," and studied them to design a "secure future for the world" (Glass et al. 2011, 1). They developed three aspirations (overarching goals) to influence CASoS: (1) to predict; prevent or cause; and prepare; (2) to monitor; recover or change; and, (3) to control (Glass et al. 2011). They defined three characteristics that must describe each aspiration: decision, robustness of decision, and enabling resilience. They also established three primary CASoS goals: to maximize security, maximize health, and minimize risk. These aspirations, components, and goals establish high-level guidance as this dissertation develops theory for CASoS characteristics and approaches to engineering CASoS solutions. Figure 11 is the Phoenix Initiative's illustration of CASoS engineering. It gives examples of CASoS (such as ecosystems, enterprises, infrastructures, economies and societies) and perturbations that affect them (such as terrorist attacks, pandemics, natural disasters, and governmental policies).

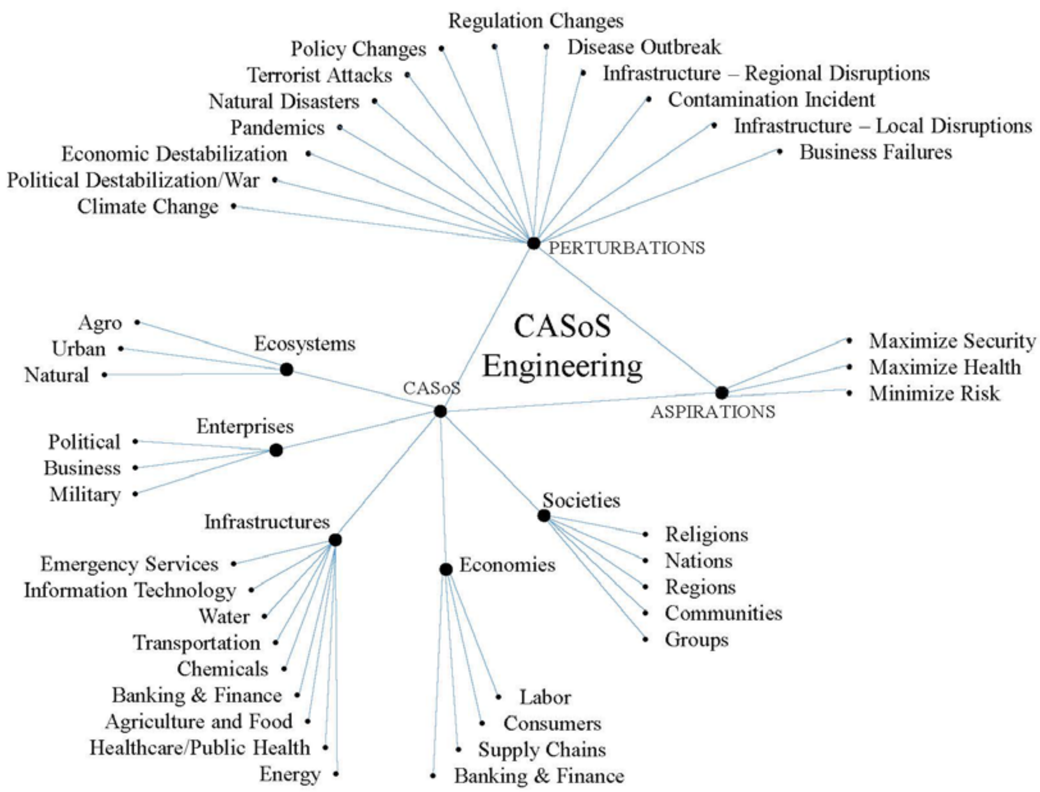

Figure 11. CASoS Engineering: CASoS, Perturbations, and Aspirations. Source: Glass et al. (2011)

Sandia's focus on understanding CASoS as a problem space provided a basis for this dissertation research. Glass et al. (2011, 13) write that "the sheer complexity of CASoS, the subtlety of their adaptive behaviors, the difficulty of running experiments, and the problems of integrating the different analytic frameworks and representations required to understand their component systems underscores the need for new theory, methods and practice." This dissertation extends the body of knowledge that Sandia initiated, by developing a detailed systems theory for the characteristics of CASoS and applying this theory to engineered solutions to highly complex problems. Sandia's work focused on identifying highly complex environments that present complex, adaptive, and distributed problems. This dissertation addresses the shortfalls of the Sandia work:

- Does not describe the characteristics and principles of a CASoS solution
- Does not identify required capabilities to engineer a solution
- Does not identify a CASoS systems engineering approach.

This dissertation produces a theory for an engineered system solution and approach, whereas Sandia identified many highly complex environments and the need for engineered solutions.

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III. RESEARCH APPROACH

A. INTRODUCTION[3]

> All research projects … need to add something of value to the body of knowledge. (Remenyi 2014, xii)

By developing a theory for engineering a CASoS, this dissertation contributes to the bodies of knowledge regarding systems, SoS, and complex systems. The application of an approach based on CASoS theory to address certain highly complex problem spaces opens a new area of research within the domain of systems engineering.

This chapter describes the method of inquiry to develop a theoretical framework of CASoS with a general discussion of classic grounded theory—an approach resulting in the emergence of theory based on creativity, reflection, conceptualization, and a self-critical iteration of ideas. The majority of the chapter discusses the detailed application of grounded theory to produce the CASoS theory.

B. GROUNDED THEORY

> A theory is systematically organized knowledge applicable in a relatively wide variety of circumstances, using a system of assumptions, accepted principles, and rules of procedure devised to analyze, predict, or otherwise explain the nature of behavior of a specified set of phenomena. But it is also simply the best explanation which is available at the time. (Remenyi 2014, 64–65)

1. Theory

Theory is a means of understanding and explaining observed phenomena. Adams et al. (2014) define theory as "a unified system of propositions made with the aim of achieving some form of understanding that provides an explanatory power and predictive ability." They go on to write (2014, 115), "a theory does not have a single proposition that

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[3] Parts of this chapter were previously published by:

The Grounded Theory Review (Bonnie Johnson, Karen Holness, Wayne Porter, and Alejandro Hernandez. 2018. "Complex Adaptive Systems of Systems: A Grounded Theory Approach." *The Grounded Theory Review* 17 (1): 52–69.)

defines it, but is a population of propositions (i.e., arguments, hypotheses, predictions, explanations, and inferences) that provide a skeletal structure for explanation of real-world phenomena."

2. Developing Theory

There are different research methods for developing theory. A common practice (deduction) follows the positivist scientific method of hypothesizing a theory and conducting experiments to test the theory, resulting in its adoption or rejection. The positivist approach is widely applied in the physical sciences. It relies on the scientific method, logic, and mathematics to develop theories that are predictive, reproducible, reliable, rigorous, and objective. Stol et al. (2016) explain that positivism assumes that the universe behaves according to inalterable, discoverable laws, and systems are merely the sum of their components.

Interpretivism, which is on the opposite side of the philosophical spectrum, is widely used in the social sciences, which aims to understand and interpret human behavior. Stol et al. (2016) explain that interpretivism relies largely on qualitative data and assumes that no universal truth or reality exists (but rather reality is what people imagine it to be), and systems exhibit emergent behaviors not reducible to their component parts.

Another approach to developing theory is the classic grounded theory method, which is based on induction, and falls somewhere between positivism and interpretivism. Induction is a method used to determine possible correlations of the deficiencies between the desired and calculated. Patton (2015) explains that the classic grounded theory method studies observations and data in a structured and analytical way, enabling theory to arise or emerge from the data analysis to describe the phenomena. The results and findings are thus grounded in the empirical world. The grounded theory method builds, rather than tests, theory.

A recent review of software engineering research projects using the grounded theory research method, revealed a wide use of mixed methods from both positivism and interpretivism (Stol et al. 2016). However, this dissertation is neither positivist nor interpretivist. It does not develop a theory concerning observed physical phenomena, or about human behavior. Instead, its objective is to develop a theory for a new class of systems that shows potential as engineered solutions to highly complex problems. The research is rooted in pragmatism, and is largely theoretical or non-empirical, relying on examination of literature, reflection, and discourse with knowledgeable experts. This dissertation focused on developing a critical theory that describes the class of CASoS solutions that can be applied to address highly complex problems. For these reasons, the classic grounded theory approach was chosen to provide a rigorous methodology for performing this theoretical engineering research. Grounded theory is an effective methodology for pragmatic research based on rationalism (a reason-based approach to understanding).

3. Grounded Theory

The classic grounded theory research method originated in the 1960s by Glaser and Strauss (1967) and was developed "due to a desire to build theories more rigorously and dispassionately by grounding them in objective reality" (Stol et al. 2016, 3). The classic grounded theory process relies on theory-method linkage, a rigorous yet iterative research methodology, and creative synthesis. Theory-method linkage is the important connection between data analysis and the formulation of theory. This theory-building results from an iterative process of gathering and analyzing data, and articulating a theory to explain the phenomena (Creswell and Poth 2018). The iterative process of data gathering, coding, and analysis is illustrated in Figure 12. This shows how the classic grounded theory process begins with low-level concepts and works toward high-level theoretical concepts using a series of analysis techniques. Data coding is the process of categorizing and organizing data about phenomena; identifying properties and causal conditions that influence phenomena; specifying strategies or actions that result from phenomena; and, characterizing the context and influencing conditions.

Theoretical sensitivity, coding, sampling, constant comparison, saturation, selective coding, and integration are additional analytical steps in the research process (Holton 2007; Glaser and Holton 2004). Theoretical sensitivity recognizes and extracts relevant information about the theory from the data. It involves conceptualizing and organizing theoretical insights and making abstract connections from the data. Theoretical sampling identifies and pursues clues that arise as data is gathered, studied, and coded. The sampling process of data collection is controlled by the emerging theory, rather than being planned ahead of time. Codes are discovered, and the researcher tries to saturate them by constant comparison with new data. Saturation occurs when no new codes are identified and data categories have been clearly articulated. Selective coding occurs once a core variable (or central theoretical theme) emerges. The selective coding focuses and delimits thee process to only analyzing data related to the emerging theory and related concepts. Integration pulls together of the abstract theoretical scheme into a final grounded theory.

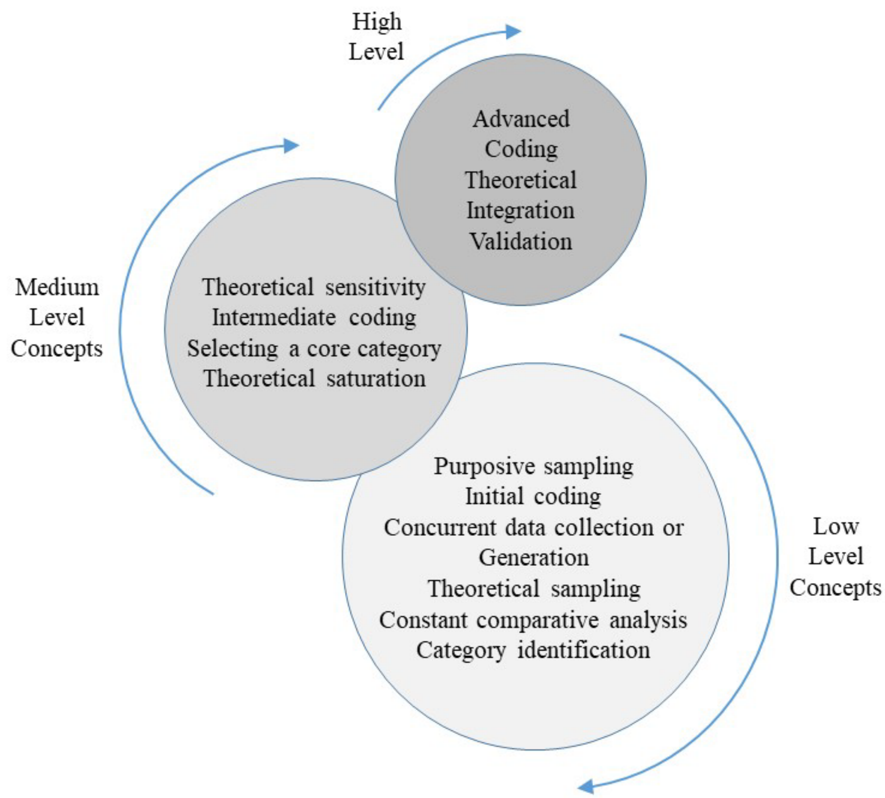

Figure 12. Conceptual Ordering of General Grounded Theory Methods.
Source: Birks and Mills (2015).

This study relied primarily on literature review as the primary source of data. Remenyi (2014) equates this approach to thought experiments performed by Einstein, which involved the application of imagination and creative thinking to a hypothetical situation. The theoretical grounded theory approach studies established ideas and theories through the literature review process. It extends these ideas to create new theories and insights with the goal of providing better or fuller explanations. This process is based on rationalism, which is the philosophical view that regards reason as the primary source of understanding. Remenyi (2014, 71) explains, “Rationalism holds reason to be a faculty that can access truths beyond the reach of sense perception both in certainty and generality.” Remenyi (2014) describes eight distinct steps in the theoretical grounded theory approach:

1. Research question formulation,
2. Literature review,
3. Explanation of why a theoretical approach is being taken,
4. Concept identification and reflection,
5. Theoretical conjecture and formulation,
6. Discourse with peers and experts,
7. Theoretical conjecture, refinement, and acceptance, and
8. Discussion on the impact, implications, and validation of the theory. (Remenyi 2014)

This dissertation incorporated Remenyi’s eight theoretical research steps as part of the classic grounded theory method as it provided insight into performing grounded theory using literature review as the primary data source. Table 1 shows how the eight steps map into the three levels of data coding from the classic grounded theory method. Steps one through four occur during the low level concept phase; step five occurs during the medium level concept phase; and steps seven and eight occur during the third phase of advanced level concepts. Step 6, discourse with peers and experts, occurs during all three phases of the classic grounded theory method.

Table 1. The Theoretical Grounded Theory Steps According to the Data Coding Levels of the Classic Grounded Theory Method

Low Level Coding	Medium Level Coding	High Level Coding
Steps 1-4	Step 5	Steps 7-8
Step 6		

Classic grounded theory was the appropriate research method for this dissertation. As an intentionally designed and engineered CASoS does not yet exist, it was necessary to gather and study data (theories, concepts, ideas, definitions, indicators, etc.) to better understand CASoS and its engineered application to real world problems. Classic grounded theory provided a rigorous qualitative approach, which was required to allow a theory to emerge from the data. Classic grounded theory is consistent with a systems approach, which made it an effective approach for this dissertation's goal of developing system theory. Classic grounded theory views reality in terms of systems and their interactions and it offers a holistic perspective. The benefit of a classic grounded theory research approach to this dissertation was that it lent formalism and rigor to the development of a CASoS theory. By using this methodology, the intent was that the CASoS theory is plausible, transferable, and applicable to real world problems.

Theory validation was also a consideration in the choice of research methods. For classic grounded theory, the process of theory validation is based on the concept of research quality. Birks and Mills (2015) write that quality in grounded theory research methodology leads to theory credibility. They equate quality with procedural rigor. A quality grounded theory approach is demonstrated through controlled research processes and methodological congruence. Remenyi (2014) writes that credibility is based on two criteria: the quality of the scholarship employed and whether the research results have added something of value to the body of knowledge. Glaser and Strauss (1967) write that a grounded theory is neither right or wrong, but instead is validated if it demonstrates fit, relevance, workability, and modifiability. A theory is fit if is based on concepts that are closely connected to what they represent. A theory is relevant if it evokes "grab" or captures the attention and is not only of interest to the academic community. A theory works when it explains how it solves a problem. A theory is modifiable if it can be altered when new relevant data arises and changes the theory when compared with existing data. These methods of theory validation were compatible with this dissertation's goals of applying a rigorous methodology and solving real world problems by extending the systems body of knowledge.

C. DISSERTATION METHODOLOGY

This section describes how the classic grounded theory approach was applied to specifically answer the research question: What are the characteristics of the CASoS as a new class of systems, and how can they be engineered to address highly complex problems?

1. Initial Coding: Low Level Concepts

The first phase of the dissertation research was the development of initial or low level theoretical concepts. Initial coding, also referred to as open coding, is a process of fracturing or opening data to: compare incidents, identify phenomena and patterns, and begin the process of identifying conceptual possibilities (Holton 2007). Figure 13 illustrates this phase, listing the types of activities that were performed (inside the circle) and showing steps 1–4 of the theoretical method, as well as step 6, which occurs throughout the process. The classic grounded theory activities (purposive sampling, initial coding, data collection, data generation, theoretical sampling, constant comparative analysis, and category identification) occurred during the four steps of this phase. The following subsections present the research activities conducted during these first four steps, with a discussion of how discourse with peers and experts (step 6), occurred in each.

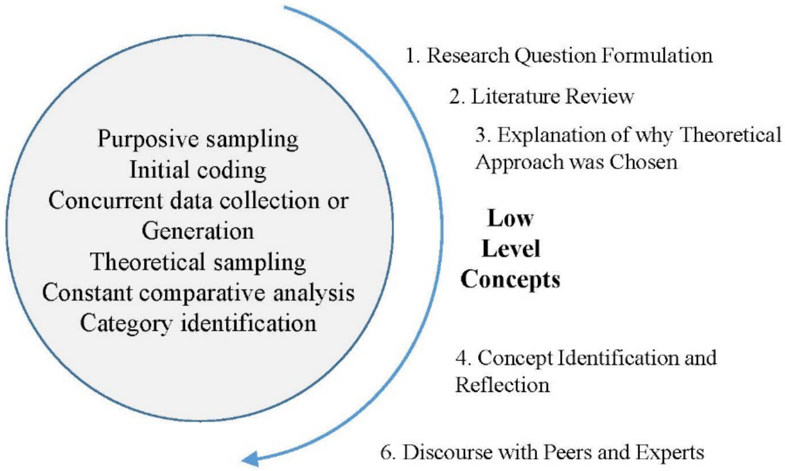

Figure 13. Initial Coding: Low Level Concepts. Adapted from Birks and Mills (2015).

a. Research Question Formulation (Step One)

Research began pragmatically with a goal of improving the U.S. naval warfighters' military advantage in complex tactical threat environments. Data collection consisted of studying maritime tactical threats, operational environments, and capability gaps in the Navy's ability to effectively address or outmaneuver tactical threats. Comparative analysis of this data exposed the challenges and surfaced patterns of complexity in the tactical problem domain. Additional data gathering and discourse with peers led to the concept that an engineered solution to the naval tactical problem domain would require the abilities to be adaptive and to rely on coordinated, yet distributed, warfare resources. Continued data gathering and open coding revealed the concept of a CASoS (Glass et al. 2011) as a potential solution to highly complex problems, such as the naval tactical domain. This resulted in the formulation of the research question, what are the characteristics of the CASoS as a new class of systems, and how can they address highly complex problems?

b. Literature Review (Step Two)

Literature review was the primary method of data collection throughout the research process. Literature review informed all three phases of the classic grounded theory coding process: initial, intermediate, and advanced. The objective of the initial coding phase was to understand how a systems approach might address complex problems based on studying existing approaches and the existing understanding of the characteristics of various systems. After reviewing many types of systems and system characteristics, a set of initial codes, establishing categories of systems, emerged. Additional forms of data collection resulted from coursework, targeted studies, and discourse with experts and peers. These initial codes and coded data are contained in Appendix A.

The process of data gathering also relied on theoretical sampling which is a process for generating theory by collecting data, coding or organizing the data, and deciding what data to collect next in order to allow a theory to emerge. Theoretical sampling was applied throughout the research process as new information sources were recommended by experts, discussed in related academic courses, and cited in the literature reviewed. Theoretical sampling was applied to the three primary knowledge domains of systems theory, SoS theory, and complex theory, as well as to the review of research methods, and complex problem domains.

c. Explanation of Why a Theoretical Approach Was Chosen (Step Three)

An intent of this dissertation was to produce methodological congruence—a state of accordance between the research philosophy, stated aims, and methodological approach (Creswell and Poth 2008). The overarching goals—to expand the body of knowledge of systems theory and identify an engineered solution approach to highly complex problems—provided a foundation for seeking an appropriate research philosophy and methodology. A review of inquiry methods and research philosophies ensued. This included a review of books and journals on research methods, as well as intellectual discourse.

Works from Remenyi (2014), Bryant and Charmaz (2007), Creswell and Poth (2018), and Patton (2015) informed the decision to use a theoretical approach, specifically the classic grounded theory approach. The major points of this research direction follow.

- The types of data available (literature review and use-cases of observed phenomena, information from discourse with experts) are suitable for the theoretical grounded theory method that can rely on qualitative data.

- The need to develop theory for engineered CASoS solutions to complex problems (Glass et al. 2011) and the desire to allow it to emerge from the process of data collection, critical analysis, comparison, and creativity, supported the decision to use the classic grounded theory research method. Classic grounded theory enables theory to emerge from constant comparative analysis and theoretical sampling of diverse qualitative data.

- Classic grounded theory is consistent with a systems approach, which views reality in terms of systems and their interactions as well as having a holistic perspective. With the objective of adding to the body of systems theory knowledge, classic grounded theory was an appropriate choice.

- The desire to provide validation and acceptance of the theory, was a strong factor in selecting classic grounded theory which provides a formal and rigorous research method for enabling valid theory to emerge from data and analysis.

- The decision to follow the classic grounded theory method was based on informed opinion, experience, and pragmatism.

d. Concept Identification and Reflection (Step Four)

The process of data collection, initial coding, and theoretical sampling, led to a deeper understanding of complex problems and initial concepts for the CASoS solution. This initial level consisted of identifying and understanding the naval tactical use-case as an exemplary complex problem. A better understanding of this use-case provided a conceptual basis for developing a theory for CASoS solutions.

The first research phase resulted in the following initial concepts: (1) the military domain is a complex problem, and therefore requires a complex solution; (2) an engineered solution for the tactical problem should take advantage of using distributed warfare systems as a SoS; and (3) taking a system approach to this problem enables a top-down holistic approach as well as a means of addressing the complexity aspects. The process of initial coding identified three primary categories for additional research: systems theory, SoS theory, and complex systems theory. The initial evidence showed that these bodies of knowledge form the basis for producing a theory for engineering a solution to certain highly complex problems. This led to a generalized approach to the problem: to describe the characteristics of complex problems; and by doing so, understand and describe the set of solution systems that could address such a problem domain. This generalized approach became the focus of the next phase of the grounded theory research approach: the development of medium level concepts or intermediate coding.

2. Intermediate Coding: Medium Level Concepts

Intermediate level coding and other associated grounded theory methods produced medium level concepts during the second phase of the dissertation research. The focus of this phase was the study of the theory and concepts that formed the foundation of the generalized treatment of CASoS as a solution approach to complex problems. Based on theoretical sampling, the decision following the first phase of initial coding was to generalize the problem domain and perform a rigorous study of the characteristics and principles of systems, SoS, and complex systems to provide the theoretical foundation for developing a theory of CASoS. Figure 14 illustrates the classic grounded theory approach followed during this phase of the research. This phase relied on intermediate coding to identify properties, dimensions, patterns, and relationships within the CASoS conceptualization. To do this, I applied theoretical sensitivity—the recognition and extraction of data elements that have relevance to the emerging theory—resulting in a focus on CASoS as a new class of system solutions. Theoretical saturation was the final state reached when the theoretical concepts were clearly articulated and any additional data reinforced the concepts rather than altering them (Glaser and Holton 2004).

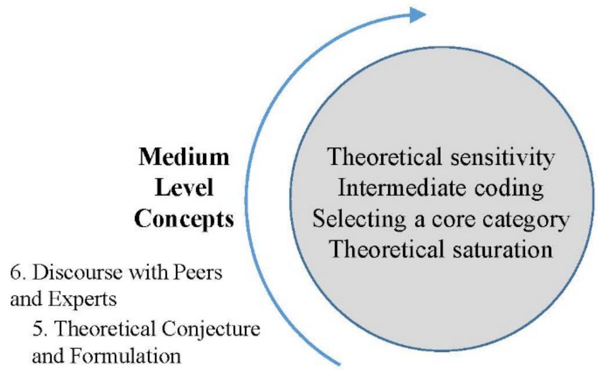

Figure 14. Intermediate Coding: Medium Level Concepts. Adapted from Birks and Mills (2015).

a. Theoretical Conjecture and Formulation (Step 5)

Data gathering for this phase consisted of a literature review of concepts, theorems, definitions, and axioms within the three core disciplines of systems theory, SoS theory, and complex systems theory. Information and feedback was obtained through coursework, discourse with peers and experts, and participation in conference presentations and publications. Data gathering was performed iteratively and concurrently with the process of intermediate coding of information into categories. The main categories of the intermediate coding were developed as: systems, purposeful systems, SoS, complex systems, complex adaptive systems (CAS) and CASoS. Figure 15 illustrates the relationships between these categories of systems. Appendix A contains the in-depth findings of the definitions, characteristics, and principles of each of these subclasses of system categories.

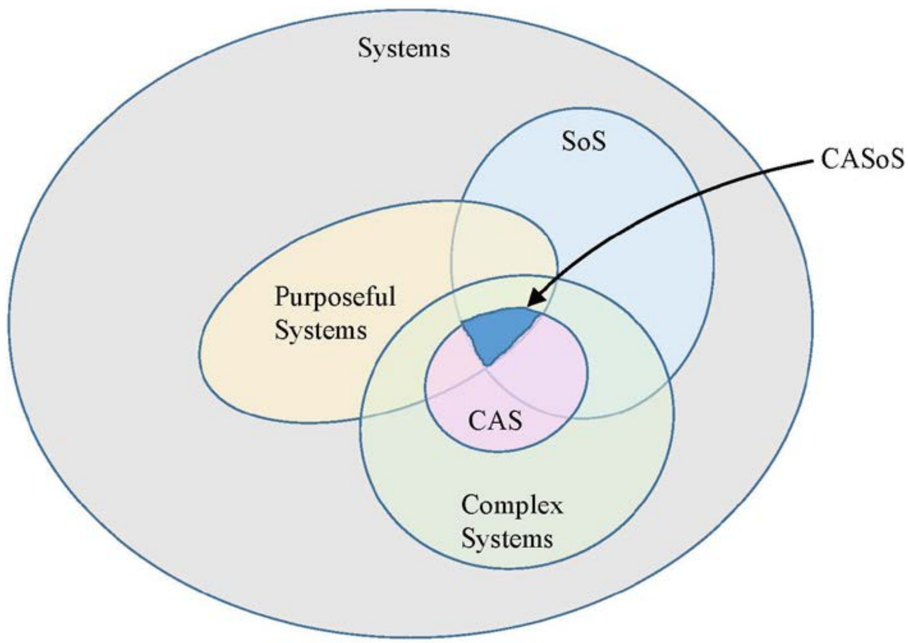

Figure 15. Intermediate Coding Categories

A study of highly complex problem domains produced a characterization of what constitutes such problem spaces based on intermediate coding. A comparative analysis of existing complex domains included problems identified by Bar-Yam (2004), Glass et.al. (2011), Braha, Minai, and Bar-Yam (2006), Alberts (2001, 2003, 2011), and Harney (2012). This data was coded and compared with data that described characteristics of complex environments: Ames et al. (2011), Calvano and John (2004), Miller and Page (2007), Mitchell (2009), Ottino (2003), Page (2011), and Stevens (2008). Data concerning these problems were gathered from literature review, coursework, and discourse with experts at conferences. The characterization of highly complex problems is discussed in Chapter IV.

The process of intermediate coding produced the theory for the CASoS class of engineered system solutions. The theory for the characteristics and principles of CASoS resulted from the identification and comparison of characteristics of systems, SoS, and complex systems from the literature review and data gathered. Appendix B contains a matrix of the data sources mapped to the CASoS theoretical codes. These codes emerged from the data as the categories of the characteristics and principles of CASoS. The process of iterative discourse with advisors and experts produced feedback and refinement of the theory. The theory reached theoretical saturation as additional data sources served only to reinforce the theory. The CASoS theoretical framework including the theory for the definition, characteristics, and principles of CASoS as well as the theoretical concepts for CASoS engineered implications is contained in Chapter IV.

A process of concept synthesis, further discourse, and evaluation, clarified the engineering implications of the CASoS theory. These implications formed the basis for the development of the conceptual design of an engineered CASoS solution to highly complex problems. Further reflection and analysis of the data gathered led to a derived set of engineered capabilities that would be required to design and build a CASoS. A number of papers were written describing these capabilities, which included distributed sensors to gain awareness of the environment, an intelligent and adaptive architecture for sharing data and information among a set of distributed intelligent agents that make decisions for constituent system actions as well as collective SoS actions. Feedback from publishing and presenting the papers led to further refinement of the CASoS required engineered capabilities. The results of this step are provided in Chapter V.

b. Discourse with Peers and Experts (Step Six)

Discourse with peers and experts was a crucial contributor to this dissertation. The exchange of ideas in every step of the research process, informed the decisions for how to proceed, provided a wealth of knowledge, and directly influenced the CASoS theory that emerged. The following methods were used to gain this discourse: taking courses (Systems of Systems, Complex Systems, and Systemic Strategic Thinking), participating in conferences (Complex Adaptive Systems Symposium, National Fire Control Symposia, Complex Systems Conferences, IEEE Systems Conferences, Military Operations Research Symposium, and the Association of the Advancement of Artificial Intelligence Symposia), and conversing, informally, with many experts from these groups and with faculty members of the Naval Postgraduate School. In many cases, the discourse led to recommendations for more sources for the literature review. In some cases, the discourse led to decisions, such as the focus of the dissertation, the choice of research method, the choice of the focused use-case application. Discourse also provided invaluable feedback for the CASoS theory and derived engineered capabilities and approach.

3. Advanced Coding: High Level Concepts

The final high-level concept phase consisted of advanced coding and theoretical integration. It focused on integrating the coded data and concepts from the intermediate phase into a coherent theory for the new class of CASoS. Figure 16 illustrates this final phase of the research approach. The steps during this phase were “theoretical conjecture, refinement, and acceptance” (step 7) and “discussion on impact and implications” (step 8). Discourse with peers and experts (step 6) occurred during steps 7 and 8.

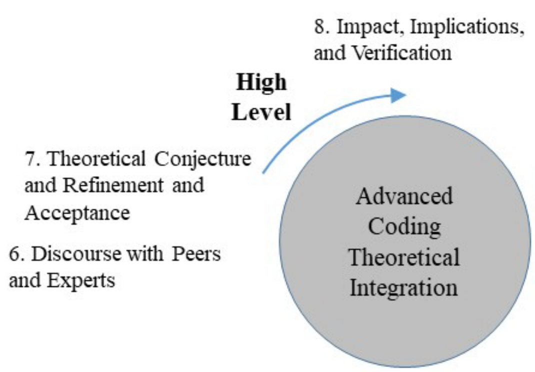

Figure 16. Advanced Coding: High Level Concepts. Adapted from Birks and Mills (2015).

a. Theoretical Conjecture and Refinement and Acceptance (Step 7)

The advanced coding and theoretical integration consolidated the abstract concepts into a final grounded theory for an engineered CASoS. This final coding process allowed refinement of the theory based on the process of mapping the CASoS theory to advanced codes representing engineered capabilities. This process produced a conceptualization of an engineered CASoS, which is presented in Chapter V. Feedback from peers and experts was incorporated as amendments and refinements to the theory. This feedback provided greater clarity, completeness, and accuracy to the theoretical concepts.

The process of theoretical conjecture provided an explanatory theory for an engineered CASoS based on the initial and intermediate levels of coding. The development of a conceptual CASoS design provided a method for understanding how the CASoS approach becomes a workable solution. The solution depended on the derived set of engineered capabilities that must exist (or be required) for an intentionally designed CASoS to be a viable solution. These capabilities must exist for the engineered solution to attain the needed CASoS characteristics.

b. Impact, Implications, and Verification (Step 8)

The final research step was a study of the theory's impact and implications. There were two areas of engineering implications from the CASoS theory: (1) a set of required capabilities, and (2) a required systems engineering approach. Advanced coding techniques produced these engineering implications. A mapping of the CASoS theoretical characteristics and principles to a set of system property codes produced a conceptualization of an engineered CASoS along with required capabilities. Secondly, a study of data gathered for three codes: traditional systems engineering, systems of systems engineering, and complex systems engineering, produced implications for a CASoS systems engineering approach.

A modeling and simulation analysis of a specific application of the CASoS approach provided data to demonstrate theory validation. This analysis compared a CASoS solution approach to the naval tactical domain with a baseline non-CASoS approach. The results of this analysis (presented in Chapter VI) provided insight into CASoS and non-CASoS interactions with a complex environment. The modeling and simulation results support the grounded theory validation objective of demonstrating that the theory has fit, relevancy, workability, and modifiability.

The final form of the theory establishes the characteristics and principles of CASoS as well as implications for how a CASoS can be engineered to address highly complex problem domains.

IV. CASoS GROUNDED THEORY

A. INTRODUCTION[4]

> A high complexity task requires a system that is sufficiently complex to perform it. (Bar-Yam 2004a, 99)

A new class of theoretical CASoS systems is intended to address highly complex problems that arise in operational environments through engineered complex solutions. This idea has led to the dissertation's central research question: How can a CASoS solution be engineered to address highly complex problems? This chapter presents a theory for CASoS, which includes the definition, characteristics, and principles for this new class of complex systems.

In the remainder of this chapter, Section B provides an explanation of the key findings and patterns that were discovered as data was gathered. Examples of the process of open coding and selective coding demonstrate the research process. Section C contains the grounded theory of CASoS. This includes a discussion on how the theory fits into systems theory. It includes the theory for what constitutes highly complex environments that require a CASoS solution. Finally, it includes the theoretical definition, characteristics, and principles of CASoS as a new class of engineered system solutions.

B. THE EMERGENCE OF THE CASoS GROUNDED THEORY

A classic grounded theory approach was taken to gather and analyze data related to complex problems and system solutions through which a potential engineered solution could be discovered. Figure 17 is an overview of the coding process, highlighting the major steps that led to a theory for CASoS, as a new class of engineered solutions.

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[4] Parts of this chapter were previously published by:

The Grounded Theory Review (Bonnie Johnson, Karen Holness, Wayne Porter, and Alejandro Hernandez. 2018. "Complex Adaptive Systems of Systems: A Grounded Theory Approach." *The Grounded Theory Review* 17 (1): 52–69.)

Proceedings of the 18th Annual International Command and Control Research and Technology Symposium (ICCRTS) (Young, Bonnie (now publishing as Bonnie Johnson). 2013a. "Complex Systems Engineering Applications for Future Battle Management and Command and Control." In *Proceedings of the 18th Annual ICCRTS*, Alexandria, VA, 19–21 June 2013.)

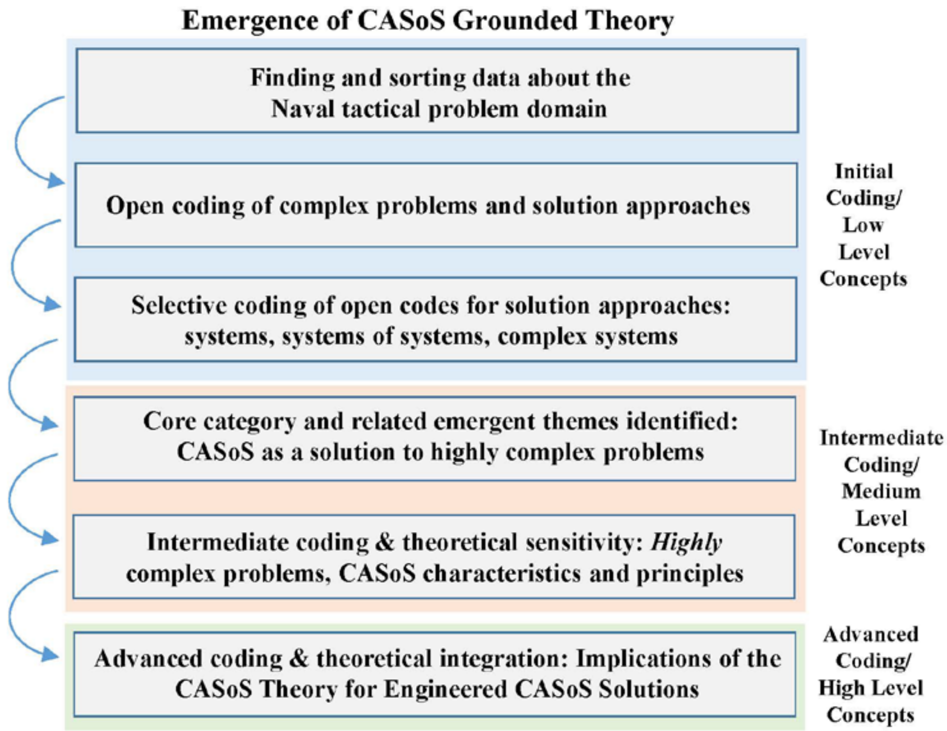

Figure 17. Overview of Coding Process

The first three steps of initial or open coding included gathering and coding data concerning (1) the naval tactical problem domain, (2) complex problems in general and their solution approaches, and (3) selective coding in three bodies of knowledge: systems, systems of systems, and complex systems. Intermediate coding consisted of the selection of the core category and related emergent themes, and the coding of highly complex problems and CASoS characteristics and principles. This process produced an emerging theory for a new class of engineered solutions to highly complex problems, designated as CASoS. Finally, the advanced coding phase studied the implications of the CASoS theory. The details of the initial and intermediate coding results are described in this chapter. The advanced coding phase and its results are discussed in Chapter V.

1. Initial Coding

a. Finding and Sorting Data about the Naval Tactical Problem Domain

Research began pragmatically with a goal of improving the U.S. naval warfighters' military advantage in complex tactical threat environments. Data collection consisted of studying maritime tactical threats, operational environments, and capability gaps in the Navy's ability to effectively address or counter tactical threats. Comparative analysis of this data was performed by identifying characteristics of the tactical maritime environment and comparing these to a set of characteristics of complex problem domains that are defined in current literature. The results of this initial coding are contained in several publications: Johnson, Green, and Canfield 2001, Johnson 2002, Johnson and Green 2002b, Young 2004a, Young 2004b, Young 2005, Young 2012, Young 2013a, Young and Green 2014, Johnson and Hernandez 2016. The analysis and publications expose the challenges and patterns of complexity in the naval tactical problem domain. Johnson, Green, and Canfield (2001) provided evidence of the potential performance benefits of a SoS approach, in which distributed warfare systems would be networked for coordination using automated intelligence. Potential benefits included significant improvements in overall probability of kill and better usage of weapon resources through improved situational awareness (SA) and a layered defense. Another key result was the observation of a pattern of complex behavior in the tactical problem domain (Young 2013a). Additional literature review (Alberts 2011, Ames 2011, Bar-Yam 2004a, Calvano and John 2004, Levin 2002) and discourse with experts, led to the concept that any engineered solution to the tactical domain would require the ability to adapt to dynamic situations and threats.

b. Open Coding of Complex Problems and Solution Approaches

Continued data gathering through literature review revealed the concept of a CASoS (Glass 2011) as both a description of highly complex problems and as an approach to addressing them. Purposive sampling identified additional problem domains that had similar phenomenon and characteristics to the naval tactical problem. These cases provided information-rich comparisons that resulted in the identification of patterns of similar complexity characteristics in the different problem domains. These patterns led to the decision to generalize the study of CASoS as a potential engineered solution beyond the single focus on the naval tactical case.

The process of data collection, initial coding, and theoretical sampling, led to a deeper understanding of complex problems and initial concepts for the CASoS solution. Initial coding included identifying and understanding the naval tactical use-case as an exemplary complex problem. A better understanding of this use-case provided a conceptual basis for developing a theory for CASoS solutions.

Viewing the problem domain through a systems approach facilitated conceptually organizing warfare assets as distributed resources. This resulted in identifying common command and control functionality across military platforms and patterns of similar system characteristics. This conceptually shifted the focus from a platform-centric paradigm to a network-centric paradigm, enabling a foundation for SoS concepts (Johnson 2002). The research process identified solution concepts based on collaborations among distributed warfare assets, such as layered defense and interoperability within the Navy (Johnson and Green 2002b). Research on distributed sensor resource management included an example of implementing a set of distributed systems as a SoS in a network-centric paradigm (Johnson and Green 2002a).

Continued emphasis on a SoS approach of using weapon and sensor systems from different ships and aircraft to operate collaboratively led to identifying categories and types of possible collaborations. The functions for combat engagement, or weapons-fire control, were identified and defined in general terms. Each function was studied to determine if it could be performed in a distributed manner. A number of distributed engagement concepts were developed, including precision cue, launch on remote, engage on remote, forward pass, remote fire, and preferred shooter determination (Young 2005).

A course on complex systems prompted a study of the tactical domain as a complex problem. Several sources from literature stated that complex problems can only be addressed by complex system solutions (Bar-Yam 2003a, 2004a; Calvano and John 2004). Based on this concept, the tactical domain was studied to determine if it had the characteristics of complexity (Young 2013a). First, the data was gathered to define the characteristics of complexity. Next, a comparative analysis related the problem domain to the characteristics of complexity. The analysis resulted in a determination that the tactical problem domain is, in fact, a complex problem space. In addition, the expected behavioral complexity of this domain was better understood and could be used to support an improved approach to the solution concepts. An additional result was a method by which future problem domains could be classified as complex or not.

The research process produced conceptualization of engineered approaches to battle-management that enable SoS collaboration among distributed warfare assets. One area of study was automated battle-management decision aids. Tactical decisions within the problem domain were identified and studied in terms of areas that could benefit from the support of automated decision aids (Johnson 2001). A number of studies produced concepts for decision aid capability and functionality as well as a distributed architecture to support these concepts (Young 2004a, 2004b, 2005, 2012). One concept resulting from this area of the research was the idea of a designer SoS—an approach in which the collaborations of warfare assets could be designed during operations to enable near-real-time adaptation to the tactical environment (Young 2013b). Another idea was to focus future tactical architectures and processes within a decision paradigm that focuses on warfare actions to be taken rather than on achieving situational awareness as the end goal (Young and Green 2014).

Initial open coding resulted in the following concepts: (1) the military domain is a complex problem, and therefore requires a complex solution; (2) an engineered solution for the tactical problem should take advantage of using distributed warfare systems as a SoS; and, (3) taking a system approach to this problem enables a top-down holistic approach as well as a means of addressing the complexity aspects. The process of initial coding identified three primary categories for additional research and selective coding: systems theory, SoS theory, and complex systems theory. The initial evidence showed that these bodies of knowledge form the basis for producing a theory for engineering a solution to certain highly complex problems. This led to a generalized approach to the problem: to describe the characteristics of complex problems; and by doing so, to understand and describe the set of solution systems that could address such a problem domain. This generalized approach became the focus of the next phase of the grounded theory research approach: selective coding.

c. *Selective Coding of Open Codes for Solution Approaches: Systems, Systems of Systems, Complex Systems*

Selective coding focused on gathering and coding data from three bodies of knowledge: systems theory, SoS theory, and complex systems theory. A number of system principles, axioms, and laws were identified, providing insight into, and explanations of system behavior and behavioral effects. Data was gathered from literature and coded according to four categories: systems, purposeful systems, systems of systems, and complex systems. This initial organization of data was based on the goal of examining systems and their characteristics and principles and then understanding three special cases of systems with potential traits for addressing complex problems: purposeful systems, systems of systems, and complex systems.

As a result of the selective coding, the primary characteristics of systems were found to be: openness (interactions with environment involving exchanges of inputs and outputs); boundary (a construct that distinguishes the system from its environment); architecture (the form of the system); and behavior (the actions performed internally or in conjunction with its environment). These characteristics formed the foundation for coding the characteristics of CASoS during the intermediate coding phase. Each of the three specialized types of systems contributes additional characteristics based upon their intrinsic traits:

- Purposeful systems were identified as being capable of self-organization, autonomy, and directiveness, which means they are goal-seeking and capable of self-regulation. They are not reliant on an external source of control. This requires purposeful systems to have situational awareness that enables them to dynamically evolve toward longer-term goals.

- Systems of systems consist of interoperable constituent systems that can act independently and also to collaborate—thus they exhibit behavior at multiple levels. They can produce constituent system level behavior as well as emergent SoS level behavior. Constituent systems can be separated from one another geographically. SoS behavior can be dynamically nonlinear and can result in cascading effects.

- Complex systems are characterized by large numbers of interconnected constituent systems that are often highly varied. The constituent systems self-organize at the local level and produce system-wide emergent behavior that can be characterized by nonlinear dynamics. Complex system behavior can be reflexive, impacting nearby constituent systems as well as the environment. This triggers environmental changes and varied feedback loops causing increased dynamic behavior.

Table 2 lists the types of characteristics and principles of each of these four codes. The characteristics and principles were based on the data gathered from literature. Appendix A contains the details of the selective coding process.

Table 2. Selective Coding

Systems	Purposeful Systems	Systems of Systems	Complex Systems
Characteristics			
Openness Boundary Architecture Behavior	Autonomy Self-organization Directiveness Situational awareness Purposeful evolution	Collaboration Interoperation Interdependence Multi-level behavior Emergence Geographic distribution Non-linear dynamics Cascade effects	Self-organization Connectedness Variety and number Governed by feedback and reflexivity Emergence Non-linear dynamics Cascade effects
Principles, Axioms, and Laws			
Principle of Adaptation & Viability Centrality Axiom Principle of Connected Variety Contextual Axiom Principle of Cyclic Progression Law of Entropy Principle of Equifinality	Goal Axiom Operational Axiom Design Axiom Principle of Conditional Dependency Principle of Counterintuitive Behavior	Principle of Sub-optimization	Principle of Holism Principle of Local Information Darkness Principle 80/20 Principle Principle of Behavior Prediction Principle of Sub-optimization Principle of Irreversibility

Systems	Purposeful Systems	Systems of Systems	Complex Systems
Principle of Multifinality Law of Evolution Principle of Expansionism Information Axiom Principle of Limited Variety Principle of Multidimensionality Principle of Plurality Principle of Preferred Patterns			Principle of Self-organization

Appendix A defines and describes the principles in detail. This section highlights the results of this part of the selective coding process that affected the selection of the core category:

- Many system principles from the data included explanations of how systems adapt to, endure, and interact with their environment; achieve states of equilibrium; and progress on goal-oriented paths of evolution and cyclical life cycles. Principles addressed the impact of initial conditions on system end states, the hierarchical nature of many systems, and the ability of systems to produce, transfer, and modify information. They also explored how limits in system variety and architecture can constrain the ability for systems to adapt, endure, interact, and achieve stability.

- The principles of purposeful systems added some useful insights: the ability for purposeful systems to achieve specific goals is dependent on system structures, relationships, interactions, resources and behavior—and that these can support reaching goals or limit them. Conditional dependency exists—the behavior of each subsystem influences the behavior of others. Also, some desired behavior is the result of counterintuitive actions or negative feedback loops.

- The study of SoS principles uncovered the sub-optimization principle which explains that if one of the constituent systems operates most efficiently, the SoS will be less than optimal. And that if the SoS has optimum efficiency, then the constituent systems will be less than optimal. Thus, a balance must be established between the optimization of independent and collaborative behavior.

- The principles of complex systems highlighted the importance of irreversibility or the history-dependent nature of complex system courses of action; explaining that self-organization can be purposeful or can occur spontaneously as a result of feedback and interaction with a changing environment. The ability to predict complex behavior and effects is dependent on the level of chaos within the system and gaining an accurate understanding of a complex system requires multiple representations dependent on the level of chaos and linearity.

2. Intermediate Coding

a. Core Category and Related Emergent Themes Identified: CASoS as a Solution to Highly Complex Problems

A process of reflection following the selective data coding process, produced several results. One was the potential of system solutions that are purposeful, comprised of systems of systems, and complex to address complex problems. Key features of the solution would include:

- the ability to produce desired multi-level, multi-minded, adaptive behavior,
- an architecture that promotes adaptive behavior, information exchange, and shared situational awareness, and,
- the ability for geographically distributed constituent systems to collaborate in a goal-oriented manner.

The initial set of characteristics and principles that resulted from selective data coding provided a framework for organizing the concepts that led to identifying CASoS as a possible class of engineered system solutions to complex problems. CASoS became the core variable selected as the focus of the intermediate coding phase. Related concepts included the need to (1) characterize highly complex problems and (2) differentiate CASoS from other types of systems and to establish how they fit into systems theory, in order to allow a theory to emerge for the definitions, characteristics, and principles of engineered CASoS as a set of solutions to highly complex problems.

b. Intermediate Coding and Theoretical Sensitivity: Complex Problems, CASoS Characteristics and Principles

The intermediate coding phase consisted of gathering, analyzing, and coding data from literature sources and discourse with experts. Data was coded according to CASoS characteristics and principles, with a goal of enabling a theory for the definition of CASoS and its characteristics and principles to emerge. The codes and subsequent understanding of the class of engineered CASoS systems emerged through a process of refinement and revision until arriving at a state of theoretical saturation when the codes remained unaltered by new data. The initial set of codes for CASoS definition, characteristics, and principles were based on the codes from the selective coding process. Some of these codes were combined, revised, and in some cases, eliminated, as the analysis uncovered what codes were appropriate for engineered CASoS to address highly complex problems.

Table 3 contains the data references that led to definition of the class of CASoS. The definition emerged from 17 data sources that included high-level definitions from the Sandia Phoenix project and many definitions of complex systems and complex adaptive systems.

Table 3. Coded Data References for CASoS Definition

Code	# of Data	Data References
Definition of a CASoS	17	Ames et.al. (2011), Bar-Yam (1997, 2003, 2004a), Fisher (2006), Glass et al. (2008, 2011), Harney (2012), Hitchins (1992, 1996, 2003, 2007), Holland (1992), Levin (2002), Miller and Page (2007), Mitchell (2009), Ottino (2003)

Table 4 presents the data references for system characteristics that were gathered and coded. The data came from sources discovered during the selective coding process, from secondary literature sources, and from sources identified through discourse with peers and experts. The codes emerged from a combination of the selective coding process and from the patterns of CASoS characteristics that were identified during the process of organizing the data. The number of data sources that referenced each type of system characteristic that related to CASoS provides an indication of the importance of that characteristic as a fundamental trait or in some form of application. Openness and boundary are each referenced seven times in the data gathered. The data indicated that there were both fundamental characteristics of all systems, but not necessarily central to the actual addressing of complex problems. Constituent variety, on the other hand, was not a fundamental characteristic of all systems, but was mentioned frequently as an important trait of complex systems. Architecture, behavior, and complexity were the characteristics mentioned most frequently in the data as distinguishing traits of system solutions to complex problems. Particular types of architecture and behavior were mentioned as being key enablers for solving complex problems. Complexity was mentioned many times in the data as a required system characteristic to address complex problems.

Table 4. Coded Data References for CASoS Characteristics

Code	# of Data	Data References
Openness	7	Adams, Hester, Meyers, and Keating (2014), Akers, Hester, Bradley, Meyers, and Keating (2014), Bertalanffy (1950, 1951), Checkland (2000), Gharajedaghi (2011), Hitchins (1992)
Boundary	7	Bertalanffy (1951, 1968), Checkland (1993, 2000), Skyttner (2005), Hitchins (1992, 2007)
Constituent Variety	19	Ackoff and Emery (1972), Adams, Hester, Bradley, Meyers, and Keating (2014), Akers, Keating, Gheorghe, and Sousa-Poza (2015), Boulding (1956), Camazine, Deneubourg, and Franks (2001), Emery (1969), Holland (1992, 1995), Levin (2002), Miller and Page (2007), Mitchell (2009), Ottino (2003), Page (2011), Petrov (2002), Richardson (2004, 2004, 2005, 2007), Skyttner (2001)
Architecture	28	Ackoff (1971), Ackoff and Emery (1972), Adams, Hester, Bradley, Meyers, and Keating (2014), Ashby (1962), Barbasi (2003), Bar-Yam (2003, 2004), Carbrera and Carbrera (2015), Dagli and Kilicay-Ergink (2009), Dahmann, Rebovich, and Baldwin (2009), Holland (1992, 1995), Keating (2009), Maier (1998), Maier and Rechtin (2000), Miller and Page (2007), Moffat (2003), Nichols and Dove (2011), Ottino (2003), Richardson (2004, 2004, 2005, 2007), Ryan (2006), Skyttner (2001), Vakili, Tabatabaee, and Khorsandi (2012), Wiener (1948, 1961)

Code	# of Data	Data References
Behavior	46	Ackoff and Emery (1972), Adams, Hester, Bradley, Meyers, and Keating (2014), Akers, Keating, Gheorghe, and Sousa-Poza (2015), Ashby (1962), Bar-Yam (1997, 2003, 2004, 2004), Boulding (1956), Carbrera and Carbrera (2015), Camazine, Deneubourg, and Franks (2001), Efatmaneshnik, Bradley, and Ryan (2016), Emery (1969), Giammarco (2017), Gould (2002), Harney (2012), Hitchins (1992, 1996, 2003, 2007), Ho, Richards, and Gonsalves (2006), Holland (1992, 1995), Keating (2009), Langford (2017), Levin (2002), Lowe and Ng (2006), Marsh (2009), Miller and Page (2007), Moffat (2003), Nichols and Dove (2011), Oliver, Kelliher and Keegan (1997), Ottino (2003), Petrov (2002), Polacek, Giannetto, Khashanah, and Verma (2012), Richardson (2004, 2004, 2005, 2007), Ryan (2006), Sheard (2007), Skyttner (2001), Stacey (1995), Sterman (2000), Stevens (2008), Vakili Tabatabaee, and Khorsandi (2012)
Complexity	39	Akers, Keating, Gheorghe, and Sousa-Poza (2015), Allen (2016), Ames, Glass, Brown, Linebarger, Beyeler, Finley, and Moore (2011), Bar-Yam (1997, 2003, 2004, 2004), Calvano and John (2004), Cilliers (1998), Efatmaneshnik, Bradley, and Ryan (2016), Harney (2012), Hitchins (1996), Ho, Richards, and Gonsalves (2006), Holland (1992, 1995), Hooper (2009), Levin (2002), Levy (2000), Lowe and Ng (2006), Miller and Page (2007), Mitchell (2009), Moffat (2003), Oliver, Kelliher and Keegan (1997), Ottino (2003, 2004), Page (2011), Petrov (2002), Polacek, Giannetto, Khashanah, and Verma (2012), Richardson (2004, 2004, 2005, 2007), Senge (2006), Sheard (2007), Stacey (1995), Sterman (2000), Stevens (2008), Suh, Furst, Mihalvov, and deWeck (2010), Vakili Tabatabaee, and Khorsandi (2012)

Figure 18 shows the codes for the CASoS characteristics and their relationships to the subcategories that resulted from the intermediate coding. The characteristics are organized according to six categories: openness, architecture, behavior, constituent variety, boundary, and complexity. Four of the six categories are further refined into a next level of greater detail. These characteristics are defined and discussed more fully in Section C of this chapter. They constitute the desired traits of an engineered CASoS solution to highly complex problems.

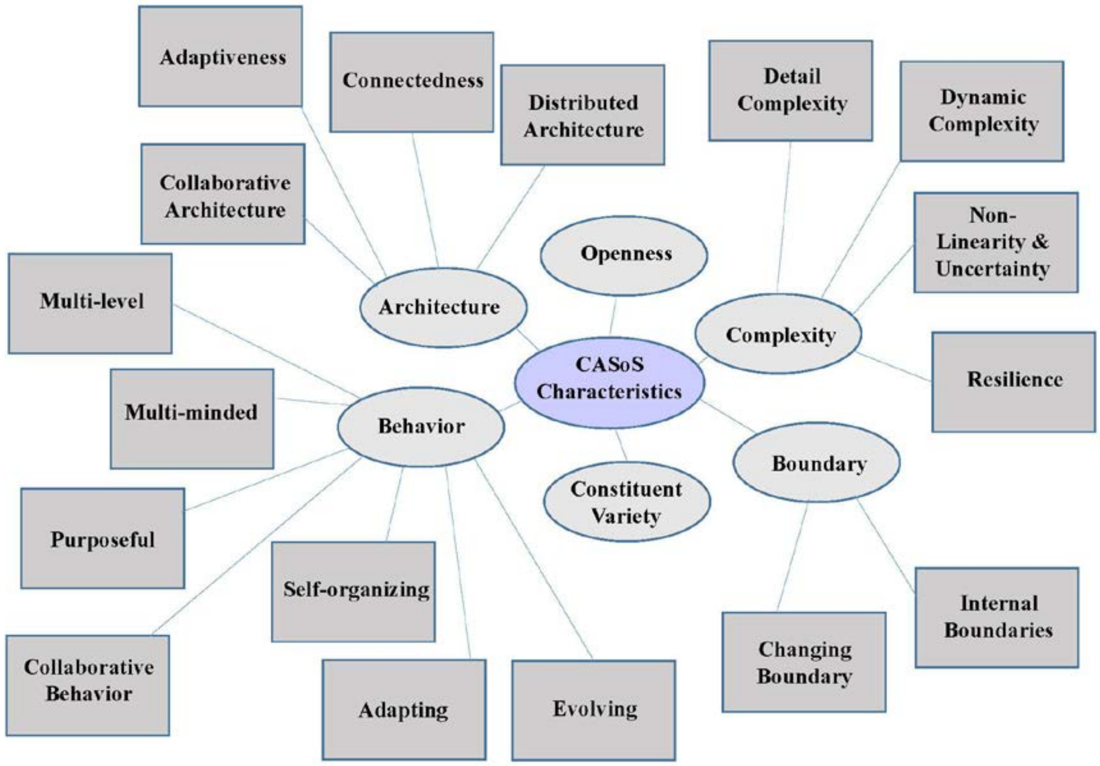

Figure 18. Codes for CASoS Characteristics

The high-level CASoS characteristic codes of openness, architecture, behavior, and boundary are based on system characteristics. The codes of constituent variety and complexity are more specific to CASoS. The sub-category codes for architecture, behavior, boundary, and complexity sub-categories reflect the unique characteristics of CASoS. This theory for CASoS characteristics is based on evidence from the data gathered and an iterative coding process that revised the organization of characteristics to reflect the data and to ensure consistency among the characteristics. For example, the CASoS architecture must support the system of system and complexity aspects of this class of systems. Therefore, the architecture must connect and support distributed constituent systems and their collaborations and interactions. Additionally, the architecture must be adaptive itself, to support the overall adaptiveness of the CASoS to its complex environment. The architecture also has an inherent connectedness which reflects a high level of interaction that is inherent to complex systems. Developing the theory for CASoS characteristics required a process of examining each code and comparing it to all of the other codes for consistency and clarity.

Some of the critical evidence from coded data that shaped CASoS characteristics included:

- Hitchins' (2009) explanations of systems of systems and their innate similarity to systems in every respect except for behavior at multi-levels and the ability for independent behavior of constituent systems. This supported a systems-thinking perspective of SoS and also provided an explanation of emergence as a result of multi-level behavior and interaction.

- Purposeful systems, as discussed by Ackoff and Emery (1992) and Boulding (1956), are explained as having intentional behavior and actions which implies intentional emergence for CASoS.

- Ashby (1962)'s description of self-organizing systems, combined with many references to self-organization as a key characteristic of complex systems, indicated that the constituent systems of a CASoS must be able to self-organize. Coupling this concept with the ideas of purposefulness, resulted in the concept of CASoS purposeful or intentional self-organization. This also implies intentional collaboration, adaptiveness, and emergence.

- Adaptiveness, in terms of behavior, is discussed in a number of systems theory articles and books. However, Akers, Keating, Gheorghe, and Sousa-Poza (2105), Holland (1992, 1995) and Ryan (2006), distinguish adaptive behavior from reactive behavior and attribute a purposefulness to intelligent adaptive behavior that requires sensing the environment and anticipating the effects of adaptive behavior. These concepts provided a basis for the defined CASoS characteristic of adaptive behavior.

- Adaptiveness as an inherent characteristic of the CASoS architecture was an idea from discourse with Dr. Hernandez (NPS 2016). Hernandez proposed the idea that the overall adaptive behavior of the CASoS would be a result of adaptive interactions between constituent systems. Thus, an adaptive architecture would be a CASoS characteristic.

- The characteristic of multi-mindedness originated from ideas from the naval tactical use-case in which a collaborative solution would need to address multiple threats or missions concurrently. Gharajedaghi (2011) was a key data source that supported this concept.

- The concept for the changing boundaries was originally a result of considering the naval tactical domain and understanding how the participation of an additional warfare resource (e.g., ship, aircraft, etc.) might affect a collaborative network and conversely, how collaboration would be affected if a warfare resource is destroyed or leaves the collaborative network (Young 2012). This concept translated to this study as the effect of additions or subtractions of constituent systems in an overall CASoS.

- Holland (1992) introduces the concept of a complex adaptive system that evolves as it steadily exhibits new forms of emergent behavior. This provided conceptual evidence for including evolving behavior as a key characteristic of CASoS.

Table 5 presents the data references for system principles that were gathered and coded. The data for system principles came from the selective coding process, from secondary literature sources, and from peers and experts. The codes emerged from a combination of the selective coding process and from the patterns of CASoS principles that were identified during the process of organizing the data. The Principle of Holism was referenced the most times as a key principle of systems and especially as an enabler of emergence and SoS meta-level behavior needed to address complex problems. Fourteen data references led to the definition of the Principle of Operational Viability for CASoS. These references discussed the importance of stability and resilience for sustaining a viable system solution. The Contextual Principle, the Goal Principle, and the Principle of Requisite Variety each had 11 data references supporting them as required abilities to address complexity in the problem space. The High Flux Principle (with 5 references) and the Information Principle (with 4 references) were based on fewer data references, but were considered important principles of CASoS as the data indicated they were specifically required to address complex problems.

Table 5. Coded Data References for CASoS Principles

Code	# of Data	Data References
Holism	26	Adams, Hester, Bradley, Meyers, and Keating (2014), Ashby (1962), Beer (1979), Checkland (1993), Cilliers (1998), Hitch (1953), Hitchins (1992, 1996, 2003, 2009), Holland (1992, 1995), Korzybski (1994), Paul, Beitz, Feldhusen, and Grote (2011), Petrov (2002), Phelan (1998), Rasch and Knodt (1994), Richardson (2004, 2004, 2005, 2006), Simon (1955, 1956), Skyttner (2001), Smuts (1926), Wiener (1961)
Contextual	11	Adams, Hester, Bradley, Meyers, and Keating (2014), Cilliers (1998), Holland (1992, 1995), Petrov (2002), Richardson (2004, 2004, 2005, 2006), Skyttner (2001), Weinberg (1975)
Goal	11	Adams, Hester, Bradley, Meyers, and Keating (2014), Hitch (1953), Holland (1992, 1995), Korzybski (1994), Petrov (2002), Simon (1955, 1956), Skyttner (2001), Wiener (1948, 1961)
Operational Viability	14	Adams, Hester, Bradley, Meyers, and Keating (2014), Hitchins (1992, 1996, 2003, 2009), Holland (1992, 1995), Paul, Beitz, Feldhusen, and Grote (2011), Petrov (2002), Richardson (2004a, 2004b, 2005, 2006), Skyttner (2001)
Requisite Variety	11	Adams, Hester, Bradley, Meyers, and Keating (2014), Ashby (1956, 1962), Holland (1992, 1995), Petrov (2002), Richardson (2004a, 2004b, 2005, 2006), Skyttner (2001)
High Flux	5	Richardson (2004a, 2004b, 2005, 2006), Skyttner (2001)
Information	4	Adams, Hester, Bradley, Meyers, and Keating (2014) McCullough (1959), Petrov (2002) Skyttner (2001)

Figure 19 shows the codes for the CASoS principles and their relationships to the subcategories that resulted from the intermediate coding. This dissertation identifies and defines seven theoretical principles of CASoS that serve as required fundamental concepts or aspirations for engineering a CASoS as a solution to highly complex problems. The seven principles are: holism, context, goal, operational viability, requisite variety, information, and high flux. Four of the seven are based on lower-level system principles that provide a conceptual foundation. The CASoS principles are defined and described later in this chapter in Section C.

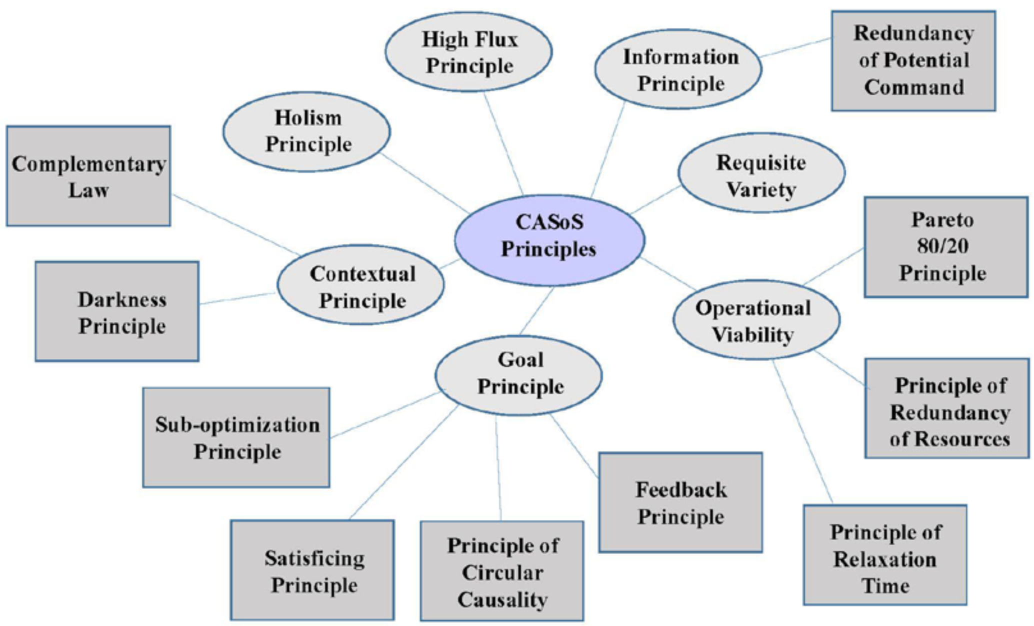

Figure 19. Codes for CASoS Principles

Table 6 contains the data references for the related themes—the supportive concepts for the CASoS theory. The data was gathered from literature sources found during the selective coding process, from secondary sources, and from discourse with experts. The codes emerged from the selective coding process that produced the core variable and the related themes. Data was then organized according to the two themes. Both themes were supported by a significant number of sources. The first theme concerning the characteristics of highly complex environments, was discussed in 13 sources that provided explanations and examples of how complex environments arise and descriptions of the root causes of complexity. A definition of the characteristics of complex environments resulted from comparing the data sources and developing a comprehensive list. The second related theme, concerning how CASoS fits into systems theory, was based on 15 data sources that discussed how complex systems, adaptive systems, and SoS fit into systems theory. A master data matrix can be found in Appendix B.

Table 6. Coded Data References for Related Themes

Code	# of Data	Data References
Characteristics of highly complex environments	13	Allen (2016), Ames et.al. (2011), Bar-Yam (1997, 2003, 2004), Calvano and John (2004), Glass et al. (2008, 2011), Harney (2012), Miller and Page (2007), Mitchell (2009), Ottino (2003), Page (2011), Stevens (2008)
CASoS within Systems Theory	15	Ackoff (1971), Azani (2009), Bar-Yam (2004a), Dagli and Kilicay-Ergink (2009), Dahmann, Lane, Rebovich, and Baldwin (2009), Dahmann, Rebovich, and Baldwin (2009), Efatmaneshnik, Bradley, and Ryan (2016), Fisher (2006), Giammarco (2017), Jackson and Keys (1984), Keating (2009), Langford (2017), Maier (1998), Nichols and Dove (2011), Zhang, Huang, Zhang, and Liu (2006)

C. GROUNDED THEORY FOR CASoS

This section presents the grounded theory for CASoS. The theory for CASoS is organized into (1) the core variable (the definition, characteristics, and principles), and (2) the related themes (complex operational environments and the relationship between CASoS and systems theory). Figure 20 illustrates the components of the CASoS theory. This section is organized as follows: (1) highly complex environments, (2) definition of a CASoS, (3), explanation of how CASoS fits within systems theory, (4) CASoS characteristics, and (5) CASoS principles. It begins with highly complex environments, as an understanding of this related theme provides necessary context for the definition of a CASoS, which follows. Next, a discussion on how CASoS differs from other classes of systems is presented. This related theme provides important context for the CASoS definition. Finally, the last two sections present the theory for the CASoS characteristics and principles.

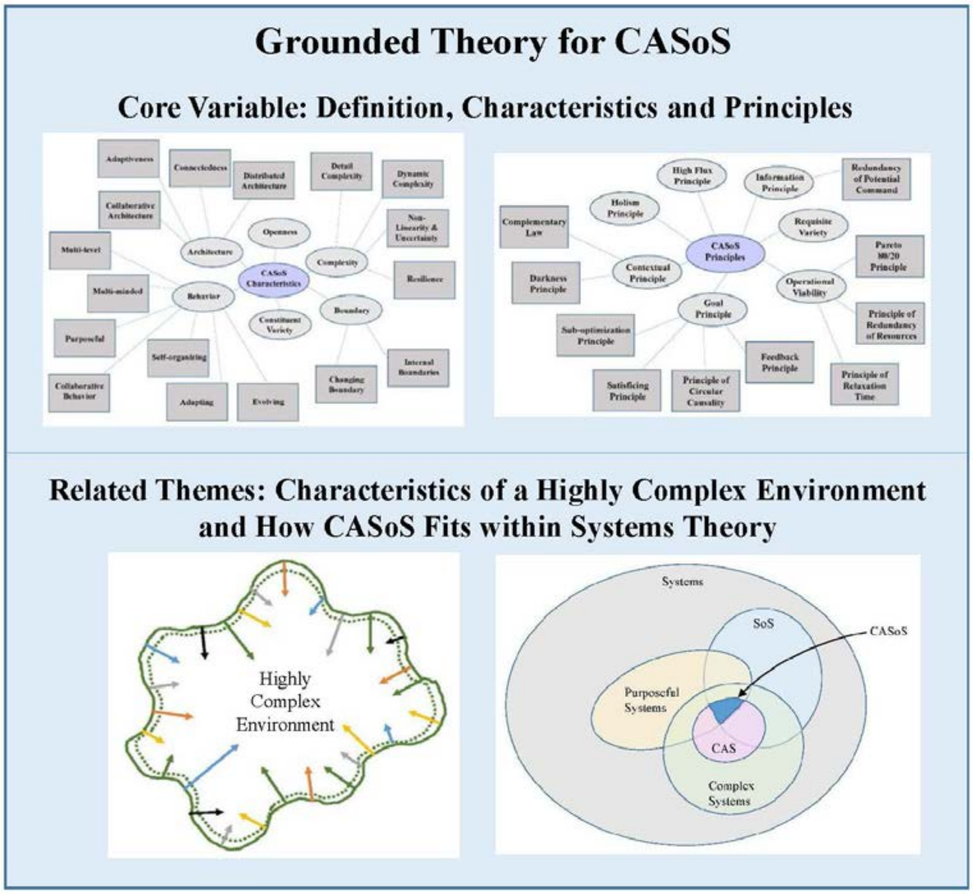

Figure 20. Components of the Grounded Theory for CASoS

1. Highly Complex Operational Environments

Complex environments give rise to complex problems. There are a number of types of complex environments that are specifically relevant to CASoS. These environments can occur naturally in the case of natural disasters such as hurricanes, wildfires, floods, and earthquakes—resulting in difficult-to-predict problems that cascade quickly and cause dire consequences if not addressed effectively. Epidemics or pandemics are difficult to predict and manage and they can spread quickly and globally with increased populations and international travel. Socio-technical environments spawn complex problems as in large organizations such as the U.S. health care system with huge financial challenges, a notorious medical error rate, and low quality of care despite an expansion of medical knowledge, increasingly sophisticated technology, and excellent physician education (Bar-Yam 2004a). A purely human-made environment that has produced unintended and far-reaching problems is the Internet, and its billions of users and connected systems now face a myriad of cyber vulnerabilities. Military conflicts are environments that pose complex problems. The war on terrorism, as an example, is based on a terrorist network dispersed globally that is nearly indistinguishable from civilians—functioning in small, independent units only loosely coordinated with one another (Bar-Yam 2004a).

From a systems perspective, a complex operational environment can be viewed as a set of entities or events presenting a diverse set of missions to be addressed by a system solution. Figure 21 illustrates the environment with a loose boundary acknowledging that while factors external to a system boundary could also affect the system, those environmental entities and events within the environmental boundary are driving the system behavior. The inwardly pointing arrows represent heterogeneous events occurring in the operational environment that affect the system. The different colors indicate the heterogeneity of the events. The different lengths, locations, and directions represent events that are occurring at different times and locations with respect to the system. These events could be threats in a military tactical environment, financial transactions in an economic environment, or various obstacles and destinations in a transportation environment. In Figure 21, the solution is depicted as a simplified single system; however, the system could be a complex and diverse set of distributed technologies, humans, and organizations. When operational environments become complex, they oftentimes produce highly complex problems that require system solutions that are capable of complex behavior and characteristics.

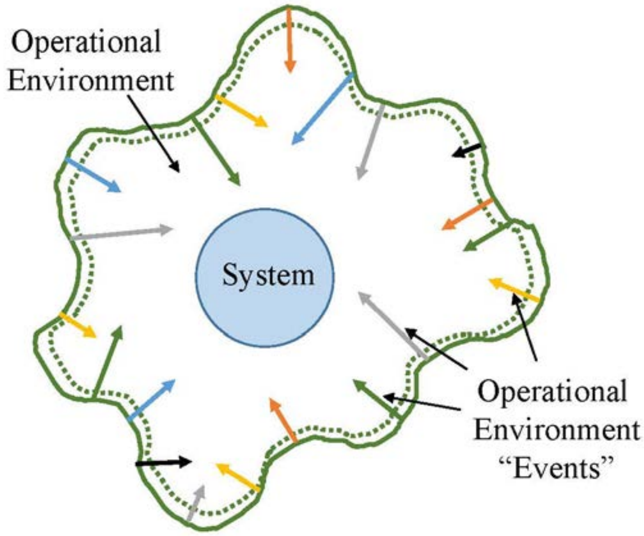

Figure 21. A Complex Operational Environment

a. Characteristics of Highly Complex Operational Environments

A number of environmental characteristics have potential for creating conditions that require a solution that can only exist in a highly complex solution space. A complex environment can contain one or more of the following characteristics, however, ***the greater the number it contains and/or the greater the value of any particular characteristic implies a greater level of complexity***.

- Large numbers of objects and/or features in the environment
- Heterogeneity and/or diversity of environment objects/features
- Distribution, kinetics, and interactions of environment objects/features with respect to each other and the system solution
- Diverse, changing, and numerous behaviors and actions
- Rapid tempo of change
- Uniqueness of situations or states
- Severe consequences of environment behaviors and events

- Large number of diverse and severe behavioral constraints, rules, and parameters

- Rapid and often unexpected shifts from non-complex to complex states of environmental behavior

Viewing the complex problem space as a dynamic system undergoing state changes, provides insight into how the problem must be addressed over time. Figure 22 illustrates an example of these state changes, starting with the environment in a non-complex state and transitioning through several different complex states. The differences in the states of the problem space arise from the many combinations of entities and behavioral events possible in the environment. The figure also shows that a complex problem space can transition back into the steady-state, in which it is not presenting a complex situation.

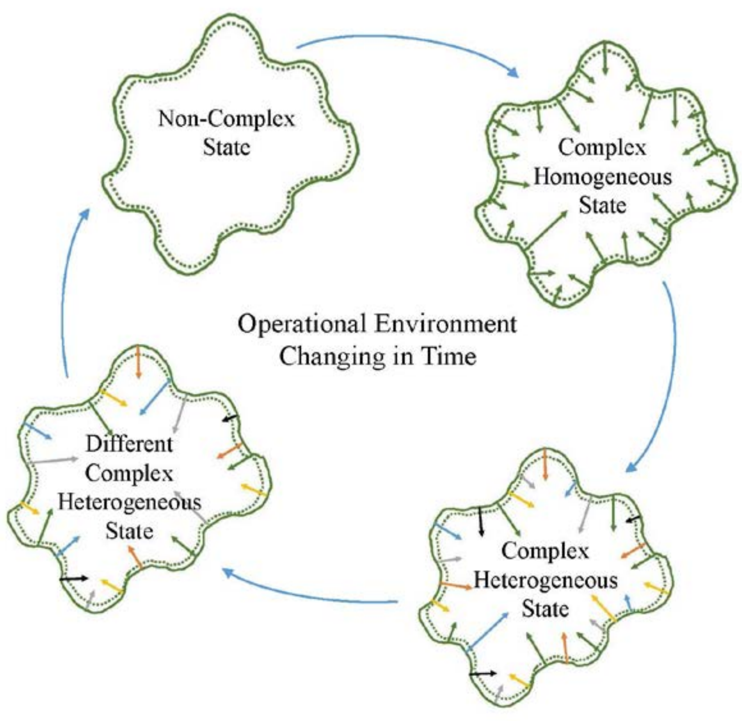

Figure 22. Complex Environment State Changes

b. *Implications of a Highly Complex Problem*

The implications of a highly complex problem on a solution system are dependent on the level of complexity and the type of complex characteristics present in the environment. In general, the complex environment's changing behavior can be translated into a set of multi-mission objectives for the system solution. These objectives are also changing in time to adapt to the environment. Often, the system solution will have both an incomplete and inaccurate awareness of its complex environment. The specific implications for a particular system solution will be directly dependent on the individual characteristics of the problem domain.

The solution system needs to develop knowledge of its environment, called an internal model, which is a picture that represents the system's understanding and reasoning about the real world. As the environment changes, the system's picture, or internal model, will have to quickly adapt to reflect those changes. This implies that as certain environmental characteristics increase to the point of high or severe complexity (such as tempo, numbers of events, heterogeneity of events, and kinetics of events), the system's awareness decreases in accuracy and completeness.

Complex problems translate into challenging conditions for system solutions. The many events translate into multiple missions, information overload, shortened reaction times, and constant change. The following list identifies and describes conditions that result from highly complex problems:

- Events and/or entities that are numerous, distributed, and heterogeneous
- Concurrent multi-missions that need to be addressed
- Information overload
- Incomplete, inaccurate, and delayed knowledge of the environment
- Time-criticality–shortened reaction times for responses
- Dire consequences–unless system solutions can negate, neutralize, or avoid events

- Cascading events due to interactions among entities
- A dynamically changing situation
- Uniqueness—the constantly changing environment translates into an ever-unique (and perhaps never before encountered and never repeating) series of situations changing in time

This environment overwhelms traditionally engineered systems that cannot collaboratively adapt within the required timescales to address the large numbers of changing and diverse missions. The following list identifies limitations in traditional systems that prevent them from adequately addressing highly complex problems:

- Cannot adapt quickly enough
- Cannot address multi-missions occurring concurrently
- Cannot flexibly reconfigure architectures, collaboration, courses of action
- Cannot process information quickly enough to make effective decisions
- Cannot manage distributed resources effectively enough
- Have fixed system behavior which can limit adaptive responses
- Are unable to gain shared knowledge of the operational environment among distributed constituent systems
- Are unable to gain accurate, timely, and comprehensive knowledge of the environment
- Cannot take into account the implications of system and SoS actions, and use these predictions to support the decision process.

In order to effectively address these limitations, a diverse set of distributed systems must very rapidly coordinate their efforts to their best individual and collective advantages to constantly adapt these behaviors as the situation changes. This requires an accurate and complete internal model of the environment and the ability to make intelligent decisions in short timeframes. For example, a threat situation in which a naval force is overwhelmed by the number and types of threats could cause reduced reaction times that can lead to deadly consequences. Information overload and inaccurate battlespace knowledge are just some of the conditions that can results in an inability to respond with defensive actions quickly or accurately enough.

Understanding the implications of complex problems provides an understanding of what is needed for a system solution. The solution system must necessarily be open, so it can interact with the highly complex environment. It must also be complex and adaptive in order to effectively respond to the changing environment and to interact nonlinearly as the complex and unpredictable situation unfolds. The system must obtain knowledge about the environment and develop behavioral objectives based on this knowledge. The system must act based on the objectives; and this action constitutes interaction between the system and its environment. Additionally, these abilities must occur continuously: updating the knowledge and objectives, and continuing to respond adaptively, as the situation changes. Figure 23 illustrates a system solution interacting with a highly complex operational environment. The illustration captures a snapshot in time—depicting complex events in the environment, and system responses.

Recalling that a SoS is merely an instance of a system that happens to be comprised of independently acting constituent systems rather than interdependent subsystems, the system solution illustrated in Figure 23 can be expanded to be viewed as a SoS. This leads to the next section that discusses the CASoS as the system solution and addresses its interaction within environments of fluctuating complexity.

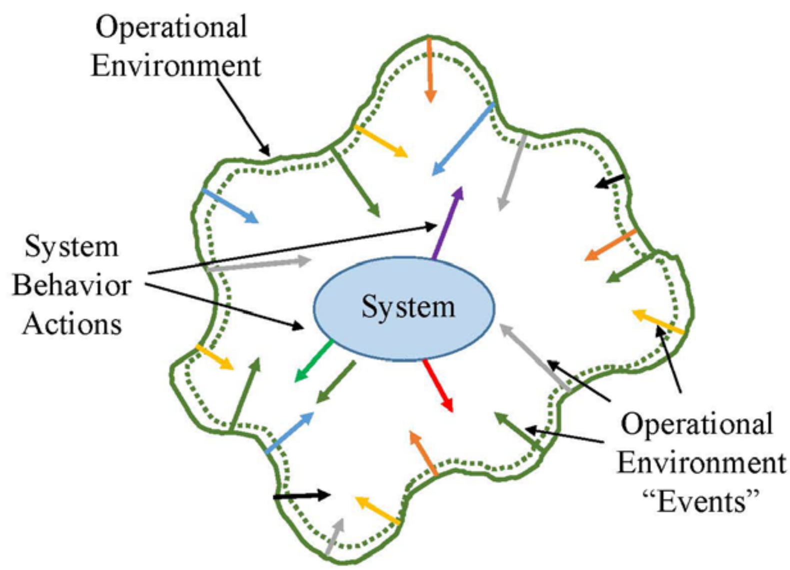

Figure 23. A System Solution Interacting with its Highly Complex Operational Environment

2. Definition of CASoS

The definition of the new class of CASoS solutions emerged from the classic grounded theory research approach. A process of studying data gathered from system theorists and complexity theorists provided a basis for defining CASoS in terms of the three primary aspects of complexity, adaptivity, and emergent behavior. The definition of CASoS is as follows:

CASoS are a class of systems that adapt to their environment through complex interactions among their self-organizing constituent systems that give rise to purposeful, emergent, meta-level, and multi-minded behavior.

An illustration of a CASoS consisting of numerous and heterogeneous constituent systems that are interacting with each other and their external environment is provided in Figure 24. It shows different thicknesses of the connections between constituent systems to illustrate different types of interactions. Thicker connections represent a behavioral collaboration among systems that is giving rise to emergent behavior with the environment. Also shown is the condition of multiple simultaneous interactions with the environment—

a fundamental characteristic of CASoS. The interactions, collaboration, and emergent behavior are changing in time and adapting to the environment.

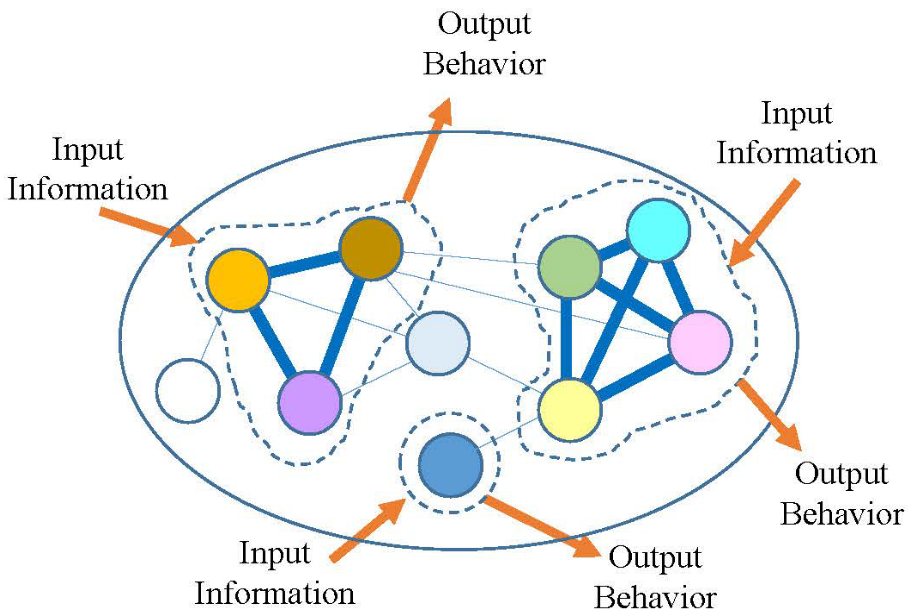

Figure 24. CASoS Illustration

This definition for a CASoS has the following fundamental elements:

- A CASoS has the potential to address highly complex problem spaces through its ability to adapt and behave at multiple levels.

- A CASoS is comprised of a relatively large number (commensurate to the number of entities/events in the environment) of heterogeneous, distributed constituent systems that give rise to emergent behavior through their interactions.

- The complex nature of a CASoS may manifest itself in a number of ways: heterogeneous and diverse constituent systems, large numbers of constituent systems (relative to the entities in the environment), and/or many and varied interactions and collaborations changing in time.

- The constituent systems in a CASoS have the ability to self-organize, behave, and collaborate; and can do this in a purposeful manner or according to a set of predetermined rules.

- CASoS complexity is a result of adaptive behavior and interaction with a complex environment.

- CASoS adaptiveness results from the CASoS performing autonomously using the outcomes of their behavior and interactions to select a subset of those behaviors for enhancement and replication.

3. How CASoS Fit within Systems Theory

This section discusses CASoS as a class of systems within systems theory. The theory for how the class of CASoS fits within the paradigm of systems, SoS, and complex systems is based on the comparative analysis of definitions of the properties and characteristics of the systems that fall within each domain. A careful analysis of the similarities and differences among the different classes of systems, combined with studying examples from each class, led to the explanation of how the class of CASoS fits within systems theory. Figure 25 illustrates how the class of CASoS lies in the intersection of the SoS set and complex systems set.

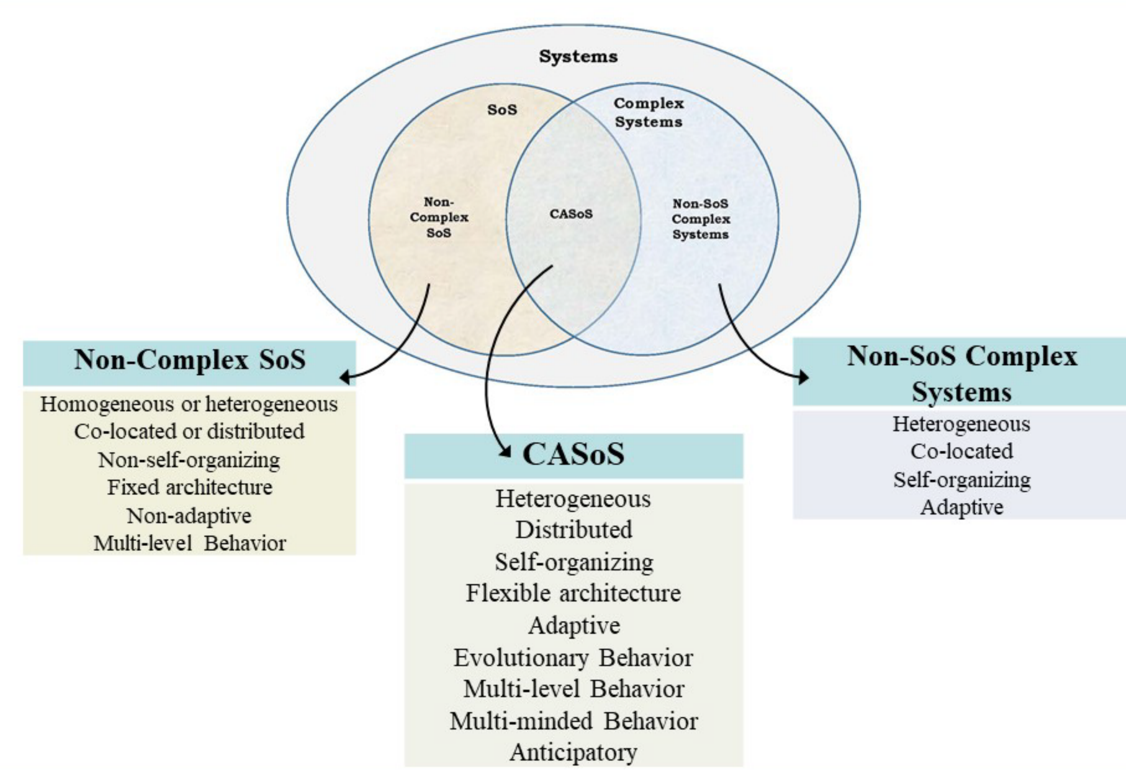

Figure 25. The Class of CASoS Lies within the Intersection of SoS and Complex Systems

CASoS are a subset of the class of SoS. They possess all of the characteristics of SoS, but also contain additional properties, as CASoS are a specialized subset of the larger class of SoS. The class of SoS exhibits multi-minded emergent behavior as well as system-level behavior from the independent actions of constituent systems. The class contains non-adaptive and non-complex SoS that produce multiple levels of behavior. These non-CASoS have connectedness and interoperate to produce multi-minded behavior addressing multiple and sometimes non-complementary goals, but they do so without exhibiting nonlinear and complex behavior. Thus, they do not freely adapt to address their environment in the same way as CASoS. Some properties that are inherent to CASoS, but not to the larger set of SoS include: self-organization, flexible architectures, and adaptiveness. These properties lead to principles such as irreversibility, darkness, and evolution, that are not found in non-complex SoS. Table 7 lists the differences between CASoS and non-CASoS systems that fall within the class of SoS.

Table 7. Differences Between SoS and CASoS

Non-Complex SoS	CASoS	Non-SoS Complex Systems
Homogeneous or heterogeneous Co-located or distributed Non-self-organizing Fixed architecture Non-adaptive	Heterogeneous Distributed Self-organizing Flexible architecture Adaptive Evolutionary Behavior Multi-level Behavior Multi-Minded Behavior Anticipatory	Heterogeneous Co-located Self-organizing Adaptive

Figure 26 shows that CASoS contain the characteristics of all systems, complex systems, systems of systems, and a set of additional characteristics that are unique to CASoS.

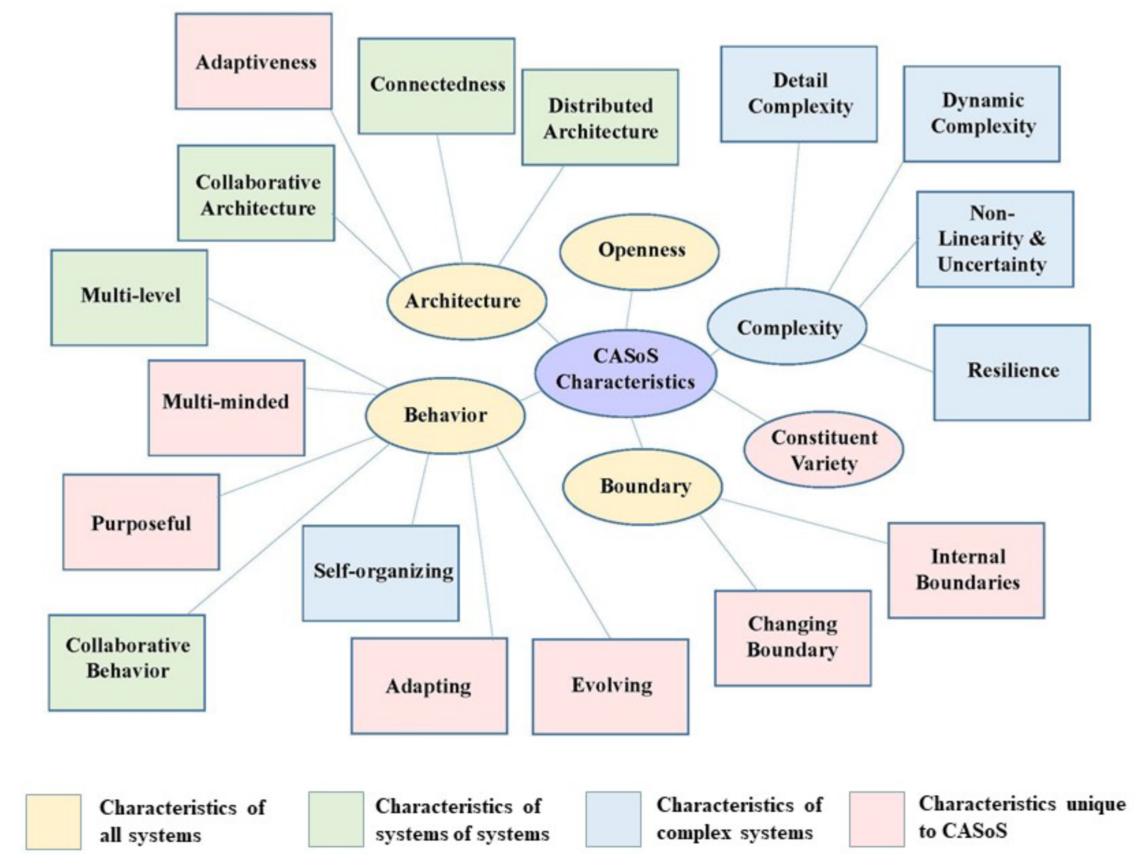

Figure 26. Characteristics Unique to CASoS

CASoS are a subset of the class of complex systems. CASoS contain the characteristics of complex systems (emergence, reflexivity, connectedness, and causality) but they also have the ability to adapt. The characteristic of adaptiveness means that CASoS perform an autonomous process that uses the outcomes of their behaviors and interactions with the environment to select a subset of those past behaviors for replication or enhancement (Levin 2002). This allows the CASoS to change its architecture to produce evolutionary behavior (based on new interactions) that adapts to address its changing environment. The behavior of the CASoS has the characteristics of complex systems, but with the additional feature of being comprised of independent constituent systems that can adapt and act in their own right. Thus, the CASoS adaptive behavior stems from both individual constituent systems acting independently, as well as emergent SoS behavior arising from the collaborative network of interactions. This results in large, difficult-to-reduce, systems that can behave dynamically with a wide range of time scales and with highly multi-minded effects.

Another differentiator between CASoS and other kinds of complex systems is the ability to anticipate the future (Holland 1992). CASoS have the ability to distinguish themselves from others and the environment. They create internal models to anticipate the future, and then direct their behavior to achieve expected outcomes (Holland 1992). Their internal models allow them to look ahead to possible future consequences of different courses of action before committing to those courses of actions (Holland 1992). The CASoS can then avoid acts that might result in negative consequences. Thus, the CASoS can purposefully control its ability to adapt based on internal models and the ability to predict.

4. CASoS Characteristics

A characteristic is a distinguishable feature of an object: a quality belonging (or inherent) to a system and serving to identify it. This section presents the characteristics of CASoS based on systems theory concepts and definitions gathered as part of the processes of initial and intermediate level coding contained in Appendix B. The codes for CASoS characteristics were identified as openness, boundary, constituent system variety, architecture, behavior, and complexity. The first five codes stemmed from systems theory concepts concerning the primary attributes of all systems. The sixth code, complexity, was identified as a necessary attribute to study, as CASoS are a subset of the class of complex systems.

a. Openness

A CASoS is an open system that interacts with its environment. This open interaction is inherent to the complexity and adaptiveness of CASoS. An important implication is that a complete understanding of a CASoS includes an understanding of its context or operational environment (Gharajedaghi 2011). This is necessary to comprehend the open and adaptive interaction. Adams et al. (2014, 119) present the Contextual Axiom, stating that "system meaning is informed by the circumstances and factors that surround the system." This means that an understanding of external circumstances, factors, and constraints, contribute to a full understanding of a CASoS. Figure 27 illustrates a CASoS interacting openly with its operational environment. CASoS actions are shown as multi-colored arrows representing different types of responses to the environment's events.

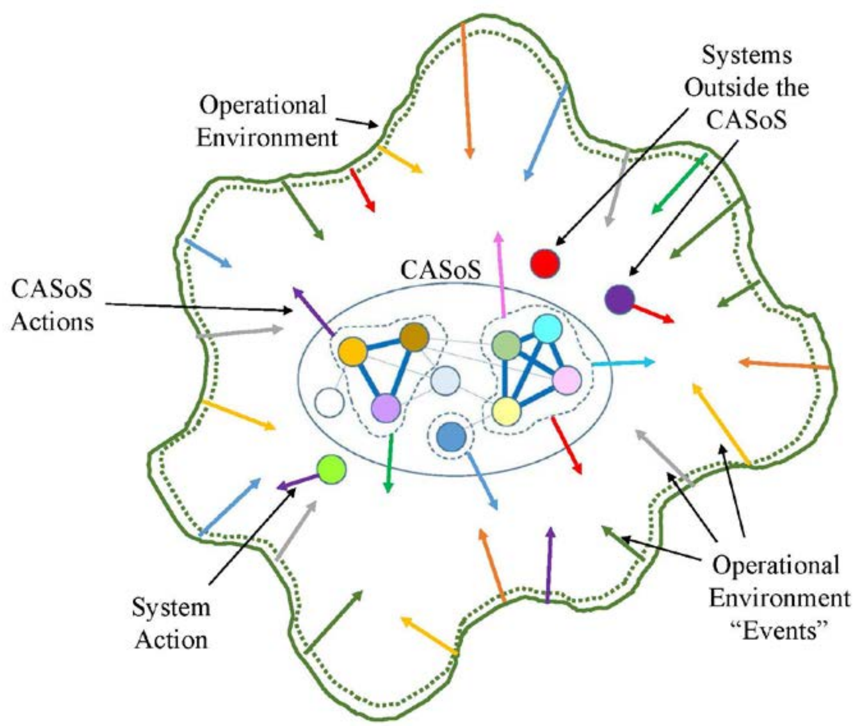

Figure 27. CASoS: An Open System in Its Environment

b. Boundary

The boundary of a CASoS delineates which systems are in the CASoS. Systems inside the CASoS boundary are constituent systems. Constituent systems primarily interact with each other by exchanging information. They have the potential to collaborate to form systems of systems and produce emergent meta-level behavior. Figure 26 shows the boundary of the CASoS as the oval surrounding the constituent systems. It also shows some systems in the environment that are outside the boundary of the CASoS. They may have potential to become collaborative constituent systems within the CASoS, but until that occurs, they are considered part of the operational environment of the CASoS.

(1) Changing Boundary

New systems join the CASoS as the boundary changes. New systems joining the CASoS become constituent systems. Existing constituent systems can leave or are excluded from the CASoS as the boundary changes over time. Boundaries occur at the interfaces of the constituent systems and therefore, the boundary changes as a result of the development or elimination of an interface. Figure 28 illustrates the changing boundary of a CASoS as four snapshots in time. The first snapshot shows constituent systems in the CASoS as well as two systems outside the boundary. The second snapshot shows that the CASoS boundary has changed and the blue and white systems have entered the CASoS, becoming interacting constituent systems and a brown system has left the CASoS giving up its role as a constituent system. Additionally, a new red system has appeared in the CASoS external environment. In the third snapshot, the boundary has changed again and the brown and red systems have joined and become constituent systems. The boundary changes once more and the forth snapshot shows several constituent systems exiting the CASoS and relinquishing their interactions with the CASoS.

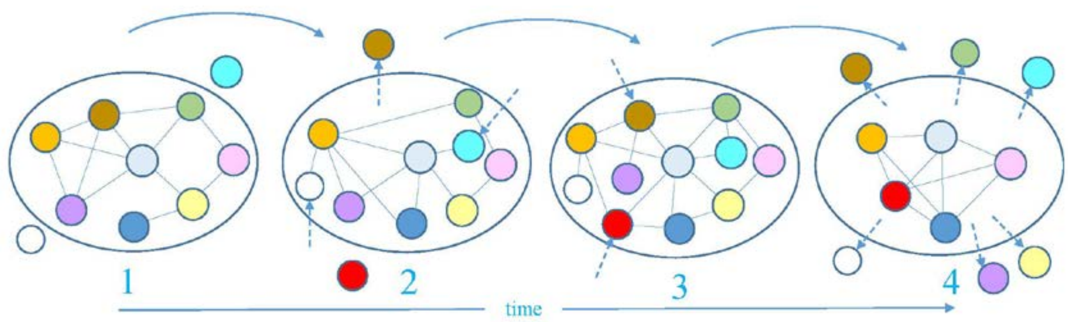

Figure 28. The CASoS Changing Boundary

(2) Internal Boundaries

Internal to a CASoS, there are inner boundaries that define collaboration among multiple constituent systems. Defining inner boundaries is a useful construct to identify and understand collaborative behavior within a CASoS. There can be multiple inner boundaries occurring simultaneously, indicating that multiple collaborative SoS can be functioning within a CASoS. There can be multiple levels of internal boundaries, or internal boundaries within other internal boundaries. This indicates the possibility of a hierarchical collaborative structure with a CASoS. Internal boundaries can overlap indicating constituent systems simultaneously belonging to more than one SoS within the CASoS. Finally, the inner boundaries within a CASoS change in time as the collaborative interactions among the constituent systems change. Figure 29 illustrates some of the internal boundary concepts for CASoS. The dotted lines surround sets of constituent systems that are collaborating as a system of systems. For this higher level of collaboration, the couplings need to be tight—indicating a greater interaction. The internal boundaries and couplings are changing in time as the CASoS adapts to the changing environment.

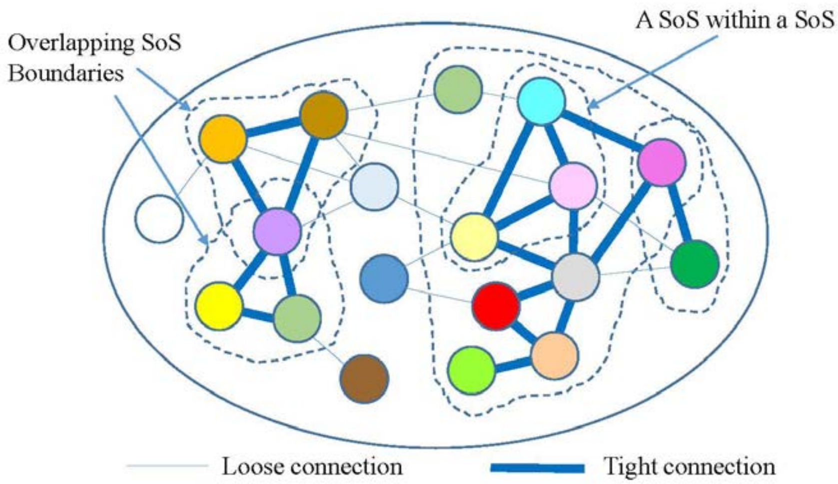

Figure 29. CASoS Internal Boundaries

c. *Constituent System Variety*

CASoS effectiveness against highly complex problems; relies on constituent system variety, in terms of heterogeneity, diversity, and individuality. These factors contribute to complexity by enabling variety in the types of responses available to address complex environments (Levin 2002). Constituent system variety also provides the continual appearance of new kinds of systems to participate as CASoS constituent systems. The degree of variation has a direct impact on the ability for the CASoS to adaptively change and evolve through the process of selection of actions and interactions. The greater the constituent system variety, the greater the number of CASoS behavioral options exist to address the complex environment.

d. *Architecture*

The CASoS architecture is the structure and form of the system. It defines the interactions of the constituent systems that enables collaboration and adaptive emergent behavior. The architecture is the configuration of the connections among the constituent systems including the exchange of information between systems. This section presents the theory for the required characteristics of a CASoS architecture, which were organized into four categories: adaptiveness, connectedness, collaborative, and distributed.

(1) Adaptiveness

Adaptiveness must be an inherent characteristic of a CASoS in order to enable dynamic, responsive, and purposeful interactions among the constituent systems to produce CASoS behavior that can address highly complex problems. The CASoS architecture's ability to be adaptive enables dynamically changing internal interactions among constituent systems. These interactions create a variety of collaboration configurations that produce multi-level behavior. The adaptiveness of the CASoS architecture is a primary enabler of the novel, evolving, and purposeful behavior that can address complex environments.

(2) Connectedness

The CASoS architecture has the characteristic of connectedness, which is the quantity of interactions or density of connections between the constituent systems. The measure of connectedness has two aspects: (1) the potential at any given time for the dynamics of a CASoS architecture to change; and (2) the level of connectedness at any given time based on the internal activity of a CASoS. The first concept is a measure of the architecture as a resource—indicating its readiness and potential to support collaboration and thus, emergent, multi-level behavior. The second concept of connectedness is a measure or indicator of CASoS activity at any given time, providing insight into the state of a CASoS at a snapshot in time.

(3) Collaborative

A CASoS architecture must support collaboration among the constituent systems. In order to be collaborative, a CASoS architecture must support information flow that includes awareness knowledge, control signals for decentralized control, and metadata for synchronization among constituent systems. The degree to which the CASoS architecture supports collaboration, will determine the number of behavioral options possible to address the complex problem space. Figure 27 illustrates both loose connections (shown as thinner lines), representing a less collaborative interaction between constituent systems, and tight connections (shown as thicker lines), representing more highly collaborative interactions involving greater communication and commitment between constituent systems.

(4) Distributed

A CASoS architecture must support distributed constituent systems. These systems can function independently from each other and can be separated geographically. The CASoS architecture must also support co-located constituent systems that function independently, but are physically connected to each other. Therefore, a CASoS architecture must accommodate a mix of constituent systems that are separated from one another, attached to one another, and potentially moving with respect to one another. The CASoS architecture must also support distributed control (or the ability of constituents to self-organize), distributed decision-making, and the flow of information among the distributed and co-located constituent systems.

e. Behavior

CASoS behavior refers to the actions and operational performance of a CASoS as it addresses its complex environment. CASoS behavior is a result of the actions and interactions of its constituent systems, which can be intended (purposeful) or unintended, can result in multi-level actions including meta-level emergence, can be multi-minded (addressing multiple missions concurrently), includes self-organization, adaptation, and evolution. This section presents the theory for CASoS behavioral characteristics.

(1) Multi-Level Behavior

Multi-level behavior is the CASoS characteristic of producing behavior at multiple hierarchical levels: at the constituent system level and at the SoS meta-level. The constituent systems within a CASoS can act independently as well as collectively through interactions. The collective local-level interactive behavior produces emergent or aggregate meta-level behavior. In addition, there can be multiple groups of constituent system within a CASoS collaborating concurrently. Thus, a CASoS can produce multiple levels of emergent behavior. The concurrent multi-level behavior of a CASoS produces behavioral variety, which supports the ability to address highly complex problems.

(2) Purposeful Behavior

A purposeful system “can change its goals in constant environmental conditions; it selects goals as well as the means by which to pursue them. It thus displays *will*” (Ackoff and Emery 1972, 31). Kenneth Boulding (1956, 202) developed the general systems framework—an “arrangement of theoretical systems and constructs in a hierarchy of complexity.” He calls the most basic level the static structure—referring to the static relationships and patterns of natural phenomena such as electrons, cells, atoms, molecules, etc. The second level is the simple dynamic system with predetermined motions—the clockworks level. The third level is the cybernetic system—differing from the control mechanism in level two due to the transmission and interpretation of information. A thermostat is an example of the third level. The fourth level is the open system or self-maintaining structure. The fifth level is the genetic-societal level, typified by the plant, and characterized by differentiated and mutually dependent parts and blueprinted growth. The sixth level is the animal level, including abilities such as mobility, teleological behavior, and self-awareness. The seventh level is the human level including self-consciousness, which is different from self-awareness, because “he not only knows, but knows that he knows” (Boulding 1956, 135). Level eight is social organization which includes interrelationships, value systems, and social systems. Finally, level nine is transcendental systems, that Boulding describes as the unknowables or higher-level questions that do not have answers but do exhibit systematic structure and relationship.

Ackoff and Emery’s purposeful system fits into Boulding’s system classification framework at level six and above. The systems below level six, such as plants with blueprinted growth (level five), the self-maintainers (level four) and the cybernetic thermostat-like systems (level three), exhibit behavior in a predetermined fashion based on environmental conditions. These non-purposive systems adapt to their environment and have characteristics that enable them to sense aspects of their environment including changes; however, they cannot change their goals in constant environmental conditions. This distinction is an important consideration for the engineering of system solutions that are purposeful and that can make decisions concerning their actions and behavior. Systems that include human participation in decision-making for behavioral actions are examples of purposeful systems. The other example is systems that include artificial intelligence or automated decision aids for determining purposeful actions.

The intent of engineered CASoS is to develop the CASoS to be purposeful: to behave with intent that not only adapts in response to its complex environment, but also to exhibit anticipatory behavior to address a problem proactively. CASoS are goal-seeking or purposeful systems that respond differently to various environmental conditions to produce particular and desired outcomes (states). Gharajedaghi (2011) refers to this ability as responsive as opposed to reactive, which is the term he uses for the non-purposeful state-maintaining systems. Responsive systems have a choice of actions and the actions are voluntary. CASoS, as a class of responsive and purposeful systems, "can produce not only the same outcomes in different ways in the same environment, but also different outcomes in both the same and different environments" (Gharajedaghi 2011, 37). Additionally, a CASoS can cause different end states (goals) under constant conditions. Gharajedaghi (2011) refers to this ability to change ends under constant conditions as free will. He writes that "such systems not only learn and adapt; they can also create" (Gharajedaghi 2011, 37).

(3) Collaborative or Aggregate Behavior

The collaborative behavior of a CASoS is the behavior that emerges from the interactions of constituent systems. The collaborative behavior can range from loosely coupled interactions to tightly coupled interactions. The collaboration can have a duration associated with it. Constituent systems can participate in multiple collaborations simultaneously. There can also be collaborations within collaborations. The CASoS collaborative behavior depends on the number of systems participating, the duration, the level of interaction, the connectedness, and in some instances, the agreements (handshakes) among constituent systems concerning the collaboration.

(4) Multi-Minded Behavior

CASoS exhibit multi-minded behavior to address multiple objectives in the environment. Multi-minded behavior is the ability to perform multiple courses of action simultaneously. Multi-minded behavior is a necessary characteristic of a CASoS that allows it to solve complex problems that result in multiple missions that are changing in time, occurring in a distributed fashion, and often overlap in time. The CASoS must be able to multi-task, functioning in multiple ways that address multiple missions simultaneously.

(5) Self-Organizing Behavior

CASoS perform self-organizing behavior. They “display organization without a central organizing authority” (Ottino 2004, 399) and without any external organizing principle being applied. Thus, their constituent systems behave in such a manner that the architecture of their interactions becomes organized for collaboration. Self-organization means that collaborative behavior occurs without external control or centralized control. In the case of purposeful CASoS, the constituent systems decide to self-organize and collaborate for desired emergence. Figure 30 illustrates a group of loosely connected systems that decide to self-organize to interact and collaborate. The illustration shows an increase in connectedness and internal boundaries surrounding groups of constituent systems that have self-organized and interact to perform collaborative behavior.

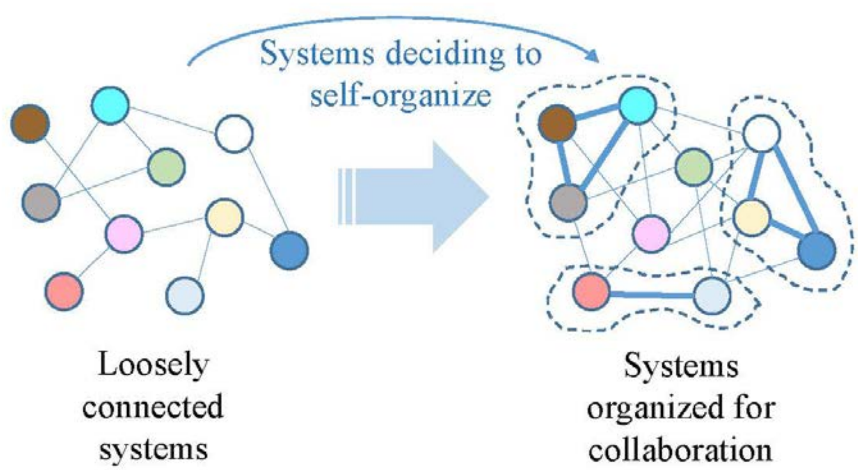

Figure 30. Self-Organizing Behavior

(6) Adaptive Behavior

CASoS exhibit adaptive behavior. Adaptation is key to addressing complex problems. Akers, Keating, Gheorghe, and Sousa-Poza (2015) identify six types of behaviors of complex systems to address their environment. The first two are non-adaptive: *endurant* behavior is the use of defensive mechanisms to deflect impacts from the environment and *regulator* behavior alters internal settings to compensate for changes in the environment. The other four behaviors are adaptive: *organizer* behavior alters its internal structure, relationships, courses of action, and configuration to address its environment; *migrator* behavior is defined as avoidance actions—or physically moving away from risks in the environment; *insulator* behavior is defined as self-protection actions—when a system uses external entities for protection; and finally, *manipulator* behavior alters the environment to reduce, eliminate, or prevent negative impacts (Akers, Keating, Gheorghe, and Sousa-Poza (2015), Akers 2015). A CASoS embodies all of these forms of complex behaviors and can exhibit them at will through the actions and interactions of its complex constituent systems. A CASoS can exhibit multiple types and/ or instances of adaptive behavior through independent constituent system actions (as well as aggregate meta-level actions).

(7) Evolving Behavior

Evolving behavior is an inherent characteristic of CASoS. Evolving behavior is the longer-term adaptation in goals and purposeful behavior as the CASoS learns to better address its complex environment. This evolution occurs through adaptive learning using positive and negative reinforcing feedback. Bar-Yam (2003a) writes about the engineering applications of co-evolution, hierarchical or multi-level selection, evolutionary programming, genetic algorithms, and other methods for artificial selection of functions and purposeful behaviors based on evolving goals over time. Petrov (2002) discusses the importance of prediction of behavioral consequences and effects, and the use of these predictions to evolve system goals over time. A CASoS must use its knowledge of itself and environment, to predict the possible effects and environmental impacts of different behavioral options. The CASoS then uses these predictions to enable evolving behavior.

f. Complexity

CASoS are, by definition, complex, and therefore contain the characteristics of complex systems. These characteristics include detailed complexity, dynamic complexity, disorganized and organized complexity. For a CASoS, this means that there are many objectives or missions, some of which may be inconsistent. Control is decentralized and distributed among the constituent systems. Change at any level may have CASoS-wide impacts due to the connectedness of the constituent systems, and change may be cascading and dramatic. The lateral interactions among constituent systems are more dominant than the hierarchical relationships. Short-term behavior is more predictable than long-term behavior. Innovation and adaptation are inherent. Complexity is also a result of constituent system heterogeneity, diversity, and individuality. This is a key property of a CASoS, as it enables variety in the types of responses available to address the complex environment.

(1) Detail Complexity

Detail complexity is the characteristic of detail in scalability and the increasing number of entities and in combinatorial complexity (Senge 2006). For CASoS, detail complexity can manifest as very large numbers of constituent systems and by very large numbers of interactions, or high connectedness. It can also result from facing many missions concurrently as a result of the problem space. This can translate into huge amounts of data and information and consequently into increased decision complexity. Detail complexity results in a situation in which humans cannot fully comprehend the CASoS and its decisions due to natural cognitive limitations.

(2) Dynamic Complexity

Dynamic complexity arises from a large number of interactions among constituent systems that creates time delays and volatile unpredictability for the state of the CASoS. Dynamic complexity is attributed to a number of factors including tight coupling, connectedness, feedback, nonlinearity, adaptiveness and self-organization. Similar to detail complexity, dynamic complexity is also a characteristic of CASoS that goes beyond the comprehensive cognitive ability of humans.

(3) Non-Linearity and Uncertainty

Complex systems can exhibit non-linear dynamics as they interact with a highly complex environment. Non-linearity may arise from sudden changes in behavior ranging from a high degree of stability to very unstable behavior. Non-linear behavior adds to unpredictability and uncertainty. In addition, common in complex systems is the tendency for relatively small changes to lead to large effects, for instance, when small changes in initial conditions leads to very different dynamics over time. The goal of an engineered CASoS is to exhibit predictable and intended behavior. This intended behavior can be non-linear in terms of the complex dynamics and multi-level and concurrent multi-level behavior; however, CASoS design approaches must include methods to address the non-linearity to ensure desired behavior (Fradkov, Miroshnik, and Nikiforov 1999).

(4) Resilience

A common characteristic of many complex systems is resilience—a system's ability to respond to environmental events by absorbing the disturbance or reorganizing to address them. (Fraccascia, Giannoccaro, and Albino 2018). A CASoS has a number of features that provide the characteristic of resilience. The greater the level of complexity inherent in the CASoS due to large numbers of heterogeneous constituent systems, an adaptive, collaborative, distributed architecture, and the purposeful, adaptive, multi-level and multi-minded behavior the larger the number of preemptive and responsive actions required to increase overall resilience.

5. CASoS Principles

In general, a principle is a fundamental assumption about an object: it is a concept that serves as a guide for the behavior or evaluation of that object. In systems theory, principles reflect a system's designed purpose and represent values that orient and rule the conduct of a system in its environment. A number of principles, axioms, propositions, and laws exist in the field of systems theory. A study to produce a formal definition of systems theory by Adams et al. (2014) contains a fairly comprehensive list and description of systems principles. Richardson (2004a, 2004b, 2005, 2006) studied how these system principles apply to complex systems and identified a subset as the principles of complex systems. This dissertation developed a theory for the principles of CASoS based on the application of systems principles to the design of CASoS solutions to highly complex problems. A classic grounded theory method produced a set of codes or categories of system principles that developed into the principles for CASoS solutions: holism, contextual, goal, operational viability, requisite variety, high flux, and information. This section defines and describes the CASoS principles.

a. CASoS Holism Principle

The CASoS Holism Principle states that a CASoS has emergent behavior that is a result of complex constituent system behavior and interactions. This principle is based on the System Holism Principle which is simply stated as the whole is greater than the sum of its parts (Richardson 2004a; Smuts 1926; Skyttner 2000). Richardson (2004a, 76) writes that "this is one of the most interesting aspects of complex systems: that micro-level behavior can lead to macro-level behavior that cannot be easily (if at all) derived from the micro-level from which it emerged." The System Holism Principle also infers that emergent wholes cannot be reduced to their parts. For CASoS, this principle manifests as the emergent, adaptive, and evolving behavior that is necessary to address its complex environment. The CASoS meta-level behavior is not reducible to its parts (constituent systems). Rather, the meta-level behavior is a result of a complex combination of constituent system behavior and interactions. For engineered CASoS, the holistic behavior is intentionally designed and purposeful. This implies the ability for the CASoS to understand and predict what types of collaborations and interactions will produce meta-level effects that will provide the courses of action to effectively address the highly complex environment. The CASoS must gain and develop knowledge for how individual behavioral contributions and their interactions can combine to provide holistic behavior that is greater than the sum of the parts.

b. CASoS Contextual Principle

The CASoS Contextual Principle states that CASoS as a solution to highly complex problems relies on the abilities to gain understanding of its context and itself. This principle is based on the System Contextual Axiom (Adams et al. 2014, 119) which states that “system meaning is informed by the circumstances and factors that surround the system.” This axiom stresses the importance of gaining an understanding of the circumstances that enable or constrain a system. The Complementary Law and Darkness Principle are additional theoretical system concepts that support the CASoS Contextual Principle.

The Complementary Law (Weinburg 1975) states that “any two different perspectives (or models) about a system will reveal truths regarding that system that are neither entirely independent nor entirely compatible” (Richardson 2004a, 76). For CASoS, the Complementary Law implies that there are multiple models that provide overlapping and potentially contradictory descriptions of the CASoS.

The Darkness Principle in complexity thinking is the concept that no system can be known completely (Richardson 2004a; Skyttner 2001). This suggests that the best representation of a CASoS is the actual CASoS itself, and all other representations are imperfect models. Therefore, no representation will be able to offer a complete and accurate understanding of a CASoS.

Taken together, the Complementary Law and Darkness Principle support the CASoS Contextual Principle by explaining that multiple descriptions with different perspectives are needed to attempt to understand and describe CASoS; however, the representations will fall short of a total and complete model. They also imply that a CASoS will have incomplete and inaccurate self-awareness; and that a CASoS will have to self-generate, or create, a variety of internal models with different perspectives in order to increase self-awareness. An example of different CASoS perspectives is illustrated in Figure 31. These models represent the types of information and perspectives that a CASoS uses to create internal models. The ability for a CASoS to be self-aware, and to understand its context, is necessary to perform purposeful behavior. However, it should be kept in mind that the CASoS ability to be completely self-aware is limited, and thus the CASoS can never be an ideal or perfect system. Therefore, according to Cilliers (1998, 4–5), the CASoS is always in the shadow of the whole.

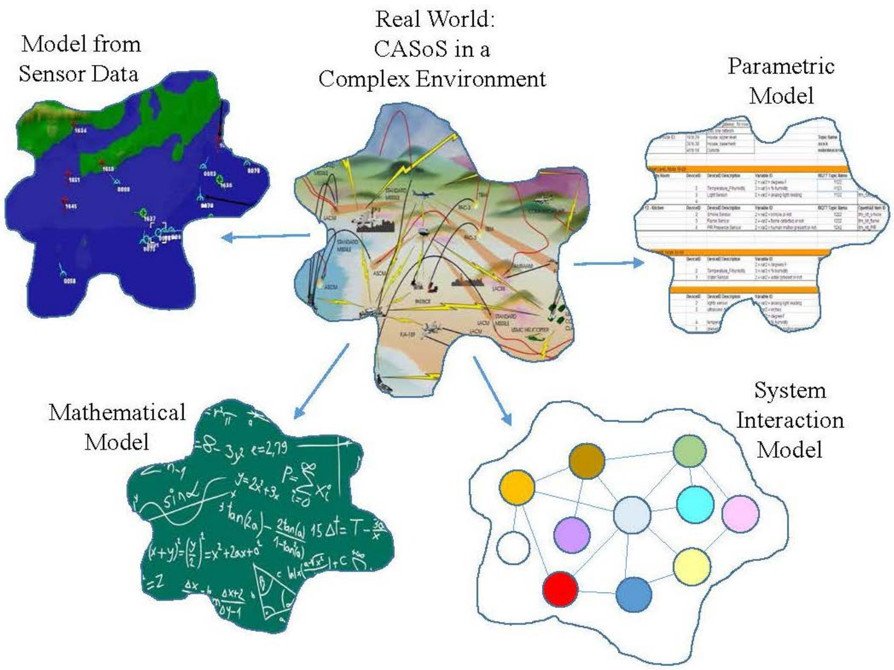

Figure 31. CASoS Contextual Principle: Multiple Models of a CASoS and its Environment

c. CASoS Goal Principle

The CASoS Goal Principle states that CASoS achieve specific goals through purposeful behavior using behavioral decisions, adaptation, and feedback from causal effects and the environment. The CASoS Goal Principle builds on several system principles: the Sub-optimization Principle, the Satisficing Principle, the Principle of Circular Causality, and the Feedback Principle.

The Sub-optimization Principle, described using many examples by Hitch (1953), refers to the condition that if each subsystem, taken individually, is made to perform with maximum efficiency, the system as a whole will not perform with maximum efficiency. The Satisficing Principle (Simon 1955, 1956) states that the decision-making process whereby a system chooses an option; may not result in the best option, but it may be good enough. Taken together, these principles infer that CASoS are not ideal systems. They cannot work at maximum efficiency or optimization at all levels, all the time. However, a balance can exist between constituent level and emergent level optimization that produces behavioral outcomes that are good enough to address highly complex problems.

Circular Causality (Korzybski 1994, Adams et al. 2014) states that a system outcome becomes a causative factor for future effects and consequences, causing influencing in a variety of different ways. The Principle of Feedback (Wiener 1948) states that all purposeful behavior requires signals from the environment to direct future behavior towards a goal. Taken together, these principles affect and guide the ability for a CASoS to meet a goal. A CASoS solution must have the ability to consider the effects of behavioral choices, as each CASoS action may cause an event in the complex problem space, which results in a circular causal loop. Additionally, a CASoS must have the ability to sense and understand feedback signals from the environment in order to adapt future CASoS behavior toward a goal.

d. CASoS Operational Viability Principle

The CASoS Operational Viability Principle states that in order for the CASoS to be a viable solution during operations, the CASoS must maintain stability and resilience. Beer (1979) described system viability as a measure of balance to be maintained in two ways: (1) subsystem autonomy versus integration and, (2) stability versus adaptation. For a CASoS, this translates into a balance between (1) constituent system autonomy vs. collaborative behavior; and (2) maintaining CASoS stability while adapting and evolving in terms of architectural changes and behavioral goals. Several system principles apply to CASoS in support of operational viability: the Pareto 80/20 Principle, the Principle of Redundancy of Resources, and the Principle of Relaxation Time.

The 80/20 Principle (that 80% of the output will be produced by 20% of the system) reflects that while many constituent systems in a CASoS may be interacting and behaving at any given time, only a small percentage of them will be contributing to the desired emergent behavior. Viewing a CASoS as a network of constituent system nodes provides a network perspective for the 80/20 Principle. In this case, a study of a number of complex systems has shown that only a fraction of the nodes contribute to the long-term behavior (Richardson 2004a). Many nodes become stable nodes demonstrating significantly less state-changes or activity. While it is possible to remove these stable nodes without significantly changing the emergent CASoS behavior, they actually serve the purpose of creating intrinsic stability. They act as a means to dissipate perturbations, and therefore create behavioral resilience.

A related system principle is the Principle of Redundancy of Resources. This principle describes a system's ability to maintain stability under conditions of external disturbance (Skyttner 2001). CASoS have a variety of means by which stability can be maintained. The CASoS's resources are their constituent systems, interactions, and behaviors (both individual and collective). A CASoS uses its resources purposefully to address its environment in intentional ways. Holistic resource management is the use of constituent systems to fulfill holistic CASoS goals. This method allows a more efficient and effective use of pooled resources than having each resource acting independently. The CASoS can build in redundancy to maintain overall stability. Providing excess resources (Paul, Beitz, Feldhusen, and Grote 2011) is a means of increasing the reliability and safety in CASoS solutions.

The Principle of Relaxation Time is another system principle that applies to CASoS that can improve operational viability. The Relaxation Time Principle (Richardson 2001) states, "system stability is possible only if the system's relaxation time is shorter than the mean time between external disturbances" (Skyttner 2001, 93). For a CASoS, the time required to act, exhibiting adaptive behavior, and then to return to a state of equilibrium (to relax before the next action), must be shorter than changes in the environment. The CASoS has the natural advantage of pursuing multiple actions concurrently, which will provide greater overall relaxation time as some constituent systems are acting while others relax. However, a better understanding, and thus prediction, of the temporal dynamics of the problem space will support a better CASoS design for operational viability.

e. CASoS Requisite Variety Principle

The CASoS Requisite Variety Principle states that the CASoS must have a greater number of courses of action possible in the solution space than there are events in the problem space in order to be an effective solution. The Law of Requisite Variety states that system control is only possible when the controlling system's variety is greater than the variety of the situation to be controlled (Ashby 1956). For a CASoS this means that the number of possible courses of actions must exceed the number of events in the problem space. If this condition is not met, the CASoS will be overcome by the highly complex problem. There are several methods for designing a CASoS to increase the "variety of the controller" or to increase the number of possible actions. These include having a greater number of constituent systems, having greater diversity of constituent systems, and having a greater number of possible interactions and aggregations.

f. CASoS High-Flux Principle

The CASoS High-Flux Principle states that the rate of resource flux must support the overall ability for adaptation to address the highly complex problem space. Resource flux refers to the availability and use of resources in a timely manner. The systems theory high-flux principle states that as the rate of resource flux through the system increases, the number of resources available to address the environment increases (Skyttner 2001). Complex systems have a greater range of possibilities for discovering and creating new patterns of resource relationships. In a CASoS, the ability for high-flux or adaptive architectural interactions can allow a transformation to a new and quite different system altogether (Richardson 2004b). Thus, High-Flux is a guiding principle for CASoS interactions and an enabler of adaptive architectures.

g. CASoS Information Principle

The CASoS Information Principle states that CASoS create, possess, transfer, and modify information. This principle is based on the Information Axiom (Adams et al. 2014) that provides an understanding of how information affects systems. A related system principle is the Redundancy of Potential Command (McCulloch 1959) which states that desired and effective system actions occur when an adequate amount of information exists. In other words, power and decisions reside where information resides. For a CASoS, this principle implies an information architecture that supports a distribution of decision-making throughout the constituent systems. Combining this principle with the Holism, Context, and Goal Principles results in a requirement for CASoS to gain and maintain shared contextual, causal, and environmental feedback knowledge in order to support holistic decision-making in each constituent system for multi-level purposeful behavior.

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V. ENGINEERING IMPLICATIONS OF THE CASoS THEORY

A. INTRODUCTION[5]

Given the existence and rise of highly complex problems and the emergence of a grounded theory for CASoS as a new class of system solutions to these problems, this chapter discusses engineering implications of the theory. Chapter IV articulated the theory for the definition, characteristics, and principles of CASoS. This chapter presents the results of the final advanced coding phase of the grounded theory methodology. The results provide an engineering framework for CASoS by presenting a conceptualization of the required capabilities of an engineered CASoS solution and a CASoS systems engineering approach.

CASoS, as a new class of engineered systems, present a solution opportunity for addressing highly complex problems through adaptive architectures and the embedding of constituent systems with the intelligence to learn, self-organize, collaborate, and evolve in order to achieve desired adaptable emergent behavior. Advances in information and computational technologies enable the potential development of complex, adaptive, and intelligent capabilities needed to engineer CASoS solutions. The implications of the CASoS theory presented in this chapter answer the second part of the original dissertation research question: how can a CASoS solution be engineered to address highly complex problems? It does this by first building on the theoretical framework to conceptualize the required engineered capabilities. Secondly, it presents implications of the CASoS theory for the systems engineering design process.

[5] Parts of this chapter were previously published by:

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IEEE Xplore © [2018] IEEE (Bonnie Johnson. 2018. "Towards a Theory of Engineering Complex Adaptive Systems of Systems." Paper published in *IEEE Xplore Proceedings of the 18^th Annual IEEE International Systems Conference,* Vancouver, BC, 23–26 April 2018.)

This chapter has three other sections. Section B describes the advanced coding phase, explaining how this final classic grounded theory process answered the research question. Section C describes the first result of the advanced coding phase—the required engineered capabilities and conceptualization of a CASoS as a solution to highly complex problems. Section D contains the second result of the advanced coding phase—the required systems engineering approach to design and develop CASoS solutions.

B. ADVANCED CODING PHASE: THEORETICAL INTEGRATION AND IMPLICATIONS

The final phase of the research process was the advanced coding or high-level concept phase. This phase used theoretical integration to provide a comprehensive understanding of the CASoS theory and its implications for an engineered solution. Advanced coding studied the selective codes of the intermediate phase to draw conclusions about required capabilities for a CASoS solution, as well as considerations for applying the systems engineering process to realize an engineered CASoS. The results of the final phase were twofold: (1) a conceptualization of the required capabilities of an engineered CASoS; and (2) an explanation of the modified systems engineering approach required to design a CASoS solution. The following two subsections describe the research approach taken to attain these results.

1. Advanced Coding Approach for the Conceptualization of an Engineered CASoS

The CASoS grounded theory presented in Chapter IV served as a source of requirements and guidance for developing an engineered CASoS. The advanced coding processes of theoretical conjecture and theoretical integration focused on the impact and implications of the CASoS definition, characteristics, and principles. This produced a coherent theory for how a new class of system solutions can address highly complex problems.

The advanced coding phase began with a study of the results of the intermediate coding phase (the CASoS theory) to conceptualize an engineered CASoS. A process of synthesis and visualization produced an illustration (shown in Figure 32) of an engineered

CASoS that consists of: an architecture, a system of intelligent constituent systems, and analytics that can perform knowledge discovery and prediction. These major parts of a CASoS became the three codes used for mapping the theory to the conceptualization.

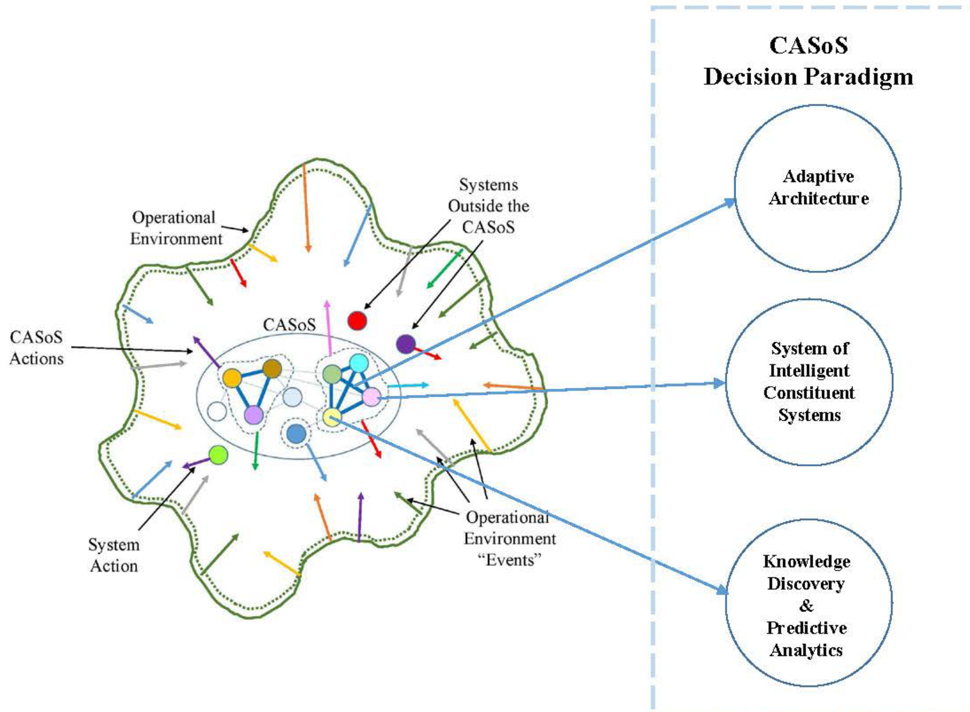

Figure 32. CASoS Advanced Phase Codes

The CASoS characteristics and principles from the intermediate coding phase were then mapped into these three CASoS codes. This process reinforced the conceptualization and provided a process for integrating the theoretical concepts into a set of capabilities required for an engineered CASoS. Table 8 contains the mapping of the CASoS theory into a CASoS conceptualization.

Table 8. Mapping of CASoS Theory to Advanced Codes

Conceptualization Codes	**CASoS Characteristics**	**CASoS Principles**
Adaptive Architecture	Architecture, Boundary, Openness, Complexity	Holism Principle, Operational Viability, High-Flux Principle, Information Principle
Intelligent System of Constituent Systems	Behavior, Constituent System Variety, Complexity	Holism Principle, Goal Principle, Requisite Variety
Knowledge Discovery and Predictive Analytics	Constituent System Variety, Behavior	Contextual Principle, Goal Principle (Principle of Feedback and Circular Causality), Information Principle

The theoretical characteristics of architecture, boundary, openness, and complexity were mapped into the adaptive architecture code for the conceptualization of an engineered CASoS. These characteristics provide a description of what capabilities are required to engineer a CASoS architecture. The architecture must support adaptive and collaborative behavior of the constituent systems. It must provide an open relationship of interactions between the engineered CASoS and its environment. It must be flexible to allow changes in the internal and external boundaries of the CASoS. Several CASoS principles affect the CASoS architecture. The Principle of Holism requires an architecture that supports collaborative interactions that produce emergent behavior. The Operational Viability Principle requires an architecture that supports stability and resilience through a balance between constituent system autonomy and integration. The High-Flux Principle requires an architecture that supports the high rates of resource flux needed to enable behavioral complexity. The Information Principle requires that the architecture support information sharing among the constituent systems.

The second conceptualization code, an intelligent system of constituent systems, has mappings from the following characteristics: behavior, constituent system variety, and complexity. A SoS concept supported by intelligent agents is required to enable the collaborative, emergent, purposeful, evolving, and complex behavior of a CASoS. Functioning as a SoS, the intelligent constituent systems need to make decisions to self-organize and form a CASoS to achieve collaborative, intentional behavior to address a complex problem space. In effect, the intelligent SoS is making resource management decisions, in which the resources are the constituent systems themselves and the CASoS architecture. Four of the CASoS theoretical principles are mapped into this code: the holism principle, the goal principle, and requisite variety. Engineering a system of intelligent constituent systems is required to enable the distributed and collective decision-making needed to produce the desired (or goal-oriented) holistic emergent behavior described by the holism and goal principles. It is also required to meet the principle of requisite variety, which involves decision-making to identify courses of action and effective solutions involving the CASoS resources.

The third conceptualization code, knowledge discovery (KD) and predictive analytics (PA), has mappings from two CASoS theoretical characteristics: constituent system variety and behavior. KD includes self-awareness; therefore, as CASoS are comprised of heterogeneous constituent systems, the KD analytics must support gaining knowledge of these different system capabilities. This knowledge is also needed to perform PA to predict the effects of these systems' actions. CASoS behavior also guides the abilities to perform KD and PA. KD is required to gain an understanding of the complex problem space and PA is required to anticipate events in the problem space and predict the effect of CASoS behavior. These capabilities are enablers of effective CASoS decision-making and behavioral responses to address complex problems. The following CASoS principles map to the third code: the contextual principle, the goal principle (principle of feedback and circular causality), and the information principle. The contextual principle explains that the CASoS must gain an understanding of its context thereby requiring KD for an engineered CASoS. The goal principle is based on the principle of feedback which explains that purposeful behavior requires signals from the environment to direct future behavior towards a goal (thus requiring a KD capability); and circular causality which explains that a system effect becomes a causative factor for future effects (thus requiring a PA capability). Finally, the information principle explains that a CASoS creates, possesses, transfers, and modifies information. Therefore, this principle also maps to a KD capability.

Section C of this chapter contains the results of this advanced coding process. It presents the conceptualization of the engineered CASoS and describes what is required in terms of an adaptive architecture, a set of intelligent constituent systems, and KD and PA analytic capabilities.

2. Advanced Coding Approach for the CASoS Systems Engineering Approach

In the advanced coding phase, data was gathered from literature sources in the following categories: Traditional Systems Engineering (TSE), Systems of Systems Engineering (SoSE), and Complex Systems Engineering (CSE). This data was gathered and analyzed in order to understand the kind of systems engineering approach required to design an engineered CASoS solution.

Appendix C contains the detailed description of the data describing the three systems engineering approaches. The advanced codes for this phase of the research were: TSE, SoSE, and CSE. Data collected from literature review and symposia were organized and evaluated according to the codes, as shown in Table 9. The advanced coding of this data produced an understanding of the differences among the three approaches, as well as an understanding of what types of systems can be engineered or produced from each of the three types.

Table 9. Coded Data References for Systems Engineering Approaches

Code	# of Data	Data References
Traditional Systems Engineering (TSE)	12	Blanchard and Fabrycky (1998), Calvano and John (2004), Haberfellner and deWech (2005), Hitchins (1992), Keating (2009), Kossiakoff and Sweet (1998), Ncube (2011), Neill et al. (2010), Paul, Beitz, Feldhusen, and Grote (2011), Polacek et al. (2012), Sousa-Poza (2015), White (2005)
Systems of Systems	14	Azani (2009), Dagli and Kilcay-Ergink (2009), Dahmann, Lane, Rebovich, and Baldwin (2009), Dahmann, Rebovich, and

Code	# of Data	Data References
Engineering (SoSE)		Baldwin (2009), Hitchins (2003, 2005, 2007), Giammarco (2017), Jackson and Keys (1984), Keating (2009) Maier (1998), Maier and Rechtin (2000), Ncube (2011), OUSD AT&L (2008)
Complex Systems Engineering (CSE)	21	Ames et al. (2011), Bar-Yam (2003, 2004), Beckerman (2000), Braha, Minai, and Bar-Yam (2006), Calvano and John (2004), Fisher (2006), Haberfellner and deWech (2005), Hitchins (1996), Holland (1992), Honour (2006), Neill et al. (2010), Norman and Kuras (2006), Oliver, Kelliher, and Keegan (1997), Ottino (2004), Polacek et al. (2012), Sheard (2007), Stevens (2008), Svetinovic (2013), Vakili, Tabatabaee, and Khorsandi (2012), White (2005)

Table 10 presents a summary of the results of the data gathered for the three SE codes. The table contains a characterization of each of the SE approaches as they relate to CASoS.

Table 10. Characterization of Advanced Codes: SE Approaches

Systems Engineering Approach	Characterization
Traditional Systems Engineering (TSE)	• Architectures based on clearly defined relationships • Well-defined functionality • Focused on the pursuit of ideal requirements that are complete, unambiguous, and testable. • Designs can be partitioned easily and with confidence • Architectural interfaces are dominated by interfaces that are well-defined and well-understood • Does not allow for adaptation • Interfaces, once designed, are fixed • Boundaries, once designed, are fixed • Requirements, once specified, are fixed • Described as design by decomposition—where a high-level description is abstracted and then partitioned into components and then each component is designed independently
Systems of Systems Engineering (SoSE)	**Bottom-up SoSE:** • Primary focus on integrating existing systems into a SoS; thus a bottoms-up approach • Focus on interoperability of existing systems • Focus on acquisition, management, governance, and funding issues

Systems Engineering Approach	Characterization
	• Bottoms-up SoSE approach is reductionist and will lead to further complexity and unintended emergence
	Top-down SoSE: • Recommendation for future SoSE to focus on a top-down approach to enable directed and desired emergent behavior and to architect and design the SoS as a whole.
Complex Systems Engineering (CSE)	• As environments become more complex and uncertain, TSE-produced systems are unable to adapt and respond as needed. • CSE is needed to develop complex systems that can adapt, change, and behave in novel ways in complex environments. • CSE is attempting to engineer systems that can produce aggregate emergent behavior while managing unpredictable emergence. • CSE must not pursue ideal requirements, which could limit the system behaviors to only specific conditions that are foreseen.
	Design the Environment: a CSE approach focused on creating an environment and process instead of an end-product or system
	Principles-Oriented: a CSE approach that exerts external influence on a complex system and is principles-oriented rather than rules-oriented
	Distributed Peers: a CSE approach in which a peer-to-peer architecture is comprised of distributed peers defined as autonomous machines
	Local Behavior and Emergence: a CSE approach with a focus on the behavior of local actions and neighbor interactions with predictions of what global properties will emerge.

The study of the advanced codes for SE approaches produced a set of SE objectives and guidelines for an engineering approach for CASoS. The codes and data in Table 10 were analyzed in terms of how these approaches would apply to an engineered CASoS. The results of this process, guidance and implications for a CASoS SE approach, are presented in Section E of this chapter.

C. CONCEPTUALIZATION OF AN ENGINEERED CASoS

A quintessential capability that an engineered CASoS must possess is decision-making. It must make decisions to intentionally determine its behavior, which must adapt and evolve to address its complex environment. This requires decisions that govern individual and collaborative behavior—resulting in purposeful behavior at multiple levels (including emergence). Decisions must take into account many different mission objectives depending on the operational situation. Thus, these decisions lead to multi-mindedness in the CASoS. The decision-making capability must be distributed among the constituent systems to enable self-organization and purposefulness at the system level. Thus, the CASoS is not a pre-determined, pre-destined system operating solely on a fixed rule set.

CASoS design and development requires a decision-centric paradigm, which essentially views the CASoS as a *system of decision systems* that share situational knowledge and make decisions for individual system actions with an aggregated SoS-level perspective in mind. These decisions must be synchronized among the constituent self-organizing systems. Thus, decision-making must take center stage for engineering CASoS—it must be the focus for designing and developing the constituent systems; and, it must be the focus for envisioning how the CASoS will operate most effectively to address the complex problem space (Young and Green 2014).

Establishing a decision-centric engineering approach ensures that CASoS behavior is intentional and desired. It relies on the three following capabilities: an adaptive architecture, a system of intelligent constituent systems, and the ability to discover knowledge and predict the effects of actions. An adaptive intelligent architecture enables agile interrelationships among the constituent systems that comprise an ultimately adaptive SoS that can respond to a changing complex environment. A system of intelligent constituent systems distributes the decision-making, enabling the systems to self-manage and decide to collaborate or act independently as the complex situation dictates. Finally, knowledge discovery and predictive analytics grants the CASoS the ability to gain and maintain shared situational knowledge of the environment and the distributed constituent systems. The CASoS uses its decision-making to analyze knowledge and prioritize missions, develop tasks and courses of action (adaptive responses to the problem space), and to develop what-if and if-then predictive scenarios to shape the synthesis of future intelligent decisions and adaptive CASoS relationships. The subsequent subsections discuss these three capability enablers in more detail.

1. An Adaptive Architecture

An adaptive architecture enables agile interrelationships among the constituent systems that comprise an ultimately adaptive SoS that can respond to a changing complex environment.

A primary CASoS capability is to be able to adapt to a changing environment. The CASoS adapts through a cycle of interactions with its environment: continuously changing its behavior in response to changes in the situation. A system must change its internal mechanisms, or undergo a physical metamorphosis, to exhibit a range of behaviors. However, in the case of CASoS, the inherent SoS nature allows it to exhibit a range of agile behaviors by adapting the interrelationships among its constituent systems. This capability, along with diversity and intelligence in its constituent systems, are the primary features that enable CASoS to address complex problem spaces. For example, when the CASoS determines that its environment has become highly complex, it will realign resource priorities and establish new interactions and collaborations in order to respond effectively.

In order to enable the CASoS adaptive behavior to be purposeful, the adaptive architecture must be intelligent. Thus, the constituent systems of the CASoS intentionally govern their own interactions with each other, and in effect, govern the architecture as a whole. The intentional interrelationships result in adaptive aggregate behaviors that enable multiple levels of behavior, including emergence, that are not simply derived from the actions of the parts, but emerge from the interactions of the parts.

Therefore, the adaptive architecture is a prime enabler of the variety of behaviors that the CASoS can exhibit. It establishes the outer boundary of the CASoS as well as the internal SoS boundaries that are changing and adapting in time and in response to the changing environment. Figure 33 illustrates adaptive relationships among the constituent systems and the changing CASoS behavior that results. The architectural structure enables CASoS adaptation and evolution through the interactions the adapting and evolving as the interactions adapt and evolve. The illustration shows an example of how a CASoS architecture changes in time. It depicts four iterations that are snapshots of the architecture at different times. In the first iteration, there are several individual systems acting (behavioral outputs are shown as colored arrows pointing up toward the environment), as well as one collaborative action. Next, the architecture three new collaborations to produce a different set of external actions. In the third iteration, the entire set of constituent systems are collaborating to produce one emergent behavioral action. Finally, in the fourth iteration, there are two overlapping collaborative systems of systems as well as two individual systems acting. This illustration shows the role that the architecture plays in enabling a variety of CASoS behaviors.

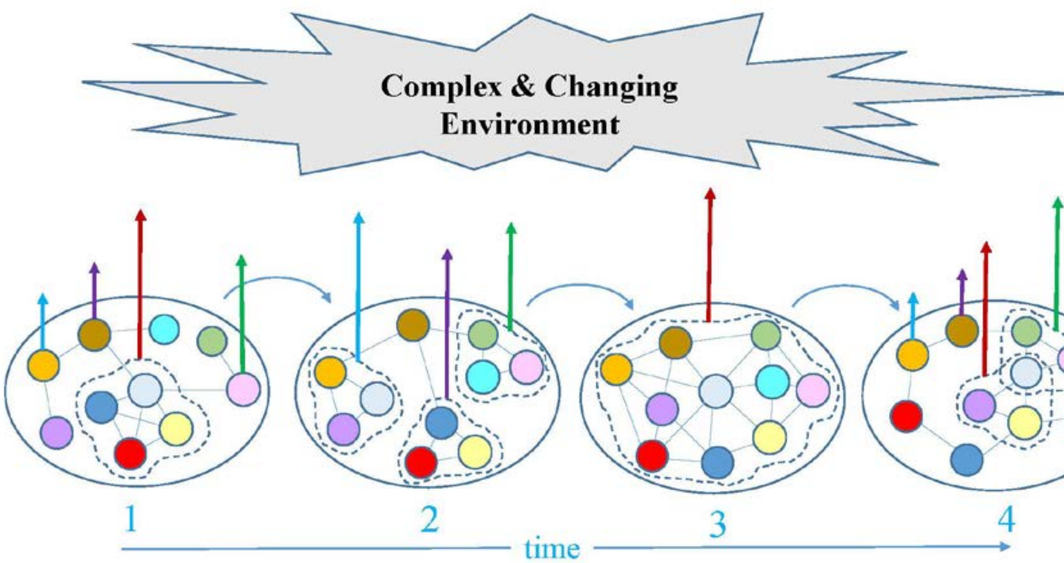

Figure 33. Desired Behavior from Adaptive Architecture

a. The Architecture as a Decision Resource

To take it a step further, the architecture can be viewed as a resource of the CASoS that can be utilized to effect desired behavior. The architecture is managed by the intelligent constituent systems that are organizing themselves through mutual interactions. Likewise, the adaptive relationships of the architecture enable the constituent systems to function in complex, adaptive, and collaborative manners. Thus, there is a symbiotic relationship between these two capabilities as illustrated in Figure 34.

The architecture, viewed as a resource, must be flexible and agile to establish interactions between systems and transmit information as needed. The ability communicate between distributed systems has real world limitations (discussed in more detail later in this section) such as data throughput and latency. These limitations can be minimized through efficient architecture usage to optimize information exchange that enables effective collaboration and ultimately CASoS behavioral actions. At times, if there are limits to data exchange, the constituent systems will have to determine which information is exchanged and to which recipients.

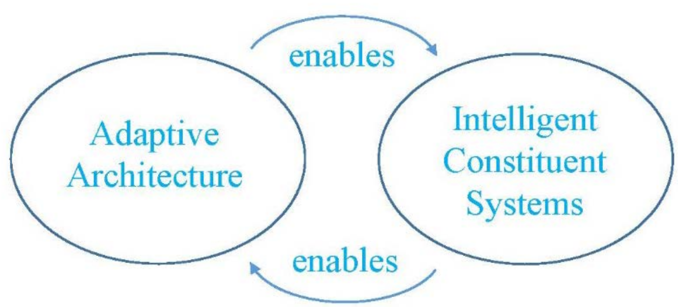

Figure 34. Symbiotic Relationship Between Adaptive Architecture and Intelligent Constituent Systems

The intelligent decision-making capability of constituent systems (discussed in more detail later in this chapter) will manage the adaptive architecture in a distributed, yet coordinated, manner. The architecture can be described as self-forming as the constituent systems self-organize and interact. This management will not be ad hoc. Rather, the systems will be managing the architecture as a resource with the needs of the whole CASoS as well as individual system needs, in mind. Thus, it will be a purposeful architecture.

b. Interaction Mechanisms

In order to be adaptive, the architecture relies on a variety of interaction types between the constituent systems. These interaction mechanisms range from simple acknowledgements to information exchanges to agreements. The information exchange is necessary to gain and maintain shared knowledge among the systems. Agreements or handshakes are necessary in certain situations to guarantee a commitment from multiple systems to collaborate for emergent behavior.

Table 11 identifies and describes some possible types of interaction mechanisms. The first two mechanisms support initial interaction: the ping, which is an acknowledgement of existence, and the baseline, which is an initial exchange of baseline information concerning system capabilities and configuration information.

Table 11. Types of Internal CASoS Interactions

Types of Internal CASoS Interactions	
1	Ping – initial contact conveying existence
2	Baseline – sharing of baseline capability information
3	Health, Status, Configuration, Capabilities (HSCC) – continuous updates of HSCC info
4	Situational Awareness (SA) Data – continuous updates of SA data, information, and knowledge
5	Synchronization – data interaction to ensure SA and HSCC synchronization among constituent systems
6	Action Intent – sharing intention to act
7	Collaboration Request – an acknowledgement of request for constituent systems to collaborate
8	Handshake – an acknowledgement of confirmation that constituent systems intend to collaborate
9	Information Request – a request among constituent systems for data/information, knowledge, synchronization, etc.

The third mechanism is the exchange of health, status, configuration, and capability (HSCC) information. This is a sharing of system information that enables systems to make decisions based on an understanding of each other’s capabilities in addition to their own. This is an important capability enabler for SoS-level decision-making that facilitates desired emergence.

The fourth mechanism is the sharing of situational awareness (SA) data, information, and knowledge. This important mechanism enables systems to gain and maintain shared knowledge of the problem space.

The fifth mechanism is the ability of systems to synchronize themselves through data interaction. Synchronization is required to ensure that SA is consistent among the systems. It is also needed to ensure that behavioral decisions are consistent.

Mechanisms six through eight support agreements between constituent systems for collaboration. In order to coordinate actions, systems may send action intent messages to one another. Systems may send collaboration requests to each other to initiate and acknowledge collaboration. In some cases for critical operations, systems may require a handshake to solidify the agreement to collaborate.

Finally, the ninth mechanism is an information request, which a system might send to its constituent system neighbors asking for data, information, knowledge, or synchronization.

The architecture allows new systems to enter the CASoS and become part of the interacting constituent systems. Likewise, the architecture allows systems to exit the CASoS. Figure 35 illustrates an example of the types of interactions occurring as a new system makes contact with a CASoS (with a ping), transmits and receives baseline information and then goes into an interactive state with other neighboring constituent systems by transmitting and receiving continuous HSCC and SA updates.

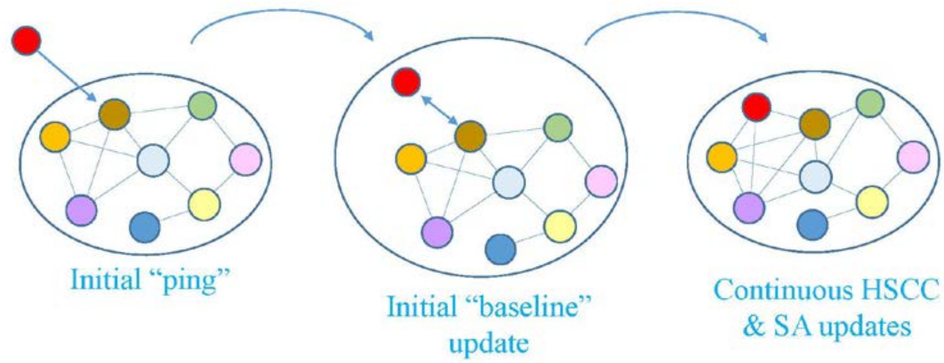

Figure 35. Interaction Sequence for Newly Entering Constituent System

c. *Architecture Limitations*

A number of challenges to the adaptive architecture capability exist due to real world limitations. These limitations may lessen in the future as information and communication technologies continue to advance. Some examples of causes of these limitations include:

- Distribution—The distance between constituent systems as well as the kinetics of systems moving with respect to one another may present challenges for communication. Distances can add latency, greater chances for error, and greater potential for negative effects from the environment.

- Connectedness—A large number of interconnections (which may be due to a large number of constituent systems) can present challenges for maintaining the required number of communication paths. This condition can also lead to bandwidth issues if the data size is large.

- Environmental Effects—Weather and other environmental conditions may adversely affect the communication technologies, adding latency, errors, and possibly causing outages.

- Communication Technologies—Limits may be inherent in the communication technologies available. These may include limits to bandwidth (or amount of data able to be transmitted in a time period), errors induced, latency, and limits to types of data transmitted.

- Outages—Communication outages (the lack of ability to share information between systems) may occur if there are technology failures, environmental effects, or a threat-based denial of service. Alternative communication paths or redundant links may provide a solution.

- Information Assurance—Communication issues could take the form of a cyber-attack, injecting unauthenticated and/or false data into the system, or causing denials of service.

2. A System of Intelligent Constituent Systems

The adaptive emergent behavior of the CASoS is governed by the self-management of the distributed constituent systems to collaborate or act independently as the complex situation dictates. Thus the engineered CASoS can be described as a system of intelligent constituent systems. This can also be thought of as distributed decision-making or a system of decision systems.

The two primary capabilities of the constituent systems are: (1) to have the ability to make decisions concerning not only their own behavior, but also about their interactions (distributed control; not centralized); and (2) the ability to develop and synchronize SoS-level decision-making. In other words, the constituent systems make decisions at the global CASoS-level and use the global decisions to govern their own behavior. Therefore, the engineered CASoS is a system and architecture that enables behavior at the system level to be optimized for overall goals as well as individual goals.

An assumption is made in this section that the constituent systems have a shared situational awareness. This capability is discussed in the next section on knowledge discovery and predictive analytics. This conceptual approach is decision-centric with a primary focus on what decisions need to be made and a secondary focus on gaining the information to support the decisions. Historically, efforts have focused primarily on acquiring data and information and fusing it and then secondarily determining what can be done with the information in terms of decision-making. Figure 36 illustrates the interdependencies of the primary engineered CASoS capabilities. The intelligent constituent systems capability has a symbiotic relationship with the adaptive architecture. It also has a strong dependency on the ability of the CASoS to perform knowledge discover and predictive analytics. All three capabilities are based on data: the ability to communicate it (adaptive architecture), develop knowledge and predictions from it (knowledge discovery and predictive analytics), and ultimately to make behavioral decisions based upon it (intelligent constituent systems).

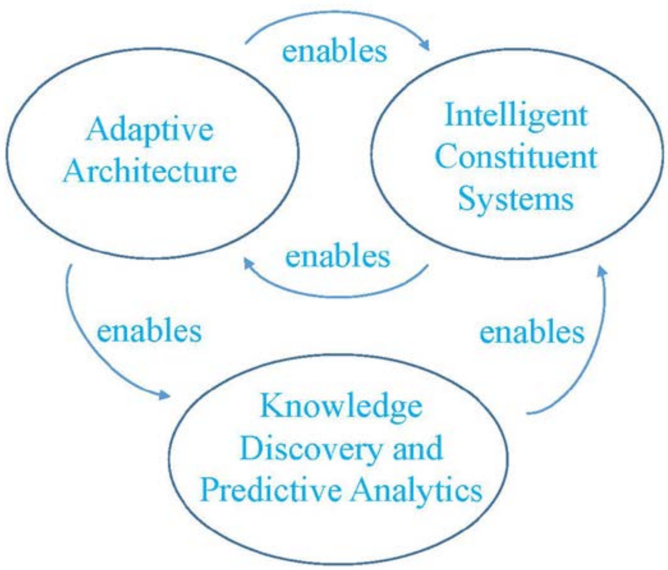

Figure 36. Interdependent Relationships between CASoS Capabilities

a. A System of Decision Systems

The engineered CASoS can be described as a system of decision systems. Instead of a central manager and controller with a god's eye view of the situation, the god's eye view is present in each of the distributed systems. Thus, this condition of distributing the situational awareness is actually replicating the intelligence among the distributed systems.

Figure 37 shows a simple example of three constituent systems collaborating to produce emergent behavior to address a complex environment. The number of constituent systems would likely be significantly greater for an actual CASoS. The red dotted arrows represent input data and information from the environment that is captured by sensor resources of the CASoS. The systems develop shared situational awareness (SA) by sharing the sensor data and implementing common processes to analyze it. The individual constituent systems then develop behavioral options or actions they can take individually and/or collectively. The green outwardly pointing dotted arrows illustrate the CASoS collective actions.

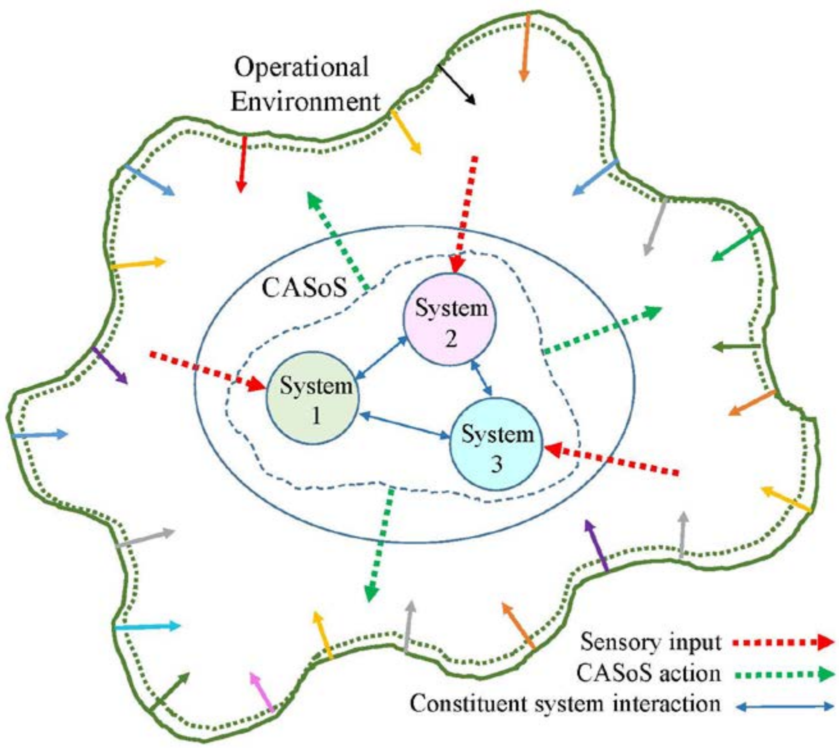

Figure 37. Simple Example of CASoS Information Sharing and Collaboration

One of the key capabilities required for the engineered CASoS is a set of decision analytics (or common data processing algorithms) to analyze data and develop CASoS behavior decisions. An instantiation of the decision analytics must be present in each constituent system to provide intelligence. Figure 38 illustrates the decision analytics concept at a high level, referring to this process as the decision space. The decision space, or intelligent agent, includes the data processing and analysis that needs to be present in each constituent system.

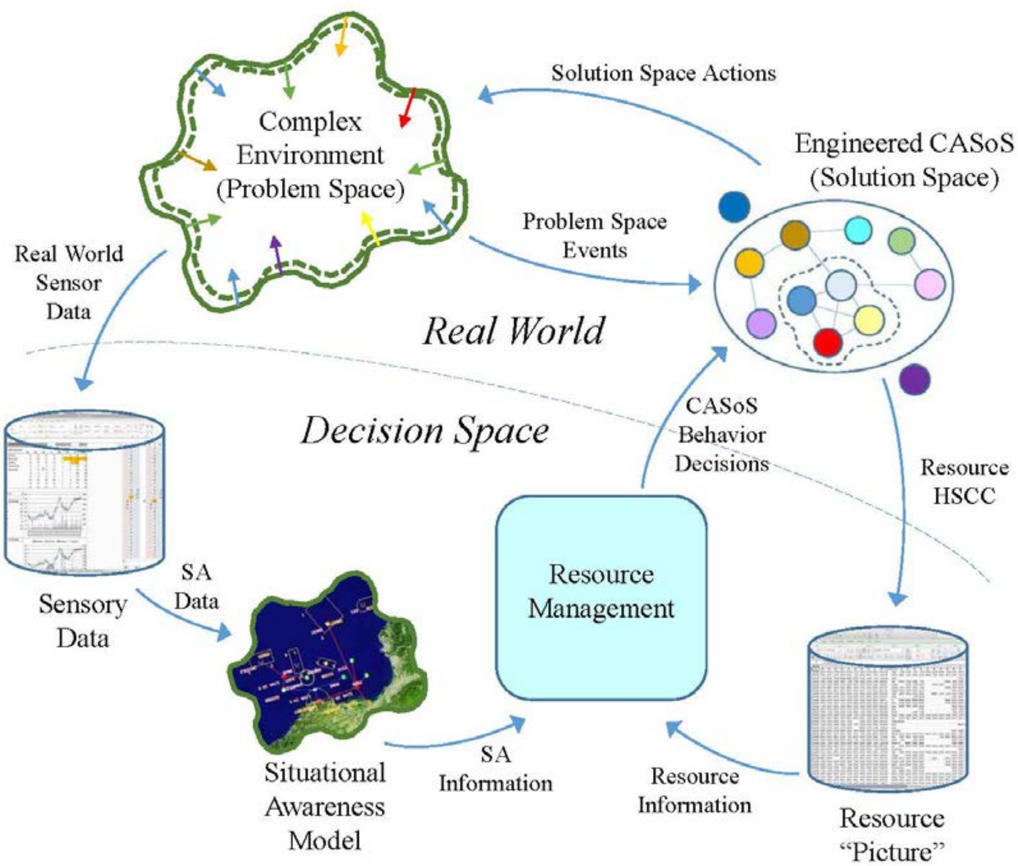

Figure 38. The Interplay between the Real World and the CASoS Decision Space

Figure 37 illustrates the interplay between the real world and the CASoS decision space. The complex environment (or problem space) is shown as distinct from the engineered CASoS solution space in the illustration to emphasize the distinct interactions of each within the decision space. In an actual real world, the problem space and solution space would have a more complex interaction and a more accurate illustration would be with the CASoS surrounded by its environment. The primary inputs from the real world to the decision space are sensory inputs providing data about the environment and information concerning the CASoS resources—including health, status, configuration, and capability

(HSCC) data. A model of the problem space (the SA model) is developed in the decision space as well as a resource picture. Note that these models would be continually changing as the CASoS and its environment change. All of this information would then feed the resource management capability, which develops decision options for ways in which the CASoS can exhibit behavior to address its problem space in the real world. Data analytics would process quantitative data based on the internal SA model to determine the complexity level of the environment and develop decisions options involving reconfiguration and reallocation of resources. These decisions are the major output of the decision space and guide the actions of the engineered CASoS.

b. Resource Management

In the context of engineered CASoS, resources are defined as individual capabilities that the CASoS possesses. A constituent system can consist of one or more resources and therefore one or more capabilities. Examples include sensor resources, mobility resources, processing resources, and communication resources. A resource is defined separately from a constituent system because there is not always a one-to-one correspondence between systems and resources and they have a slightly different purpose within the CASoS. Each constituent system has an instantiation of the distributed intelligent processing capability that includes resource management (RM), knowledge discovery (KD), and predictive analytics (PA). Each resource is a capability that is managed to address the CASoS mission objectives. The mission objectives would be determined based on the analysis of the environment and its level of complexity. Figure 39 shows a simple example of three constituent systems in a CASoS. Each system contains the intelligent processing capability and one or more resources, illustrated by the yellow circles.

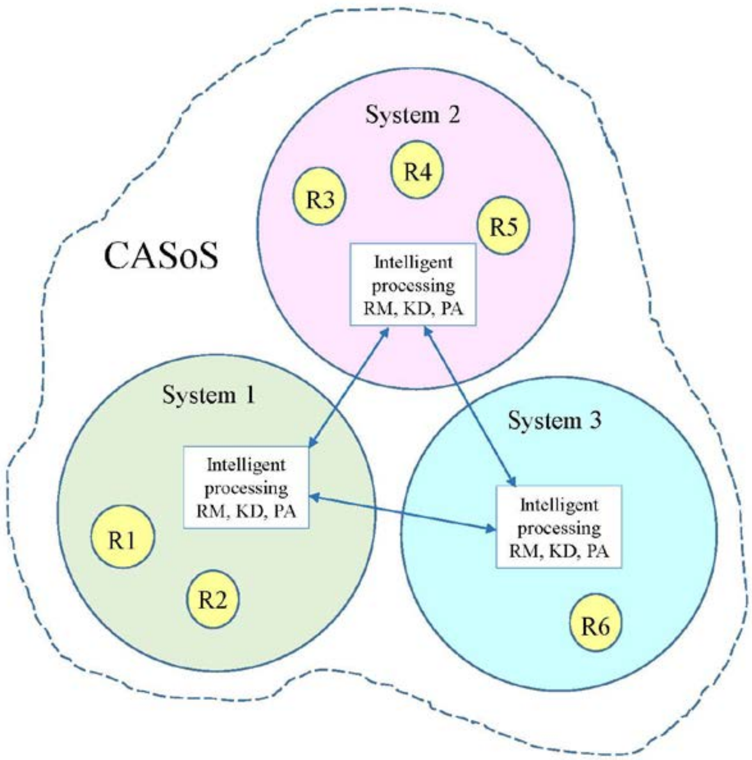

Figure 39. Intelligent Constituent Systems and Their Resources

Figure 40 is a modified version of the data fusion model that was originally developed by the Joint Directors of Laboratories (JDL) (Steinberg, Bowman, and Wright 1998). This version emphasizes the level 4 resource management function that decides how to manage resources based on assessments of signals, entities, situations, and impacts in data fusion levels 0 through 3. The JDL's model was data-centric, focusing on what kinds of fusion, processing, and analysis could be performed on data to gain the most knowledge and utility from it. The adaptation of their model shown in Figure 39 focuses on resource management as a starting point for conceptualizing an engineered CASoS with a decision-centric focus. By emphasizing resource management, the design of the engineered CASoS is focused on its behavioral interaction with the environment rather than this interaction being an afterthought.

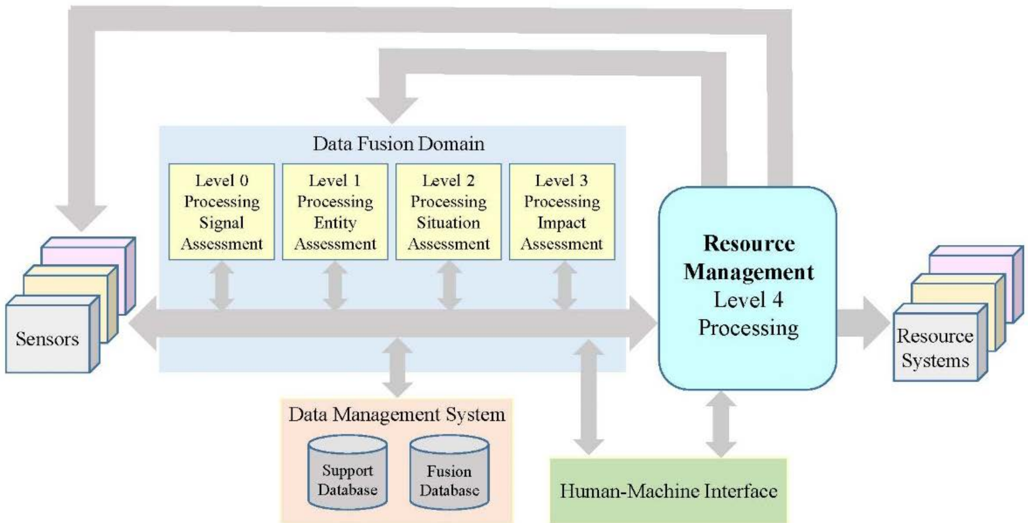

Figure 40. Decision-Centric Resource Management.
Adapted from Steinberg, Bowman, and Wright (1998).

The ability to manage resources is a primary component of the constituent system's intelligence. Resource management involves decision making to guide or control the CASoS's resources, including the data fusion domain itself. In this concept, the resource manager contains the intelligence to determine how the sensors should be tasked or prioritized or made to be more cooperative to improve the data collection and ultimately the knowledge of the situation. The resource manager could control the data fusion domain to optimize the fusion processing of the data for better assessment of signals, entities, situations, and impacts. Also, the resource manager would task the resource systems which provide capability to interact with the problem domain (environment). In a military example, this could be tasking weapon systems to engage threats or tasking ships or aircraft to maneuver.

Figure 41 shows a concept for the high-level functionality of the resource management capability along with its interactions with the resources and other capabilities. In other words, this is the common decision capability or intelligence that would be embedded in each constituent system. Examples of resources are shown in yellow boxes along the bottom of the illustration. These include sensors for observing events and entities in the real world operational domain as well as weather and other environmental conditions. Another example is data fusion, which would be part of the knowledge discovery capability. The adaptive architecture is also viewed as a resource. Additionally, there would be other CASoS resources depending on the type of solution domain.

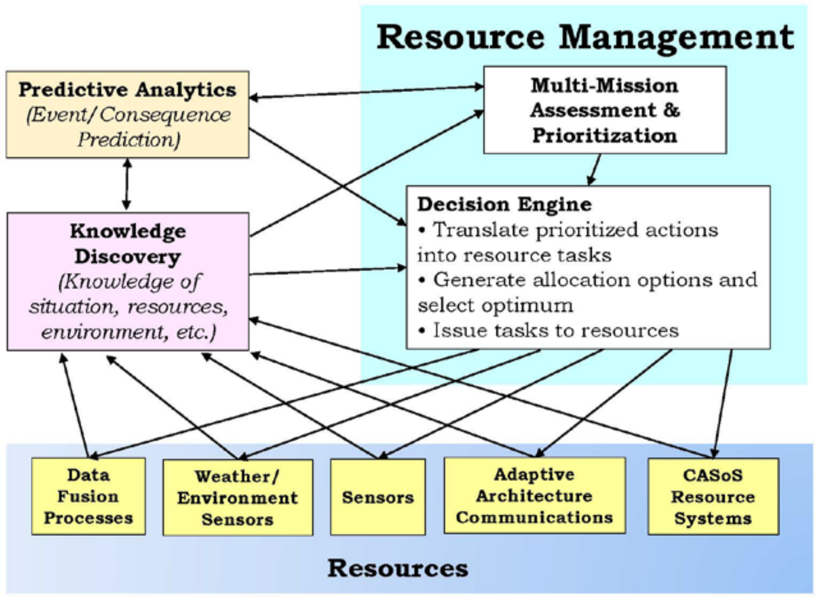

Figure 41. Resource Management Functionality

The resources provide sensory data as well as information about themselves and their status to the knowledge discovery capability. This capability develops, maintains, and updates knowledge of the problem domain and the resources. It provides this knowledge to the resource management capability as well as to the predictive analytics capability. The resource manager translates this knowledge into new mission objectives for the CASoS to address the problem domain. It assesses and prioritizes the mission objectives, which in complex situations could include multiple conflicting objectives. It has a conceptual decision engine, which would develop behavioral resource course of action (COA) options to address the missions. This process is envisioned to be continuous in its operation and changing as information is acquired and assessed, reflecting an evolving environmental situation (i.e., converting from complex to highly complex). The resource management capability would conceptually, work in concert with the predictive analytics capability—which would assess the likely consequences of different COA options. Conceptually, the decision engine translates prioritized objectives into resource tasks; generates resource allocation options; coordinates with the predictive analytics capability; and, selects an optimum option. The resource management options may include independent system resource action or collaborative action. It may also change COAs depending on how the missions are changing. All of the capabilities would be performed continuously and simultaneously in each constituent system that is part of the engineered CASoS.

Another important feature of this capability is the ability to synchronize decisions among the distributed constituent systems. The ability to synchronize decisions would be an additional function of the adaptive architecture and would involve data communication among the systems to ensure consistency and to identify when decision are not consistent.

c. Considerations for Engineering Self-Organizing and Emergent Behavior in CASoS

The constituent systems, with their embedded and synchronized common intelligence, and the adaptive architecture, collectively decide to organize themselves. They can coordinate their individual behavior and interactions to create emergent behavior. This subsection describes how this would conceptually work.

The combination of a common processing capability resident in each distributed constituent system and the adaptive architecture, allows the engineered CASoS to be effectively designed on the fly. This novel concept brings the ability to design a system to near-real-time operations. In traditional systems engineering, system behavior (in terms of functionality and projected performance) is determined during the design phase, prior to operations. This results in a limited set of possible behavior for a system to perform operationally.

For engineered CASoS, this limitation would still exist at the system level. Each constituent system would still be comprised of resources with established functionality and performance capability. However, the adaptive architecture and distributed decision-making intelligence would enable highly flexible design options at the SoS level during operations. The engineered CASoS would be able to reconfigure itself into numerous collaborative configurations to create emergent behavior. These SoS configurations and resulting emergence would only be limited by the number and heterogeneity of the participating constituent systems. This conceptual capability is referred to as design-on-the-fly. It enables the engineered CASoS to self-organize, adapt, evolve, and even learn.

Table 12 presents four different types of CASoS collaboration that lead to emergent behavior. Level 1, referred to as divide and conquer, is a form of coordination in which each constituent system agrees to address a different and unique mission objective. They divide these tasks among themselves and each conquer or fulfill them separately. Level 2 is similar, but in this case, systems coordinate to act independently while addressing the same objective or set of objectives. For level 3, multiple constituent systems dedicate resources to cooperatively meet an objective together. In level 4, multiple constituent systems collaborate in a more highly interactive way (requiring action synchronization, action intent, handshakes, etc.) that might include multiple dedicated resources, multiple objectives, and longer durations of collaboration. Conceptually, these various forms of collaboration would occur continuously and at time, simultaneously, dictated by the complexity of the operational environment.

Table 12. Collaboration Levels for CASoS Emergence

Engineered CASoS Emergence Levels		
1	Divide & Conquer	Systems each address different objectives (tasks); but agree and commit to do so. They "divide" the tasks among themselves; and "conquer" or fulfill the tasks separately.
2	Coordinate	Systems each act independently, but address the same objective (or same set of objectives).
3	Cooperation	Systems dedicate resources to meet an objective together
4	Collaboration	Systems dedicate resource for highly interdependent interaction and action to address complex objectives (may include multiple dedicated resources, multiple objectives, longer duration, etc.)

d. *Human-Machine Decision-Making*

An important aspect of engineered CASoS is the incorporation of humans in the decision-making process. The engineered CASoS must be engineered as a system that supports human decision makers. Thus, the CASoS is conceptualized as a decision-making process that supports human decisions through its adaptive architecture and automated intelligence.

Automated decision aids, or machines, can support human decision-makers in a number of ways. Three models for human-machine decision-making interaction are shown in Figure 42. The manual decision-making model encompasses situations in which humans cognitively collect and store relevant information as well as perform the decision analysis (processing and decision-making). This model implies a fairly simple and straightforward decision space in which the amount of data and number of variants is manageable manually. In the semi-automated model, the human decision-maker relies on machines to manage, store, fuse, and process the input information to display decision analytics. For the engineered CASoS, decision analytics will consist of knowledge discovery, resource management, COA options, and quantitative measures of expected event successes and consequences. Finally, in the fully automated model, the human's role is to monitor the automated machine decision processes and to override or change decisions when necessary.

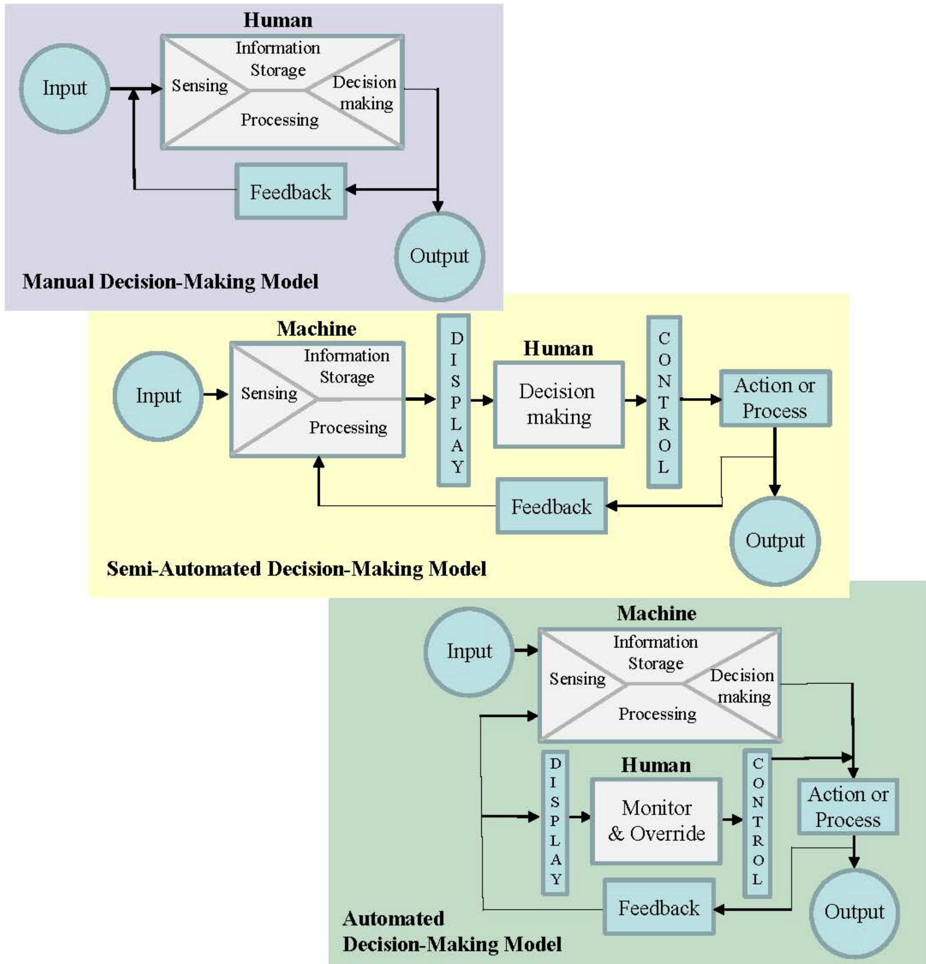

Figure 42. Human-Machine Interaction Models.
Source: Johnson, Green, and Canfield (2001).

It is important to establish the appropriate mechanism for the type of decision being made. In general, decision-making can be performed manually when the problem space is relatively simple and the number of factors to be considered and the amount of information is manageable by the human decision-maker. For some types of decisions, a semi-automated human-machine interface (HMI) mechanism is most appropriate. This is effective for more complex decision spaces with potentially critical or dire consequences; requiring the support of automated decision aids, but with significant human involvement. A fully automated HMI mechanism is appropriate for decision spaces that are complex in terms of large amounts of information that must be processed and fused, but that involve relatively straightforward heuristics in terms of the types of decisions being made. Fully automated decision modes are for relatively non-complex operations where decisions do not have dire consequences or for highly complex operations where the decision reaction time is too compressed for humans. Fully automated decision modes are appropriate when there is very high confidence in the information and knowledge of the situation.

Conceptually, the engineered CASoS could treat the HMI mode as a managed resource to appropriately respond to changes in the complexity of the problem space. The complexity of the decision space would have to be continuously assessed. Increased complexity could be due to increases in mission objectives, greater amounts of information and data to process, compression in decision timelines, or a combination of these factors.

Another important characteristic of the engineered CASoS that relates to HMI is trust. Some studies have indicated the importance of establishing the right level of human trust in intelligent (decision support and artificial intelligence) systems (Hengstler, Enkel, and Duelli 2016, Marsh 2005). The engineered CASoS is a system of decision systems. It is critical that human decision-makers interacting with the CASoS and relying on this artificial intelligence can have confidence in the decision options and assessments presented. Human operators must have an adequate level of trust in their machine partners. They must know when it is appropriate to have confidence in the decision options and when they should question decisions. An over-reliance on artificial intelligence can also lead to undesired COAs. The engineered CASoS can provide a capability of self-assessment to provide a level of confidence estimate to accompany decision options. This capability would also support the resource management, knowledge discovery, and predictive analytics capabilities.

3. Knowledge Discovery and Predictive Analytics

Knowledge discovery (KD) and predictive analytics (PA) are two key capabilities required for engineered CASoS. They go hand in hand as PA is directly dependent on KA for knowledge and information to predict possible consequences of CASoS actions. KD and PA are both components of a constituent system's intelligence. They both must be implemented in a common fashion among the constituent systems to enable synchronized self-organization and emergence as a cohesive system of systems. Here in this subsection, we focus on these capabilities in more detail. Figure 38 illustrates the interdependencies among the three CASoS capabilities that enable purposeful intelligence in constituent systems. It shows that KD provides the knowledge that enables RM and PA to perform their functions. It also shows that RM provides decision option information (concerning possible options for the CASoS to act) to PA. PA uses its analysis processes to make predictions about the effects of these actions. It then provides these predictions back to the RM, so the RM can take this information into account as final decisions are made for CASoS actions. Finally, Figure 43 shows that these capabilities exist in each constituent system. Thus, an instantiation of the capabilities are resident in each constituent system of the CASoS.

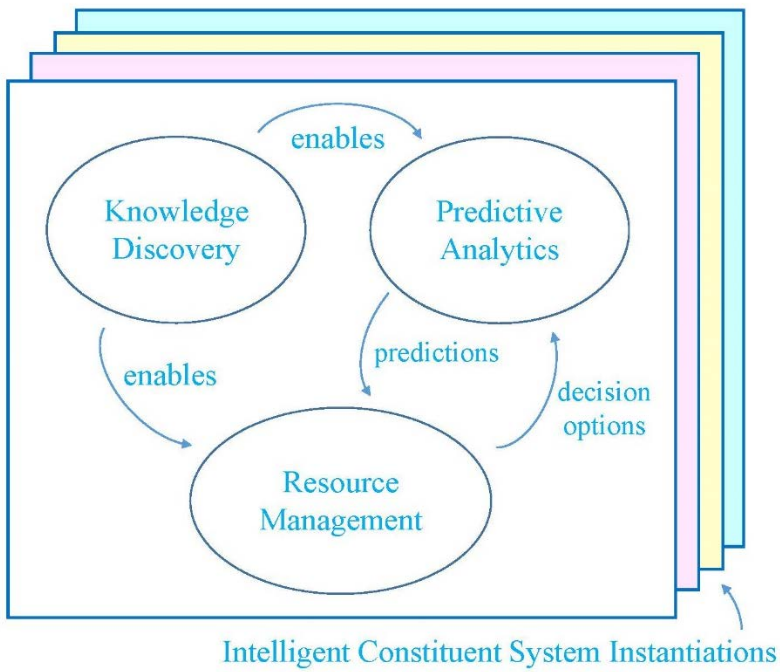

Figure 43. Interaction among CASoS Capabilities: KD, PA, and RM

a. Knowledge Discovery

Decades of research have provided (and continue to provide) significant technology and engineered methods to achieve KD for operational environments. This research has focused on the development of a variety of sensors to observe the environment and collect data, and data analysis and fusion techniques to process the sensor data and develop a picture of the real world environment. Recent efforts have included the use of Big Data processing and artificial intelligence techniques for fusing heterogeneous data sets that include non-traditional data sources such as social media to improve knowledge. Research has also focused on improving knowledge through sensor resource management techniques to provide feedback controls to enhance the overall picture based on changing sensor parameters or coverage.

Attempts to achieve shared operational knowledge (or shared SA) among distributed systems have resulted in a number of data architectures to communicate and manage data. These attempts have uncovered a number of challenges to achieving synchronized knowledge among distributed systems, such as induced errors, limited bandwidth, limiting architectures, and latency issues (especially with the need for real-time imagery). These challenges often result in significant differences between the operational images produced at different locations. Fortunately, these challenges are a focus of on-going research and improvements are being made. However, these limitations must be taken into account as they would affect CASoS performance.

Table 13 lists and describes the required capabilities for an engineered CASoS to perform KD. Obtaining sufficient data sources is required—whether they are external sources or sensor resources that are part of the CASoS. The advantage of having sensors internal to the CASoS is that they can be managed or retasked to improve or optimize the CASoS's collective knowledge of the real world. For example, if there is data missing from a certain area of the environment, the sensors can be tasked to widen their field of view or point toward the area that needs coverage. The ability to manage, fuse, and share the data among the constituent systems is also a required capability for achieving shared knowledge or SA.

Table 13. Engineered Capabilities for CASoS Knowledge Discovery

Engineered Capabilities for CASoS Knowledge Discovery	
Heterogeneous Sensors	Sensors that are resource systems within the CASoS to provide heterogeneous types of data about the environment
External Sources	Sources of data and information about the environment that observed by external sources and made available to the CASoS
Data Fusion & Management	The ability for each constituent system in the CASoS to fuse, managed, process, and assess data to develop a living model of the real world environment
Data Architecture	The CASoS adaptive architecture will provide the capability to share and synchronize data and information among the CASoS constituent systems.
Sensor Resource Management	CASoS sensor resource systems can be managed (tasked) to improve overall CASoS shard knowledge of the environment. This is envisioned as a continuous feedback management capability.
Self-Aware	CASoS KD needs to be holistic, including information about itself (its distributed resource systems) in addition to information about the real world environment.
Knowledge of the Unknown	The ability to identify and assess what is unknown, incomplete, or less than accurate about the real world environment or the CASoS resource systems.

Two new areas of KD capability need research and attention. The first is sensor resource management. Single sensor feedback management is focused on the tasking of a sensor to change its parameters or pointing to improve the coverage or accuracy of its observations. The new extension of this is to manage the set of distributed CASoS sensors. In this way, the sensors are managed in a cooperative manner—so their collective ability improves the overall shared picture of the real world environment.

The final required KD capability for an engineered CASoS is to be holistic in the types of knowledge discovered. The CASoS should not only discover knowledge about the real world environment, but should also discover knowledge or develop a living picture of itself and other external systems that may be part of the solution space. In essence, the KD capability must maintain a picture of the entire decision space, as illustrated in Figure 44.

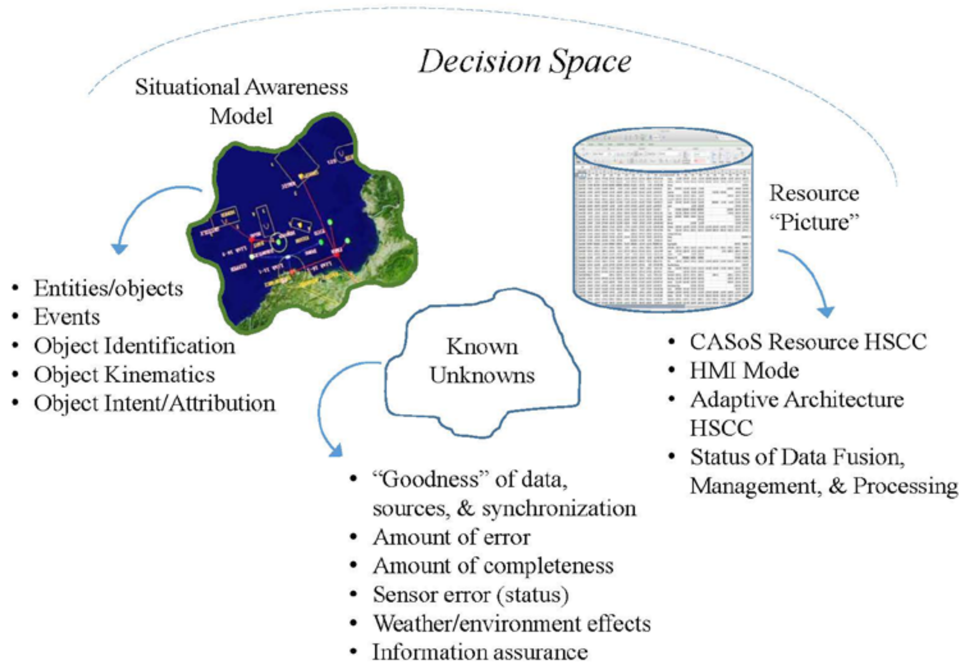

Figure 44. Types of Knowledge Required for the CASoS Decision Space

An additional important component of KD is the knowledge of what is not known. In order to make the best decisions possible based on the knowledge, it is also important to identify areas of incompleteness and inaccuracy in the knowledge of the decision space and fill those gaps. Some examples include: identifying areas of the real world environment that do not have sensor coverage for a period of time; areas of the environment where the data was less accurate; periods of time when there is known error for sensors (based on weather, non-optimal performance, introduced errors, etc.); and periods of time when pictures among constituent systems are not synchronized. The results of this type of analysis lead to the ability for the RM to assess the level of confidence for decision options. A quantitative capability can be developed to assign confidence levels based on assessed knowledge goodness.

Another matter to consider for KD is the authenticity of the knowledge. Such a large and distributed information and decision system as a CASoS must be sure to stress information assurance and to defend against cyber-attacks.

b. Predictive Analytics

A PA capability is key to enabling a strategic CASoS—one that takes into account possible consequences and effects of decision-making. The PA capability would develop what-if and if-then predictive scenarios to shape the synthesis of future intelligent decisions and adaptive relationships. This conceptual capability enables the CASoS to evolve in its purposefulness. It gives the CASoS the ability to make behavioral decisions concerning its courses of action based on what the longer-term effects are projected to be. It enables the CASoS to have short-term and longer-term objectives and to weigh these as resources are managed and actions are taken.

Figure 45 illustrates some of the notional capabilities of the conceptual PA. The PA would receive knowledge of the real-world SA and CASoS resource HSCC from the KD capability. It would receive COA options from the RM capability. As it assesses the consequences of CASoS COAs on the operational environment, it would develop projected future states of the environment (real world) and of the CASoS resources. It would use these projections to assess the COA options and determine which options have the most desired consequences. The PA provides the ability for the CASoS to ensure purposeful behavior that aligns with short and longer-term goals. The PA could assess, for example, the possible effects of weather predictions on CASoS COAs and the availability/depletion and projected capability of CASoS resources that factor into COA decisions. It could also assess overall CASoS readiness, resilience, and project capabilities.

The engineered CASoS PA capability would have to be highly tailored to its problem space. For example, for an operational environment that has the potential to cause harm to human safety, the predictive assessment would have a capability that includes future projections of how COAs might affect safety. Another example is a problem space that includes an adversary. In this case, the PA capability would include a wargaming or red-cell assessment to predict enemy responses to tactical resource actions. It would also develop and maintain a model of the adversary’s predicted knowledge, capabilities, intents and strategies. This could be used to better understand and predict adversary responses in the short and long-term.

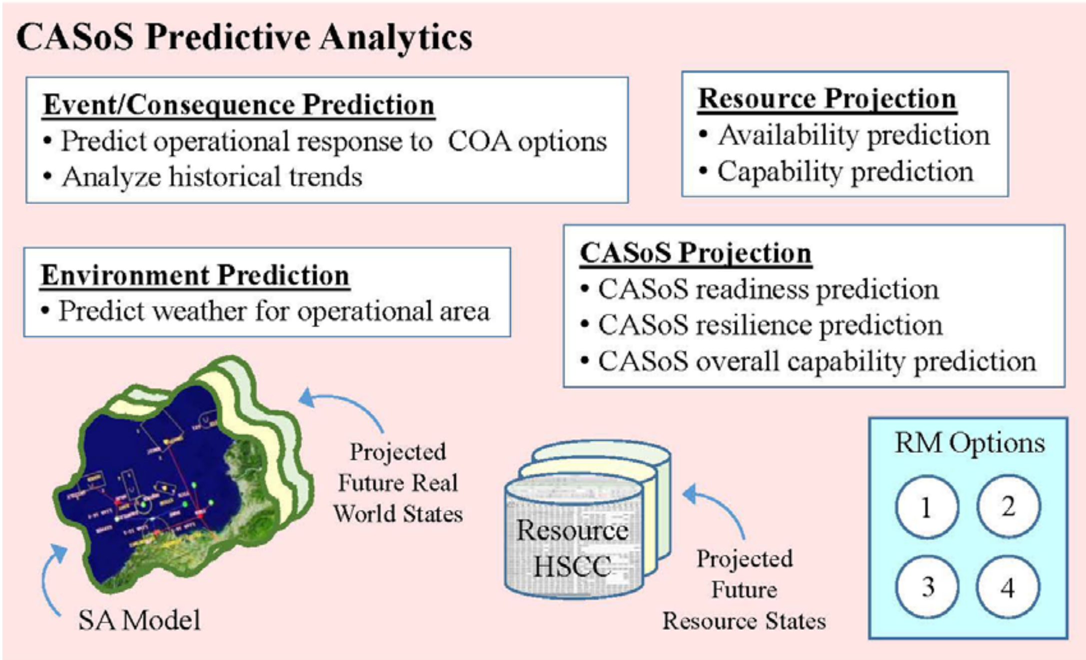

Figure 45. Engineered CASoS Predictive Assessment Capability

An important aspect of the PA capability is the development and management of CASoS goals. These goals may be predetermined as part of deliberate planning for the overall CASoS and its intended ability to address its complex problem space. The goals would be implemented as quantitative measures of effectiveness (MOE) and rule sets to guide behavioral decision-making. They would be used as preferences and evaluation criteria for analyzing resource COA options and performing design on the fly decision-making. However, the CASoS would benefit from the ability to perform dynamic planning, which would have the capability to modify these goals (and their associated MOEs, rule-sets, and quantified preferences) during operations. This would enable the CASoS to evolve in its purposefulness in an adaptive manner as the problem space changes.

D. IMPLICATIONS AND GUIDANCE FOR CASoS SYSTEMS ENGINEERING

The CASoS theory identifies differences between CASoS and other more traditional systems and systems of systems. This section discusses several topics related to engineering a CASoS that reflect these differences and provide guidance for addressing these differences within the SE process. The five topics discussed are: (1) systems engineering goals for CASoS, (2) the necessity of a top-down systems engineering approach, (3) employing an intelligent distributed peer architecture approach, (4) considerations for engineering the constituent systems, and (5) a continuous design approach throughout the CASoS life cycle.

1. CASoS Engineering Goals

There are three overarching goals for engineering a CASoS based on their unique characteristics. These are:

- to engineer a solution that can address a given highly complex problem,
- to engineer desired CASoS emergent behavior and avoid undesired and unpredicted emergence, and
- to engineer a solution that can evolve over time as the complex operational environment changes.

The first goal, to develop a CASoS that can address a highly complex problem, relies on designing and developing a system that possesses the characteristics, principles, and implied conceptualization that have been theorized for a CASoS. This challenging endeavor involves the engineering of a system of constituent systems with the three primary capabilities outlined in Section C of this chapter: an adaptive architecture, an intelligent system of systems, and the capabilities of knowledge discovery and predictive analytics. It also involves tailoring these conceptual engineered capabilities to the particular problem domain being addressed.

The second goal of ensuring that the emergent behavior is intentional and desired requires several engineered capabilities. These include the architecture of distributed, identical, and synchronized intelligence among the constituent systems. This also implies shared and synchronized information among the peers. Additionally, each peer must produce and maintain a holistic perspective of the CASoS awareness and decisions, so self-organized behavior at each constituent system is intentionally performed for the overall goals of the CASoS. In effect, a CASoS must be engineered to take advantage of its complexity while managing unpredictability (Calvano and John 2004).

The third goal is engineering a CASoS as an evolving system. The purpose of a CASoS is to function in complex environments with unforeseeable contingencies. Therefore, the SE approach must seek to produce a "system capable of adaptation, change, novelty, and even surprise" (Braha, Minai, and Bar-Yam 2006, 9). A couple of CSE methods have been proposed to address this challenge. One approach is to design an environment or a process instead of a system (Bar-Yam 2003; White 2005). The idea is that the environment or process creates a situation for systems to appear and evolve. The Internet is an example of this approach. A second idea is to use a principles-oriented approach that involves using external influence on a complex system to achieve desired behavior and to avoid undesired behavior (Polacek et al. 2012). This method does not rely upon a rules-oriented approach to control processes and behavior. One take-away from these ideas is that the CASoS adaptive architecture and intelligent agents must be engineered to support the participation of new constituent systems and many different combinations of constituent system interactions. The large number of interacting constituent systems, providing diverse capabilities, will give rise to numerous possible multi-level behaviors. This will enable adaptive, evolutionary responses to address highly complex problems. A second take-away is that the system of intelligent agents resident in the constituent systems must be capable of developing decision options and choosing among them in a way that is principles (or mission)-oriented instead of rules-oriented to enable responses to unanticipated events in the problem domain.

2. Necessity of a Top-Down Approach

In order to produce purposeful emergent behavior and avoid undesired emergent behavior, a CASoS solution must be engineered and designed from top-down. Although several bottom-up engineering methods have been proposed for engineering complex systems, these methods produce systems that will behave in unpredictable ways. Bottom-up CSE methods are based on the premise that the constituent systems self-organize based on their own perspective and prioritization of actions, rather than with a holistic SoS perspective. A bottom-up method would produce a complex system of constituent systems that self-organize and interact with each other based on a bottom-up perspective. Therefore, the resulting emergent behavior would be based on the interactions of a set of distributed systems with limited perspectives of the universal system and wider environment. Each system would develop its own internal model of the real world and base its actions on this individual knowledge and on its own projected capabilities. Constituent systems could perhaps negotiate collaborations with each other, but this would be based upon their own narrow world view and missions. A bottom-up engineering method would lead to undesired emergent behavior and a set of actions that are not optimized at the holistic SoS level to address complex problems. A bottom-up approach would start with each resource and determine what small part of the problem it could address. In this approach, an endless number of small actions are potentially taken that never fully address the universal problem confronted by the SoS (which, for a complex problem, would be changing over time). Additionally, undesired emergent behavior could arise from many systems acting and interacting in an uncoordinated manner.

Therefore, a top-down holistic systems engineering approach is required for engineering a CASoS. A top-down approach designs a solution with a focus on the overall mission and performance objectives. It emphasizes multi-level and multi-mission behavior from a holistic perspective. This results in an architectural design that enables both collaborative (emergent) and constituent system level behavior to address the problem domain.

3. An Intelligent Distributed Peer Architecture Approach

Vakili, Tabatabaee, and Khorsandi (2012) describe a CSE approach for designing a complex SoS comprised of distributed peers that they define as autonomous machines. They cite the peer-to-peer architecture in Internet applications as an example, explaining that it demonstrates improved performance by providing a large set of contributions from constituent assets. They explain that the distributed peers use cooperation policies between them to enhance the overall performance. They also propose a method to use incentives for peers to benefit from contributing to the overall system.

A modified version of this approach can be applied to engineering CASoS solutions. The idea of a CASoS being comprised of a system of intelligent and distributed systems was discussed as a required capability of CASoS in Section C of this chapter. Instead of coordinating peer behaviors through incentives, the intelligent agents at each peer or constituent system in the CASoS would have already developed an understanding of the problem space and the decision space with a holistic perspective of how each peer would behave and interact. This approach requires designing the CASoS architecture as well as the intelligent agents to support this capability.

4. Constituent System Considerations

Dahmann et al. (2008) write that the main challenge of engineering SoS is coordinating the use of existing systems to meet stakeholder needs. They point out that the systems engineers do not have oversight of the constituent system development efforts, and that each has its own management, funding sources, and engineering processes. Thus, a bottom-up SoSE process to integrate and interoperate existing systems has generated much industry, government, and academic attention. Significant effort has focused on addressing the technical challenges of interoperability; however, an equal, if not greater, effort has focused on overcoming the acquisition, management, and governance challenges. This dissertation acknowledges these issues, but focuses solely on the technical aspects of engineering the constituent systems.

The overall success of a CASoS to address complex problems relies on the ability to combine the individual functional and performance capabilities of numerous and diverse constituent systems. These capabilities can be viewed as resources for the CASoS. An ideal approach to benefit from the diverse capabilities is to allow a combination of legacy (already-existing), in-development, and future systems to participate in a CASoS. This can only be possible if the CASoS architecture and system of intelligent agents are engineered to accommodate this diversity. The proposed approach to accomplish this, while still meeting the theoretical characteristics and principles of a CASoS, is to embed the intelligent agent in each constituent system. The intelligent agent would then perform the control and management functions of the individual systems as well as synchronize decisions and share information with the other intelligent agents in the CASoS. Therefore, in order for a constituent system to be a member of a CASoS, it must have an embedded intelligent agent.

5. A Continuous Design Approach

CASoS must adapt and evolve in order to effectively address a changing problem space. The CASoS does this through its engineered capabilities (an adaptive architecture and system of intelligent constituent systems) and through a revolutionary systems engineering approach in which design and development are continuous (or living) processes throughout the CASoS life cycle. As shown in Figure 46, the initial CASoS architecture and intelligent agents are designed and embedded into legacy constituent systems similarly to a traditional SE process. However, during CASoS operations, a process of continuous needs analysis continues to occur. This is possible because of the CASoS abilities to perceive and study the problem domain and constantly develop course of action options. Thus, the CASoS has a built-in ability to anticipate future events in the problem domain and to predict gaps in its own resource capabilities. This continuous analysis provides the real-time ability to reorganize (or redesign) itself to exhibit intentional behavior and the longer-term ability to identify additional resources that could be added as constituent systems in the future.

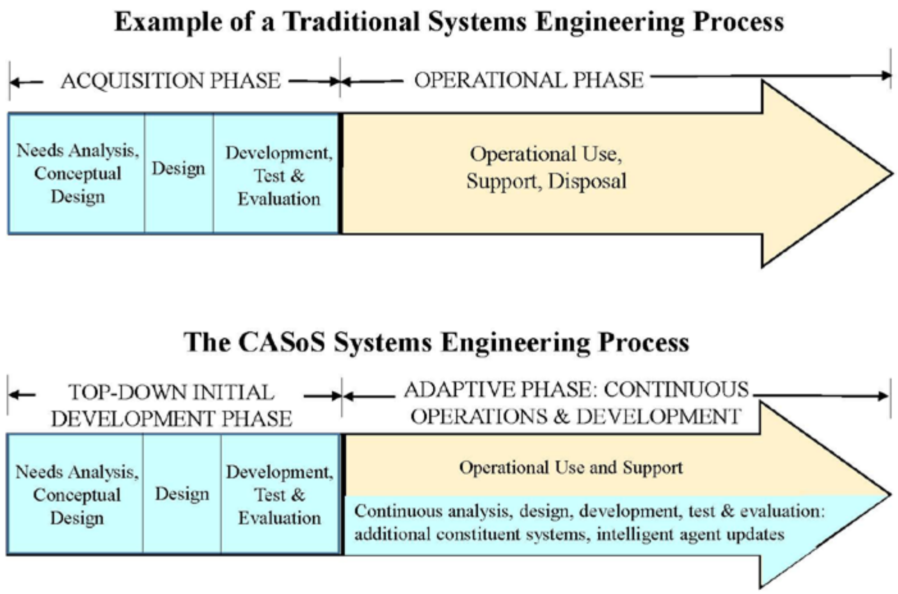

Figure 46. CASoS Systems Engineering Process Compared to a Traditional Systems Engineering Process

E. CASoS SYSTEMS ENGINEERING APPROACH

This section presents the CASoS Systems Engineering (SE) approach. This process is a result of the grounded theory advanced coding process, which studied the implications of the CASoS theory on the CASoS systems engineering approach. The guidelines presented in section D of this chapter are results of this advanced coding process. The CASoS SE approach is based on those guidelines.

The CASoS SE approach is top-down, beginning by articulating mission objectives of the CASoS as a whole system solution and designing the CASoS architecture, intelligent agents, and constituent systems from this holistic perspective. The SE process, illustrated in Figure 47, provides a methodology to address the challenging engineering aspects of a CASoS, which include developing an adaptive architecture and system of intelligent decision systems which continues to evolve as the problem space evolves. The figure illustrates that the problem space continues to change and evolve and that an ongoing recursive process of needs analysis, design, development, test, and evaluation need to continue in parallel with CASoS operations. These recursive development cycles produce additional constituent systems and updates to the intelligent agent.

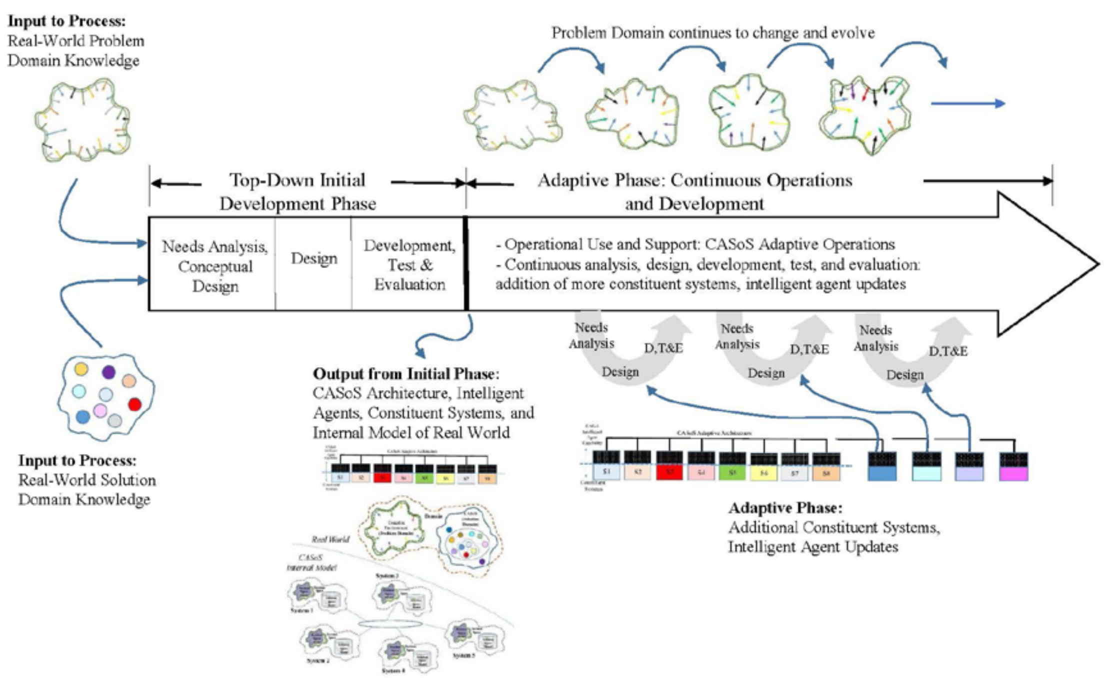

Figure 47. The CASoS Systems Engineering Process

1. Initial CASoS Development Phase

An initial CASoS is designed, developed, and evaluated during the initial development phase of the CASoS SE process. This initial CASoS is a fully functional solution system with an adaptive architecture and intelligent agents integrated into an initial set of constituent systems. The initial set of constituent systems may include legacy and newly developed systems. The initial phase is a top-down process of needs analysis, conceptual design, detailed design, development, test and evaluation.

a. CASoS Needs Analysis and Conceptual Design

The initial SE phase begins with the conceptualization of the problem and solution domain in the context of a CASoS. This top-down needs analysis and conceptualization leads to an understanding of the problem and solution domains. It produces a characterization of the problem domain in terms of complexity factors and a solution conceptualized as a CASoS. Conceptualization provides a holistic foundation for tailoring the CASoS design to fit the given highly complex problem. Figure 48 shows the steps involved in the needs analysis and conceptual design. The ensuing discussion describes the activities in each step of Figure 48.

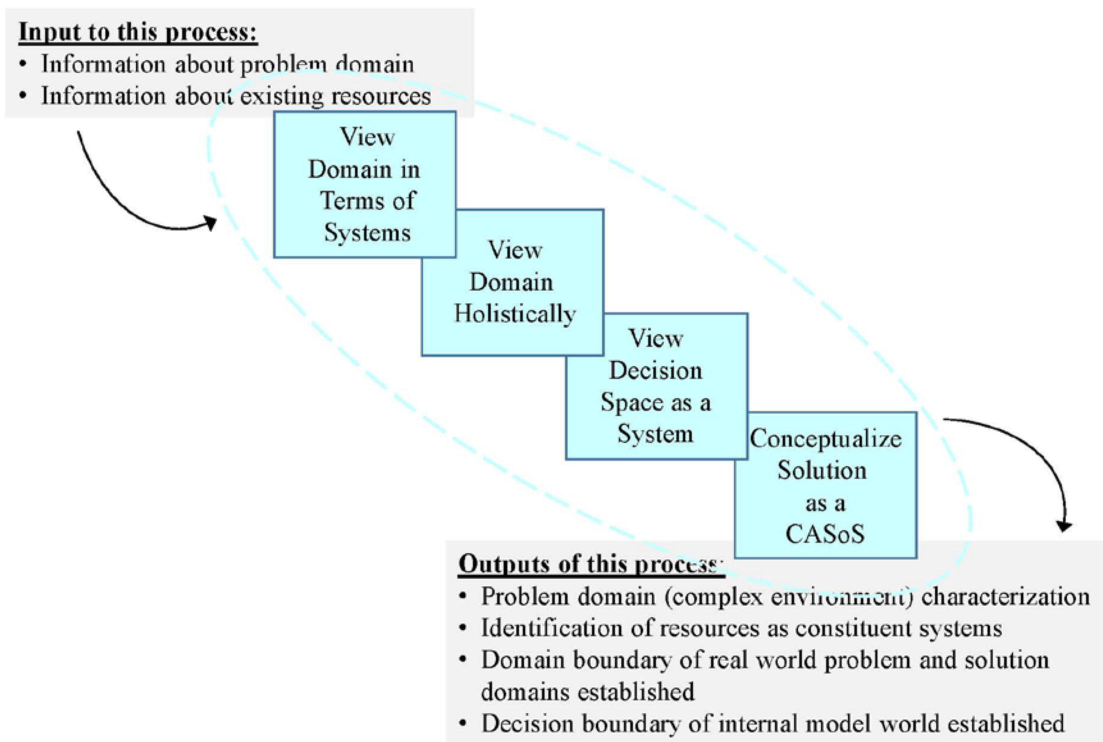

Figure 48. CASoS Initial Needs Analysis and Conceptual Design

A first step is to define the real-world domain in terms of systems. Resources and assets that play a role in addressing the problem space must be identified and defined in terms of systems. These resources and assets may already exist, may be currently in development, or may be identified as future capabilities that are needed. This process of identifying systems does two things: (1) it begins the process of understanding what capabilities exist and are needed to address the problem domain; and, (2) it identifies the constituent systems that will comprise the CASoS conceptual design. It begins the process of analyzing interactions (through their boundaries, inputs, and outputs), and functional performance, and behavioral capabilities. Expected performance as well as performance gaps can be identified and evaluated. To posit the domain in terms of systems, supports the definition of the basic building blocks (constituent systems) of the CASoS, which also provides a starting point for CASoS architecting. It provides a method for identifying which systems will be information producers and receivers and for understanding the actions (behaviors) they are capable of performing individually. It also supports the process of identifying collective SoS behaviors and actions that can enhance performance to address the problem domain. Further, it supports the definitions of the intelligent agent, knowledge discovery, and predictive analytic capabilities.

A second step is to view the real-world domain holistically—with the goal of understanding the problem space as a whole in order to engineer the CASoS solution from the top down. Characterizing the domain will identify high level operational objectives for the CASoS solution and will begin the process of understanding how to design CASoS intelligent agents that can create an internal model of the domain. This will support the engineering of the constituent systems' ability to develop decision options (and evaluate these options) from a holistic view—determining what the individual and collective actions of the CASoS should be. The ability for the constituent systems to view the problem domain holistically allows them to look at the entire spectrum of problem entities, events, and dynamics to develop holistic SoS-level behavioral responses by the solution. It enables them to define the solution response in terms of the problem as a whole. They must develop and maintain an internal model of the entire domain, including the problem space and solution space. This holistic view will allow them to predict the performance of the CASoS to address the problem and adjust the CASoS behavior as needed at each level.

A third step is to develop the decision scope as an initial effort to define the adaptive boundary of the domain. An initial definition of a decision boundary provides a starting point for conceptualizing the complexity of the problem and solution spaces. This initial boundary captures all aspects of the problem space (expected entities, events, etc.) and solution space (existing resources, assets, and systems). The domain boundary will change, but once the initial boundary is established, the changes in the domain boundary can be identified and understood in context of the initial boundary. Figure 48 illustrates the scope of the real world domain through the initial establishment of the domain boundary. The CASoS internal model reflects the establishment and maintenance of this domain boundary by establishing the decision space.

Continued study of Figure 49 shows that the lower half of the figure depicts the decision space. The decision space contains internal models of the problem space (reflecting the complex environment) and the solution space (reflecting what is known about the constituent systems and their capabilities and expected performance). Viewing the decision space as a system supports an understanding of the decision boundary and a clear definition of inputs, outputs and what information needs to be considered as decisions for courses of action are made. The decision space is flexible—adapting as the situation in the real world domain changes. For example, as a new system joins the CASoS as a constituent system or as a new event occurs within the problem domain, this is reflected in the decision space.

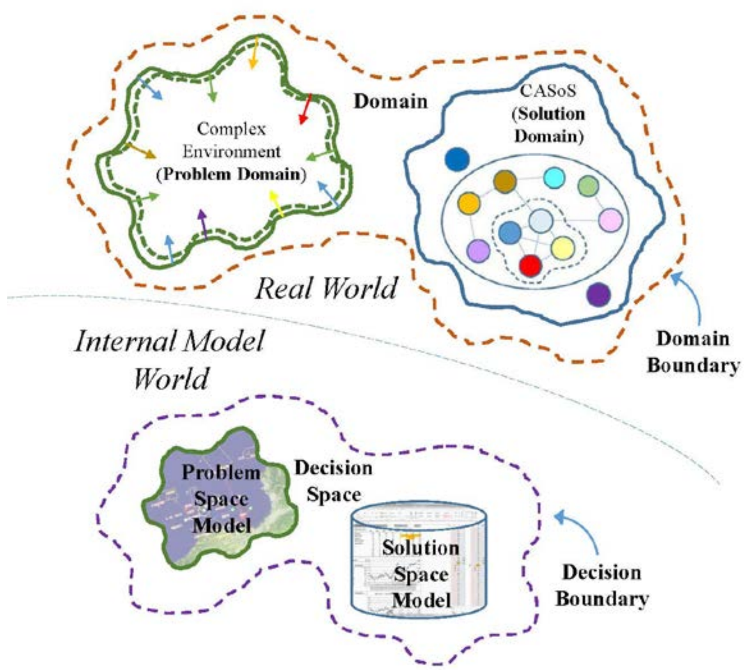

Figure 49. Establishing the Domain Boundary and the Decision Boundary

The final step in CASoS needs analysis and conceptual design is defining the solution space as a CASoS solution. The earlier steps articulate the problem space and decision space. This step develops a conceptualization of the solution as a CASoS system of decision systems. Figure 50 illustrates the CASoS as a system of constituent systems interacting with a connected architecture to collectively produce and manage an internal model of the real world. The figure shows the system of interacting decision spaces—each containing a representation (internal model) of the real world domain, developing course of action decisions for the CASoS with a holistic perspective, and determining effective actions at the system level and emergent behavior level to best address the problem domain.

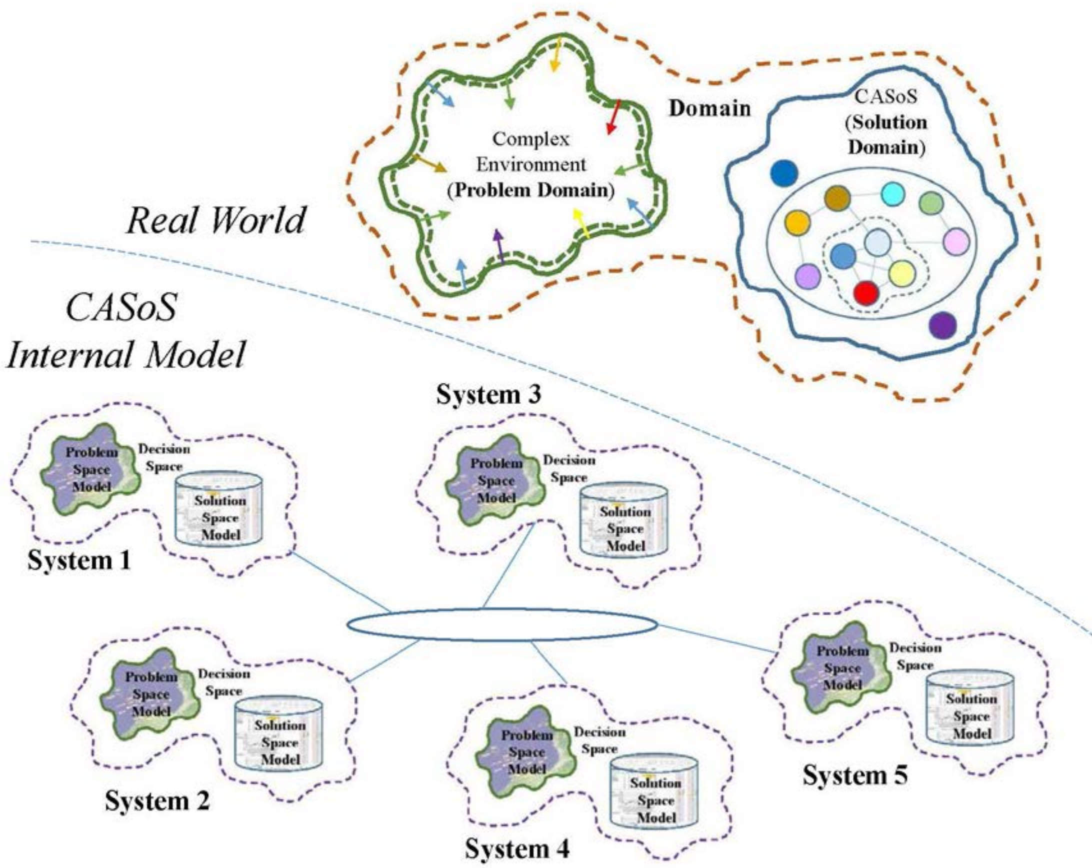

Figure 50. CASoS Decision Space: A System of Decision Systems

Once the solution is conceptualized as a CASoS, a set of design requirements and measures of performance must be developed. The requirements will guide the CASoS design process and the measures of performance will guide the test and evaluation process.

b. CASoS SE Approach: Initial Design

The next part of the CASoS SE approach is the initial design of the CASoS solution space. The design phase has the following inputs as shown in Figure 51: a characterization of the problem domain, identification of resources and assets of the solution domain, and initial boundaries for the real-world decision problem and solution domain as well as the internal model decision domain. A design for the CASoS architecture and intelligent agents is developed. This holistic design is based on desired functionality and performance for the CASoS as a whole to address the expected problem domain. An evaluation of the legacy resources determines whether additional resources are needed to meet the required performance.

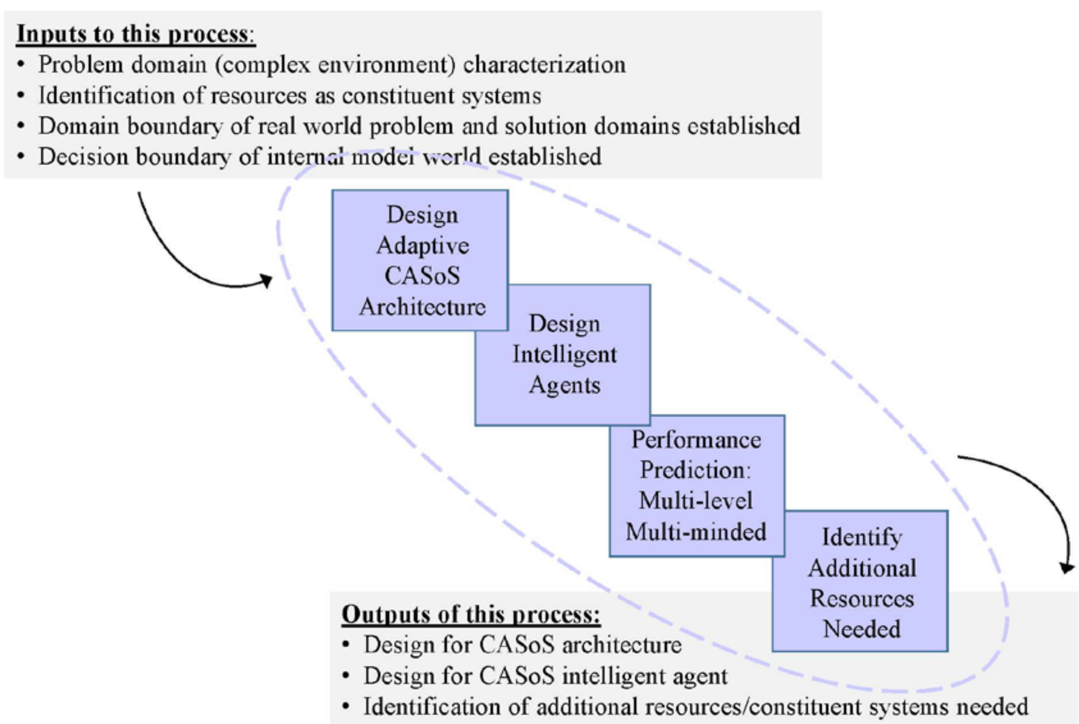

Figure 51. CASoS SE Design Approach Steps

The adaptive architecture design must include information management for sharing, storing, and processing data and knowledge; methods for communicating with new constituent systems as CASoS boundaries change; and interaction mechanisms that support different levels of communication and collaboration. The design of the CASoS intelligent agents must include a common set of data analytics to develop knowledge of the real world (both the problem and solution domains), develop internal models, develop multi-level decision options, synchronize knowledge and decisions, and predict effects of actions. The design needs to include a continuous process of information sharing and synchronization among the constituent systems that supports continuity among the internal models and decisions. Figure 52 illustrates a set of constituent systems that are collaborating (and participating in) as a CASoS. The black upper halves of each constituent system represent the embedded intelligent agents and how they connect to form a CASoS. The CASoS agents work together and interact to form and continuously update a shared internal model of the operational domain. They develop COA decisions at the CASoS level that are based on what set of collaborative and independent behaviors of each constituent system are most effective to address the problem domain.

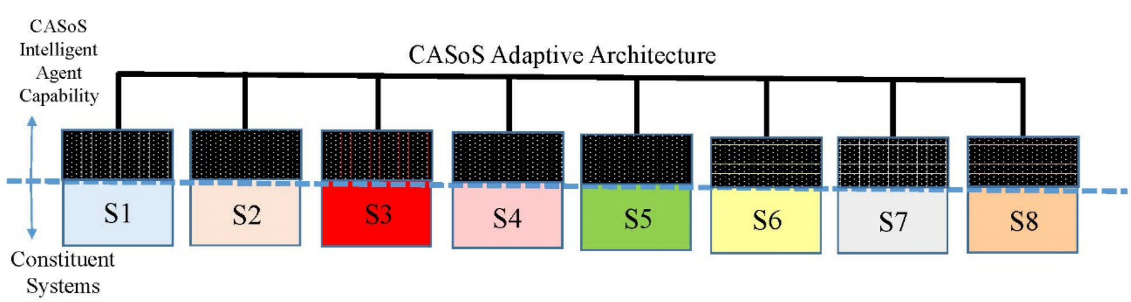

Figure 52. Conceptualization of CASoS: Adaptive Architecture and Intelligent Agents

Performance prediction is the analysis of the CASoS functional and performance capabilities based on the many combinations of independent and collaborative behaviors possible. This analysis explores the possible multi-level and multi-minded capabilities that the CASoS could perform given the set of constituent systems resources under development. This process identifies performance gaps to determine what additional resources (or additional constituent systems) need to be developed for the CASoS to address the problem space.

c. CASoS SE Approach: Development, Test, and Evaluation

CASoS development, test, and evaluation phase has four primary tasks: to develop the CASoS architecture and intelligent agents, to retrofit legacy resources (creating constituent systems), to develop new constituent systems, and to perform test and evaluation. Figure 53 illustrates these tasks, showing that designs and analysis results are the inputs to this process and that the output is the initial operational version of the CASoS solution system.

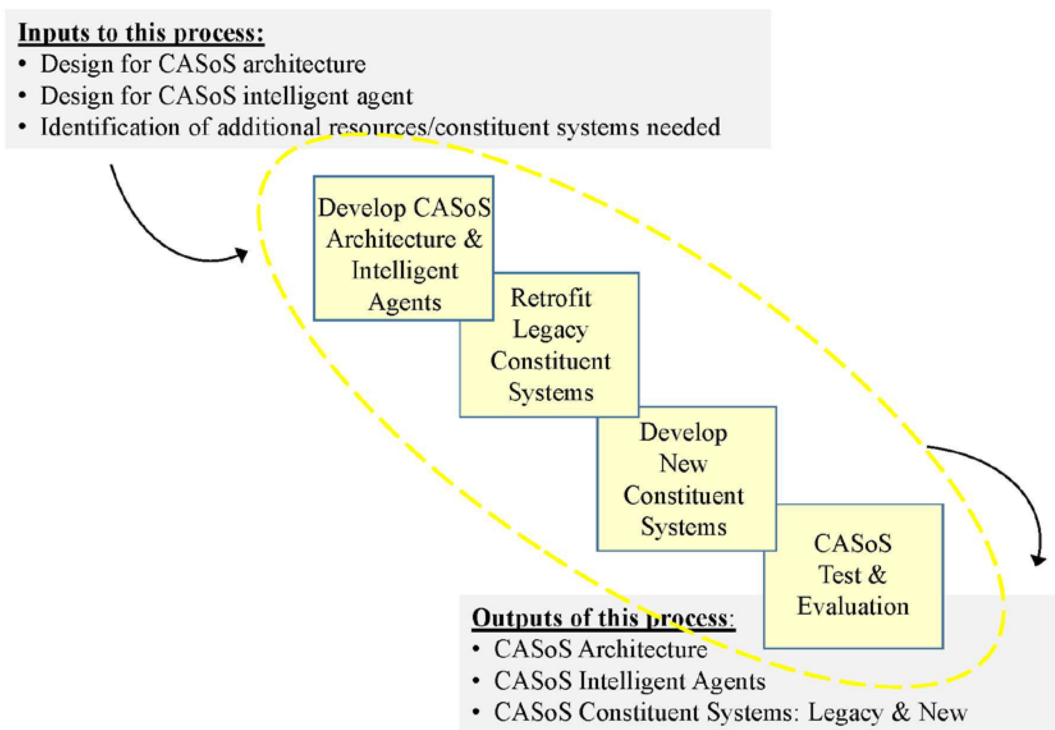

Figure 53. CASoS SE Development Approach Steps

The initial CASoS must have a fully functional adaptive architecture and initial intelligent agent designed to accommodate additional future constituent systems. As the problem space changes over time, additional resources may be needed. As new constituent systems are developed and added to the CASoS, they will generate additional data and produce additional functional and performance capabilities. The CASoS architecture and intelligent agents must be able to accommodate these additions, relying on their holistic and future-minded design—emphasizing adaptation and evolution.

Legacy, or existing, resources are retrofitted with a CASoS intelligent agent that replaces the existing situational awareness, control, and decision functions. Integrating the CASoS intelligent agent into existing resources transforms them into CASoS constituent systems. Equipped with an intelligent agent, these systems are then capable of fully participating as part of the CASoS. It enables them to purposefully self-organize to collaborate with other constituent systems.

Constituent systems can be developed from scratch as additional resources may have been identified as required to address the problem space. These newly developed systems are designed to provide needed functional and performance capabilities. Their original design will be based on the CASoS intelligent agent providing the situational awareness, control, and decision functions.

The initial testing will evaluate the CASoS based on the original characterization of the problem space. Therefore, it will evaluate how well the initial CASoS addresses the problem space as it was understood initially, or as it was initially projected to be. However, as the nature of highly complex problems changes over time, the process of test and evaluation must be a living process that is continuously evolving to evaluate the performance of the CASoS against a changing problem. This evolution will occur in the adaptive phase. This initial phase provides a test and evaluation starting point.

2. Adaptive Phase: Continuous Operations and Development

The CASoS SE process must be adaptive to enable the CASoS to evolve as the problem domain evolves. The changing problem domain may require additional performance and functionality. Thus, the development processes of needs analysis, design, and evaluation must be continuously performed in parallel with CASoS operations. This on-going process of development is a living process that continues to develop new constituent systems and updates to the intelligent agent throughout the life cycle of the CASoS.

At the start of the adaptive phase, the initial CASoS becomes operational. It uses its decision-making capability to perform its purposeful multi-level and multi-minded behavior. This capability is inherent to the CASoS as a result of the adaptive architecture and system of intelligent constituent systems. The capabilities of the CASoS inherently produce a decision-making system that has self-awareness and situational awareness and can be thought of as a system that is able to effective reorganize or redesign itself in real-time. It uses its knowledge to design the solution space that addresses the complex problem. It decides effective behaviors of its parts and interactions to produce desired multi-level and multi-minded actions. The CASoS configures and reconfigures itself to provide intentional actions that can be reactive, proactive, and/or preemptive.

Although this capability is inherent to the CASoS, it supports a new paradigm of adaptive systems engineering—basically engineering or designing itself during operations to produce adaptive behavior in response to a changing problem domain.

The CASoS built-in abilities to gain situational awareness and anticipate future events in the problem space enable them to continuously perform a needs analysis. In addition to developing near-term course of action options, they also analyze their own future resource needs to address the anticipated future environment. This information can be used to identify new resources needed for the CASoS. Additional resources can be added as constituent systems if they are designed to participate and become embedded with the CASoS intelligent agent. This is essentially a process of continuous design, development, test, and evaluation of possible updates to the intelligent agent and additional constituent systems to address the changing problem space. This process of acquiring additional constituent systems allows the CASoS to adapt to the changing problem space and to evolve over time.

VI. VALIDATION OF THE CASoS THEORY

A. INTRODUCTION

This chapter presents an application of the CASoS solution in a modeling and simulation environment to validate the CASoS theory. Analysis of the outcomes of the modeling and simulation effort supports the grounded theory validation methodology in terms of fit, relevancy, workability, and modifiability.

The naval tactical domain provides a highly complex operational environment that is conducive for demonstrating the application of the CASoS approach. Section B discusses the characteristics of this problem domain and describes the challenges that this specific scenario poses to existing traditionally engineered naval systems. It describes how the CASoS approach would apply to the naval tactical domain and compares the CASoS approach with the existing traditionally engineered "baseline" approach. Section C presents the modeling and simulation experimentation effort and associated analyses to compare the CASoS and baseline approaches to challenges in the naval tactical domain. Section D concludes this chapter, with how the simulation analysis of the naval tactical domain problem validates the CASoS grounded theory.

B. APPLYING THE CASOS THEORY AND APPROACH TO THE NAVAL TACTICAL DOMAIN

The naval tactical domain encompasses naval assets in the maritime environment that are engaged in combat. The situation can very quickly and unexpectedly escalate into a highly complex environment, as in the case of an unconventional or surprise attack, or more slowly as tension builds with a known adversary. Offensive measures can also initiate a tactical situation. The naval tactical domain can occur in deep water or in a littoral region and can involve threats and assets in the sea, air, space, cyberspace, underwater, and on land. The domain can include affected civilians and participating coalition partners. Actions and events in the tactical domain include threats, countermeasures, evasion, retaliation, defensive and offensive measures, stealth, sensing and tracking, jamming, blinding, cyber-attacks and combat readiness. The tactical domain includes military assets that are in a state of combat readiness—either in a defensive or offensive posture—preparing for a warfighting situation. In this tactical domain, the actual warfighting is a fraction in duration of strategic campaigns and often spans a smaller area that is part of a larger theater of war.

1. The Naval Tactical Domain Presents a Highly Complex Environment

Naval tactical warfare is highly complex (Bar-Yam 2004). Table 14 summarizes how the naval tactical domain exhibits characteristics of a highly complex operational environment that requires a CASoS solution. The naval tactical domain is comprised of potentially large numbers of diverse, distributed, and often interrelated threat objects and events. Examples of adversarial threats include ships, aircraft, missiles, countermeasures, submarines, decoys, surveillance systems, and cyber means. Threat events include weapon deployment, asset placement, sensing, jamming, and hacking. The enemy is generally attempting to increase its tactical advantage by avoiding detection, presenting a false depiction of its location and capabilities, and attempting to outmaneuver and overwhelm our military forces (Hughes and Girrier 2018).

Table 14. Highly Complex Characteristics of the Naval Tactical Operational Environment

Characteristics of Highly Complex Environments	Naval Tactical Environment
Large numbers of objects/events/ features	The naval tactical environment contains potentially large numbers of: Objects: threat assets (ships, aircraft, missiles, weapons, countermeasures, underwater assets, space assets) Events: weapon deployment, asset placement, sensing, jamming, decoys) Features: weather, geographical features, civilians
Heterogeneity and/or diversity of environment of objects/events/ features	Adversarial threats in the naval environment can be very diverse and span multiple mission areas (undersea, surface, air, cyberspace, and space): submarines, mines, ships, aircraft, UAVs, satellites, and many diverse kinds of sensing and weapon assets. Events and features are also diverse.

Characteristics of Highly Complex Environments	Naval Tactical Environment
Geographically distributed	Objects/events/features in the naval environment are widely distributed—both horizontally across the sea and littoral surface and vertically underwater and in the air and space.
Diverse kinematics among objects in the environment	Objects in the naval environment can present highly diverse kinematics—undersea, on the surface, and in the air/space.
Environment's objects/events/ features are highly interrelated and/ or highly related to the solution	Adversarial objects and events are often related and causal; the maritime environmental features play a large role in affecting both adversarial and blue force actions; and adversarial weapons and countermeasures can directly affect blue force systems.
Highly dynamic/rapid tempo of change	Events can vary widely in tempo, rapid events (weapon strikes) occur.
Uniqueness of situations or states	The combination of a large variety of objects/ events/features create a continuum of unique situations (environments) that are novel, changing, and never-before-encountered.
Severe consequences of environment behaviors and events	Consequences include warfighter casualties, civilian casualties, destruction of military & civilian assets, negative consequences to DIME initiatives.
Unexpected and rapid shifts in states (unanticipated events); behaviorally unpredictable	Adversarial intent includes surprise attacks, stealth location, denied access, distributed assets, obfuscation; unintended consequences.
Unknowable—difficult to gain accurate and complete situational awareness	Combat identification and the tactical picture are challenging pursuits involving sensors, communications, and processing
Accompanied by constraints, rules, and parameters on behavioral responses	Rules of engagement, tactics/techniques/ procedures, no-fly zones, civilian population avoidance

The tactical domain is constantly changing and presenting a continuum of unique operational environments. Many tactical objects are in motion, have dynamic interactions, and are surrounded by both fixed and changing environmental features. The climate, weather, atmosphere, humidity, sea states, hydrography, and topography can affect sensor and weapon performance and affect the ability to gain situational awareness. Nearby urban areas and other civilians in the area can confuse combat identification and change the dynamics of combat. These features contribute to creating a dynamic and complex environment.

The tactical domain is unpredictable and often challenging in terms of gaining complete and accurate situational knowledge. Adversaries purposely attempt to create a fog of war to confuse naval forces (Hughes 2000). Methods include unexpected attacks, stealth, denied access, distributed assets, decoys countermeasures, and cyber actions. Gaining and maintaining shared battlespace awareness, or “collective consciousness among the elements of the warfighting ecosystem” (Alberts, Garstka, and Stein 2000, 135) is a critical enabler of tactical effectiveness. Human warfighters must manage uncertainty in the data collected by sensors and processed. Often the uncertainty, coupled with the amount and diversity of information and the shortened decision timescales, overwhelms human cognitive abilities (Talbot and Ellis 2015).

Complexity in the tactical environment can also a result in severe and dire consequences. Devastating results can include warfighter casualties, civilian casualties, and destruction of military and civilian assets. The severity of consequences places a criticality on tactical responses and actions that increases complexity for decision-making.

2. The Highly Complex Naval Tactical Domain Overwhelms Existing Solution Approaches

The Navy has the mission of preparing its forces to achieve and maintain tactical superiority. In practice, this involves understanding and anticipating the tactical environment and adversarial threat. The Navy has recognized the tactical environment’s growing complexity and actively seeks engineering and technology solutions to address this challenge. Figure 54 highlights some of the limitations of current naval tactical systems when faced with complex problems within the tactical operational environment. Worst-case examples are when naval forces cannot defend against threats that are unexpected, too fast moving, or too-numerous; or friendly fire incidents when civilians or blue force partners are mistaken for threats. These situations arise when the reaction time is too short, or the decision space is too complex for an effective decision.

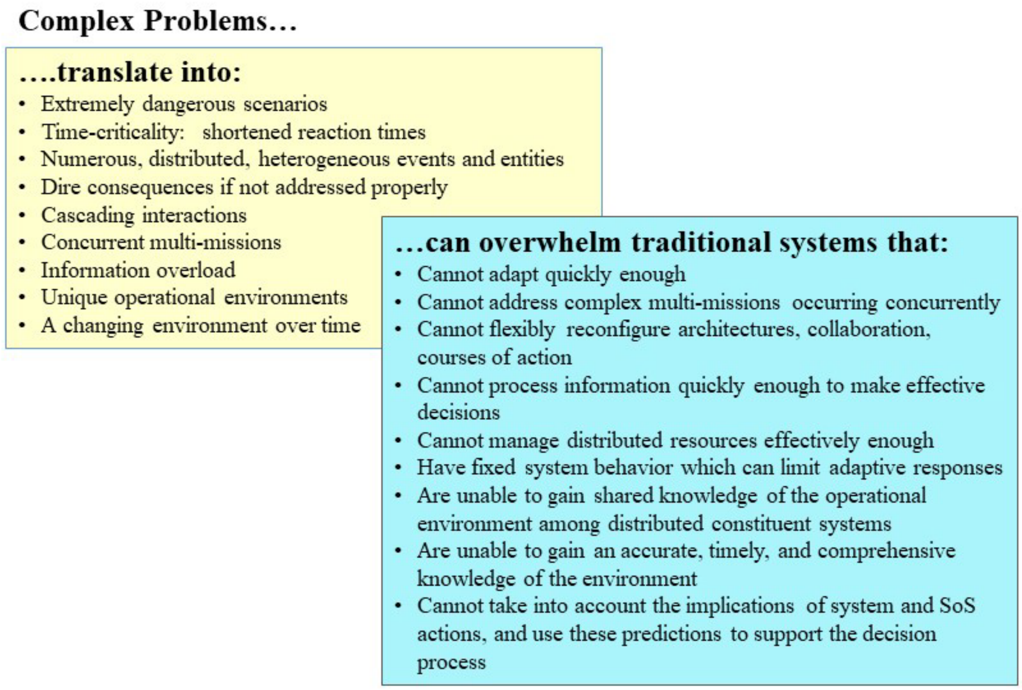

Figure 54. Limitations of Existing Naval Approaches to Address the Complex Tactical Domain

Two types of naval capabilities limit overall tactical ability: the performance of individual resources (sensor detection range, sensor resolution, sensor multi-function ability, weapon range, weapon accuracy, weapon destructive ability, etc.) and the decision making process, which relies on the naval architecture, to use these individual assets most effectively. Improving these capabilities is a critical part of achieving tactical success.

Current naval approaches rely on a combination of human decision-making and automated processes to make tactical decisions. The process of threat detection, involving collecting and processing sensor data, is largely automated. However, humans play a role in threat identification. Fully automated engagement decisions are possible for air and missile self-defense on some naval ships—this capability (using the Aegis weapon system) is platform-centric, relying on only resident (or organic) sensors and weapons (Young 2004b). However, in general, engagement decisions rely on manual decision-making, groups of decision-makers, and significant negotiation between humans on the multiple platforms (Treadway 2019). The Navy is working on future capabilities to enable collaborative engagements involving distributed platforms, such as the ability for a weapon to be fired based on remote data (the Navy Integrated Fire Control—Counter Air (NIFC-CA) program plans to use Cooperative Engagement Capability (CEC) data from a remote aircraft sensor to provide tracking data to support a weapon system on a ship). However, these capabilities are currently limited to threat cues (Young 2005). These cues provide an alert, identifying the existence of an incoming threat. The weapon platform must still use its resident (organic) sensor to detect and track the threat to provide this data to the weapon system (Young 2005). Thus, the current use of naval weapon systems for air and missile defense is a largely platform-centric capability. As tactical warfare missions become more complex, human decision-makers become overwhelmed by information uncertainty, diversity, and overload and by the challenge of identifying effective decision options involving distributed warfare assets (Miller 2019). The time-critical nature of many tactical warfare missions often provides only minutes to make these complex decisions (Treadway 2019).

3. A CASoS Solution to the Naval Tactical Domain

This section describes how a CASoS approach would be implemented in the naval tactical domain. The CASoS approach would identify the systems in the tactical realm that constitute constituent systems. For this domain, the constituent systems would be the distributed warfare assets: platforms (ships, aircraft, submarines, helicopters, etc.), weapons, sensors, jammers, decoys, countermeasures, and other resources that contribute to tactical operations. The CASoS approach would reengineer these existing assets by implementing an adaptive architecture to support enhanced interaction and collaboration and embedding each platform with an intelligent agent (software and computing environment) for enhanced decision-making. Figure 55 provides a high-level illustration of a future CASoS approach with an adaptive architecture connecting distributed naval assets that are embedded with intelligent agents. The CASoS approach would maximize the use of the distributed warfare assets by requiring the means for purposeful, adaptive, collaborative, and emergent behavior, thus improving overall tactical operations.

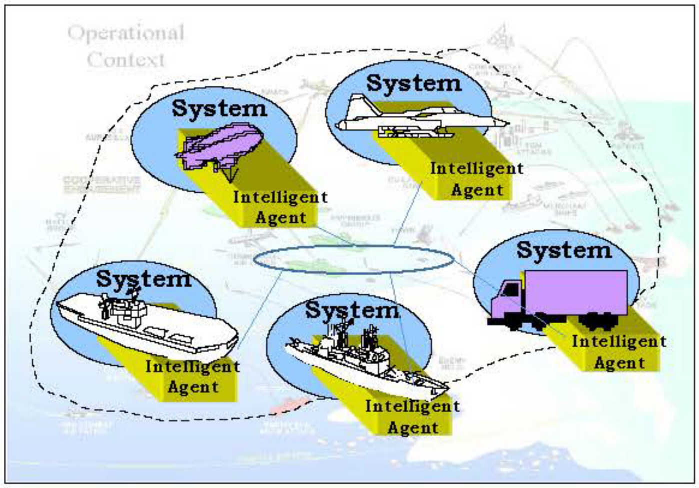

Figure 55. Illustration of the CASoS Architecture and Intelligent Agents Embedded in Naval Tactical Systems

The mission-oriented SoS approach designs constituent systems to meet the required capabilities of the SoS, as a whole, to address different missions (Silva, Batista, and Oquendo 2015, Giachetti 2015). The CASoS approach enables a mission-oriented approach during the design phase as well as during operations. The naval CASoS approach, as illustrated in Figure 55, provides the capabilities desired in mission-oriented SoS—to identify what desired behaviors are needed from the constituent systems according to overall mission needs. The CASoS intelligent agents and adaptive architecture enable the constituent systems to individually and collectively self-organize to address naval missions adaptively and in near-real-time during operations.

The following subsections describe how the CASoS engineering framework would shape the capabilities that are necessary to address the operational challenges in this specific instantiation of the naval tactical domain. As such, a notional solution is presented in a modeling and simulation environment for a comparative analysis with a baseline solution.

a. Naval Tactical CASoS Adaptive Architecture

The CASoS adaptive architecture connects the distributed warfare platforms and assets through their embedded intelligent agents. The architecture shares data, information, and knowledge so each intelligent agent can develop and maintain both situational awareness and self-awareness. The architecture shares data between them to support synchronization of these internal models and synchronization of the COA decision options. The architecture enables the distributed warfare assets to collaborate to an automated degree that is not currently possible. As a CASoS, the distributed warfare assets are effectively managed as if they were all collocated on one ship or aircraft. The CASoS architecture, as illustrated in Figure 56, enables the distributed ships and aircraft to truly become a fully integrated system of systems.

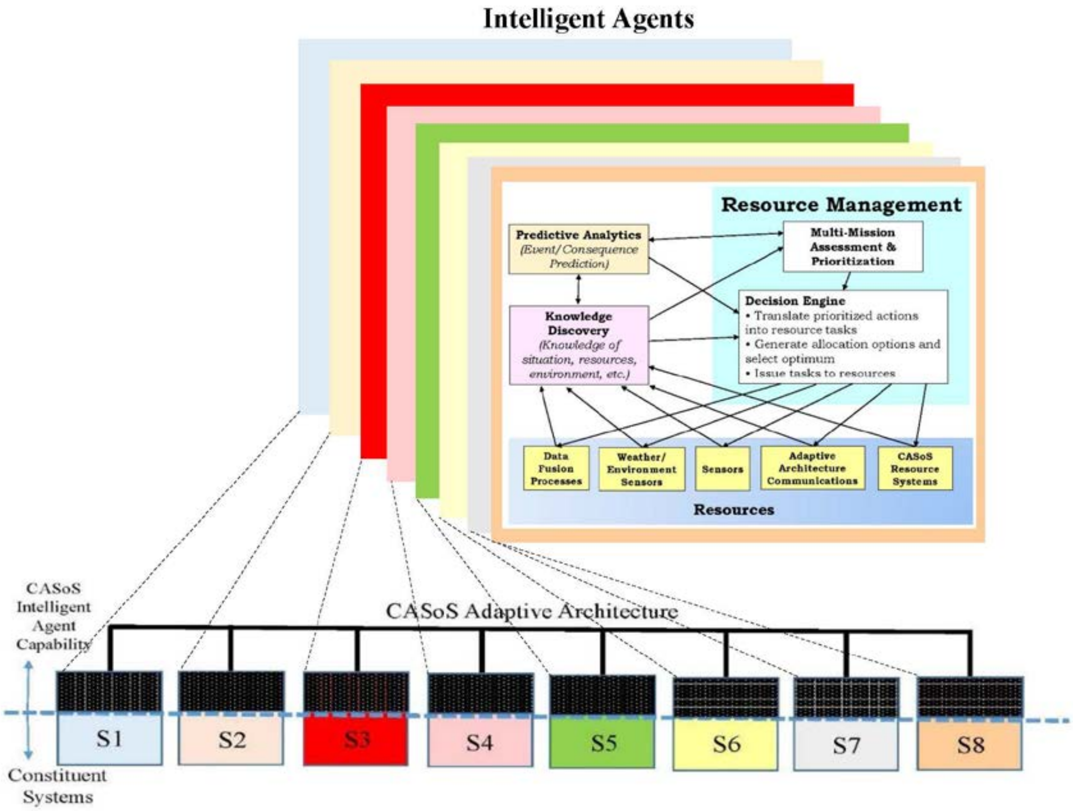

Figure 56. Adaptive Architecture with Embedded Intelligent Agents

The CASoS architecture enables the naval battle group to adapt as a whole to the dynamic threat environment through the interaction of the distributed ships and aircraft.

Enabling these interactions creates many more permutations of possible force-level behaviors—limited only by the number and types of warfare assets participating.

The CASoS architecture supports the changing boundary of this solution system. For the naval tactical domain, warfare assets (constituent systems) can join (or leave) the CASoS as new aircraft or ships move near (or away from) a CASoS or as assets are damaged or destroyed during combat.

The CASoS architecture provides interaction mechanisms for the naval tactical domain to support collaborative operations. For integrated fire control, in which distributed weapons and sensor participate in an engagement, the architecture provides "handshakes" of commitment between these assets to support the collaboration for the duration of the engagement. Participation from a remote sensor may include providing a precision cue that detects the threat, fire control quality data to the weapon system, in-flight-target-updates to a missile interceptor in flight, or illumination of a target for endgame missile guidance.

The CASoS architecture must support the following types of adaptation:

- Adaptation in the relationships of the warfare resources, resulting in multi-level and multi-minded responsiveness (at system level and force level).
- Adaptation as changes occur for the rules, doctrine, plans, and polices governing tactical missions and engagements.
- Adaptation in the level of collaboration: formation of new SoSs, addition or deletion of systems from a collaborative SoS, different levels of collaboration within a SoS.

b. Naval Tactical CASoS System of Intelligent Constituent Systems

In the naval tactical CASoS solution, an identical intelligent agent is embedded in each distributed warfare platform (ship, aircraft, submarine, etc.). The intelligent agents work together to develop shared knowledge and collaborative decisions regarding tactical courses of action (COA). Through this system of intelligent constituent systems approach, the CASoS empowers each platform—giving each a "god's eye" view of the operational environment (shared situational awareness) and a "god's eye" view of the distributed warfare resources (shared self-awareness). With this knowledge, each platform develops force-level COAs—meaning they can collectively use their distributed warfare resources from a holistic perspective. The adaptive architecture allows the intelligent agents to share data, information, knowledge, and decisions (COAs), so that COAs are synchronized and coordinated across the CASoS. Figure 57 is a context diagram of the CASoS intelligent agent—showing high level functionality, external interactions, and interactions with the other CASoS intelligent agents.

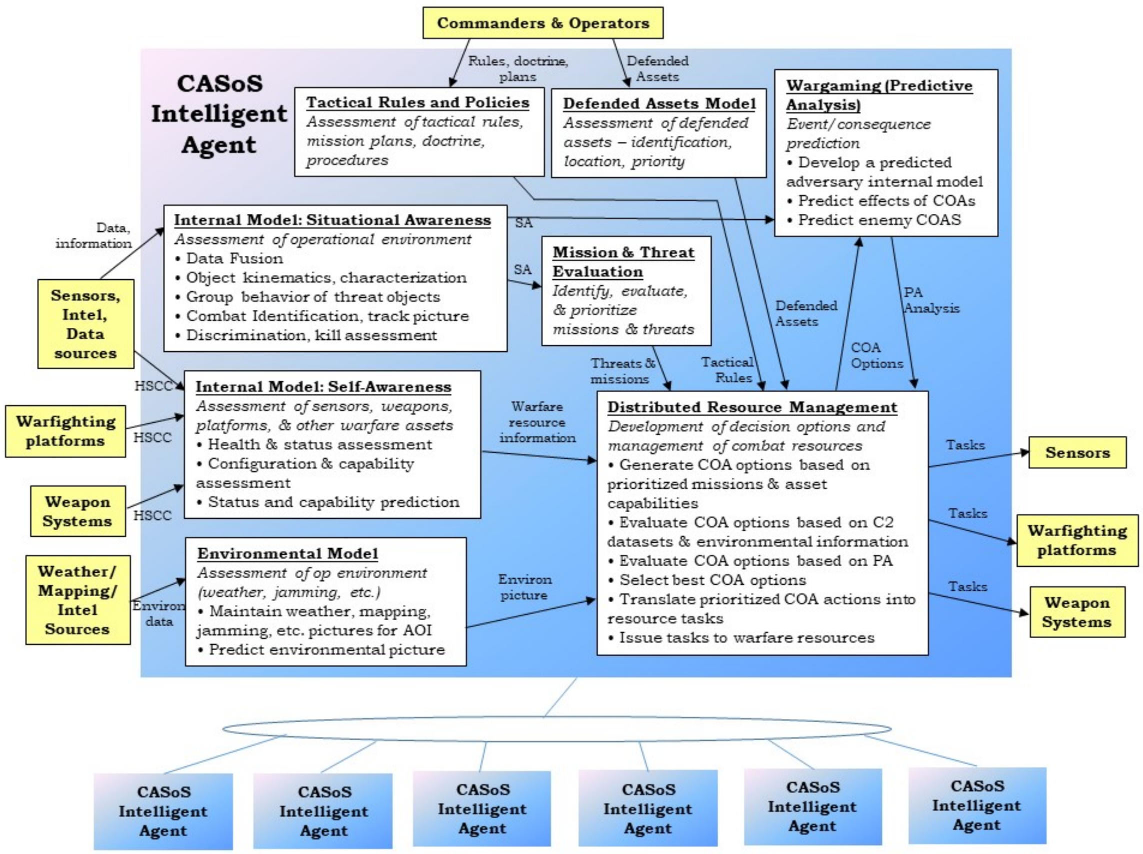

Figure 57. CASoS Intelligent Agent Context Diagram

By avoiding a central warfare decision-maker, the CASoS approach of distributing intelligence allows each warfare platform to participate collaboratively as a strike group or to operate independently when stealth or "emissions control" operations are tactically advantageous. Figure 57 shows that each intelligent agent develops internal models, performs mission and threat evaluation, performs wargaming (predictive analytics), and uses the analysis results to manage the distributed warfare resources by developing COA tasks. The models, analysis, wargaming, and COA tasks are synchronized with the other participating intelligent agents within the CASoS.

Several domain specific aspects of the naval tactical environment contribute to CASoS complexity. One aspect is a dynamic feedback loop that exists between the warfare resources and the intelligent agents. Tactical sensors, for example, provide the primary source of data and information by which the intelligent agents develop knowledge and make decisions. These sensors are also resources that are managed by the intelligent agents. Another aspect is that many warfare resources are multi-functional and multi-mission. Some tactical sensors have the ability to sense the environment for broad area coverage and threat detection, focus their energy on a specific target for higher resolution and higher update rate tracking, and illuminate threat targets to support endgame weapons guidance. In a highly complex operational environment, warfare resources may be in high demand and choices will have to be made about how best to use them.

c. Naval Tactical Knowledge Discovery and Predictive Analytics

Discovering knowledge (or gaining battlespace awareness) and predicting outcomes of actions are both key to a CASoS solution to the naval tactical domain. CASoS knowledge discovery is the attainment and management of knowledge of the entire domain (both problem space and solution space) within the naval tactical decision space. This includes situational awareness (knowledge of the operational environment or problem space) and self-awareness (knowledge of all the assets and resources comprising the solution space). The CASoS knowledge is shared and synchronized among constituent systems to ensure that each constituent has the same knowledge. Figure 58 illustrates examples of shared and self-awareness information in the naval tactical domain.

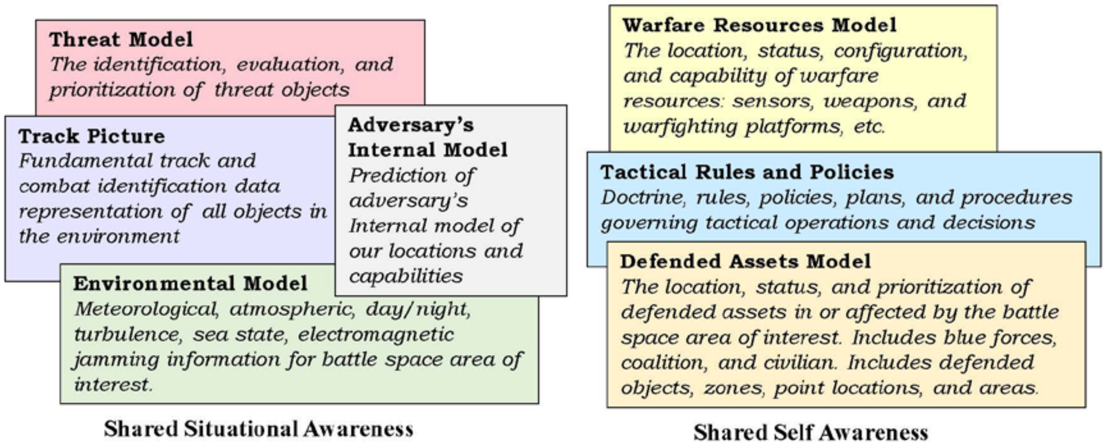

Figure 58. CASoS Internal Models for Knowledge Discovery

The four blocks on the left side of Figure 58 describe types of situational awareness information concerning the problem domain. For the naval tactical domain, this includes: a "track picture" or representation of objects (ships, aircraft, drones, submarines, missiles, etc.) in the environment. CASoS intelligent agents would process, fuse, and analyze different types of data to determine the location, kinematics, and identification of the objects. The intelligent agents would perform object identification (i.e., friendly, neutral, or adversarial), object intent (i.e., neutral or hostile), and object attribution (identifying which country or organization it belongs to). The intelligent agents would develop an internal model of the environment for the region of interest to be considered for calculating environmental effects on resource capability predictions. The intelligent agents would develop a predictive model of the adversary's situational awareness—the adversary's internal model —to support wargaming analysis.

The right side of Figure 58 shows three types of information that contribute to shared self-awareness: knowledge of the distributed warfare assets within the CASoS, knowledge of rules and policies affecting the CASoS, and knowledge of defended assets within the area of interest. By developing an internal model of the participating distributed warfare resources, each intelligent agent is able to manage CASoS resources with a "god's eye" perspective. This opens up a much larger selection of behavior based on the many combinations of interactions between distributed resources that can produce desired emergent behavior. Managing knowledge pertaining to rules and policies that guide allowable courses of action ensures that the tactical operations are compliant. Keeping track of defended assets within the area of interest supports courses of action that maximize objectives. In a highly contested area, if resources are limited, the CASoS can prioritize engagements to defend the highest value targets.

Conceptually, the CASoS acquires data from CASoS sensor assets as well as from data and information sources external to the CASoS. This data is shared among the constituent system intelligent agents. The intelligent agents perform data fusion and processing and the adaptive architecture supports synchronization among the agents to develop the shared internal models. The intelligent agents analyze these models for uncertainty and incompleteness. The results of this analysis are used to update the tasking of sensor assets—to collect more data for specific objects or regions to improve the uncertainty or incompleteness in the situational awareness. Thus, the CASoS process of developing situational awareness is an adaptive process of managing knowledge uncertainty through continuous analysis and sensor feedback tasking.

CASoS predictive analytics (PA) provides a real-time wargaming capability to assess decision options during all phases of tactical operations: for force readiness, offensive operations, and even during defensive and combat operations when the decision reaction time is very short. The CASoS PA concept is illustrated in Figure 59. The PA is a set of data analytics that assess decision options based on knowledge and information from the internal models. The PA capability produces assessments of COA decision options.

Input to the CASoS PA capability includes COA decision options and knowledge from the internal models of the operational environment (situational awareness and the environmental model), self-awareness, defended assets, and the prediction of the adversary’s picture. The PA capability uses this information to predict and assess the situation and the possible decision options (COAs).

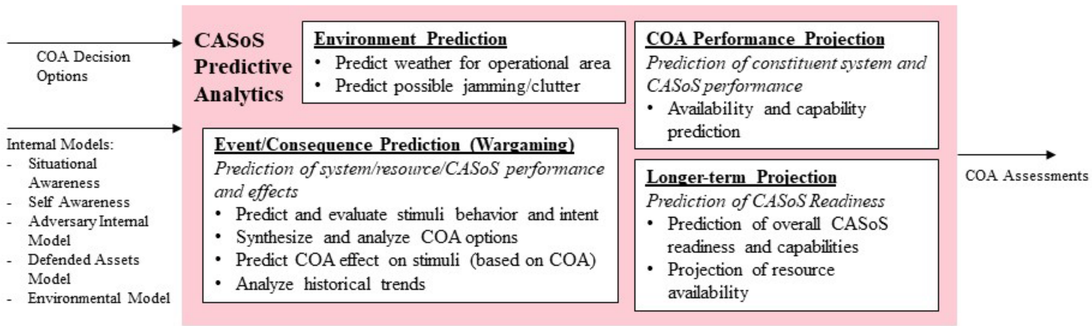

Figure 59. Predictive Analytics for a Naval Tactical CASoS

PA assessments include predicting environmental effects on the COAs based on the current and projected weather, turbulence, sea states, day/night condition and atmospheric conditions. They may also include the prediction of adversarial electronic warfare, jamming, and clutter conditions based on possible adversary capabilities. Environmental effects can greatly influence sensor performance and can therefore be used to assess the sensor tasking options. Environmental effects can also affect weapon selection—weapons that depend on sensors may diminished performance in certain conditions. Directed energy weapons performance is largely affected by environmental effects. Weapons may be affected by possible adversarial jamming or countermeasures.

PA assessment includes the performance projection of warfare assets. The PA capability would assess COA options based on the warfare resource internal model of self-awareness. For example, from this knowledge, the PA could calculate the probability of detection or probability of kill based on sensor or weapon status, location, and expected capability performance.

The PA capability could perform longer-term assessment of CASoS force readiness. This prediction capability would coordinate tactical readiness with planning and strategic goals. The PA could predict the adversary's projected capabilities and intent and then develop and assess longer-term tactical plans and strategies to prepare warfare resources (sensor coverage, weapons load-out), platform locations, stealth and emission control operations, and overall force readiness.

The PA capability could also provide a real-time tactical wargaming capability that adds strategic thinking to time critical tactical operations. PA wargaming would predict the effects of COA options—predicting adversarial responses based on the estimated adversarial internal model (situational awareness of the blue forces), strategies, and capabilities. Predicted adversarial responses could be taken into account in the selection of COA alternatives. PA wargaming would also assess COA alternatives to determine which has the highest probability of success and the best chance of protecting defended assets. Consequence prediction and assessment would provide additional insight into the selection of COAs for tactical operations.

4. Comparison of the CASoS Approach to the Existing Naval Tactical Approach

There are several major differences between the existing approach to naval tactical operations and the proposed CASoS approach. The existing approach has evolved over many years as technology has advanced and as the threat space has changed. Warfare assets have been developed to be largely platform-centric—meaning that the sensors and weapons on a given aircraft or ship platform have been designed to be highly integrated with each other and the platform to coordinate their functions to support the missions of that platform. As an example, on some ship platforms, there are automated modes (using the AEGIS weapon system) in which defensive weapons can be automatically fired based on threat detection and identification from sensors onboard the same platform. This has resulted in a platform-centric paradigm for naval tactical operations with each platform designed to maximize its performance based on its individual missions (Treadway 2019, Johnson, Green, and Canfield 2001). The commanding officer of the USS Howard destroyer, CDR John Fay (2014) explained that strike group collaboration primarily occurs through mission planning with the battlegroup commander assigning a mission to each ship. Fay (2014) explained that a current short-coming is that when each ship receives its mission, only a subset of the ship's warfare assets is needed for the mission, leaving the other assets under-utilized. Fay (2014) acknowledged the potential benefits that could be gained through increased collaboration for tactical missions and by using distributed naval assets to support force-centric multi-missions.

The CASoS approach shifts this platform-centric paradigm to a force-centric paradigm for tactical missions to take advantage of emergent behavior that can result from the closely coordinated interactions of the distributed naval platforms. Managing naval assets with a force-centric perspective enables emergent tactical behavior—extending the warfare capabilities of each individual platform asset—and therefore, creating many more defensive and offensive options. This increases overall tactical superiority—especially when faced with highly complex threat environments.

Table 15 compares the existing naval tactical approach with the CASoS approach—describing differences for specific naval tactical attributes. The current naval tactical approach is largely platform-centric (Treadway 2019). The attribute that is most advanced in terms of a force-centric capability is situational awareness. The navy has developed a number of data architecture approaches to work towards a common tactical picture across the battle force. However, the extent to which situational awareness is shared across the current battle force is limited (Treadway 2019). Identical and synchronized battle space awareness is highly desired by the navy (Treadway 2019).

Table 15. Comparison of Existing Naval Tactical Approach with CASoS Approach

Attribute	Existing Approach	CASoS Approach
Situational Awareness	Platform-centric—each platform develops situational awareness. Several different data architectures exist that support some data sharing between platforms. A shared tactical picture is limited and does not support collaborative engagements	Force-wide (CASoS-wide) shared situational awareness is achieved. Identical and synchronized situational awareness is developed and continuously updated and managed by the system of intelligent constituent distributed systems.
Self-Awareness	Platform-centric—each platform has knowledge (self-awareness) only of its resident (onboard) resources. Knowledge of off-board resources is conducted manually by human communication between platforms.	Force-wide (CASoS-wide) shared self-awareness is an automated capability. Knowledge of CASoS resources is shared and synchronized across the distributed platforms (constituent systems).

Attribute	Existing Approach	CASoS Approach
Internal Models	Platform-centric; includes shared tactical pictures, limited shared situational awareness, platform-centric self-awareness (resource pictures), some environmental data.	Force-wide (CASoS-wide) shared knowledge: situational awareness (track picture, combat identification, threat model), self-awareness (warfare resource model), environmental model, model of tactical rules and policies, defended assets model, adversary models.
Decision Time	Platform-centric decision time ranges from manual to semi-automated to fully automated for specific tasks on specific platforms. Force-level decision time (for coordinating distributed resources) is manual and requires human coordination and communication between platforms.	Provides real-time decision options that may involve a single platform's resources or the collaboration of distributed platform resources. The CASoS is constantly developing decision options and updating these options as new data and knowledge is acquired. This maximizes the amount of time for reactions and courses of action to be implemented.
Distributed Collaborative Resource Management	Manual, informal	Primary capability of CASoS (automated)
Predictive Analytics (Tactical Wargaming)	Manual, informal	Primary capability of CASoS (automated)

The other attributes in Table 15, such as shared self-awareness across distributed platforms, internal models, decision time, distributed resource management, and predictive analytics are currently largely platform-centric and are conducted informally and manually by the warfighters. A CASoS approach would provide these attributes as primary capabilities within a force-centric paradigm.

The CASoS approach offers new capabilities in the naval tactical domain. Engineering naval systems as a CASoS provides enhanced force readiness and preparedness (sensor coverage, predicted adversarial actions, early detection and identification of threats and unknown objects) during all phases of operational environments. However, the CASoS becomes a truly critical tactical enabler during highly complex states of the operational environment. It offers a solution capability to manage decision complexity, manage distributed resources as a system of systems, and provide a PA wargaming capability. Table 16 lists improvements over the traditional solution that CASoS enables for naval tactical operations.

Table 16. CASoS Improvements for Naval Tactical Operations

CASoS Improvements for Naval Tactical Operations
Sensor coverage—extension of range
Situational awareness accuracy—completeness, less error
Combat identification—more accurate and timely identification of threats
More efficient use of sensor coverage (less wasted overlap of sensor detection coverage)
Earlier threat detection
Improved threat targeting
More decision reaction time
Synchronized track picture and combat identification throughout the force
Improved force readiness and preparedness
Improved efficiency of weapons utilization
Increased probability of raid annihilation
Improved battle damage assessment
Integrated fire control
Improved layered defense

C. A NAVAL TACTICAL MODELING AND SIMULATION ANALYSIS COMPARING THE CASOS SOLUTION TO THE EXISTING BASELINE APPROACH

This section presents the results of the modeling and simulation (M&S) analysis of the CASoS application to the naval tactical domain. This analysis provides evidentiary support that validates the CASoS theory by presenting data results showing tactical improvements using a CASoS solution as compared with a baseline non-CASoS approach.

The M&S analysis was conducted using the Map Aware Non-Uniform Automata (MANA) tool. MANA (Lauren and Stephen, 2002) is an agent-based, time-stepped, stochastic mission-level modeling environment developed by the New Zealand Defense Technology Agency. The MANA modeling environment is based on the ideas of complexity science and was developed to represent some of the non-linear dynamics inherent in complex combat environments. It accomplishes this by treating many aspects of combat behavior as simple rules subject to stochastic random probabilistic processes.

The model represented abstractions of a complex tactical problem domain and naval tactical solution to highlight the differences between a baseline (non-collaborative) approach with a CASoS approach. Many aspects of a real-world tactical scenario were simplified in the model; however, the model provided further understanding into how the collaborative and adaptive behavior of distributed constituent systems produce desired emergence. The model did not provide an exact and exhaustive solution to the tactical problem domain; but instead, used this complex domain as an example to explore the CASoS approach.

1. CASoS Modeling and Simulation Description

In order to validate the CASoS theory, the M&S scenario had to contain the characteristics of a highly complex operational environment. Table 17 lists the characteristics of highly complex operational environments and describes how these characteristics are represented in the model's scenario.

Table 17. Characteristics of a Highly Complex Environment Represented in the Model

Characteristics of a Highly Complex Environment	Present in Model?	How the Characteristics are Represented in the Model
Large numbers of objects/events/ features	**Yes**	A relatively large number of red force missile threats
Heterogeneity and/or diversity of environment objects/events/ features	**Yes**	Multiple types of threats: anti-ship missiles and anti-aircraft missiles
Geographically distributed	**Yes**	The red force launch sites are distributed in the scenario

Characteristics of a Highly Complex Environment	Present in Model?	How the Characteristics are Represented in the Model
Diverse kinematics among objects in the environment	**Yes**	Threat missiles are launched from different locations and at different (random) times—results in diverse threat kinematics
Environment's objects/events/ features are highly interrelated and/or highly related to the solution	**Yes**	The threats are aimed at the blue forces, thus creating a highly interrelated situation between the blue force and its environment
Highly dynamic/rapid tempo of change	**Yes**	The kinematics and speed of the threats creates a rapidly dynamic tempo of events
Uniqueness of situations or states	**Yes**	The randomly generated threats create a unique set of states in each run of the model
Severe consequences of environment behaviors and events	**Yes**	The threats can kill blue forces if not successfully engaged
Unexpected and rapid shifts in states; behaviorally unpredictable	**Yes**	The threats are unexpected and can only be known by the blue forces once they enter the sensor detection range
Unknowable—difficult to gain accurate situational awareness	**Yes**	The threats are unknown until they enter the detection range of the blue force sensors
Accompanied by constraints, rules, and parameters	**Yes**	The threats cannot be engaged until they are within the allowable weapons engagement range

The resulting scenario in MANA is a littoral A2/AD missile threat environment able to demonstrate the characteristics of a highly complex operational environment. Incorporating sea-based and shore-based components enabled the scenario to easily represent geographically-distributed red force ships and land-based launchers. This allowed the simulation to randomly generate two different types of missile threats being fired from distributed locations in relation to the blue force strike group. As listed in Table 17, this created a model scenario with objects, features, and events that were distributed, randomly-generated, unpredictable, kinematically diverse, rapidly occurring, and lethal.

The incoming missiles were given an initial set of parameters: number of missiles (32 anti-ship and 12 anti-aircraft), lethality (0.8), and speed (1111 km/hr anti-ship and 5186 km/hr anti-aircraft); which could be increased to represent higher levels of complexity. The initial parameters were set so they would present a complex situation without overwhelming and quickly annihilating the blue force. The intent was to study how the blue force's systems behavior could address the threat environment as a comparison of a baseline non-CASoS set of blue force actions with a CASoS approach of blue force collaborative interactions. The randomness of red force missile launches presented unique and unexpected threat scenarios for each simulation run. This created an environment that was challenging in terms of the blue force's ability to gain adequate situational awareness and defend with engagement weapons. The blue forces were equipped with sensors with set detection ranges and weapons with set parameters for engagements. The sensor and weapon constraints represented real world limits on the abilities to detect and engage missile threats.

The M&S scenario, illustrated in Figure 60, contains a blue force high value unit (HVU) ship escorted by a strike group consisting of six destroyers (DDG), and two airborne early warning (AEW) aircraft. Two blue force fighter aircraft happen to be nearby. The blue force strike group must safely escort the HVU through highly contested waters. The A2/AD littoral region contains a red force with threats consisting of 32 anti-ship missiles launched from ships and eight anti-aircraft missiles launched from land.

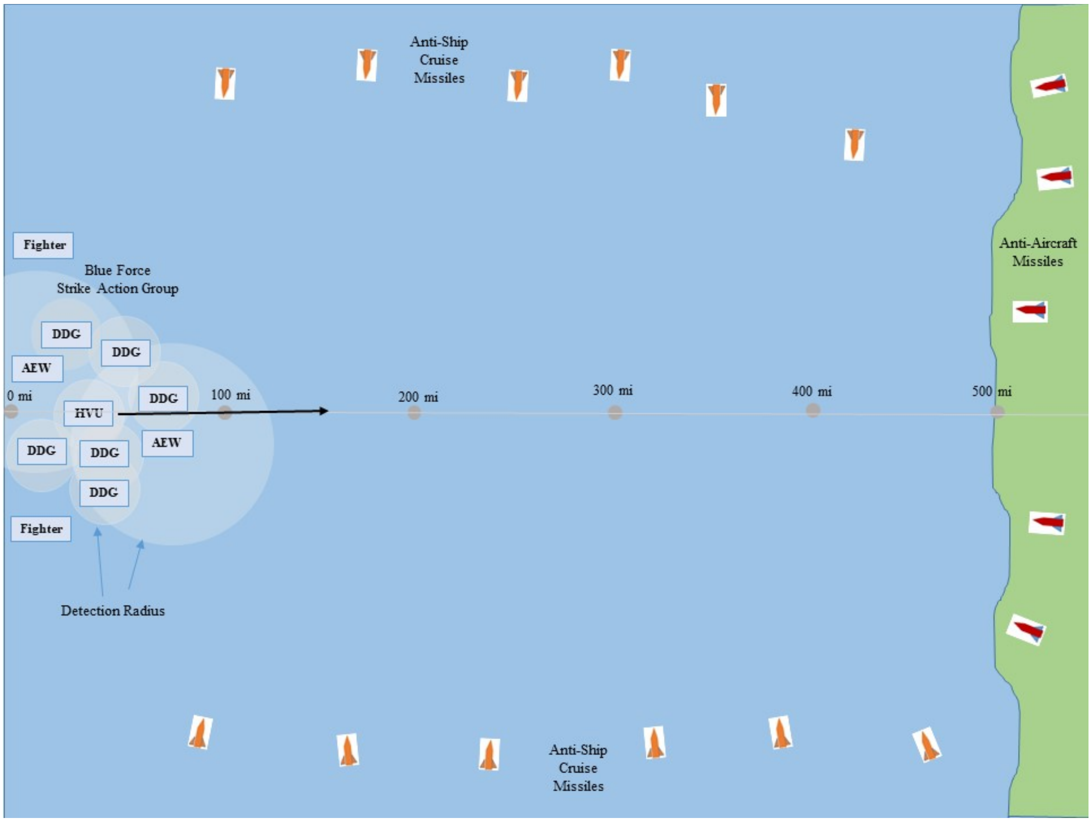

Figure 60. Naval Tactical Modeling and Simulation Scenario

The blue force strike group must traverse the operational area, reach land, and then traverse back out of the operational area. The blue force strike group consists of a HVU ship, accompanied by six DDGs and two surveillance aircraft (AEW). The blue force is also aided by two fighter aircraft that are not initially part of the force group but join in the battle. The overall mission objective is for the HVU to safely reach the land and then safely traverse back out of the A2/AD region.

The threat consists of anti-ship missiles which only attack the HVU and DDGs, and anti-aircraft missiles which are land-based and only attack the AEWs and fighter aircraft. The HVU and destroyers can engage both anti-ship and anti-aircraft red force missiles. The fighter aircraft can only engage anti-aircraft red force missiles.

The blue force strike group moves together at a constant speed and in a constant, fixed formation (distances between the ship and aircraft platforms are set and with an approximate separation of 20 nautical miles). They are traveling at a higher-than-normal cruising speed of 30 nm/hour as they are in an A2/AD environment. They approach the land along a perpendicular trajectory, and then leave the land along the same trajectory. The two fighter aircraft move at a higher speed and each enters the scenario at a random time after the start.

Tables 18 and 19 contain the initial model parameters for the blue and red force assets. These parameters include the sensor detection ranges, the weapon ranges and lethality (probability of kill), and the speeds of the blue force assets. The threat parameters include the numbers of missiles, the missile lethality (probability of kill), and the missile speeds.

Table 18. Initial Model Parameters for Blue Force Assets

Warfare Asset	**Number**	**Detection Capability**	**Weapon**	**Speed**
Surveillance Aircraft—Airborne Early Warning (AEW)	2	100 mi range (all directions)	None	300 nmi/hour
High Value Unit (HVU) Ship	1	30 mi range	Short range weapon: 20 mi range $P_{kill} = 0.9$ 1 launch per second	30 nmi/hour
Destroyer Ship (DDG)	6	30 mi range	Long range weapon: 100 mi range $P_{kill} = 0.9$ 1 launch per 10 seconds	30 nmi/hour
			Short range weapon: 30 mi range $P_{kill} = 0.9$ 1 launch per second	
Fighter Aircraft	2	30 mi range	AMRAAM: 30 nmi range $P_{kill} = 0.9$ 1 launch per 2 seconds	400 nmi/hour
			JDAM: 15 nmi range $P_{kill} = 0.7$ 1 launch per 2 seconds	

Table 19. Initial Model Parameters for Red Force Threats

Threats	Lethality	Number	Speed
Anti-Ship Missiles	$P_{kill} = 0.8$	32 (8 per each of 4 red ships)	1111 km/hr
Anti-Aircraft Missiles	$P_{kill} = 0.8$	12 (4 per each of 3 Launchers)	5186 km/hr

Two approaches were modeled: (1) a baseline (or non-CASoS approach) representing the current approach to naval tactical operations, and (2) a CASoS alternative representing a CASoS approach to naval tactical operations.

a. *Baseline (non-CASoS approach)*

Currently, naval ship and aircraft assets are connected through Link-16, over-the-horizon message types, chat, message traffic and voice communications (Treadway 2019). Miller (2019) explains that a variety of naval decision-makers, including the Joint Interface Control Officer (JICO), the Command, Control, Communications, and Computer (C4) Officer and the N2 (Naval Intelligence) officer, are equally responsible for ensuring the assets work together. The current approach is highly manual and slow in response and decision time; and, miscommunication and misunderstanding are rampant (Miller 2019).

The model represented the naval baseline approach as a set of distributed blue force assets without shared situational awareness for this real-time scenario. Each asset used only its own organic (or resident) sensor to gain detection of the threat. Further, the distributed blue force assets did not coordinate their defensive engagements. Each individual ship and fighter aircraft was configured to fire at an enemy threat missile after detection and when the threat was within range of its defensive weapon. In the baseline model, the two fighter aircraft were configured with random movement, independent situational awareness and engagements with red force anti-aircraft missiles.

b. *CASoS Alternative*

In the CASoS alternative, the model was configured to represent a CASoS approach to naval warfare. In this model, the distributed blue force assets functioned collaboratively as a CASoS. The blue force ships and aircraft have shared situational awareness, meaning that as soon as one of their sensors detects a threat, all of the blue force assets gain this knowledge. The blue force also shared self-awareness, or knowledge of each other's weapon capabilities. This is represented in the model as coordinated engagements against the threats. This was modeled by selecting the blue force asset closest to the threat to fire an engagement shot first and then allowing another asset to fire if the first shot failed.

In the CASoS alternative model, the two fighter aircraft are initially not part of the CASoS. As soon as each fighter aircraft gets within 30 miles of one of the blue force strike group's assets, it becomes part of the CASoS force structure network and gains shared situational awareness (both as a contributor of detected threats and as a recipient of the blue force's detected threats). The aircraft joins the formation and changes its speed to cover the strike group. Its movement is no longer random, but instead matches the strike group movement. The fighter aircraft are equipped with Joint Direct Attack Munitions (JDAM) for bombing red force missile launchers and Advanced Medium-Range Air-to-Air Missiles (AMRAAM) for engaging anti-aircraft missiles.

2. How the CASoS Characteristics and Principles are Represented in the Model

This section describes how the model's CASoS alternative represents CASoS characteristics and principles. The objective of the model was to reflect as many of the theoretical CASoS characteristics and principles as possible to study how a CASoS approach might improve a complex situation or at least differ from a traditional non-CASoS approach. The model was able to reflect many of the CASoS characteristics and some aspects of all of the CASoS principles.

The CASoS characteristics that were represented in the model are shaded in yellow in Figure 61 and described in more detail in Table 20. Figure 61 shows that most of the CASoS characteristics are represented in the model, with the exception of multi-minded behavior, evolving behavior, changing internal boundaries, and non-linearity/uncertainty. Modeling and studying how these characteristics might improve a solution to highly complex scenarios is left for future research. This model focused on demonstrating the CASoS characteristics of collaboration, adaptation, self-organization, and purposeful multi-level (emergent) behavior through distributed and heterogeneous constituent systems that form a system of systems with a changing boundary. The model also presented a threat environment that required the CASoS to manage detailed and dynamic complexity and to demonstrate resilience in terms of providing a defense even when some blue force assets might be destroyed.

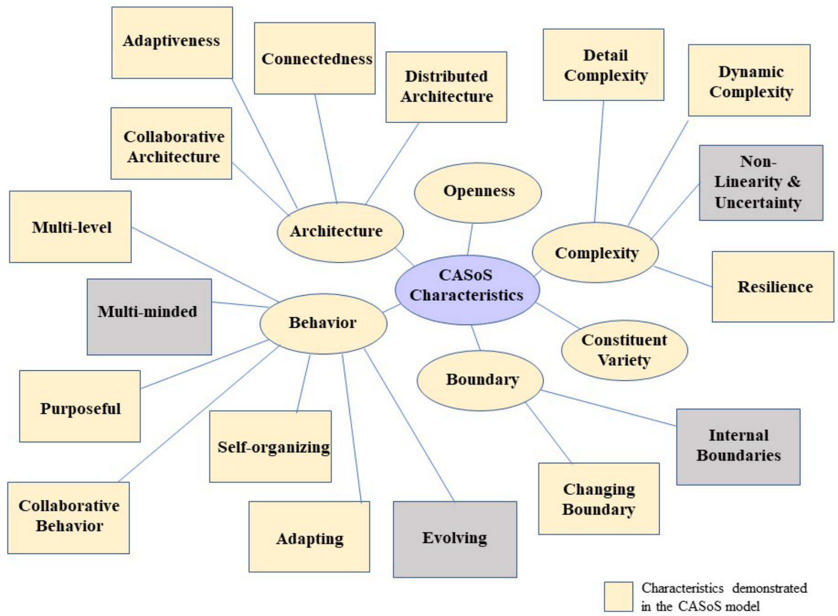

Figure 61. CASoS Characteristics Represented in the Model

Table 20 describes how the model was able to represent and demonstrate many of the CASoS characteristics. The set of CASoS characteristics contains some characteristics that are present in almost all systems and groups of systems (such as openness, constituent variety, and purposefulness). Therefore, these more universal characteristics were present in both the baseline and CASoS model variants.

Table 20. Descriptions of how CASoS Characteristics are Represented in the Model

CASoS Characteristics Represented in the Model	Descriptions of how these Characteristics are Represented in the Model
Openness	The blue force strike group is an "open" CASoS because it exchanges information (sensing) and kinetic weapons with its environment.
Architecture (collaborative, adaptive, connected, distributed)	The CASoS blue force strike group in the model has an architecture that is collaborative, adaptive, connected, and distributed. The ships and aircraft in the model are geographically distributed but connected as they share information concerning situational awareness and self-awareness. Their architecture allows them to collaborate to gain shared situational awareness and to coordinate engagements. The CASoS architecture in the model is adaptive as it "adapts" to include the fighter aircraft when they join.
Behavior	The CASoS in the model exhibits the following behavior: multi-level, collaborative, purposeful, self-organizing, and adaptive. The model CASoS exhibits multi-level and collaborative behavior as constituent systems act independently or collaboratively. The CASoS is purposeful in terms of exhibiting desired defensive behavior. An example of self-organization and adaptation is when the fighter aircraft change their behavior after joining the CASoS.
Changing Boundary	The CASoS in the model has the characteristic of changing boundary. The boundary of the CASoS changes as the fighter aircraft join the CASoS.
Constituent Variety	The CASoS in the model has constituent variety, as it consists of different types of constituent systems: DDGs, AEWs, and fighter aircraft. Each of these types of constituent systems has different properties and capabilities.
Complexity (detail, dynamic, resilience)	The CASoS in the model exhibits the following characteristics of complexity: detail complexity, dynamic complexity, and resilience. Detail complexity is represented in this model by the numbers of constituent systems and their interactions (in this case shared situational awareness and coordinated engagements). Dynamic complexity is represented by the short timeframe in which the systems must behave to address the situation (which in this case is the engagement of threat missiles). Resilience is a characteristic of this CASoS model as the blue force responds to the threat missiles by engaging the threats.

Additionally, Table 20 contains descriptions of the more CASoS-specific characteristics that were also represented in the CASoS model alternative, such as collaboration, self-organization, adaptation, and detail and dynamic complexity.

Some aspects of all of the CASoS principles were represented in the CASoS model alternative. Figure 62 reflects this, as all of the CASoS principles are shaded yellow.

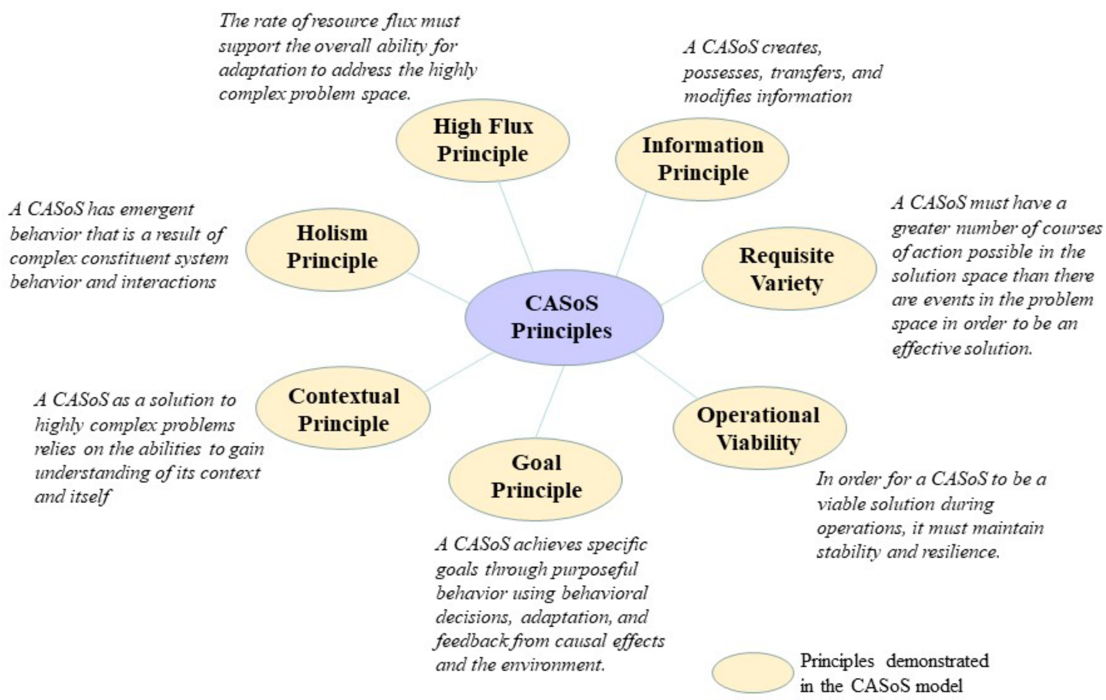

Figure 62. CASoS Principles Represented in the Model

Descriptions of how the CASoS model represents and demonstrates aspects of the CASoS principles are contained in Table 21. The model demonstrates high flux by having blue force weapon and sensor resources that are capable of detecting and intercepting the threats. Holism is demonstrated by the blue force's ability to coordinate engagements and develop shared situational awareness. The blue force's sensors and data architecture in the model provide the capabilities that demonstrate the contextual and information principles. The CASoS model alternative achieves the goal principle through its ability to purposefully defend the HVU and strike group by engaging the threats. Finally, the model demonstrates some levels of requisite variety and operational viability by allowing behavior courses of action that provide a threat defense even when some blue force assets are destroyed.

Table 21. Descriptions of how CASoS Principles are Represented in the Model

CASoS Principles Represented in the Model	Descriptions of how these Principles are Represented in the Model
High Flux Principle *The rate of resource flux must support the overall ability for adaptation to address the highly complex problem space.*	The high flux principle is represented when the blue force weapons are capable of intercepting the threats (in terms of weapons range, speed, and lethality) and when the blue force sensors can detect the threats (in terms of sensor range).
Holism Principle *A CASoS has emergent behavior that is a result of complex constituent system behavior and interactions.*	Holism is demonstrated through the emergent behavior arising from the interaction and collaboration of the distributed blue force ships and aircraft in the model. Examples of the emergent behavior include shared situational awareness and engagement coordination.
Contextual Principle *A CASoS as a solution to highly complex problems relies on the abilities to gain understanding of its context and itself.*	In this model, the blue force CASoS gains an understanding of itself and its environment using the blue force sensors and data-sharing architecture.
Goal Principle *A CASoS achieves specific goals through purposeful behavior using behavioral decisions, adaptation, and feedback from causal effects and the environment.*	The goal principle is demonstrated in the model by the blue force CASoS's ability to purposefully defend itself and its HVU by making decisions to launch engagement missiles, adapt with the inclusion of additional fighter assets, and perform battle damage assessment to take additional shots when engagements are not successful.
Operational Viability *In order for a CASoS to be a viable solution during operations, it must maintain stability and resilience.*	Operational viability is demonstrated in this model by the blue force CASoS's ability to maintain its collaborative architecture and ability to support CASoS behavior even as some of its constituent warfare systems were destroyed.
Requisite Variety *A CASoS must have a greater number of courses of action possible in the solution space than there are events in the problem space in order to be an effective solution.*	In this model, the law of requisite variety is demonstrated by the blue force CASoS having enough engagement courses of action to defend the HVU against the red force threats.
Information Principle *A CASoS creates, possesses, transfers, and modifies information.*	The information principle is demonstrated in the model by the blue force's ability to sense and detect threats, share this data within the CASoS, and update this awareness information as the environment changes.

3. Modeling and Simulation Results

Two M&S analyses were conducted. The first M&S analysis compared the behavior of the baseline approach with the behavior of the CASoS approach using the initial threat scenario parameters. The second M&S analysis studied the effects of increased complexity in the environment by comparing its effect on the baseline and CASoS alternatives. In the second M&S analysis, an increase in the operational environment's complexity was modeled by increasing the number, lethality, and speed of the red force threats. The same set of evaluation metrics were used in both analyses. Each M&S experiment involved 200 simulation runs (100 for the baseline and 100 for the CASoS). The metrics for the analyses are shown in Table 22.

Table 22. Evaluation Metrics for M&S Analysis

Metric	Metric Description
Blue Force Casualties	Total blue assets killed
Time Required to Kill 50% of the Red Threat	Time, in time steps, that it took to kill 50% of the red force
Number of DDG Long Range Weapons Fired	Total DDG long-range weapons used (sum over all 6 DDGs)
Number of DDG Short Range Weapons Fired	Total DDG short-range weapons used (sum over all 6 DDGs)
Number of Fighter AMRAAMs fired	Total Fighter AMRAAMs used (sum over both fighters) (AMRAAM = Advanced Medium Range Air-to-Air Missiles)
Number of Fighter JDAMs Fired	Total Fighter JDAMs used (sum over both fighters) (JDAM = Joint Direct Attack Munition)

The evaluation metrics provide insight into the interactions of the blue force solution approaches with their complex operational environment. Collecting data showing the number of blue force casualties, the time required to defend against (or kill) red forces, and the expenditure of weapons resources, provided evidence of the differences between a CASoS and non-CASoS approach to implementing a set of distributed constituent systems, or in this case, blue force assets.

The number of blue force casualties is an overarching indicator of the performance of the layered defense—of how well and how quickly the distributed and heterogeneous weapons resources are used. This metric indicated the contributions of an adaptive and collaborative architecture and purposeful emergent behavior, which the CASoS approach provided. It also showed implementation of important CASoS principles such as the information principle, the contextual principle, the goal principle, and the principle of holism.

The time required to kill 50% of the red forces provided a means to evaluate whether the CASoS approach would be able to decrease the decision reaction time, thereby defending assets more quickly. This evaluation measure demonstrated the contribution of shared and improved situational awareness, which is enabled by the CASoS collaborative architecture, information principle, and contextual principle.

The amount of weapons resources expended is indicated by the evaluation metrics for numbers of DDG long and short range weapons fired and fighter aircraft AMRAAMs and JDAMs launched. These metrics provided insight into the ability of the two approaches to provide a layered defense. They measured how well the two approaches were able to make use of the different types of distributed weapons resources. The results indicated the contributions of CASoS characteristics (adaptiveness, collaboration, purposefulness, self-organization, emergence, constituent variety, changing boundary) and principles (holism, high flux, information, contextual, requisite variety).

The following two subsections contain the results of the two M&S analyses.

a. M&S Analysis #1—Comparison of the Current (Baseline) Approach with a CASoS Approach

The first M&S analysis compared the baseline and CASoS alternatives to study the similarities and differences of naval tactical behavior in the two approaches. The two model variants were set up as “CASoS No” (for the baseline) and “CASoS Yes” (representing the CASoS approach). Each model variant was run 100 times and data was collected according to the evaluation metrics shown in Table 22.

Figures 63–68 show comparison plots of the data results from the simulation runs according to the evaluation criteria. The data results were developed using JMP statistical software. In the graphical representations of the data, the plots in the left-hand portion represent the baseline case (“CASoS = no”) and the plots in the right-hand portion represent the CASoS case (“CASoS = yes”).

(1) M&S Analysis #1—Blue Casualties

The number of blue forces destroyed, on average, was lower in the CASoS alternative than in the baseline alternative. Figure 63 shows that the average number of blue force casualties in the baseline alternative was 2.01 and in the CASoS alternative was 0.78.

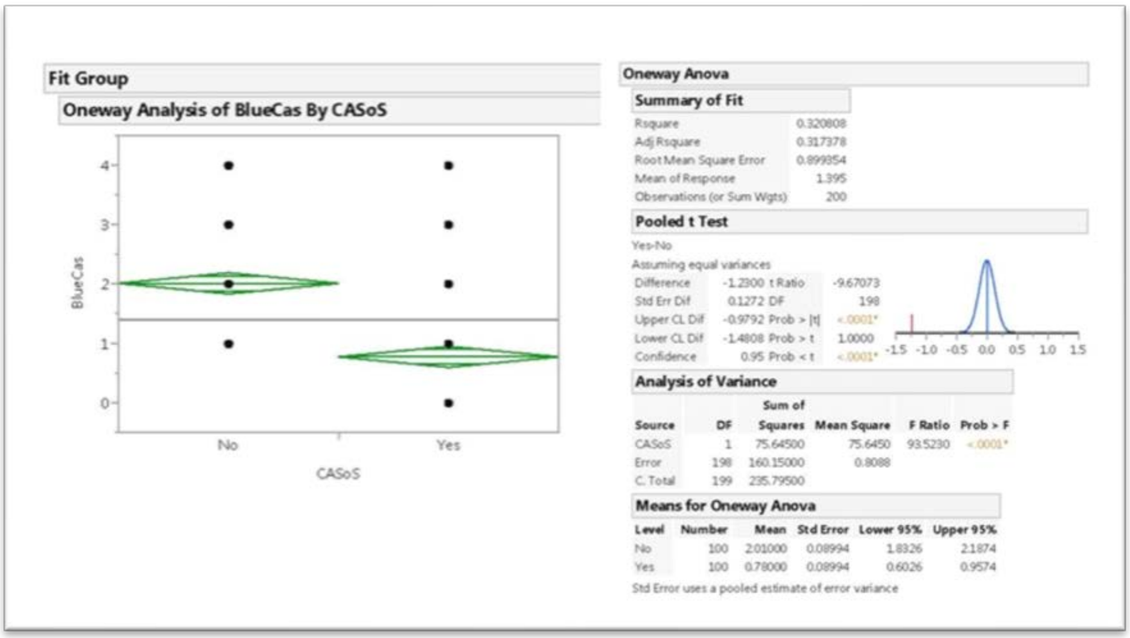

Figure 63. M&S Analysis #1—Comparative Results of the Number of Blue Force Casualties

A one-sided hypothesis test was performed with the alternative hypothesis that the mean value of blue casualties in the CASoS alternative is lower than the mean value of blue casualties in the baseline alternative. The null hypothesis was that the two means were equivalent. The results showed a t-value of -13.108 and a p-value < 0.001 using a significance level of 0.05. This statistical test showed that the CASoS approach really does have a positive effect on the defense of blue forces; significantly fewer casualties.

The CASoS alternative's improvement in the overall number of blue force casualties demonstrated the CASoS ability to enhance naval tactical operations. The CASoS approach offered improvements in the layered defense of the HVU by optimizing the use of the distributed blue force sensor and weapon assets through purposeful collaboration and multi-level behavior.

(2) M&S Analysis #1—Time Required to Kill 50% of Red Forces

The amount of time required to destroy 50% of the red forces, on average, was lower in the CASoS alternative than in the baseline alternative. Figure 64 shows that the average time steps required in the baseline alternative was 40.9 minutes (2454.23 time steps) and in the CASoS alternative was 25.53 minutes (1531.89 time steps).

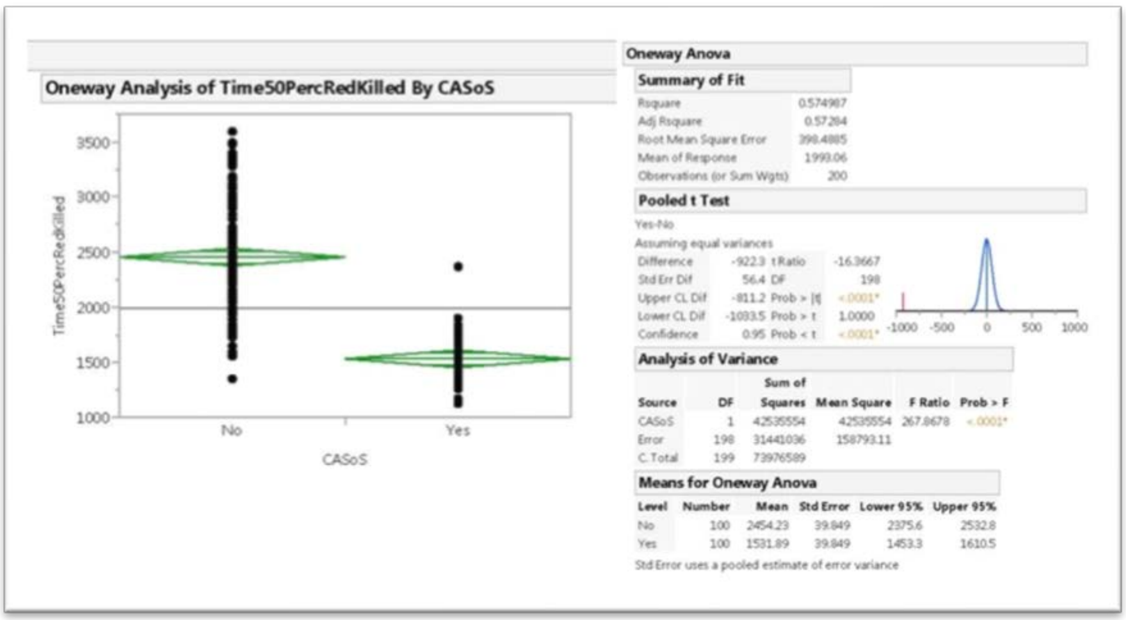

Figure 64. M&S Analysis #1—Comparative Results of the Time Required to Kill 50% of the Red Forces

A one-sided hypothesis test at a significance level of 0.05 was performed with an alternative hypothesis that the mean value of time required to kill 50% of the red forces in the CASoS alternative is lower than the mean value in the baseline alternative. The null hypothesis was that the two means were equivalent. The results showed a t-value of -50.2935, which corresponded with a p-value < 0.001. This statistical test showed that the CASoS approach really does have a positive effect on the amount of time it takes to make engagement decisions and defend blue forces: it took significantly less time in the CASoS approach for the blue forces to defend themselves.

The CASoS alternative's improvement in the decision reaction time demonstrated the CASoS ability to enhance naval tactical operations. The CASoS approach offered improvements in the decision reaction time through its collaborative and adaptive architecture that enables shared situational awareness among the distributed blue force assets.

(3) M&S Analysis #1—Number of DDG Long Range Missiles Fired

The number of long range engagement weapons fired by the blue force DDGs was, on average, significantly greater in the CASoS alternative than in the baseline alternative. Figure 65 shows that the average number of DDG long-range weapons fired in the baseline alternative was 26.43 and in the CASoS alternative was 174.7.

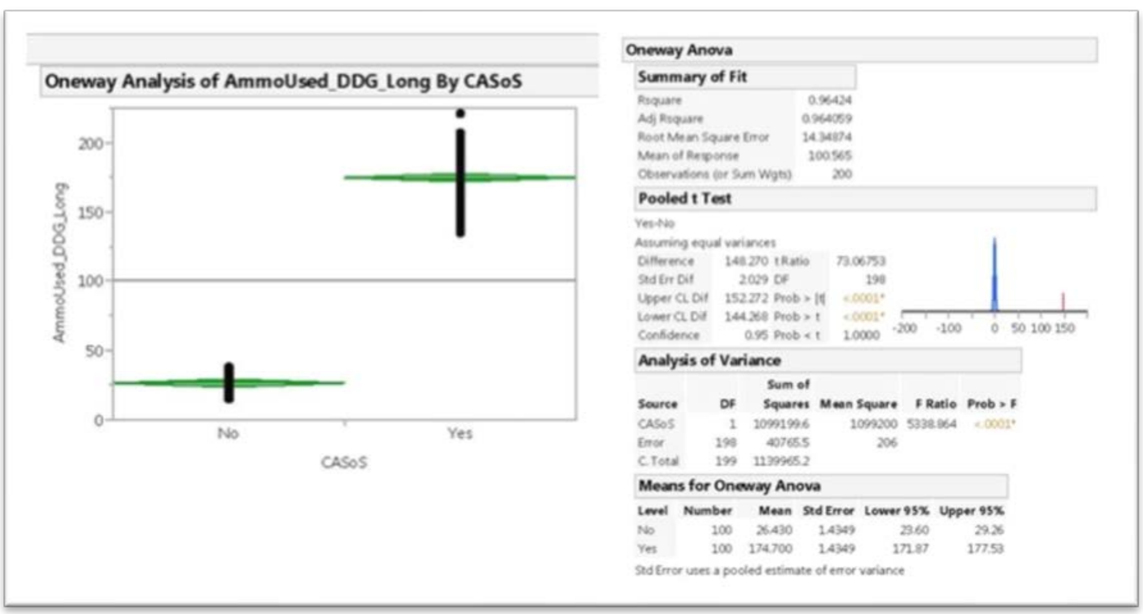

Figure 65. M&S Analysis #1—Comparative Results of the Number of DDG Long Range Weapons Fired

A one-sided hypothesis test at a significance level of 0.05 was performed with an alternative hypothesis that the mean value of long-range engagement missiles fired by the blue force DDGs in the CASoS alternative is higher than the mean value of those fired in the baseline alternative. The null hypothesis was that the two means were equivalent. The results showed a t-value of 75.2599 and a p-value < 0.001. This statistical test showed that the CASoS approach really does have a positive effect on the number of long-range engagement missiles that can be fired by DDGs; significantly more long-range weapons were used. This implies that CASoS engagements can take place earlier and at longer distances from the blue forces; thus providing a more layered defense.

The analysis shows that many more long range engagements were possible in the CASoS approach. This indicates that due to shared and increased situational awareness, the CASoS approach takes advantage of the distributed sensor detection ranges to launch long-range weapons based on "remote" data. In effect, the CASoS approach in enabling engage on remote capabilities. This results in a CASoS improvement for naval layered defense options.

(4) M&S Analysis #1—Number of DDG Short-Range Missiles Fired

The number of short range engagement weapons fired by the blue force DDGs was, on average, less in the CASoS alternative than in the baseline alternative. Figure 66 shows that the average number of DDG short-range weapons fired in the baseline alternative was 60.02 and in the CASoS alternative was 48.83.

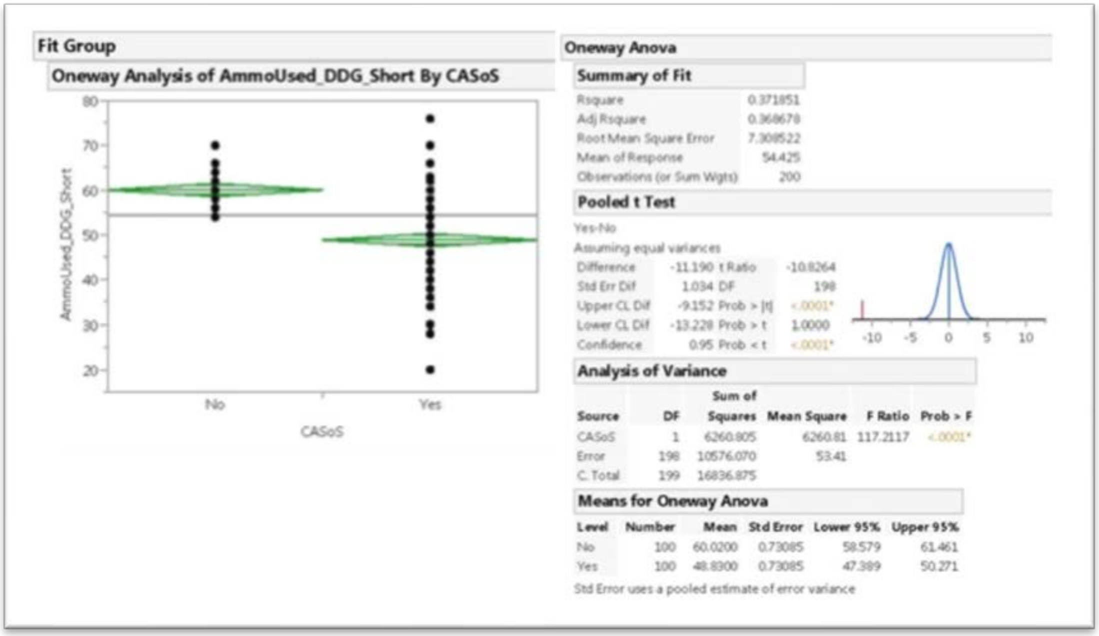

Figure 66. M&S Analysis #1—Comparative Results of the Number of DDG Short Range Weapons Fired

A one-sided hypothesis test at a significance level of 0.05 was performed with the alternative hypothesis that the mean value of short-range engagement missiles fired by the blue force DDGs in the CASoS alternative is lower than the mean value of those fired in the baseline alternative. The null hypothesis was that the two means were equivalent. The results showed a t-value of -11.0786 and a p-value < 0.001. This statistical test showed that the CASoS approach really does have a positive effect on the number of short-range engagement missiles used by DDGs; in this scenario the CASoS solution used fewer short-range weapons to defend against the red force. The implications of this result is that CASoS engagements can take place earlier and at longer distances from the blue forces; thus, providing a more layered defense.

The analysis shows that the CASoS approach relied primarily on its long-range weapons for its defense, while the baseline approach relied heavily on the use of short-range weapons. Each blue force asset in the baseline approach had a much more limited situational awareness, which kept them from being able to use their long range weapons and significantly reduced their ability to have a layered defense. The results of this evaluation metric demonstrate that the CASoS approach enables an improvement over the baseline in layered defense options.

(5) M&S Analysis #1—Number of Fighter Aircraft AMRAAMs Fired

The number of advanced medium range air-to-air missiles (AMRAAM) weapons fired by the blue force fighter aircraft was, on average, significantly higher in the CASoS alternative than in the baseline alternative. Figure 67 shows that the average number of fighter AMRAAM weapons fired in the baseline alternative was 3.96 and in the CASoS alternative was 21.8.

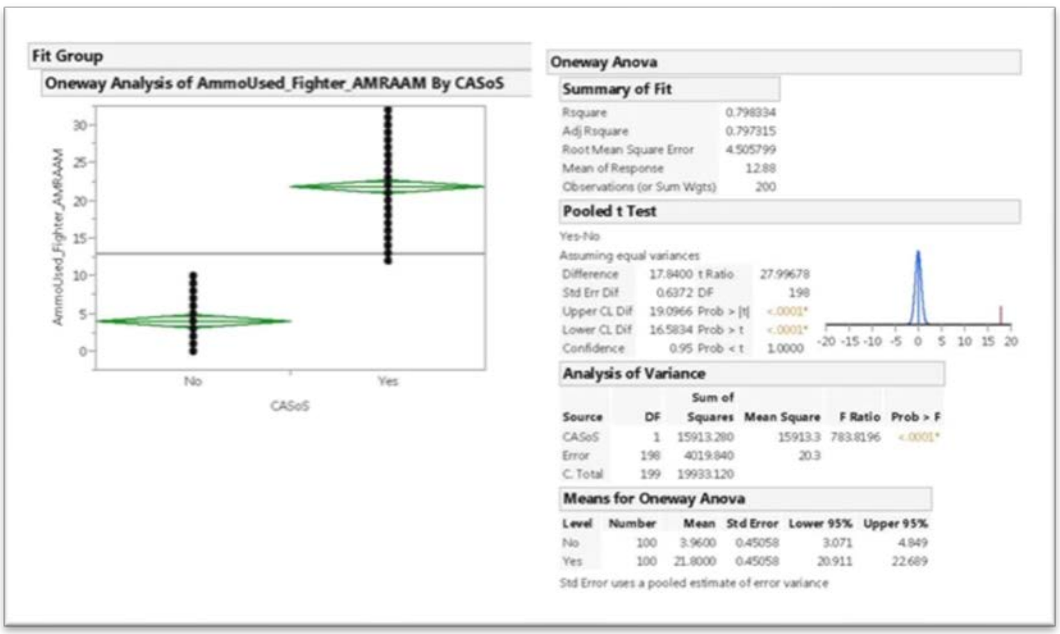

Figure 67. M&S Analysis #1—Comparative Results of the Number of Fighter Aircraft AMRAAMs Fired

A one-sided hypothesis test at a significance level of 0.05 was performed with the alternative hypothesis that the mean value of AMRAAMs fired by the blue force fighter aircraft in the CASoS alternative is higher than the mean value of those fired in the baseline alternative. The null hypothesis was that the two means were equivalent. The results showed a t-value of 30.9561 and a p-value < 0.001. This statistical test showed that the

CASoS approach really does have a positive effect on the number of fighter aircraft AMRAAMs used in this scenario; significantly more AMRAAMs were fired. This resulted in the fighter aircraft having much greater participation in the defense of the blue forces in the CASoS approach. This implies that the CASoS ability to have a changing boundary and adaptive architecture to allow additional blue force systems to join and collaborate, allows these additional resources (in this case, the fighter aircraft) to be better utilized for addressing the complex environment.

The CASoS approach enabled the fighter aircraft to purposefully and adaptively fire more AMRAAM weapons. This is attributed to the ability of the fighter aircraft to join the CASoS and in doing so, greatly improve their situational awareness and enable them to adapt their behavior to collaborate with the blue force strike group and participate in the layered defense of the HVU.

(6) M&S Analysis #1—Number of Fighter Aircraft JDAMs Launched

The analysis of the JDAMs launched, shown in Figure 68, indicated that the average number of JDAMs dropped in the baseline and CASoS alternatives were roughly the same -- approximately seven and a half, which corresponds with the number of red force launchers.

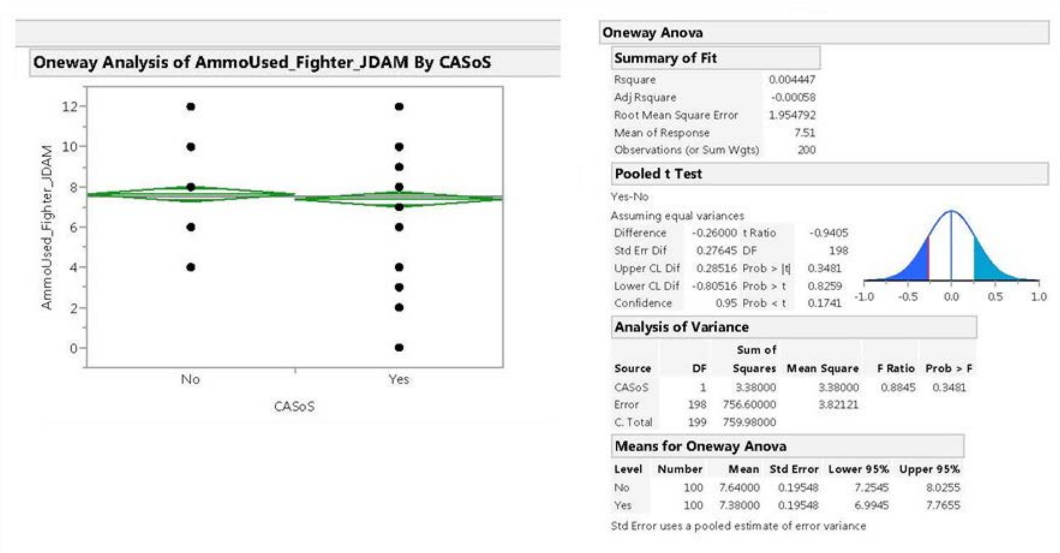

Figure 68. M&S Analysis #1—Comparative Results of the Number of Fighter Aircraft JDAMs Launched

For this evaluation metric, there was not enough evidence to support rejecting the null hypothesis. An analysis of individual simulation runs showed that the fighter aircraft got approximately the same chance to bomb red force launch sites in the baseline alternative with random fighter aircraft motion as in the CASoS alternative with the fighter aircraft joining the blue force strike group formation. There were seven red force launchers in the scenario; and in approximately 70% of the simulation runs (for both the baseline and CASoS approaches), all seven red force launch sites were destroyed. Therefore, in both the baseline and CASoS approaches, the fighter aircraft were able to detect and destroy all of the distributed red force launch sites about 70% of the time. This indicates that even though the fighter aircraft had significantly increased situational awareness in the CASoS approach, they had adequate individual detection ranges and speed in the baseline approach to cover the tactical area and gain close enough proximity to the distributed red force launch sites so they could successfully launch JDAMs and destroy the launchers.

(7) M&S Analysis #1 Summary

For the case of the CASoS alternative, there were significantly fewer blue force casualties and the time required to kill 50% of the red force was significantly lower. The ability for the distributed blue force assets to function collaboratively and exhibit desired emergent behavior in terms of shared and increased situational awareness and cooperative engagements, resulted in these tactical improvements.

In the CASoS alternative, the DDGs used many fewer short range weapons and many more longer range weapons because they had greater situational awareness and could detect threats in time to support the longer range weapons engagement requirements. The CASoS approach was, in effect, able to employ a layered defense tactic; whereas the baseline approach was only able to employ a short-range close-in defense tactic.

In the CASoS alternative, the fighter aircraft used more of the AMRAAM missiles because they were called into the fight much sooner and could respond adaptively to the threat. This indicated that the fighter aircraft took many more shots (or exhibited more purposeful and participatory behavior) when they were able to collaborate as part of the CASoS.

Table 23 contains a summary of the M&S #1 analysis results. The analysis demonstrated that the CASoS improved layered defense options, reduced casualties, and improved the engagement decision reaction time.

Table 23. M&S #1 Analysis Results

Evaluation Metrics	Baseline Mean	CASoS Mean	Analysis Results	Implications for the CASoS Theory Validation
Blue Force Casualties	2.01	0.78	Alternative Hypothesis Accepted: Mean number of blue casualties was lower in the CASoS alternative.	Indicates that the distributed, collaborative, and adaptive architecture, which enables shared situational awareness and behavior that is collaborative, adaptive, and purposeful led to fewer blue force casualties.
Time Required to Kill 50% of the Red Threat	40.9 minutes	25.53 minutes	Alternative Hypothesis Accepted: Mean time required to kill 50% of the red forces was lower in the CASoS alternative.	Indicates that the CASoS architecture and behavior leads to increased and shared situational awareness which decreases the time required to make engagement decisions and increases the effective engagement range of the blue force weapons. Earlier and more effective engagement shots lessens the amount of

Evaluation Metrics	Baseline Mean	CASoS Mean	Analysis Results	Implications for the CASoS Theory Validation
				time required to defend against the red force threats.
Number of DDG Long Range Weapons Fired	26.43	174.7	Alternative Hypothesis Accepted: Mean number of DDG long range weapons was higher in the CASoS alternative.	Indicates that the CASoS architecture and behavior enables increased and shared situational awareness. This earlier and shared detection of red force threats increases the number of long range weapons that can be fired—giving the blue force a significantly improved layered defense.
Number of DDG Short Range Weapons Fired	60.02	48.83	Alternative Hypothesis Accepted: Mean number of DDG short range weapons fired was lower in the CASoS alternative.	Indicates that the CASoS's increased use of long range weapons decreases the number of short range weapons that need to be used. This is due to the fact that the red force threats are engaged by the long range weapons at larger ranges from the blue force assets. Fewer red force threats get close enough to the blue force assets to require the use of the short range weapons.
Number of Fighter AMRAAMs fired	3.96	21.8	Alternative Hypothesis Accepted: Mean number of fighter aircraft AMRAAMs fired was higher in the CASoS alternative.	This indicates that the ability of the fighter aircraft to join the Blue Force CASoS enables them to participate in the CASoS mission of defending the blue force HVU. Upon joining the CASoS, the fighter aircraft have increased and shared situational awareness with the rest of the blue force assets. They have significantly improved awareness of red force threat location and can purposefully coordinate their use of AMRAAM weapons as part of the blue force layered defense.
Number of Fighter JDAMs Fired	7.64	7.38	Null Hypothesis Accepted: The mean numbers of fighter aircraft JDAMs fired was equivalent in the baseline and CASoS alternatives.	There was not a significant difference in the number of JDAMs fired in the baseline and CASoS alternatives. In the baseline alternative, the fighter aircraft motion was random. In the CASoS alternative, the fighter aircraft moved in conjunction with the blue force strike group. The blue force movement and random movement created approximately the same number of opportunities for the

Evaluation Metrics	Baseline Mean	CASoS Mean	Analysis Results	Implications for the CASoS Theory Validation
				fighter aircraft to launch JDAMs.

The improvements in blue force defense and decision reaction time demonstrate the benefits of a CASoS approach. The adaptive architecture connecting the distributed blue force assets enable the strike group to function as a CASoS. This enables solution behavior that is multi-level, emergent, adaptive, purposeful and collaborative. The model demonstrates that enabling a changing boundary and maximizing the use of constituent variety (a diverse set of warfare resources) provided a layered defense approach that resulted in tactical improvements.

b. M&S Analysis #2—Effects of Increasing the Complexity of the Scenario Environment.

The second M&S analysis increased the complexity of the threat scenario by increasing the number, speed, and lethality of the red force threat to analyze these effects on the baseline and CASoS alternatives. The purpose of this analysis was to study the behavior of the two approaches (baseline and CASoS) as they encountered a heightened level of complexity in the operational environment with a greater number of events (more missiles), a faster tempo of events (with greater missile speed), and more deadly consequences (greater missile lethality). The same evaluation metrics (listed in Table 22) were used in this second M&S analysis.

A design of experiments (DOE) was conducted to vary the number, speed, and lethality of the red force threats to identify values for these threat parameters that would provide a more stressing environment without completely overwhelming the blue force strike group. The DOE crossed a model alternative factor (2 levels, CASoS/baseline) with a 33 Design Point (DP) Nearly Orthogonal Latin Hypercube (NOLH) for the three threat factors, resulting in 2x33 = 66 DPs, each run with 100 stochastic replications. The analysis was based upon 6600 runs. The evaluation produced the following parameters to represent the more stressing environment: a threat number of 12 missiles per launcher, a threat speed of 6000 km/hr, and a threat lethality (probability of kill) of 0.9. Therefore, there were 48 anti-ship missiles and 36 anti-aircraft missiles in this second M&S scenario, as compared with 32 anti-ship missiles and eight anti-aircraft missiles in the first M&S scenario. The threat speeds in the first M&S scenario were 1111 km/hr for the anti-aircraft missiles and 5186 km/hr for the anti-aircraft missiles. These speeds were increased to 6000 km/hr for both the anti-aircraft and anti-ship missiles in the second scenario. Finally, the probability of kill was raised from 0.8 in the first M&S scenario to 0.9 in the second M&S scenario. These values increased the complexity of the threat environment without completely destroying the blue force assets as represented in both the baseline and CASoS approaches.

Figures 69–74 show comparison plots of the data results from the simulation runs according to the evaluation criteria. The data results were developed using JMP statistical software. In the graphical representations of the data, the plots in the left-hand portion represent the baseline case ("CASoS = no") and the plots in the right-hand portion represent the CASoS case ("CASoS = yes").

(1) M&S Analysis #2—Number of Blue Casualties

The number of blue forces destroyed, on average, was lower in the CASoS alternative than in the baseline alternative. Figure 69 shows that the average number of blue force casualties in the baseline alternative was 3.56 and in the CASoS alternative was 2.74. A one-sided hypothesis test at a significance level of 0.05 was performed with the alternative hypothesis that the mean value of blue casualties in the CASoS alternative is lower than the mean value of blue casualties in the baseline alternative. The null hypothesis was that the two means were equivalent. The results showed a t-value of -6.11 and a p-value < 0.001. This statistical test showed that the CASoS approach had a positive effect on the defense of blue forces and there were fewer casualties.

Figure 69. M&S Analysis #2—Comparative Results of the Number of Blue Casualties

The CASoS alternative's improvement in the overall number of blue force casualties is a positive indicator in the CASoS ability to enhance naval tactical operations. The CASoS approach offered improvements in the layered defense of the HVU by optimizing the use of the distributed blue force sensor and weapon assets through purposeful collaboration and multi-level behavior.

(2) M&S Analysis #2—Required Time to Kill 50% of Red Forces

The amount of time required to destroy 50% of the red forces, on average, was lower in the CASoS alternative than in the baseline alternative. Figure 70 shows that the average time required in the baseline alternative was 28.3 minutes (1698.19 time steps) and in the CASoS alternative was 20.84 minutes (1250.43 time steps).

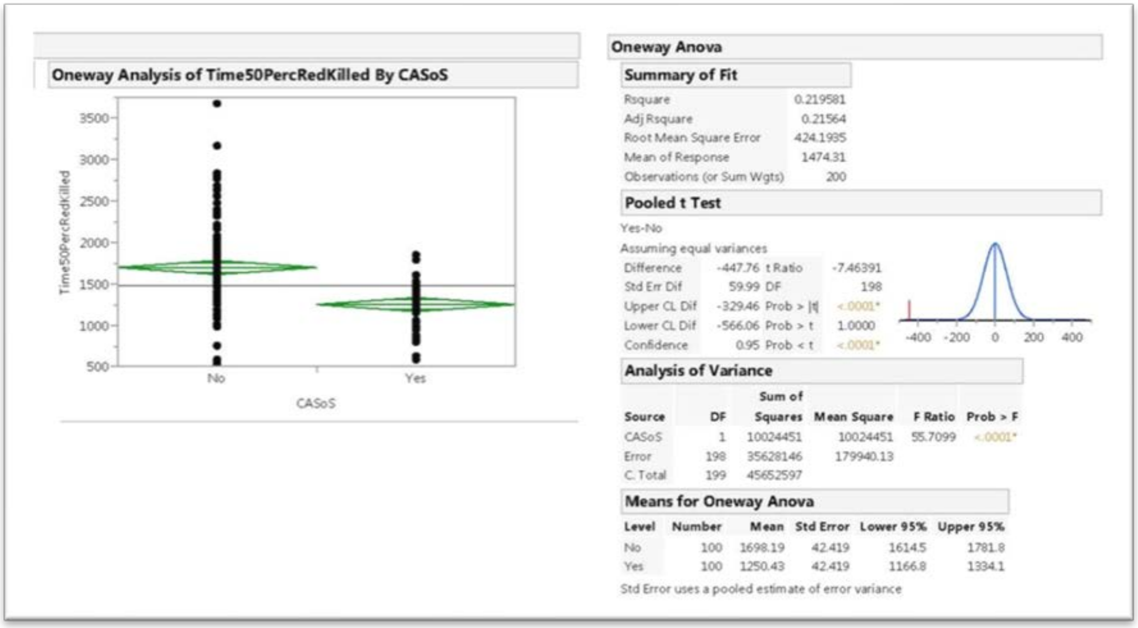

Figure 70. M&S Analysis #2—Comparative Results of the Time Required to Kill 50% of the Red Forces

A one-sided hypothesis test at a significance level of 0.05 was performed with an alternative hypothesis that the mean value of time required to kill 50% of the red forces in the CASoS alternative is lower than the mean value in the baseline alternative. The null hypothesis was that the two means were equivalent. The results showed a t-value of -7.46 and a p-value < 0.001. This statistical test showed that the CASoS approach really did have a positive effect—significantly reducing the amount of time it takes to make engagement decisions and defend blue forces.

This result implies that even as the threat environment became more stressing, the CASoS alternative was still able to react more quickly, providing a more rapid defense. This ability is attributed to the adaptive and collaborative architecture and intelligent agents that share information and gain increased and shared situational awareness of the battlespace enabling earlier threat detection and extended weapons range.

The graphical depiction in Figure 70 shows that the spread of data results for the baseline alternative had a much larger range of values than for the CASoS alternative. This result indicates that the CASoS approach behaves more consistently than the baseline approach. This demonstrates the CASoS ability to purposefully adapt to a changing environment—and by doing so collectively, the distributed blue force assets are able to reduce the decision reaction time.

(3) M&S Analysis #2—Number of DDG Long Range Missiles Fired

The number of long range engagement weapons fired by the blue force DDGs was, on average, significantly greater in the CASoS alternative than in the baseline alternative. Figure 71 shows that the average number of DDG long-range weapons fired in the baseline alternative was just 22.14 and in the CASoS alternative was 167.42.

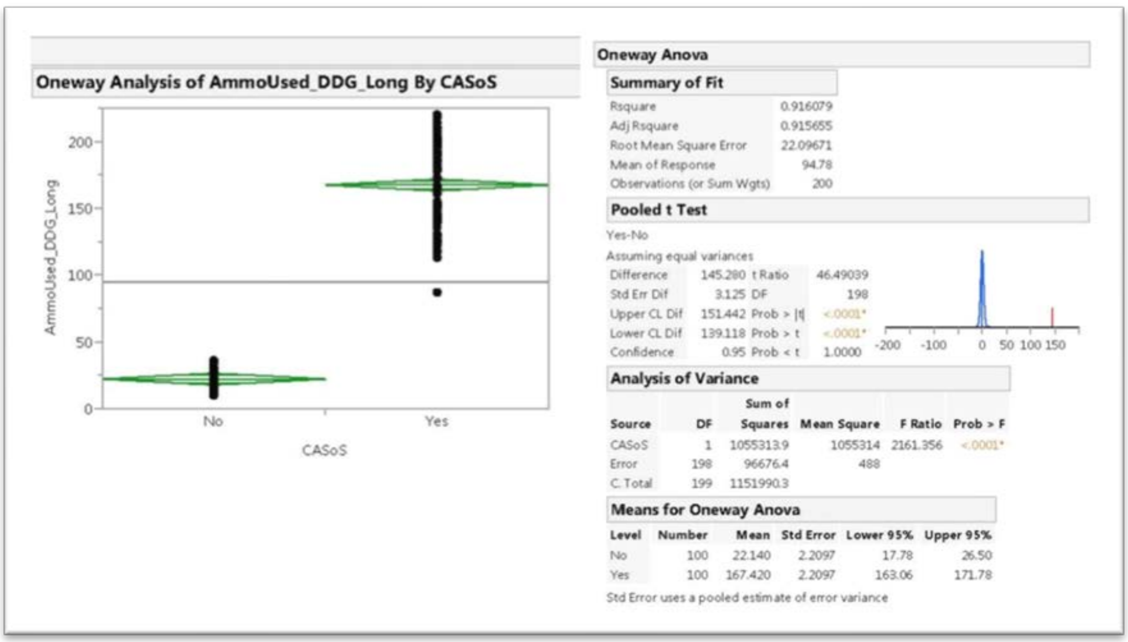

Figure 71. M&S Analysis #2—Comparative Results of the Number of DDG Long Range Missiles Fired

A one-sided hypothesis test was performed at a significance level of 0.05 with the alternative hypothesis that the mean value of long-range engagement missiles fired by the blue force DDGs in the CASoS alternative is higher than the mean value of those fired in the baseline alternative. The null hypothesis was that the two means were equivalent. The results showed a t-value of 46.49 and a p-value < 0.001. This statistical test showed that the CASoS had a positive effect on the number of long-range engagement missiles that could be fired by DDGs; significantly more long-range weapons were used. This demonstrated that CASoS engagements took place earlier and at longer distances from the blue forces; thereby greatly improving the layered defense. It also demonstrated that even with a more highly complex threat environment, the CASoS approach was still able to make greater use of its long-range weapons.

(4) M&S Analysis #2—Number of DDG Short Range Missiles Fired

The mean number of short range engagement weapons fired by the blue force DDGs was not statistically distinguishable between the baseline and CASoS alternatives in the second M&S analysis. The plots in Figure 72 show that the mean was slightly lower in the baseline alternative (with 77.38 shots fired) than in the CASoS alternative (with 82.16 shots fired). A one-sided hypothesis test was performed with an alternative hypothesis that the mean value of short-range engagement missiles fired by the blue force DDGs in the CASoS alternative was lower than the mean value of those fired in the baseline alternative. For this one evaluation metric, there was not enough evidence to support rejecting the null hypothesis. Therefore, the difference between the average number of short-range DDG weapons used by the baseline and CASoS alternatives was indistinguishable in the more stressing threat scenario of M&S #2.

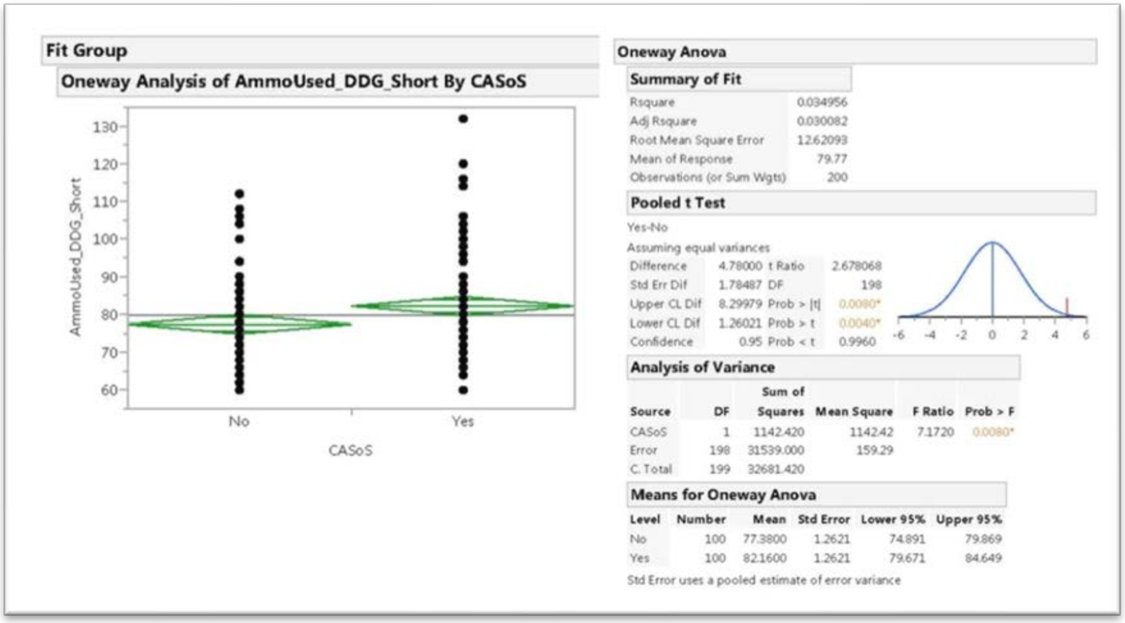

Figure 72. M&S Analysis #2—Comparative Results of the Number of DDG Short Range Missiles Fired

This analysis shows that DDG short-range missiles were put to great use in both the baseline and CASoS alternatives. The baseline alternative relied heavily on short range missiles for their close-in defense, and the CASoS alternative took advantage of shared and improved situational awareness and coordinated engagements to rely on both long and short range missiles for a more layered defense.

(5) M&S Analysis #2—Number of Fighter Aircraft AMRAAMs Fired

The number of advanced medium range air-to-air missiles (AMRAAM) weapons fired by the blue force fighter aircraft was, on average, significantly higher in the CASoS alternative than in the baseline alternative for M&S #2. Figure 73 shows that the average number of fighter AMRAAM weapons fired in the baseline alternative was just 4.31; whereas in the CASoS alternative it was 23.19.

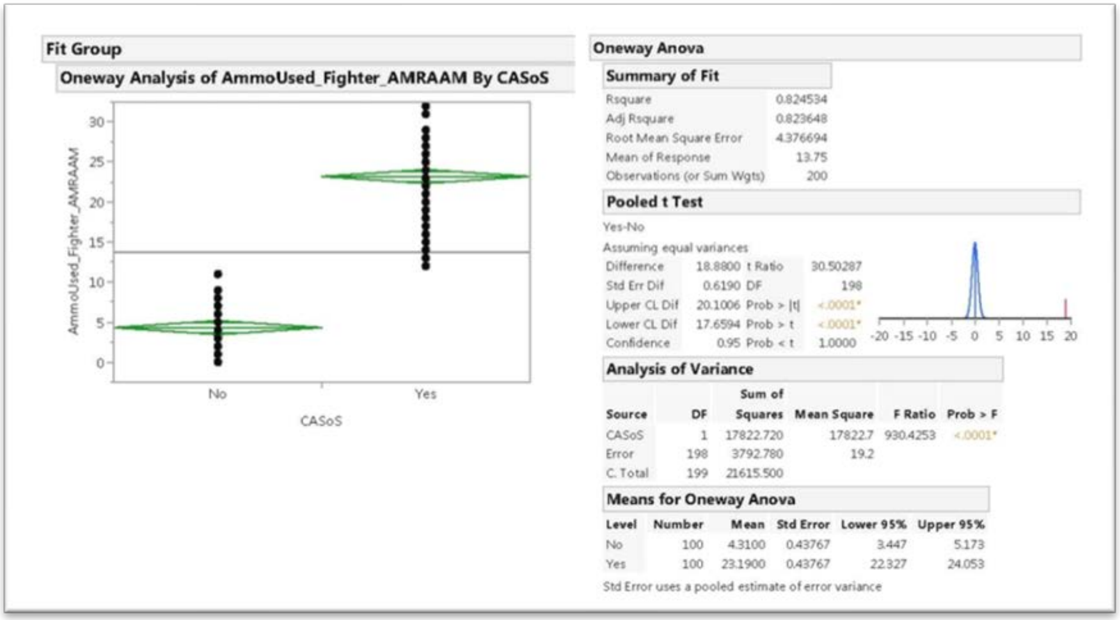

Figure 73. M&S Analysis #2—Comparative Results of the Number of Fighter Aircraft AMRAAMs Fired

A one-sided hypothesis test at a significance level of 0.05 was performed with the alternative hypothesis that the mean value of AMRAAMs fired by the blue force fighter aircraft in the CASoS alternative is higher than the mean value of those fired in the baseline alternative. The null hypothesis was that the two means were equivalent. The results showed a t-value of 30.50 and a p-value < 0.001. This statistical test showed that the CASoS approach had a significant positive effect—with significantly more fighter aircraft AMRAAMs used in the CASoS solution. This indicated that the fighter aircraft had greater participation in the defense of the blue forces in the CASoS approach; even in this more stressing threat environment. The results demonstrated the CASoS benefit of fighting as a collaborative SoS whose boundary could change to incorporate additional warfighting assets (or constituent systems) when they were available. Adding the assets to the CASoS allowed them to be used in a much more effective manner to support tactical missions.

(6) M&S Analysis #2—Number of Fighter Aircraft JDAMs Launched

The analysis of the JDAMs launched, shown in Figure 74, indicated that the average number of JDAMs dropped in the baseline and CASoS alternatives were roughly the same -- approximately seven and a half.

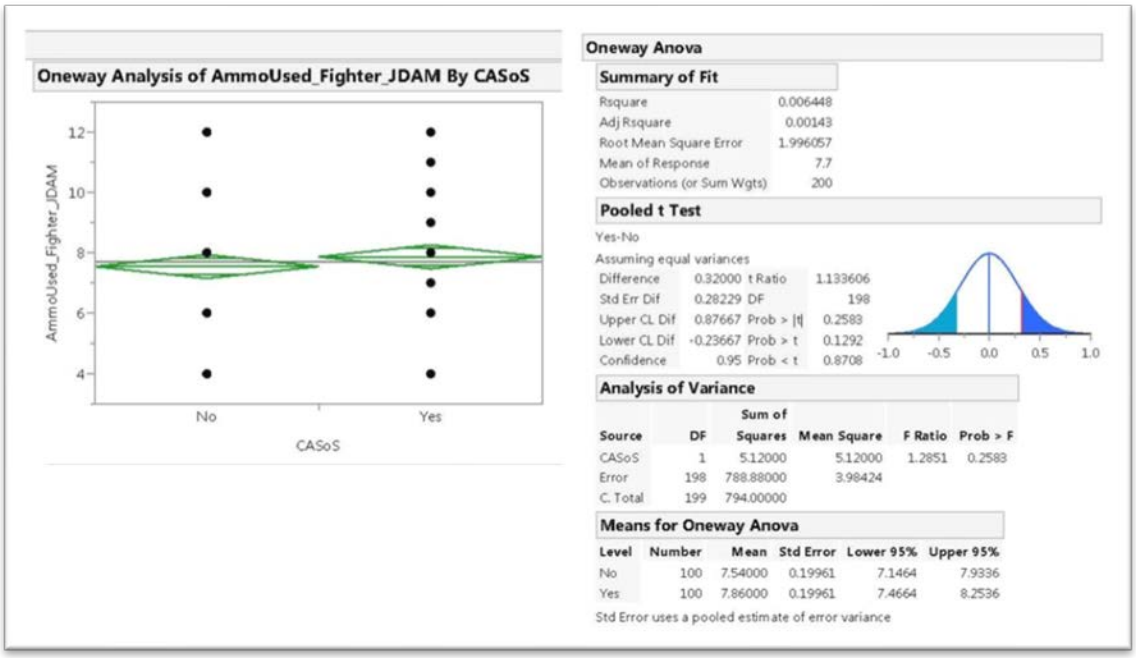

Figure 74. M&S Analysis #2—Comparative Results of the Number of Fighter Aircraft JDAMs Fired

A hypothesis test showed that there was not enough evidence to support rejecting the null hypothesis. Therefore, the mean numbers of JDAMs launched in the two alternatives were roughly equivalent. Therefore, in this naval tactical scenario, the CASoS approach didn't change the way the fighter aircraft used their JDAM bombs. In both alternatives, the fighter aircraft had approximately the same number of opportunities to bomb red force launch sites in the baseline alternative with random fighter aircraft motion as in the CASoS alternative with the fighter aircraft joining the blue force strike group formation.

(7) M&S Analysis #2 Summary

For the more stressing threat scenario of M&S #2, the CASoS solution alternative continued to have fewer blue force casualties, and a shorter time required to kill 50% of the red forces than the baseline approach. This demonstrates the tactical benefits of implementing the distributed warfare assets as a CASoS—a collaborative and adaptive system of distributed constituent systems with desired (purposeful) emergent behavior.

In M&S #2, the CASoS used a significantly greater number of long range DDG weapons and fighter aircraft AMRAAMS than the baseline approach. However, the CASoS used approximately the same number of short range DDG weapons and fighter aircraft JDAMs, on average, as the baseline approach. The use of the fighter aircraft weapons resources followed a similar behavior as in M&S #1. Upon joining the CASoS, in the CASoS alternative, the fighter aircraft were able to fire many more AMRAAMs, benefitting from the collaborative, adaptive architecture with improved and shared situational awareness (earlier threat detection), and changing boundary to allow the fighters to join the CASoS. This clearly demonstrates the utility of these CASoS characteristics and principles.

The use of fighter aircraft JDAMs followed a similar behavior pattern as in M&S #1. In both the first and second M&S analyses, the fighter aircraft fired a little over seven JDAMs on average in both the baseline and CASoS solution approaches. This coincided with the number of red force launch sites, which in both M&S #1 and M&S #2, was seven. On average, the fighter aircraft destroyed the seven red force launch sites in the simulation runs and then ran out of targets. In some cases, the JDAMs missed their target and fired again—resulting in more than seven total JDAMs fired. In some cases, fewer than seven JDAMs were fired because the fighter aircraft were not close enough proximity to the launch sites. The use of JDAMs in the modeling analyses did not end up being a distinguishing factor between the baseline and CASoS alternatives; however, it provided more insight into the behavior and utility of having constituent variety in the available resources. A closer examination of individual simulation runs, showed that in both the baseline and CASoS variants, there were instances in which the JDAMs destroyed red launch sites early in the run, resulting in fewer blue force casualties and decreasing the time required to kill 50% of the red forces. The CASoS approach could evolve to improve the use of the JDAMs with more sophisticated predictive analytics and intelligent agents.

Table 24 contains a summary of the M&S #2 analysis results. The analysis demonstrated that the CASoS continued to decrease blue force casualties, improve decision reaction time, and maximize the use of distributed heterogeneous assets as a layered defense; even as the threat situation grew in complexity.

Table 24. M&S #2 Analysis Results

Evaluation Metrics	Baseline Mean	CASoS Mean	Analysis Results	Implications for the CASoS Theory Validation
Blue Force Casualties	3.56	2.74	Alternative Hypothesis Accepted: Mean number of blue casualties was lower in the CASoS alternative.	Demonstrates that the distributed, collaborative, and adaptive architecture, which enables shared situational awareness and behavior that is collaborative, adaptive, and purposeful led to fewer blue force casualties.
Time Required to Kill 50% of the Red Threat	28.3 minutes	20.84 minutes	Alternative Hypothesis Accepted: Mean time required to kill 50% of the red forces was lower in the CASoS alternative.	Demonstrates that the CASoS architecture and behavior leads to increased and shared situational awareness which decreases the time required to make engagement decisions and increases the effective engagement range of the blue force weapons. Earlier and more effective engagement shots lessens the amount of time required to defend against the red force threats.
Number of DDG Long Range Weapons Fired	22.14	167.42	Alternative Hypothesis Accepted: Mean number of DDG long range weapons was higher in the CASoS alternative.	Demonstrates that the CASoS architecture and behavior enables increased and shared situational awareness. This earlier and shared detection of red force threats increases the number of long range weapons that can be fired—giving the blue force a significantly improved layered defense.
Number of DDG Short Range Weapons Fired	77.38	82.16	Null Hypothesis Accepted: The mean number of DDG short range weapons fired were not dissimilar enough between the two alternatives to reject the null hypothesis.	Demonstrates that given a more stressing threat environment, the CASoS relied as heavily on short range DDG weapons as the baseline approach. This indicates that the CASoS adapts its behavior to use both long range and short range weapons

Evaluation Metrics	Baseline Mean	CASoS Mean	Analysis Results	Implications for the CASoS Theory Validation
				in a collaborative way as the threat grows in complexity.
Number of Fighter AMRAAMs fired	4.31	23.19	Alternative Hypothesis Accepted: Mean number of fighter aircraft AMRAAMs fired was higher in the CASoS alternative.	Demonstrates that the ability of the fighter aircraft to join the Blue Force CASoS enables them to participate in the CASoS mission of defending the blue force HVU. Upon joining the CASoS, the fighter aircraft have increased and shared situational awareness with the rest of the blue force assets. They have significantly improved awareness of red force threat location and can purposefully coordinate their use of AMRAAM weapons as part of the blue force layered defense.
Number of Fighter JDAMs Fired	7.54	7.86	Null Hypothesis Accepted: The mean numbers of fighter aircraft JDAMs fired was equivalent in the baseline and CASoS alternatives.	There was not a significant difference in the number of JDAMs fired in the baseline and CASoS alternatives. In the baseline alternative, the fighter aircraft motion was random. In the CASoS alternative, the fighter aircraft moved in conjunction with the blue force strike group. The blue force movement and random movement created approximately the same number of opportunities for the fighter aircraft to launch JDAMs.

The improvements in blue force defense and decision reaction time demonstrate the benefits of a CASoS approach. The adaptive architecture connecting the distributed blue force assets enable the strike group to function as a CASoS. This enables solution behavior that is multi-level, emergent, adaptive, purposeful and collaborative. Analyzing how the CASoS solution approach behaved in a more complex environment, provided more insight into the value of the CASoS characteristics and principles. The model demonstrated that the CASoS solution approach was able to adapt to the changing threat environment by doubling its use of short range weapons to continue to provide tactical advantages over the baseline approach. The CASoS adapted its behavior and maximized the use of its constituent variety (diverse warfare resources) to provide an improved layered defense strategy.

c. Overall Summary of M&S Analysis Results

In summary, the CASoS solution alternative demonstrated tactical improvements over the baseline alternative in an initially complex threat environment; and continued to demonstrate improvements in a more stressing threat environment. The results showed significant improvements in (1) blue force defense (lowering the number of casualties), (2) decision reaction time (destroying red forces more quickly), and (3) layered defense (maximizing the use of different warfare weapon assets).

As the threat environment grew in complexity (from M&S #1 to M&S #2), the mean number of blue force casualties increased for both the baseline and CASoS approaches. However, there were fewer blue force casualties using the CASoS approach; and therefore, the CASoS was better able to address the increased threat than the baseline approach.

The overall time required to kill 50% of red forces, for both the baseline and CASoS alternatives, decreased as the threat environment became more complex. The scenario had a much faster tempo as the speeds of the incoming red threat missiles were much faster in the second scenario. The CASoS alternative had a significantly higher speed of defense—killing 50% of red forces much faster than the baseline, even as the threat environment was more stressful.

The CASoS alternative employed a layered defense—making better use of the variety of weapons than the baseline alternative. The baseline approach used a close-in defense, depending primarily on the DDG short range weapons to defend the blue force ships. The baseline used only roughly 15% of the amount of long range DDG weapons and 18% of the AMRAAMs used by the CASoS. These percentages stayed the same as the threat environment became more complex. The baseline also took advantage of the random path of the nearby fighter aircraft to launch JDAMs at the red force launch sites if they happened to be within proximity. The CASoS approach used a layered defense strategy, making the most of the different types of weapons available. In the initial scenario, the

CASoS primarily depended on long-range DDG weapons as well as fighter aircraft AMRAAMs and JDAMs. As the scenario became more complex, the CASoS approach doubled the number of short-range DDG weapons fired while still using about the same numbers of long-range weapons, AMRAAMs, and JDAMs. This demonstrated the ability of the CASoS to adapt to the changing circumstances and to take advantage of the constituent system variety.

Table 25 compiles the results of M&S #1 and #2 to summarize the mean values computed for each evaluation metric. The table compares the results gathered in the initial complex scenario of M&S #1 with the more stressing scenario of M&S #2. The last column in the table contains descriptions of how the results demonstrate the CASoS theory.

Table 25. Summary of M&S Analysis Results

Evaluation Metrics	**Initial Complex Scenario: Baseline Mean**	**More Stressing Scenario: Baseline Mean**	**Initial Complex Scenario: CASoS Mean**	**More Stressing Scenario: CASoS Mean**	**Implications for the CASoS Theory Validation**
Blue Force Casualties	2.01	3.56	0.78	2.74	Demonstrates that the CASoS distributed, collaborative, and adaptive architecture, which enables shared situational awareness and behavior that is collaborative, adaptive, and purposeful, led to fewer blue force casualties; even with an increase in threat complexity.
Time Required to Kill 50% of the Red Threat	40.9 minutes	28.3 minutes	25.53 minutes	20.84 minutes	Demonstrates that the CASoS architecture and behavior leads to increased and shared situational awareness which decreases the time required to make engagement decisions and increases the effective engagement range of the blue force weapons. The CASoS's earlier and more effective engagement shots decrease the amount of time required to defend against the red force threats.
Number of DDG Long Range Weapons Fired	26.43	22.14	174.7	167.42	Demonstrates that the CASoS architecture and behavior enables increased and shared situational awareness. This earlier and shared detection of red force threats increases the number of long range weapons that can be fired—giving the blue force a significantly improved layered defense.
Number of DDG Short Range	60.02	77.38	48.83	82.16	Demonstrates that the CASoS approach enabled adaptive behavior by doubling the number of short-range weapons fired as the

Evaluation Metrics	Initial Complex Scenario: Baseline Mean	More Stressing Scenario: Baseline Mean	Initial Complex Scenario: CASoS Mean	More Stressing Scenario: CASoS Mean	Implications for the CASoS Theory Validation
Weapons Fired					scenario became more complex. The CASoS used its adaptive behavior and constituent variety to employ a more layered defense to address the increased threat.
Number of Fighter AMRAAMs fired	3.96	4.31	21.8	23.19	Demonstrates the CASoS changing boundary, adaptive architecture, purposeful collaborative behavior, and constituent variety. The CASoS continued to take advantage of the fighter aircrafts' contributions even as the threat increased.
Number of Fighter JDAMs Fired	7.64	7.54	7.38	7.86	Demonstrates that the baseline and CASoS alternatives took advantage of the fighter aircraft JDAMs. In the baseline, the fighter aircraft's random movement placed them in proximity of red force launch sites. In the CASoS, the fighter aircraft joined the CASoS and then fired JDAMs as the strike group as a whole approached red force launch sites.

The M&S analyses demonstrate many aspects of the CASoS theory. Table 26 lists and describes the CASoS characteristics that were represented in the model and explains how the M&S results demonstrated these characteristics.

Table 26. Validation of CASoS Characteristics through M&S Effort

CASoS Characteristics Represented in the Model	Descriptions of how these Characteristics are Represented in the Model	Demonstrated Value of the CASoS Characteristics
Openness	The blue force strike group is an "open" CASoS because it exchanges information (sensing) and kinetic weapons with its environment.	Blue and red casualties demonstrated that the CASoS was an open system. If the CASoS had been a closed system, it would not have been able to launch engagement missiles to defend itself against the red forces.
Architecture (collaborative, adaptive, connected, distributed)	The CASoS blue force strike group in the model has an architecture that is collaborative, adaptive, connected, and distributed. The ships and aircraft in the model are geographically distributed but connected as they share information concerning situational awareness and	The CASoS solution's improved tactical operations were directly dependent on the collaborative and adaptive architecture that connected the distributed blue forces. The CASoS architecture provided shared and increased situational awareness

CASoS Characteristics Represented in the Model	Descriptions of how these Characteristics are Represented in the Model	Demonstrated Value of the CASoS Characteristics
	self-awareness. Their architecture allows them to collaborate to gain shared situational awareness and to coordinate engagements. The CASoS architecture in the model is adaptive as it “adapts” to include the fighter aircraft when they join.	enabling earlier threat detection and weapon launches. The CASoS architecture also enabled the coordination of engagements among the distributed blue assets.
Behavior	The CASoS in the model exhibits the following behavior: multi-level, collaborative, purposeful, self-organizing, and adaptive. The model CASoS exhibits multi-level and collaborative behavior as constituent systems act independently or collaboratively. The CASoS is purposeful in terms of exhibiting desired defensive behavior. An example of self-organization and adaptation is when the fighter aircraft change their behavior after joining the CASoS.	The CASoS solution’s improved tactical operations were directly dependent on the CASoS behavioral capabilities: collaborative and emergent behavior enabled coordinated engagements; adaptive behavior enabled a layered defense, participation of the fighter AMRAAMs, and the use of more short range weapons as the threats grew more complex; the fighters self-organized to join the CASoS (thereby improving the defense); and all blue force assets behaved purposefully to achieve force-level goals.
Changing Boundary	The CASoS in the model has the characteristic of changing boundary. The boundary of the CASoS changes as the fighter aircraft join the CASoS.	The fighter aircraft were able to join the CASoS because of the characteristic of allowing its boundary to change. The addition of the fighter aircraft improved tactical operations.
Constituent Variety	The CASoS in the model has constituent variety, as it consists of different types of constituent systems: DDGs, AEWs, and fighter aircraft. Each of these types of constituent systems has different properties and capabilities.	The CASoS maximized the use of its constituent variety (diverse set of warfare assets) by taking advantage of the strengths of the different assets—long range missiles, short range missiles, AMRAAMs, and JDAMs
Complexity (detail, dynamic, resilience)	The CASoS in the model exhibits the following characteristics of complexity: detail complexity, dynamic complexity, and resilience. Detail complexity is represented in this model by the numbers of constituent systems and their interactions (in this case shared situational awareness and coordinated engagements). Dynamic complexity is represented by the short timeframe in which the systems must behave to address the situation (which in this case is the engagement of threat missiles). Resilience is a characteristic of this CASoS model as the blue force responds to the threat missiles by engaging the threats.	The CASoS’s innate complexity characteristics demonstrated value in the model. The CASoS was modeled to address detail complexity by making automated force-level engagement decisions; whereas the baseline model represented manual decision-making by making only platform-centric engagement decisions. This ability resulted in a decrease in decision reaction time (or time to kill 50% of the red forces). Dynamic complexity was demonstrated in M&S #2 as the CASoS was able to still show tactical improvements as the tempo of the scenario increased (due to faster threat

CASoS Characteristics Represented in the Model	Descriptions of how these Characteristics are Represented in the Model	Demonstrated Value of the CASoS Characteristics
		missiles and greater numbers of threat missiles). The CASoS demonstrated resilience by continuing to operate collaborative and with shared situational awareness even as assets, such as AEW or blue ships, were destroyed during the scenario runs.

In summary, Table 26 describes how the CASoS characteristics demonstrate value as a solution approach to the naval tactical domain. Through a combination of openness, architecture, behavior, changing boundary, constituent variety, and complexity, the CASoS solution improved tactical operations; even as the threat environment became more complex.

Table 27 lists and describes the CASoS principles that were represented in the model and explains how the M&S results demonstrated these principles.

Table 27. Validation of CASoS Principles through M&S Effort

CASoS Principles Represented in the Model	Descriptions of how these Principles are Represented in the Model	Demonstrated Value of the CASoS Principles
High Flux Principle *The rate of resource flux must support the overall ability for adaptation to address the highly complex problem space.*	The high flux principle is represented when the blue force weapons are capable of intercepting the threats (in terms of weapons range, speed, and lethality) and when the blue force sensors can detect the threats (in terms of sensor range).	The CASoS solution created many more possible courses of action for tactical responses to the threat. This was demonstrated by the use of more types of weapons as an improved layered defense. High flux was a contributor to the decrease in blue force casualties and decision reaction time.
Holism Principle *A CASoS has emergent behavior that is a result of complex constituent system behavior and interactions.*	Holism is demonstrated through the emergent behavior arising from the interaction and collaboration of the distributed blue force ships and aircraft in the model. Examples of the emergent behavior include shared situational awareness and engagement coordination.	The CASoS solution's ability to be holistic allowed the blue force strike group to fight at the force-level—to use its distributed resources for force-level goals and coordinate engagements. Holism was a contributor to the improved tactical operations.
Contextual Principle	In this model, the blue force CASoS gains an understanding of	The CASoS's ability to gain contextual knowledge, or

CASoS Principles Represented in the Model	Descriptions of how these Principles are Represented in the Model	Demonstrated Value of the CASoS Principles
A CASoS as a solution to highly complex problems relies on the abilities to gain understanding of its context and itself.	itself and its environment using the blue force sensors and data-sharing architecture.	situational assessment, played a crucial role in its improved tactical operations. The CASoS had both shared and increased situational awareness, resulting in earlier threat detection and earlier launch of weapons.
Goal Principle *A CASoS achieves specific goals through purposeful behavior using behavioral decisions, adaptation, and feedback from causal effects and the environment.*	The goal principle is demonstrated in the model by the blue force CASoS's ability to purposefully defend itself and its HVU by making decisions to launch engagement missiles, adapt with the inclusion of additional fighter assets, and perform battle damage assessment to take additional shots when engagements are not successful.	The CASoS's ability to purposely select courses of action (or behaviors) that were goal-oriented and addressed force-level goals and also adapted in response to feedback from the environment, allowed it to maximize the use of the various distributed weapons for force-level goals. Goal-oriented and adaptive behavior enabled the CASoS to address the threat environment, even as it became more complex.
Operational Viability *In order for a CASoS to be a viable solution during operations, it must maintain stability and resilience.*	Operational viability is demonstrated in this model by the blue force CASoS's ability to maintain its collaborative architecture and ability to support CASoS behavior even as some of its constituent warfare systems were destroyed.	The CASoS's ability for operational viability enabled it to continue operations, even when blue force assets were destroyed. This meant that if an AEW or blue ship was destroyed, the overall situational awareness would decrease, but would still be shared and would still contain detections from the remaining asset's sensors. Likewise, the CASoS strike group would have to accommodate lost weapon systems as ships were destroyed.
Requisite Variety *A CASoS must have a greater number of courses of action possible in the solution space than there are events in the problem space in order to be an effective solution.*	In this model, the law of requisite variety is demonstrated by the blue force CASoS having enough engagement courses of action to defend the HVU against the red force threats.	The CASoS's requisite variety was demonstrated by the number of possible courses of action to defend against the red force missile threats. The CASoS had more requisite variety than the baseline approach, as was demonstrated by the numbers of different weapons fired. The CASoS also increased its requisite variety as the environment increased in complexity. The CASoS had to use double the number of short range missiles to defend against the more stressing threat environment.

CASoS Principles Represented in the Model	Descriptions of how these Principles are Represented in the Model	Demonstrated Value of the CASoS Principles
Information Principle *A CASoS creates, possesses, transfers, and modifies information.*	The information principle is demonstrated in the model by the blue force's ability to sense and detect threats, share this data within the CASoS, and update this awareness information as the environment changes.	The CASoS ability to manage (create, share, etc.) information and enable shared and increased situational awareness using data from its distributed sensors, enabled a huge advantage over the baseline approach. The demonstrated value of the CASoS information principle was indicated by the earlier detection of threats and earlier weapon launches.

In summary, Table 27 describes how the CASoS principles demonstrate value as a solution approach to the naval tactical domain. Through a combination of high flux, holism, context-knowledge, goal-oriented, operational viability, requisite variety, and information management, the CASoS solution improved tactical operations; even as the threat environment became more complex.

D. THEORY VALIDATION

This chapter concludes with an explanation of how the naval tactical modeling and simulation analysis of the CASoS approach demonstrates GT theory validity. The GT research method enables the discovery, development, refinement, and validation of a theory using data from observation, literature review, and case study. Theory validation results from theoretical saturation and through constant comparison which results in concepts that explain observed phenomena. GT validity is judged by fit, relevance, workability, and modifiability (Glaser and Strauss 1967). This section discusses the CASoS theory validation as it relates to these four aspects.

1. Fit

A theory that "fits" has concepts that are closely connected to what they represent. For the CASoS theory, "fit" is demonstrated through the representation and analysis of the CASoS approach to address a highly complex naval tactical problem domain using modeling and simulation.

The naval tactical domain exhibits the characteristics of highly complex environments. The theory describes characteristics of highly complex problem domains and prescribes using a CASoS approach when a problem demonstrates enough of the characteristics to overwhelm existing solution approaches. The analysis of the naval tactical domain found evidence that as this operational environment becomes increasingly complex, existing warfare systems cannot react quickly enough or manage the decision complexity to maintain tactical superiority. Therefore, this problem domain is an application that "fits" the CASoS theory as a highly complex operational environment.

The M&S analysis demonstrated that a CASoS solution approach improves warfighting operations in comparison with a baseline non-CASoS approach. The analysis showed that a CASoS approach improved the tactical performance of existing warfare resources. Even as the threat environment grew in complexity, the CASoS approach had fewer blue force casualties, required less time to defeat red forces, and was able to employ a more layered defense, maximizing the use of distributed and heterogeneous warfare assets. The M&S analysis results demonstrated the "fit" of the CASoS approach to the naval tactical domain.

2. Relevance

A relevant theory evokes "grab." It captures attention and exceeds or goes beyond academic interest. The CASoS theory provides a solution approach to real world problems that have been observed. The CASoS theory provides a critical solution to a number of problem domains that are growing in complexity as a result of technological advances.

The naval tactical domain presents an example of a highly complex operational environment that poses a current challenge as well as an evolutionary challenge—one that continues to change and grow. The Navy is highly aware of a growing threat space resulting from advances in technology, political changes, increases in adversarial military asset development, globalization, and the exploitation of new technology as weapons. The Navy's own growing reliance on information technologies creates new vulnerabilities as cyber threats increase. Developing an engineered solution approach to this complex domain is a relevant endeavor with interest from the academic community, defense community, and political community.

Interest in tackling the naval maritime domain to gain tactical advantage has been a long-standing mission for many centuries. Historically the ability to maintain warfare superiority is a critical component to a nation's defense and for negotiating in the realm of global politics. Developing and applying a theory for engineering a new solution to address complexity in the naval tactical domain supports this higher-level relevant mission.

The relevancy of the CASoS theory can be further demonstrated as it is applied to additional problem domains such as future self-driving transportation, cyber warfare, and the future complex airspace. The introduction of self-driving cars into society presents a challenging domain of millions of highly automated and sensing vehicles that are distributed (Hanebrink et al. 2016). Applying a CASoS approach offers an opportunity to create an adaptive architecture to connect the smart vehicles and provides increased situational awareness and a holistic perspective. Enabling self-organized purposeful cooperative behavior can decrease traffic jams (Walter 2017), increase energy efficiency (Wadud 2016), and improve road safety (Laris 2017). Cyber warfare presents a complex problem domain with computer hacking arising from distributed and unpredictable sources including nation-states, terrorist groups, and individual actors (Genge, Kiss, Haller 2015). As more systems become automated and networked, there are more cyber vulnerabilities. A CASoS approach would take advantage of the cyber domain's networked architecture of distributed systems to provide a holistic perspective that could improve early detections of cyber-attacks and attempt to reduce their negative cascading effects. Characterizations of the future complex airspace predict significant increases in volume and variety resulting in crowded skies, safety issues, longer delays, more congestion at airports and less response time for air traffic controllers (Katina and Keating 2013). A CASoS approach with distributed intelligent agents and an adaptive architecture to connect aircraft and share knowledge can create a holistic solution for a highly interconnected domain.

3. Workability

A theory "works" when it explains how a problem is being solved. This chapter's modeling and simulation analysis demonstrated how the CASoS approach provided an improved solution to the naval tactical problem domain. The naval tactical model of a highly contested A2/AD scenario provided insight into how a CASoS approach to blue force operations could improve layered defense options and increase the amount of decision reaction time available. The model demonstrated how the CASoS solution would work in practice to solve real-world problems.

The CASoS theory's engineering framework with required capabilities and systems engineering approach apply as a workable solution to real world problems. For the naval tactical domain, the CASoS engineering approach takes advantage of existing warfare assets. The existing naval warfare assets are a result of many years of research, development, and investment. The CASoS approach incorporates these assets into the solution framework, implementing them with a new adaptive and intelligent system of systems architecture to benefit from their individual performance and create new opportunities for emergent collaborative behavior. This approach maximizes the performance of existing warfare assets to improve tactical warfighting operations. The CASoS systems engineering approach is workable—establishing an architecture that can implement a new solution and approach by adding new warfare assets as they become available and replace or update legacy assets. This allows for a naval tactical solution that can evolve as the threat space evolves and as technology evolves.

4. Modifiability

Grounded theories can continue to evolve (or be modified) as new relevant data is discovered and compared to existing data, and when this results in a required change to the theory. A theory is modifiable that can be altered in this situation. As the field of complex systems science continues to develop, it is possible that new data (from observing new phenomena) may be discovered that modifies our understanding of complexity. The growth of new technologies might enable new observations or offer new solution capabilities. This new data may result in a necessary change to the characteristics of a complex operational environment which might require additional or revised characteristics and principles of a CASoS to address them. The CASoS theory is organized and described in a way that allows for possible revisions. Possible modifications could include revisions to the:

- Characterization of highly complex operational environments
- Characteristics of a CASoS
- Principles of a CASoS
- Conceptualization of the required engineered capabilities of a CASoS
- CASoS systems engineering approach

VII. CONCLUSION

A. SUMMARY OF RESULTS

This dissertation was motivated by the existence and rise of highly complex problems, and the need to engineer solutions to address them. These problems are characterized by their unpredictability, numerous and distributed negative (and often dire) effects, and non-linearity. They present a complex decision space for solutions, in which situational knowledge is incomplete and inaccurate, reaction times are highly shortened, and there are a large number of diverse and distributed resources to direct. Evidence has shown that highly complex problems overwhelm traditionally engineered systems that are not adaptive and do not produce the necessary complex behavior. This dissertation developed a theory for a new class of systems, CASoS, which can be engineered to address these complex problems. The CASoS theory establishes the definition, characteristics and principles for this new class of system solutions. The research also studied the implications of this theory, producing a conceptualization of an engineered CASoS and a CASoS systems engineering approach.

The dissertation research followed a classic grounded theory approach, studying systems theory knowledge domains and engineering process domains to allow the conceptual CASoS theory to emerge. As an intentionally designed and engineered CASoS does not yet exist, it was necessary to gather and study data from systems and complexity theorists to understand what characteristics and principles would be needed to address the problem domain. Classic grounded theory provided a rigorous qualitative approach necessary to allow a theory to emerge from the data. This study relied primarily on literature review as the source of data. The data consisted of established ideas and theories that were then extended to create the new CASoS theory. The research followed three phases: an initial phase with low level coding that produced the CASoS as a core variable; an intermediate phase with medium level coding that produced the CASoS theory; and an advanced phase using theoretical integration to analyze the engineering implications of the theory.

The primary results of the dissertation were twofold: (1) the establishment of a theory for the new class of systems solutions: CASoS, and (2) the derived conceptualization and approach for engineering a CASoS. The dissertation research focused on producing these results as a response to the original research question: what are the characteristics of CASoS and how can they be engineered to address highly complex problems?

The CASoS theory established a definition and a set of characteristics and principles of this new class of systems. CASoS are systems that adapt to their environment through complex interactions among their self-organizing constituent systems, giving rise to purposeful, emergent, meta-level, and multi-minded behavior. CASoS are a unique blend of complex systems with major elements and characteristics from systems of systems and complex adaptive systems. They are comprised of a large number of heterogeneous, distributed constituent systems that are highly connected and can adapt by performing autonomous processes that use the outcomes of their interactions and behavior to select a subset for replication and enhancement. The characteristics of CASoS are openness; dynamic internal and external boundaries; constituent system variety; adaptive architectures that promote collaboration among highly connected and distributed constituent systems; behavior that is multi-level, multi-minded, purposeful, self-organizing, collaborative, adaptive, and evolving; and complexity that is detailed, dynamic, resilient and at times, nonlinear. The principles that apply to CASoS are the Principle of Holism, the Contextual Principle, the Goal Principle, the Principle of Operational Viability, the Principle of Requisite Variety, the High Flux Principle, and the Information Principle. The class of CASoS lie within the intersection of the class of SoS and the class of complex systems. CASoS distinguish themselves from these classes of systems through their purposeful adaptive behavior, through their ability to self-organize, through their adaptive architecture, and through their ability to anticipate the future by creating internal models and hypothesizing the effects and consequences of their intended behaviors.

The implications of the CASoS theory produced a conceptualization of an engineered CASoS and a CASoS systems engineering approach. Engineered CASoS rely on several capabilities: an adaptive architecture, a system of intelligent constituent systems, the ability to discover knowledge, and the ability to predict the outcomes and effects of actions and use this to guide desired behavior. These capabilities rely on an underlying decision paradigm in which distributed intelligent agents share information, produce a shared awareness, identify actions necessary to address a problem space, and make decisions to self-organize and produce emergent behavior based on a holistic and collaborative perspective. Constituent systems must synchronize their decision-making to enable purposeful multi-minded and multi-level behavior that can be responsive, reactive, and proactive, to address the dynamically changing problem space. These engineered capabilities produce a solution that is both adaptive and evolving.

CASoS solutions require a top-down and adaptive systems engineering process. The CASoS SE approach is based on three goals: (1) to engineer a solution that can address a highly complex problem; (2) to ensure that CASoS emergent behavior is desired and that undesired emergence is avoided; and (3) to engineer a solution that can evolve over time as the problem domain changes. The CASoS SE approach has two phases. The first phase is a top-down needs analysis, design, and development, test, and evaluation of an adaptive architecture and set of initial constituent systems embedded with intelligent agents. The second phase is the adaptive operational and development phase during which CASoS operations occurs in parallel with an on-going process of continued needs analysis, design, development, test, and evaluation. During the second phase, an operational CASoS has the ability to adaptively address the changing problem domain. A parallel process of recursive development of additional constituent systems and intelligent agent updates relies on the CASoS built-in ability to anticipate the future problem space and additional resource needs.

Theory validation was accomplished by a modeling and simulation analysis using a highly complex naval tactical problem domain as an application of the CASoS approach. The analysis compared a baseline non-CASoS approach that represented an abstraction of current tactical operations with the CASoS solution approach. These two variants were applied to a blue force strike group in a highly complex A2/AD threat environment. The analysis evaluated each variant according to their ability to defend blue assets, react and kill red forces quickly, and take advantage of a set of diverse weapon assets. The analysis demonstrated that the CASoS solution approach was superior to the baseline approach—

decreasing blue casualties, decreasing the time required to kill red forces, and implementing an improved layered defense. The analysis also demonstrated that the CASoS solution was superior to the baseline approach even as the threat environment increased in complexity. The analysis showed that if Navy SoS are designed with more of the characteristics and behaviors of complex adaptive systems, they will have improved tactical performance in complex operational environments. The modeling and simulation analysis demonstrated the value of the CASoS characteristics and principles as enablers of the improved solution for the naval tactical problem domain. The naval tactical application and modeling and simulation results demonstrated the four validation criteria of grounded theories: fit, relevance, workability, and modifiability.

B. DISSERTATION CONTRIBUTIONS

The primary contribution of this dissertation is a theory for an engineered system solution and approach to address highly complex problems. This theory describes a new class of systems, a conceptualization of required engineered capabilities, and a systems engineering approach to produce them. The engineered CASoS theorized in this dissertation overcomes the challenges of highly complex problems that emerge from operationally complex environments by taking advantage of the capability opportunities from information technology advancements and applying a holistic and adaptive systems engineering architecture and process.

The second contribution is an addition to the body of systems theory knowledge in the form of a theory for a new class of systems: CASoS. Systems theory is a discipline that began in the 1920s as Ludwig von Bertalanffy identified the benefits of a holistic perspective for conducting biological research to overcome the limitations of a reductionist approach. The discipline had significant advancements in the 1940s as academics contributed systems theories in information theory, cybernetics, game theory, and the social sciences. The field has continued to grow through advancements in systems engineering with the recognition of vast improvements in technology development by employing a systems approach. This dissertation contributes to this field through the definition, characteristics, and principles of the new CASoS class of systems. This theory relied on a grounded theory methodology, which roots (or grounds) the theory in a foundation of concepts, ideas, and existing theories from the systems discipline body of knowledge.

The third contribution is the addition of a novel approach to the discipline of systems engineering. This new SE approach provides guidance for engineering an adaptive solution to a changing problem domain. Specifically, this dissertation describes a proposed CASoS SE approach for a top-down adaptive process, which promotes continuous design and development in parallel with operations following an initial build of an adaptive architecture and system of intelligent constituent systems. The CASoS SE approach extends the systems engineering body of knowledge and opens up a new field for studying CASoS as engineered solutions to complex problem domains.

C. FUTURE WORK

This dissertation identifies a number of new and interesting applications and research areas. The high-level conceptualization and systems engineering approach that derived from the CASoS theory present rich areas for further research, modeling, and development. This section describes opportunities for future work resulting from this dissertation.

Studying CASoS applications to complex problem domains is an immediate need with critical implications. This area of future work begins with the identification of highly complex problems, which could be addressed by a CASoS solution. Problem domain applications include: military tactical operations (including naval tactical maritime operations, army land-based tactical operations, joint and coalition theater and area operations, littoral combat, missile defense, special forces operations, space as a military domain); future complex airspace (including commercial, personal, military, and unmanned aviation); future automated land-based transportation (with future self-driving cars and associated automation in navigation and traffic control); cyberspace (as automation and networks continue to increase presenting great vulnerabilities); and global logistics operations (military, shipping, and commercial operations involving global distribution). Future work would focus on developing conceptual designs for engineered CASoS solutions to these problem domains.

A number of interesting studies involving modeling CASoS behavior can be conducted to better understand CASoS behavior. Studies can include: understanding emergent behavior as designed from a top-down perspective; studying the effects of uncertainty that can result from incomplete and inaccurate data (studying how this affects knowledge discovery, predictive analytics, and decision-making); studying the expected performance capabilities of multi-level, multi-minded constituent systems under a variety of operational scenarios; studying complex problem domains based on different operational scenarios; studying temporal effects on CASoS decision-making (how decision time affects decisions and their outcomes); studying predictive analytic methods (studying their effect on decisions and decision outcomes).

An important contributing study would be the review of data analytic methods to support a more detailed design of CASoS intelligent agents. Many data analytics and artificial intelligence method exist and continue to be developed. A review of these methods could identify effective capabilities and applications in support of CASoS decision-making, prediction, knowledge discovery, data management, self-awareness, situational awareness, synchronization among distributed intelligent agents, developing confidence levels associated with knowledge and decision. Identifying these methods will support the eventual detailed design of a CASoS intelligent agent.

Developing a more detailed design of the CASoS adaptive architecture is an area of future work. This dissertation lays the foundation for the characteristics, principles, and high-level capabilities required for a CASoS architecture. Next steps would include the development of detailed requirements, detailed design, and modeling of the architecture structure and functionality. Specific detailed architecture designs would require the identification of a problem domain application. Areas of study would include distributed data management architectures, data formats, data basing, knowledge representation and management, data mining, and data communications (required data rates and bandwidth).

Another important and interesting area of study would be the human machine interaction (HMI) with a CASoS system. Much of the CASoS knowledge discovery and decision-making would require automation. However, depending on the problem domain, human interaction with this process would be necessary. One type of HMI study would be to identify required human interaction for each specific problem domain application. This would first require understanding the types of decisions that need to be made and then to study how humans need to participate in this process. Areas that need to be studied include: the use of HMI modes (manual, semi-automated, fully automated), the design of effective interfaces for human participation, a study of human trust to better understand what types of information and interactions support appropriate levels of human trust and skepticism in HMI decision-making; and the role of multiple humans given a system of distributed systems requiring HMI for synchronized decision-making.

A final area of future work that would extend the knowledge of CASoS implementation would be a detailed study of the systems engineering life cycle for a CASoS. This dissertation presents a high-level approach for a top-down adaptive SE approach to engineering a CASoS. This framework requires more detailed studies in a number of areas. These include studying CASoS acquisition, program management, test and evaluation, production, integration of intelligent agents into existing systems, supportability, logistics, configuration, and risk management.

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APPENDIX A. SELECTIVE CODING: TYPES OF SYSTEMS

This appendix explores what it means to view the world in a "systemic" way. Understanding systems theory, systems thinking, characteristics of systems, and purposeful systems provides a background, context, and theoretical basis for developing theories for system of systems and complex system solutions.

A good starting place is the definition of a system as "an open set of complementary, interacting parts with properties, capabilities and behaviors of the whole set emerging both from the parts and from their interactions" (Hitchins 2005, 1).

A. SYSTEMS THEORY

Scientists seek to understand phenomena. Historically they have reduced objects into parts to determine what each part does in an attempt to better understand the whole. Douglas Hofstadter (1979) jokes that "reductionism is the most natural thing in the world to grasp. It's simply the belief that 'a whole can be understood completely if you understand its parts, and the nature of their 'sum''" (Hofstadter 1979, 312). Scientists have continued this reductionist approach, discovering that each part is comprised of smaller parts and so on (Bar Yam 2004a). What is left out of this approach are the relationships that exist internally between the parts of objects and externally with their environment. Systems science recognizes the limitations of reductionism and takes a holistic and expansionist approach to understanding phenomena. This approach views the world in terms of "systems," studying system behaviors and how they interact with their environments.

Systems theory had its beginnings in the late 1920s as the need for a systems approach arose when the biologist, Bertalanffy realized that the reductionist and mechanistic approach of physicists and other scientists up until that point failed to provide a complete understanding of physical phenomenon. Specifically, a mechanistic approach cannot fully explain the biological phenomena of life. Bertalanffy advocated an approach to biology that considered the organism as a whole or a system. He based this approach on the fact that organisms are open systems. He developed the General Systems Theory (GST) that included "physical systems" and "models from different scientific fields" that needed to address system concepts such as: order, organization, wholeness, and teleology (purposeful phenomena or behavior); all of which had been neglected by mechanistic science (Bertalanffy 1950, 1951, 1968, 1972).

Bertalanffy saw organismic and systems theory as representing what Kuhn (1962) called paradigm shifts, or revolutions in scientific thought and theory. He saw this as a departure from classical analytical (reductionist) science that was dependent on 1) the isolation of component parts and, 2) the linear behavior of the parts themselves. He cited Rapoport (1966) who asserted that systems represent organized complexity with interactions that are non-linear.

In the late 1940s, further theoretic advancements contributed to the rethinking and broad applications of system science. Norbert Wiener published his theory of cybernetics in 1948, based upon emerging developments in computer technology, self-regulating machines, and information theory. Cybernetics focuses on the servomechanisms that provide for negative feedback behavior in teleological (self-regulating, goal-seeking) systems. Bertalanffy saw cybernetics as a special case of the general theory of systems, focused on control systems that use communication and information transfer between the system and its environment and feedback of the system's function about the environment. The development of cybernetics coincided with Shannon's information theory (1948), and Neumann and Morgenstern's game theory (1944). Wiener suggested the application of cybernetics and information theory went far beyond engineering to the fields of biology and the social sciences. The mathematics and principles of cybernetics developed by Wiener, Rosenblueth, Bigelow, Ashby, and others—informed by social scientists Lewin, Bateson, Mead, and Deutsch—was promoted as having equal weight in mechanical, biological, and social systems (Porter 2016). Shannon and Weaver's information theory, which plays a large role in both cybernetics and GST, can be described as the isomorphic mapping of information onto the concepts of negative entropy in thermodynamics of open systems. However, much more recently, Hitchins (1992) reminds us that classical science and engineering concentrate on closed systems. He points out that although the second law of thermodynamics shows that entropy, the amount of disorder, increases with time in a closed system, this knowledge is not very useful since the systems we normally see and interact with are open systems.

Ackoff and Emery (1971) explain this revolution in thought as a methodological key to open doors previously closed to science. Before the systems revolution scientists derived their understanding of how things function using reductionist methods to study the parts and their structure. Now scientists tend to derive an understanding of the parts and their relationships by first understanding the functioning of the whole. The advent and evolution of computers has supported this revolution. Computers have enabled scientists to study systems that are far more complex by using non-linear computational models. Computer simulation has replaced some laboratory and field experimentation to expedite an understanding of complex systems. Adams et al. (2014) write that systems theory is necessary for understanding multidisciplinary systems. They point out the benefits from the application of systems theory to multidisciplinary systems and their related problems. The multi-disciplinary and systemic-perspectives of this 20th century paradigm shift in scientific inquiry established an ideological foundation for the current focus of systems science on nonlinearity and uncertainty in the behavior of complex systems.

B. SYSTEMS THINKING

Systems thinking is a way of understanding problems and developing solutions using a systemic approach. Modern system theorists are concerned with system thinking and its many applications. A number of recent books and articles discuss the use of systems thinking for business applications as well as for addressing complex problems. This section describes systems thinking and highlights aspects of using it as an approach for grappling with complex problems. Note: There is a distinction between *systems thinking* and *systematic thinking*: systems thinking focuses on relationships and interdependencies; systematic thinking is process driven and tends to be reductionist.

Systems thinking fits in alongside science and engineering as a type of inquiry for gaining knowledge and truth (Zandi 2000). Employing expansionism over reductionism enables the inclusion of context and environment into inquiries. Systems thinking necessarily includes more real world considerations than classical science inquiries. These real world inquiries include irreversibility, complexity, emergent properties, indeterminism, complementarity, and open systems. Zandi (2000, 12) writes that “the most important implication of system thinking is that almost every problem that is perceived to be well-structured is at best really an approximation of an ill-structured one, and it depends on the purpose of inquiry whether or not the approximation is acceptable.”

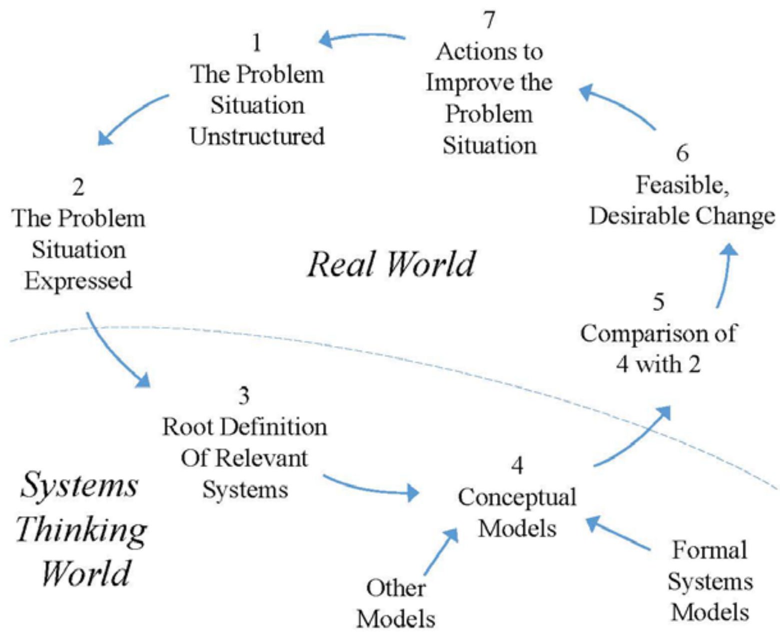

Figure 75. Systems Thinking Process. Source: Hitchins (1992).

The systems thinking method begins with a description of the real world in terms of systems. Real world entities are identified and represented as systems and their boundaries, components, structure, and relationships are defined. Principles and characteristics of the systems are elicited from the system’s relationships and behavior. Finally, their behavior is described in terms of inputs, outputs and state descriptions (Checkland 1993). Hitchins (1992) developed a cyclical model of a systems thinking process based on Checkland’s soft systems methodology. Figure 75 shows this cyclical model. It illustrates a series of steps that begin and in end in the real world. The real world problem is mapped into the “systems thinking world” in steps 3 and 4. These steps view and model the problem systemically. The next steps compares the system model of the world with the real world problem to ascertain desirable changes (step 6) and determines improvements and actions (step 7).

There are a number of benefits to approaching a problem using system thinking. Systems thinking in terms of structure, connectedness, relationships, and context are enablers for understanding complex systems and behaviors. A systems view facilitates holistic knowledge of systems in their context. It enables objects to be viewed as networks of related systems, embedded within larger networks (Capra 1996).

According to Gharajedaghi (2011), in his book on applying systems thinking to business applications, there are three categories of systems thinking: holistic thinking, operational thinking, and design thinking. He writes that the three are interrelated and complementary, and that they are all necessary to deal with the complexities of emerging chaotic environments. His work focuses on applying system thinking to sociocultural business organizations, but his systems methodology has application for engineered systems as well. Holistic thinking is acquiring and iteratively expanding one's understanding of the structure, function, and process of a system concurrently. Operational thinking is a focus on relationships: understanding interactions, interconnections, activity flow, and the rules of the game. It provides insight into how systems do what they do: how system structural elements produce desired functions. Design thinking focuses on a desired outcome or future and developing ways to get there. Design thinking often requires dealing with real world, ill-defined, and ill-structured problems. All three types of thinking are important aspects of systems thinking and provide a foundation for engineering CASoS.

C. CHARACTERISTICS AND PRINCIPLES OF SYSTEMS

This section provides definitions, concepts, and theories concerning the characteristics and principles pertaining and related to systems. Hitchins (2009, 1) defines systems as "open sets of complementary, interacting parts with properties, capabilities and behaviors of the whole set emerging both from the parts and from their interactions." He generalizes systems in his book, *Putting Systems to Work* (1992), as containing interrelated components, interactions with their environment in the form of inflow and outflow and with a set of characteristics including physical properties, capacity, order, structure, and information. Figure 76 presents his illustration of a generalized system.

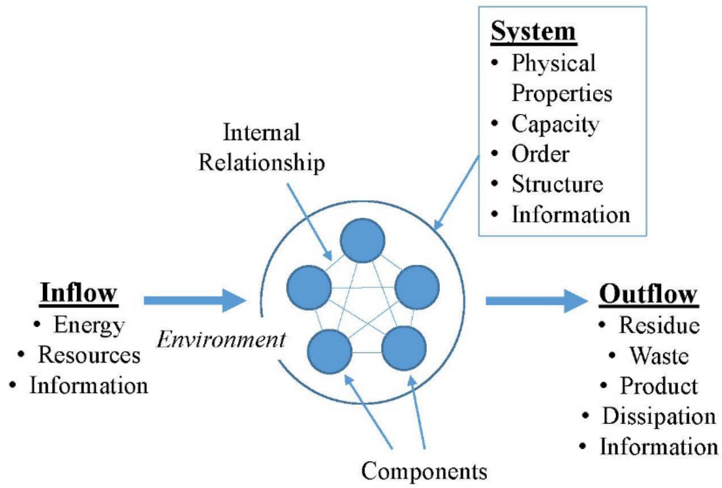

Figure 76. A General View of Any System. Source: Hitchins (1992).

Before discussing the characteristics and principles of general systems, the concept of an "absolutely ideal system" is presented. Petrov (2002) defines an absolutely ideal system as one that is perfect in terms of performing all possible functions at the right time and in the right place with total effectiveness and no negative effects. He explains that an absolutely ideal system would not consume power, material, energy, or information. Although such systems do not exist, the concept of an ideal system provides a good construct for understanding the characteristics and principles of real-world systems.

This section presents general characteristics and principles of systems. System characteristics are distinguishable features or qualities that belong to systems and serve to identify systems. System principles are fundamental assumptions or concepts that serve to guide system behavior or conduct in their environment. Axioms are established principles that are regarded as accepted or self-evidently true.

1. System Characteristics

a. Architecture

The architecture is the form of the system. It is the structure in which the subsystems or components are organized in relation to each other. The components may be physical entities or abstractions. The relationships may be physical or logical interfaces and examples of component exchanges include information, power, and heat. Checkland (1993) writes that systems must show some degree of organization beyond a random aggregate of components. He also explains the importance of hierarchy in understanding system architecture, noting that systems are usually part of a hierarchy being comprised of subsystems and are often part of a wider system.

b. Behavior

A system's behavior is another fundamental distinguishing characteristic. System behavior is defined as the actions performed internally in conjunction with itself or externally in conjunction with its environment. System behavior may arise in response to external stimuli or may be purposeful. System behavior can be conscious or subconscious; internal or external; and voluntary or involuntary. Emergent system behavior is that which arises from a combination of internal subsystem relationships and behaviors. One method for understanding system behavior is to identify system states. Ashby (1956) describes behavior as the internal state of the system in terms of suitable variables and changes from one state to another. Another method for understanding system behavior is in terms of a "black box." Checkland (1993) explains that a system can be viewed as a "black box" embodying a transformational process, which converts inputs into outputs. This method focuses on the beginning and end states rather than on the internal system mechanisms creating the behavior.

c. Boundary

The boundary of a system distinguishes it from its environment, defining what entities are inside the system and which are not. The system boundary is a construct that defines inputs and outputs as anything which crosses it, including physical entities, people, machines, money, information, energy, and influences (Checkland 1993). The system boundary can be defined by the set of interactive variables under the control of the system. Alternatively, entities outside the system boundary can be described as all those variables that may affect the system, but which are not controlled by the system. According to Zandi (2000), if an entity affects the purpose of a system and is controlled by the system, then it belongs to the system and is within the system's boundary. He writes that if an entity affects a system, but is not controlled by the system, then it belongs to the environment and is outside the system's boundary. Finally, he explains that if an entity has no effect on a system and is not controlled by the system, then it is irrelevant in terms of the system description.

d. Openness

Open systems interact with their environments and maintain a continuous inflow and outflow in a state of thermodynamic equilibrium called a steady state (Hitchins 1992). Gharajedaghi (2011) points out that this interaction means that open systems can only be understood in the context of their environment. Checkland (1993) reiterates this idea that no problem or solution involving open systems is valid free of its context.

2. System Principles and Axioms

a. Principle of Adaptation and Viability Axiom

The principle of adaptation describes the ability of a system to endure in a changing environment if it has the ability to adapt. Hitchins (1992, 63) writes "a set of open, interacting systems in a changing environment will endure only if they can adapt to that environment. Hence the mean rate of adaptation must exceed the mean rate of change of environment." This indicates that a system must not only have the ability to adapt, but must also be able to adapt quickly enough to endure the tempo of changes in the environment.

The viability axiom is intrinsically linked to the principle of adaptation. The viability axiom explains that key system parameters need to be controlled to ensure the system can endure in a changing environment (Adams et al. 2014). The viability axiom implies that a system's design should allow it to identify and address changes in its environment to sustain itself.

b. Centrality Axiom

The centrality axiom as applied to systems refers to two pairs of mutually dependent propositions that exist in (or are central to) all systems. The first pair is emergence and hierarchy. The second pair is communication and control. Checkland (1993, 75) writes about these concepts at length and argues that "systems thinking is founded upon two pairs of ideas, those of emergence and hierarchy, and communications and control." In simple terms, a system's hierarchy is intrinsically related to its emergent behavior. This implies that the system's architecture of relationships between elements at one level and between hierarchical levels is associated with the system's emergent properties. Similarly, a systems ability to control its behavior is intrinsically related to its ability to communicate information. For open systems that interact with a changing environment, the ability to adapt is dependent on the communication of information for purposes of regulation or control. Thus, these two abilities are mutually dependent and "central" to enduring open systems.

c. Principle of Connected Variety

The principle of connected variety states that interacting systems create a condition of stability within an environment that increases with system variety and/or degree of connectedness. Therefore, as more systems interact and as their interactions increase and diversify, the more probable it will become that the output and input of systems will lead to a condition of stability (Hitchins 1992, 63). This principle is evident in complementary systems, which are open systems that have mutually satisfying inputs and outputs. Stability within an environment is likely to increase as the number of complementary systems and their interactions increase. This principle has beneficial implications for achieving stability in changing and complex environments.

d. Contextual Axiom (Environment)

The contextual axiom states that a system is only fully understood by also understanding its context or environment. Adams et al. (2014, 119) write that "system meaning is informed by the circumstances and factors that surround the system." The contextual axiom implies that understanding a system's environment is a necessary part of understanding the system itself. This axiom conveys the importance of thinking expansively and holistically when defining systems to ensure that the system's environment is part of the definition.

e. Principle of Cyclic Progression

The principle of cyclic progression explains a cyclic relationship between system variety and a system life cycle of decay and regeneration. This principle addresses the phenomenon that systems do not last forever (Hitchins 1992). Figure 77 shows that as a dominant mode emerges and suppresses system variety, the dominant mode decays or collapses and survivors emerge that eventually regenerate variety. The cycle then repeats itself. The dominant mode might represent a particular system behavior that is favored over others. It could also represent a dominant interaction or hierarchical level.

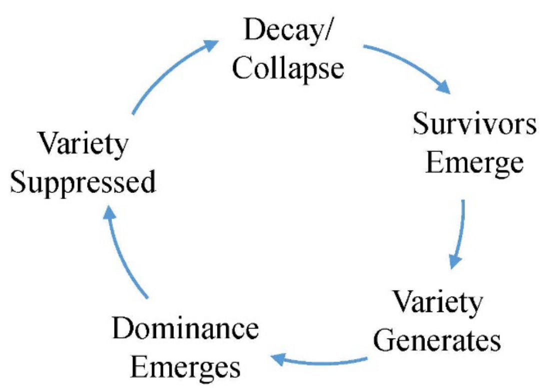

Figure 77. Cyclic Progression. Source: Hitchins (1992).

f. Law of Entropy

Entropy can be seen as a measure of the probability in which a closed system leads to a state of most probable distribution (disorder). Open systems maintain themselves in a steady state (dynamic equilibrium) that can avoid the increase of entropy and self-organize toward increased order and organization. A good example of this difference is seen in the law of dissipation in closed systems in physics and the law of evolution in open systems in biology. On the one hand, the second law shows closed system events in nature tending toward dissipative states of disorder and on the other hand, evolution demonstrates an open system tendency toward higher order, heterogeneity, and organization.

g. Principles of Equifinality and Multifinality

The Principle of Equifinality states that the final state of an open system can be reached by different initial conditions and by different processes. Open systems exchange materials with their environment via inflows and outflows. These processes can allow different paths to lead to the same end state. However, the opposite is true for closed systems. Closed systems do not interact with their environment, so there is a direct cause-and-effect relationship between the initial and final states of a closed system. Therefore, the final condition of a closed system is determined by the initial conditions. The principle of equifinality highlights an important distinction between open and closed systems. This concept was originated by the biologist, Hans Driesch and applied later by Bertalanffy.

The Principle of Multifinality describes the condition in open system when similar initial conditions lead to dissimilar end states. Multifinality leads to the concept of emergence.

h. Law of Evolution

For biological systems, evolution is the change in the inherited characteristics of populations over many successive generations (Gould 2002). Evolution is a process of selection among variation. Petrov (2002) developed a set of laws that define a general direction of evolution for human-made technology systems. He identified system behaviors that lead to evolution in human-made systems. These include the purposeful goal of improving the degree of ideal performance; irregularity within the evolution of system components that lead to new dominant features; an increase in system dynamics due to environmental changes; new variations of coordination among systems; and transitions from systems to super systems. System evolution can lead to novel methods of addressing complexity.

i. Principle of Expansionism

The principle of expansionism refers to the process of embedding a system under consideration into a larger system in order to better understand the system's emerging properties. It can be thought of as zooming out from the perspective of the original system to understand its context within a larger perspective. Zandi (2000) points out that the problem with the process of expansionism is that as the problem under study enlarges, it inevitably ends up at the level of the entire universe.

j. Information Axiom

The information axiom simply states that systems have the ability to create, possess, exchange, and modify information (Adams et al. 2014). The information axiom provides insight into how systems produce information and how information affects systems.

k. Principle of Limited Variety

The Principle of Limited Variety explains that a limit exists in terms of system differentiation that ultimately limits stability of interacting systems within their environment. Hitchins (1992, 64) writes that "variety in interacting systems is limited by the available space and the minimum degree of differentiation." There are only so many different types of systems that can exist and only so much "space" for increased specialization and differentiation. The limits to differentiation create a limit to the ability for connected and interacting systems to address and adapt to their environment. Therefore, the principle of limited variety affects the principle of connected variety.

l. Principle of Multidimensionality and Principle of Plurality

The Principle of Multidimensionality explains the ability for systems with opposing tendencies to coexist, interact, and form complementary relationships (Gharajedaghi 2011). In some cases, this principle extends to more than two variables within a system. Gharajedaghi (2011) discusses a fallacy that has dominated thought—that opposing tendencies comprise a zero-sum game in which conflicting entities are conceptualized as mutually exclusive and discrete. He gives sociological examples such as security vs. freedom; collectivity vs. individuality; modernity vs. tradition; rights of victims vs. rights of accused. However, within system frameworks, it is possible for opposing tendencies to coexist through a variety of system behaviors or interconnected multi-system behaviors.

The Principle of Plurality simply means that systems can have multiple structures, functions, and processes. The principle of plurality is the means by which systems can exhibit the principle of multidimensionality. Gharajedaghi (2011, 43) argues that this principle "denies the classical view of a single structure with a single function in a single cause-and-effect relationship." Plurality of function can manifest itself as implicit and explicit functions. Plurality of structure refers to heterogeneity and variability in system elements and relationships. Plurality of process implies that the process, in addition to the initial conditions, contributes to the future state of the system.

m. Principle of Preferred Patterns

The Principle of Preferred Patterns refers to interactions between systems and that particular patterns of interactions are likely to be preferred or to become more dominant over time. Hitchins (1992) writes that as system interactions increase and become more complex, it is more probable that feedback loops and mutual causality will arise through recursive system exchanges. These loops may result in stability or locally stable configurations (patterns) among the interacting systems. This principle addresses the emergence of dominance. Hitchins (1992) describes several examples of this principle. He explains that the short-term dominance of some high-tech organizations indicate a "preferred pattern" of behavior that is counter to the long-held theory of supply and demand as moderating this type of dominance. He cites a physical example of locally stable configurations in a discovery made by Duncan and Rouvray (1989) of small aggregates of atoms forming discrete phases of matter in very stable configurations.

D. PURPOSEFUL SYSTEMS

A type of system that is of particular interest is the purposeful system. This type of system is defined as "one that can change its goals in constant environmental conditions; it selects goals as well as the means by which to pursue them. It thus displays *will*" (Ackoff and Emery 1972, 31). The intent of engineered systems that are both complex and adaptive is to develop them in a way to enable them to select new goals in response to a changing environment. Thus, this section explores the nature of purposeful systems.

This section begins with a discussion of the general classification of systems to provide context for purposeful systems. Kenneth Boulding (1956, 202) developed the general systems framework—an "arrangement of theoretical systems and constructs in a hierarchy of complexity." He calls the most basic level the "static structure"—referring to the static relationships and patterns of natural phenomena such as electrons, cells, atoms, molecules, etc. The second level is the "simple dynamic system" with predetermined motions—the "clockworks" level. The third level is the "cybernetic system"—differing from the control mechanism in level two due to the "transmission and interpretation of information." A thermostat is an example of the third level. The fourth level is the "open system" or "self-maintaining structure." The fifth level is the "genetic-societal level," typified by the plant, and characterized by differentiated and mutually dependent parts and "blueprinted" growth. The sixth level is the "animal level," including abilities such as mobility, teleological behavior, and self-awareness. The seventh level is the "human level" including self-consciousness, which is different from self-awareness, because "he not only knows, but knows that he knows" (Boulding 1956, 135). Level eight is "social organization" which includes interrelationships, value systems, and social systems. Finally, level nine is "transcendental systems," that Boulding describes as the "unknowables" or higher-level questions that do not have answers but do exhibit systematic structure and relationship.

Based on Ackoff and Emery's (1972) definition of a purposeful system, they fit into Boulding's system classification framework at level six and above. The systems below level six, such as plants with "blueprinted growth" (level five), the self-maintainers (level four) and the cybernetic "thermostat-like" systems (level three), exhibit behavior in a predetermined fashion based on environmental conditions. These "non-purposive" systems adapt to their environment and have characteristics that enable them to sense aspects of their environment including changes; however, they cannot change their goals in constant environmental conditions. This distinction is an important consideration for the engineering of system solutions that are purposeful and that can make decisions concerning their actions and behavior. Systems that include human participation in decision-making for behavioral actions are examples of purposeful systems. The other example is systems that include artificial intelligence or automated decision aids for determining purposeful actions.

State-maintaining systems react to change to maintain their state under different environmental conditions. These types of system reactions are not necessarily purposeful or goal-seeking. Goal-seeking, or purposeful, systems have the ability to respond differently to a various environmental conditions to produce a particular and desired outcome (state). Gharajedaghi (2011) refers to this ability as "responsive" as opposed to "reactive," which is the term he uses for the non-purposeful state-maintaining systems. Responsive systems have a choice of actions and the actions are voluntary. Additionally, purposeful systems can cause different end states (goals) under constant conditions. Gharajedaghi (2011) refers to this ability to change ends under constant conditions as "free will." He writes that "such systems not only learn and adapt; they can also create" (Gharajedaghi 2011, 37).

1. Characteristics of Purposeful Systems

a. Autonomy

Autonomy refers to the independence of purposeful systems whose behavior is not under the control of other systems or entities. Autonomous purposeful systems are capable of independent action and decision-making. Engineering autonomous systems implies a need for artificial intelligence to enable automated decision-making.

b. Self-organization

Self-organization is a type of autonomous behavior. It refers to the ability of a system to adapt its structure (organize itself) to perform goal-driven behavior. This behavior is self-generated and self-initiated rather than being directed by an external entity (Nichols and Dove 2011). Azani (2009) describes self-organization as a process that results in increased order. Camazine et al. (2001) describe it as the emergence of patterns stemming from interactions among elements. Engineering self-organizing systems requires system knowledge of its own structure and the capability to reorganize itself to enable desired behavior.

c. Situational Awareness

Situational awareness (SA) is the ability to have a clear understanding of current events in the operational environment (Nichols and Dove 2011). SA requires a system's ability to sense its environment and create a picture (or model) of its real world environment. In a changing environment, a system's SA must also change over time to reflect changing events in the environment. SA has attributes such as spatial boundary, accuracy in time, completeness, accuracy per environment object or event. Endsley (2000) defines three levels of SA: (1) basic perception—monitoring the environment and identifying objects, (2) object correlation–understanding how objects influence objectives, and (3) prediction—projection of possible futures involving how the environment might change. The level of SA varies according to the sophistication of the purposeful system.

d. Directiveness

Directiveness refers to the level of direction levied on a system. Bertanffy (1950) mentioned "directiveness" as a characteristic of systems in his GST. Eckstein (1997) describes directiveness as an authority pattern that determines the extent of free choice of purposeful systems. Directiveness can be described as a continuum between total regimentation and total permissiveness. It is dependent on the extent to which directives exist. Directives can add value or constrain action. They can also be accompanied by consequences for non-compliance. Directiveness is an important consideration for engineered systems. Directives can be used to constrain purposeful systems from undesired behaviors. Mechanisms for issuing directives and ensuring compliance with directives must be designed into engineering purposeful systems.

e. Purposeful Evolution

Purposeful evolution is the ability of a system's goals to evolve. This characteristic is necessary for systems that address complex environments whose changes over time require highly adaptable system solutions. Such environments may have unforeseen changes and problems. Alternatively, they may cause many different problems and missions for systems to address. Engineering systems that can handle evolving goals requires creative design processes that focus on flexible and evolving architectures allowing new variants of system interactions and behaviors.

2. Principles and Axioms of Purposeful Systems

a. Goal Axiom

The Goal Axiom refers to systems achieving specific goals through purposeful behavior (Adams et al. 2014). The goal axiom is inherent to purposeful systems. For engineering purposeful systems, the aim is to design system structures and capabilities so that interactions and behaviors can lead to the pathways and means to achieve desired goals.

b. Operational Axiom

The Operational Axiom states that purposeful systems can only be fully understood (or described) in their operational environments. This axiom provides guidance to system designers who must understand how the system will function to produce behavior and performance within their environment (Adams et al. 2014).

c. *Design Axiom*

The Design Axiom refers to an intentional imbalance of relationships and resources in the design of a system. This purposeful imbalance arises from trades among limited resources that are never sufficient to satisfy all possible system behaviors and characteristics. This is related to the nonexistence of ideal systems. The Design Axiom provides guidance on planning and evolving a system how a system in a purposeful manner, given limited resources (Adams et al. 2014).

d. *Principle of Conditional Dependency*

The Principle of Conditional Dependency refers to how the behavior of each component in a system influences the behavior of all others. Ashby (1962) explains that system organization requires dependencies between all components and that self-organizing systems have conditional dependency. Nichols and Dove (2011) point out that this does not require every system to be connected to every other system, but that dependencies will exist within systems.

e. *Principle of Counterintuitive Behavior*

The Principle of Counterintuitive Behavior refers to the condition in which desired behavior is the result of counterintuitive actions. This can also be described as a negative feedback loop in which actions in a certain direction have the opposite effect. An example is a thermostat in which applying a cold source to a thermostat's sensor causes the furnace to turn on and produce heat. A sailboat is another example in which the rudder in the rear of the boat is turned to the left to cause the boat to steer to the right. Designers of engineered purposeful systems may employ this principle in certain circumstances.

E. SYSTEMS OF SYSTEMS

The concepts, "Systems within systems" and the more well-known "system of systems" (SoS), were first written about by Berry (1964) and Ackoff (1971). These new types of systems came into popularity in the 1990s as a number of systems engineers began to study them with regard to "joint warfighting" (Manthorpe 1996), "large-scale concurrent and distributed systems" (Kotov 1997), and "large networks of systems" (Shenhar 1994).

The SoS concept has continued to gain interest and assert itself as a sub-discipline of systems engineering, referred to as SoS engineering (SoSE). SoSE has evolved to address the unique challenges that characteristics of a SoS present. Much of the focus of SoSE has been on integrating existing systems with the prospect of purposefully gaining emergent capabilities through their interactions. Hitchins (2005, 5) criticizes the bottom-up integration of joining or networking existing systems together. He writes that such efforts are "very likely to inadvertently couple functions that were previously not coupled which may unwittingly be creating a complex mesh of unforeseen unwanted couplings, the behavior of which can be both unexpected and counter-intuitive." SoSE is discussed later in this chapter. This section covers SoS theory and characteristics.

A SoS is the meta-level system structure resulting from the collaboration of independent systems. The SoS exhibits increased functionality and performance capabilities, referred to as emergent behavior. Additionally, if any part of the SoS is lost or degraded, this will degrade the performance of the whole (Dagli and Kilicay-Ergin 2009). The concepts of collaboration and the meta-level within the SoS structure are important features for addressing complex problems. Both offer potentially significant advantages for engineered SoS—with the possibility of functionality at multiple levels and emergent behavior. Coupling these ideas with the system feature of purposefulness enables intentional goal-driven emergent functionality at multiple levels. This capability is the basis for seeking a SoS solution to complex problems.

Hitchins (2005, 8) defines a SoS as "an open set of complementary, interacting systems with properties, capabilities and behaviors of the whole SoS emerging both from the systems and from their interactions." Hitchins' definition adds the important feature of openness and highlights the interaction of the systems to achieve the emerging capabilities and behaviors. Hitchins' illustration of a SoS is shown in Figure 4. Hitchins explains that a SoS is the same as a system except with a simple hierarchy twist. He stressed the importance of approaching SoS from top-down, explaining that a bottom up approach will cause chaos as systems interact. He points to cooperation/coordination (or collaboration) and non-linear behavior as two essential aspects of SoS to study. However, the "other constituent systems" shown in Figure 78 are not SoS's since their subsystems are not independently functioning systems in their own right.

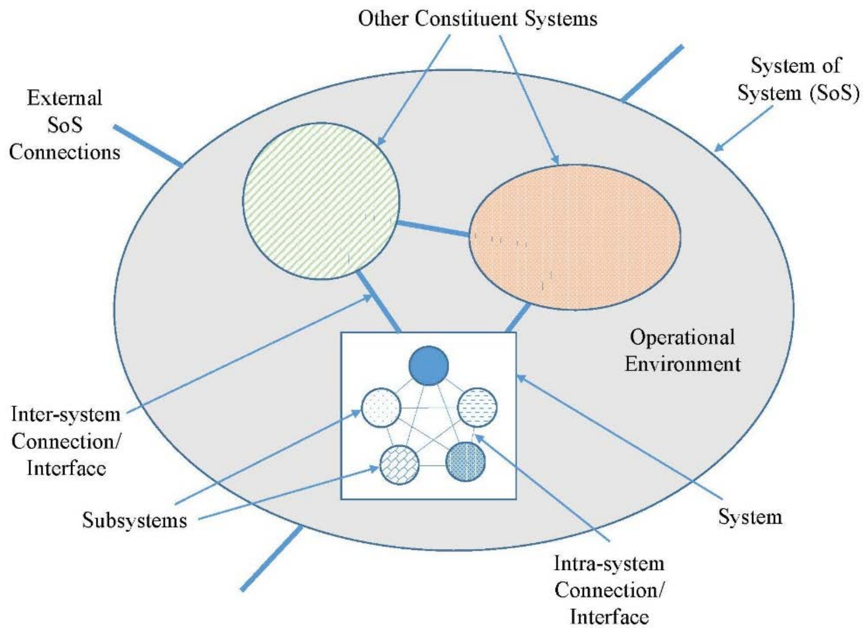

Figure 78. A System of Systems. Adapted from Hitchins (2003).

1. Characteristics of SoS

a. Collaboration

Collaboration is goal-oriented interaction among systems to create emerging new functionality and/or increased performance. Collaboration is the cooperation and coordination of the actions of various independent systems. Different levels of collaboration exist. Collaboration among independent systems for desired external effects is the capability required to enable super systems or SoS to exist (Hitchins 2009).

b. Non-linear Dynamics and Behavior

Non-linear dynamics and behavior describes physical systems in which the change of the output is not proportional to the change of the input. The behavior of nonlinear systems can be described by changes in variables over time, which may appear chaotic, unpredictable, or counterintuitive. Nonlinear behavior is often the byproduct or result of complex systems interacting with each other and their environment (Hitchins 2009). Most open SoS's exhibit nonlinear behavior—often at both the system level as well as the emergent meta-level, as it is interacting with its operational environment at both levels.

c. Emergence

Emergence in SoS is the meta-level behavior that arises due to the interactions and behaviors of the constituent systems. This behavior emerges from system interactions, cooperation, distributed control, cascade effects and orchestration. (Fisher 2006). Emergent behavior enables a SoS to achieve its purpose or the shared goals of the autonomous constituents. Emergent behavior refers to system behaviors as a whole that are not a simple resultant combination of the subsystem actions. It refers to the "whole" being greater than the "sum of the parts." Fisher (2006) discusses how SoS have holistic properties that cannot be accounted for by simply combining the actions of the constituents. In other words, SoS are not simply reducible.

d. Interdependence

Interdependence describes the connections between constituent systems in a SoS. Bar-Yam (2004a) writes that when the constituent systems are independent of one another, they are free to respond in an independent manner to their environment. However, when the environmental demands on the systems become interlinked, an interdependence can arise if they are connected and can collectively respond to the demands. Effective SoS's depend on interdependent systems to connect and collaborate. However, Bar-Yam (2004a) cautions that systems should only connect and become interdependent when the need arises and should otherwise remain independent.

e. Interoperation

Interoperation refers to the cooperative interactions of constituent systems to generate adaptive emergent SoS behavior. Interoperation enables desired SoS emergent effects in continuously changing situations. Fisher (2006) discusses how this characteristic contrasts with traditional integration processes that are based on centralized control and coordination among predictable components in predetermined solutions. He explains that interoperability depends on independent constituent systems sharing a common purpose and being able to act and interact to achieve that purpose. He writes that not all of the actions need to be coordinated, and that not all of the constituents need to support all aspects of the purpose. Further, that the constituents do not need to function correctly all of the time. However, Fisher explains that a sufficient degree of interoperation, cooperation and consistency of action must exist to produce the desired emergent behavior.

f. *Geographic Distribution*

Geographic distribution refers to the situation in which constituent systems are not collocated, but are spread out with geographic distance between them. Fisher (2006) and Maier (1998) list "geographic distribution" as a common characteristic of many, but not all, SoS. This characteristic affects the ability for constituent systems to interact and collaborate. It can have negative effects on the ability of a SoS to achieve desired emergent behavior. However, it can support the maintenance of autonomy among the constituent systems. It is an important consideration for the design of engineered SoS.

g. *Evolution*

SoS evolution refers to the evolution of goal-oriented emergent behavior over time in response to changing environments. Fisher (2006) describes most SoS as evolving with their behavior changing continuously as they adapt to their environment.

h. *Cascade Effects*

Cascade effects results from a single initial event or influence that causes a succession of system state changes (Fisher 2006). Cascade effects are commonly found in SoS as a result of multiple independent systems behaving and interacting. The cascade effect occurs whenever an external influence forms a chain of events in multiple systems. Cascade effects often occur in the interactions of constituent systems in a SoS. Their effects can amplify or dampen during the sequence of cascading state changes (Fisher 2006).

i. *Connectedness*

Connectedness is a term in graph theory that refers to paths between vertices (or communication links between systems). For a SoS, the measure of connectedness describes the density of the interfaces and interactions between constituent systems. It is an especially useful measure for SoS's with distributed constituent systems; indicating the density of the interactions between the constituent systems, which is an indicator of interdependence, likeliness of cascade effects, likeliness of collaboration, and likeliness of emergent behavior.

j. *Multi-mindedness*

Multi-mindedness is the ability of a SoS to address opposing (or non-complementary) goals. Gharajedaghi (2011) introduces the concept of the "multi-minded" system of systems. He discusses this in the context of a multi-dimensional framework in which opposing tendencies can be complementary if considered in the plurality of function, structure, and process. With an emphasis on the interaction of systems within a SoS, an outcome of synergy, stability and an order of magnitude improvement of performance can be created. The multi-mindedness principle applies to a system of purposeful systems that share in the decision-making of their individual and collective actions. However, it "requires a collective understanding" among the constituent systems.

F. COMPLEXITY

"Armageddon is not around the corner. This is only what the people of violence want us to believe. The complexity and diversity of the world is the hope for the future" (Palin 2003, 1).

Complexity is a result of open systems and their nonlinear interactions with each other and their environments. As mentioned earlier, the ever-advancing progression of computers and analytic computational methods has enabled a better understand complex behavior. These methods of identifying and understanding complex behavioral dynamics have spread to many disciplines that span the understanding of complexity in natural systems (e.g., weather, climate effects, group animal behavior [such as swarms, colonies, migrations, and epidemics]) and socio-technical systems (e.g., financial networks, social media interaction, communication systems, information systems, power systems, military conflicts, transportation, urban studies). Many universities and institutes are applying complexity theories and approaches to study a variety of natural and human-generated phenomena. They seek to understand the complexity and its causes and to prevent or lessen the damaging results of financial crises, natural disasters, and epidemics, to name a few. They hope that by studying complexity, they can better identify and predict complex behavior.

This section provides an overview of complexity theory, defining complex systems and their principles and characteristics. It provides a literature review of existing concepts and theories for complex adaptive systems (CAS) and complex adaptive systems of systems (CASoS).

1. Theories of Complexity

A simple way to introduce complexity is with the BOAR principle: "complexity lies **B**etween **O**rder **A**nd **R**andomness" (Page 2011, 32)

Complexity theory has arisen from observed phenomena that produced surprisingly unpredictable results from simple structures. (Honour 2006). Scientists and theoreticians studying these phenomena were unable to explain the behavior. Waldrop (1992) explains that complexity is operating at the "edge of chaos." Complexity occurring in systems can be described as exhibiting chaotic behavior while also characterized by recognizable patterns (Honour 2006). Theorists explain that complex systems can withstand chaotic environments even as their structure or components change and adapt. The complex systems have enough adaptability to respond and survive by altering their behavior. Complex systems, therefore, provide useful solutions to complex environments through their dynamic characteristics (Honour 2006).

Complexity theory contributes to an understanding of how environments affect complex systems and how they can learn by attempting alternative behavioral approaches for improvement (Dagli and Kilicay-Ergin 2009). This dissertation is grounded in a foundation of complexity theory—particularly as it applies to understanding complex problems and developing complex system solutions. However, we keep in mind a cautionary principle that complexity is **DEEP**: "complexity cannot be easily **D**etected, **E**volved, **E**ngineered, or **P**redicted" (Page 2007, 32).

Combining biology and system science with an understanding of thermodynamic equilibrium and entropy, has formed a foundation that has produced new theories of complexity and chaos. These theories are attempting to explain the non-linearity of interactive behavior in organic and inorganic systems (Ackoff 1981, Prigogine and Stengers 1984, Simon 1996). This section describes some of these theories.

a. Chaos

Systems can be studied according to their behavior. Static systems do not change. Dynamic systems change with time. Dynamic system can exhibit linear and nonlinear behavior. Nonlinear dynamic systems can have behavior that ranges from orderly (even predictable) to chaotic (unpredictable). Complexity appears to belong in the region between order and chaos. Chaos refers to the long-term aperiodic behavior of a deterministic system that has a sensitive dependence on initial conditions. Long-term aperiodic behavior means that the behavior does not exhibit long-term regularity. "Common sense" would wrongly suggest that the future behavior of the chaotic system could be determined exactly from the behavior. The irregular behavior comes from the nonlinearity of component interactions, not from random driving forces. Sensitive dependence on initial conditions means that small changes in initial conditions lead to arbitrarily large differences in behavior over time. (Harney 2012)

b. The 2^{nd} Law of Thermodynamics

The 2^{nd} Law of Thermodynamics states that in any closed system the amount of order can never increase, only decrease over time. Thus, in closed systems, entropy always increases. This law has important implications for complexity theory since many observed open systems (and life itself) contradicts this law. Richardson (2004a) points to the phenomena of self-organization in complex systems as being based on order emerging from disorder, to show an example of a contradiction of the 2^{nd} Law.

c. Interacting Agents

Complexity can arise from the interaction of many systems or "agents." Honour (2006) refers to these agents as "relatively independent" as they work together to produce emergent properties. The agents perform functions and their interactions produce emergent behavior. An example is the stock market with individual investors and individual public corporations as "agents" that buy and sell shares. Each agent attempts to achieve a better profit from their participation in the market. It is the purchases and sales of many agents that create the large-scale behavior of the stock market.

d. Detail Complexity

Detail complexity is the characteristic of detail in the scalability and increasing numbers of entities in complex systems that humans cannot comprehend due to natural cognitive limitations (Miller 1956, Senge 2006). This can manifest in limiting the abilities of larger and larger teams to communicate effectively (Cockburn 2001). Sterman (2000) writes that detail complexity is due to high levels of combinatorial complexity. He describes these as "needle-in-the-haystack" problems. An example is the task of optimally scheduling airline flights and crews. The complexity lies in finding the optimal solution out of an enormous number of possibilities.

e. Dynamic Complexity

Dynamic complexity occurs when the interaction between entities becomes more dominant than vertical influences. This can occur as the scale of the numbers of agents or and/or interactions grows (Robinson, Pawlowski and Volkov 2003, Senge 2006). As dynamic complexity increases, humans are no longer able to cognitively work with the large amounts of information and interactions. (Simon 1962). Sterman (2000) explains that dynamic complexity arises from the interactions among the agents over time. Often, the agents are simple systems and the complexity arises from the large number of components or combinations of possible courses of action. Dynamic complexity, instead, arises from the agent interactions, which often introduce time delays that add volatile unpredictability for the state of the system. Dynamic complexity is attributed to a number of factors including tight coupling, feedback, nonlinearity, adaptiveness, and self-organization.

f. Disorganized Complexity

Disorganized complexity occurs when the interactions of local entities tend to smooth each other out. For very large numbers of agents, disorganized complexity can cause an “unusually high value for one random value to be compensated for by an unusually low value of another” (Miller and Page 2007, 48). Thus, some fairly precise predictions can be made for the emergent behavior of complex systems exhibiting disorganized complexity.

g. Organized Complexity

Organized complexity refers to unanticipated statistical regularities emerging in complex systems. These regularities “go beyond the usual bounds covered by the Central Limit Theorem (CLT) (Miller and Page (2007, 49–50).” For systems characterized by the CLT, interactions cancel one another out and result in a smooth bell curve. However, in cases of organized complexity, the interactions reinforce one another and result in abnormal behavior. Examples include earthquakes, floods, fires, stock market crashes, riots, and traffic jams. These types of complex systems exhibit emergent behavioral patterns that do not occur in normal distributions.

h. Self-Organized Criticality

Self-organized criticality (SOC) refers to behaviors that cause self-organizing systems to converge to a critical point at which a small event can have a huge impact (Miller and Page 2007. 165–176). An example is a house of cards. The addition of some cards cause the structure to become unstable or perhaps for a card to fall. However, it the point at which the entire structure collapses when a card is added that is a condition of SOC.

2. Complex Systems

The science of complex systems studies how component systems and their interactions can give rise to emergent behaviors and how such systems interact with their environment (Bar-Yam 1997, 2004a). Complex systems are defined as large combinations of interacting elements (or components) that have no central control and whose interactive behavior produces emergent level behavior (Mitchell 2009). They require the ability to sense their environment and are able to process this information. They adapt to their environment through learning and evolution. They produce emergent and self-organizing behavior.

The following is a list of properties of complex systems (Miller and Page 2007, Dagli and Kilicay-Ergink 2009).

- A large number of decisions exist regarding design
- A complex operational environment
- The degree of control is decentralized rather than centralized
- There are many objectives and some are inconsistent with others
- The implications of design decisions are less predictable
- Change at any level in the system may have system-wide impacts due to the interrelationships of parts and small changes within the system can have large effects at the system-level
- Lateral influences in the system structure are stronger and more dominant than hierarchical relationships
- System risk is dominated by system-level risk rather than local risk
- Long-term planning is impossible
- Dramatic change can occur unexpectedly
- Short-term behavior can be predictable, but long-term behavior is unpredictable
- Innovation and adaptation are possible

Hitchins (2012) defines complexity as having just three components: variety, connectedness, and disorder. He explains that a system is more complex if there is greater variety in the components; if the number of connections between the components is large;

and if the variety and the connections are mixed and tangled-up, rather than orderly. Figure 79 illustrates the difference between a noncomplex system that is weakly integrated and a complex system that is highly integrated.

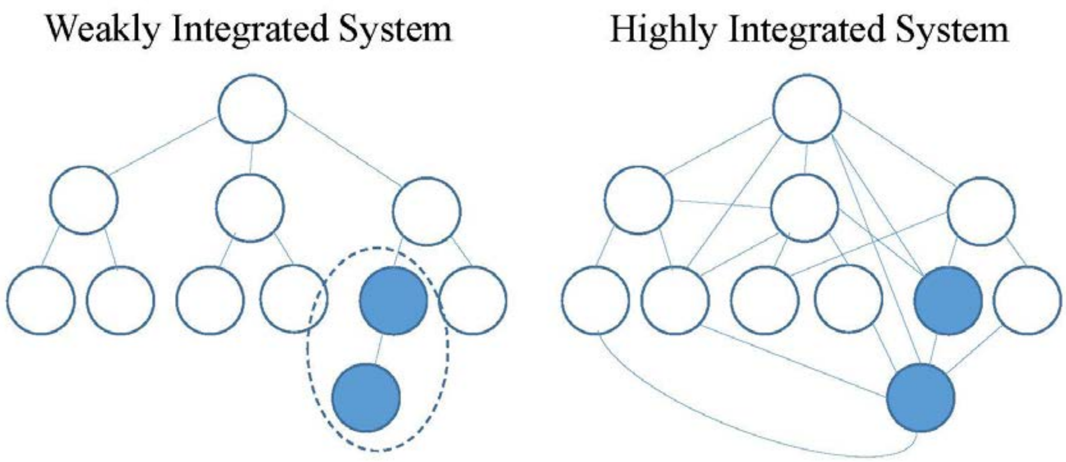

Figure 79. Weakly vs. Highly Integrated Systems. Source: Calvano and John (2004).

Figure 80 illustrates three categories of systems: ordinary, systems of systems, and complex systems. It shows examples of real world systems in each category.

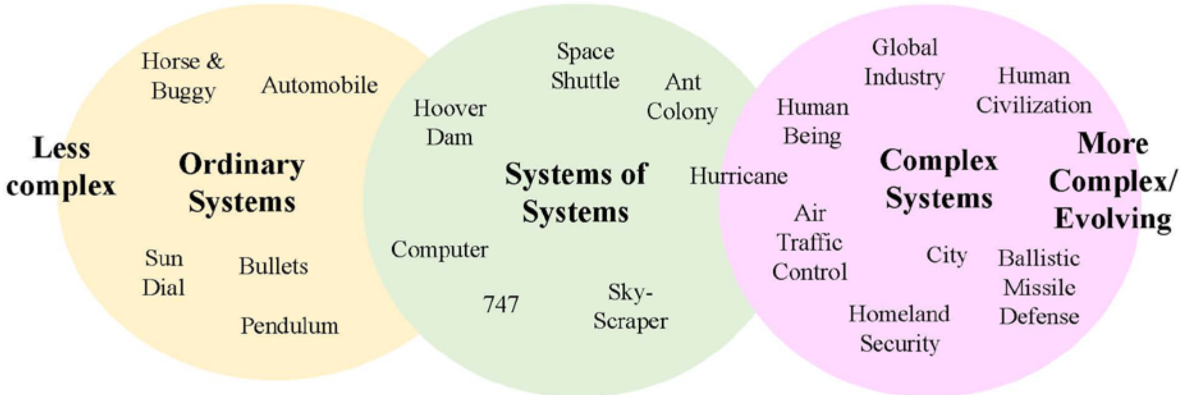

Figure 80. Systems According to Degree of Complexity. Adapted from White (2005).

An important distinction to make is the difference between a complicated system and a complex system. Miller and Page (2007) explain that in complicated systems, the constituent systems are somewhat independent from one another. Therefore, if one constituent is removed, it doesn't cause the total system to collapse. On the other hand, in a complex system, the constituents are more highly interrelated. Therefore, if a constituent system is removed from a complex system, it will have a negative affect and the complex system will no longer be able to accomplish its mission. Thus, complexity is known as a deep property of a system. Complicatedness is not a deep property of a system. Allen (2016) distinguishes between complex and complicated systems by their outcomes: complicated systems have a relatively high degree of certainty of outcome repetition; whereas complex system outcomes are often uncertain. The implication is that complex systems built from scratch will likely behave in unintended ways.

The next two subsections present the characteristics and principles of complex systems.

3. Complex System Characteristics

a. Emergent Behavior

Complex systems exhibit emergent behavior. These meta-level properties are only perceptible at the holistic level and cannot be understood or predicted from the lower-level constituent behavior (Honour 2006). Emergent properties may be desirable, purposeful, unintentional, unpredictable, and/or destructive.

b. Reflexivity

Reflexivity refers to the reflexive nature of the interactions of constituent systems in a complex system. Honour (2006) explains that as the constituent systems behave, their actions have impacts on other systems, which cause these systems to act in response. He explains that this reflexive response behavior causes a cascading effect of even more reflexive actions.

c. Connectedness

Connected refers to the "tightly coupled" nature of agents within a complex system (Sterman 2000). Complex systems have strong internal interactions as well as strong interactions with their environment. This is consistent with Alberts (2011) descriptions of the "Age of Interactions" in which everything is connected to everything else.

d. Governed by Feedback

Complex systems are governed by feedback. Because of their connectedness and strong interactions, the actions of complex systems alter their environment, which then triggers actions in other systems, giving rise to new situations, which influence the original complex system. Sterman (2000) writes that dynamic behavior arises from these many and varied feedback loops.

4. Principles of Complex Systems

a. The Principle of System Holism

The principle of system holism is that the whole is greater than the sum of its parts. This implies that lower-level constituent behavior leads to higher-level behavior that cannot be derived from the micro-level from which it emerged (Richardson 2004a). Another label for this phenomenon is "vertical emergence."

b. The Principle of Local Information

The principle of local information explains that in many complex systems, agents act on local information rather than global information (Honour 2006). Many complex system structures contain numerous agents, each of which communicates with only a few other nearby agents.

c. The Darkness Principle

The darkness principle explains that an outside viewer cannot have a complete understanding of a complex system (Richardson 2004a). Richardson (2004a) explains that representations of systems that are complex will automatically misrepresent certain aspects. He explains that the implication of this is that for complex systems, the only correct representation is the system itself. Richardson (2004a) explains that the darkness principle is due to the nonlinearity of complex systems, which he explains is irreducible.

d. The 80/20 Principle

The 80/20 principle explains that in a large complex system, only 20% of the system produces 80% of the output.

e. The Principle of Behavior Prediction

The principle of behavior prediction refers to the ability to predict the behavior of complex systems. This ability is dependent on gaining adequate knowledge of the system and its environment. It is also dependent on the forces of chaos and anti-chaos. Richardson (2004b) writes that the forces of chaos make prediction impossible while the forces of anti-chaos make prediction possible. He explains, however, that most complex systems live somewhere between the two extremes so that effective prediction, while difficult, is actually possible.

f. The Principle of Sub-Optimization

The principle of sub-optimization refers to the efficiency of a complex system's performance. If each constituent systems behavior is optimized, then the whole system's behavior will not be optimized. Also, the reverse is true—that if the system as a whole is optimized, then the constituent systems will not be optimized (Richardson, 2004b).

g. The Principle of Irreversibility

The principle of irreversibility refers to the history-dependent nature of complex systems (Sterman 2000). Path dependence is when a system goes down one "path" (or takes one course of action) which then precludes it from taking others. The path taken ultimately determines the system's end state or future. This notion of path-dependence explains how the behavior of complex systems is irreversible. An example of irreversibility is how it is impossible to unscramble an egg.

h. The Principle of Self-Organization

The principle of self-organization explains how patterns of organized behavior arise spontaneously in complex systems. Sterman (2000) explains that small behaviors within complex systems are amplified and reoccur with feedback, causing the generation of higher level patterns of behavior. He describes examples such as the pattern of stripes on zebras, our rhythmic heartbeats, patterns in the real estate market, and the shapes of seashells. He explains that self-organizing behavior emerges spontaneously from the interactions and feedback among the small components within a large complex system. Nicolis (1989) add the idea that self-organization occurs without the control of an external source.

5. Complex Adaptive Systems

"Complexity often leads to adaptation, in which the complex structure changes to better fit its environment. The complex structure responds to inputs from the environment that act as either threats or opportunities" (Honour 2006, 4). The complex structure then modifies itself to enhance its performance and courses of action to address the environment. Evolution is an example of adaptation, leading to the selection and proliferation of some systems while others become extinct (Sterman 2000). Purposeful adaptation can arise from learning. Adaptation occurs when a complex system has self-modifying abilities, local information, and some self-attaining measure of fitness (Honour, 2006).

Complex adaptive systems (CAS) are a subset of complex systems. Such systems contain the characteristics of complexity described in the previous section; but they also have the additional ability of being able to adapt. CAS are identified by three properties: "(1) diversity and individuality of components, (2) localized interactions among those components, and (3) an autonomous process that uses the outcomes of those interactions to select a subset of those components for replication or enhancement" (Levin 2002, 4). An important aspect of CAS is the emergent behavior from the cooperation, coalition, and network of interaction. This emergent behavior can provide feedback to influence those behaviors.

"The study of CAS, from cells to societies, is a study of the interplay among processes operating at diverse scales of space, time, and organizational complexity. The key to such a study is an understanding of the interrelationships between microscopic processes and macroscopic patterns, and the evolutionary forces that shape systems" (Levin 2002, 3)

Figure 81 illustrates the adaptive nature of cells within the life cycle of the amoeba. Given an environment with bacteria as a food source and the right conditions, independent cells begin to interact and aggregate to form higher structures of connected cells that produce an emergent structure that exhibits higher forms of behavior in its environment and even provides spores for reproduction and replication.

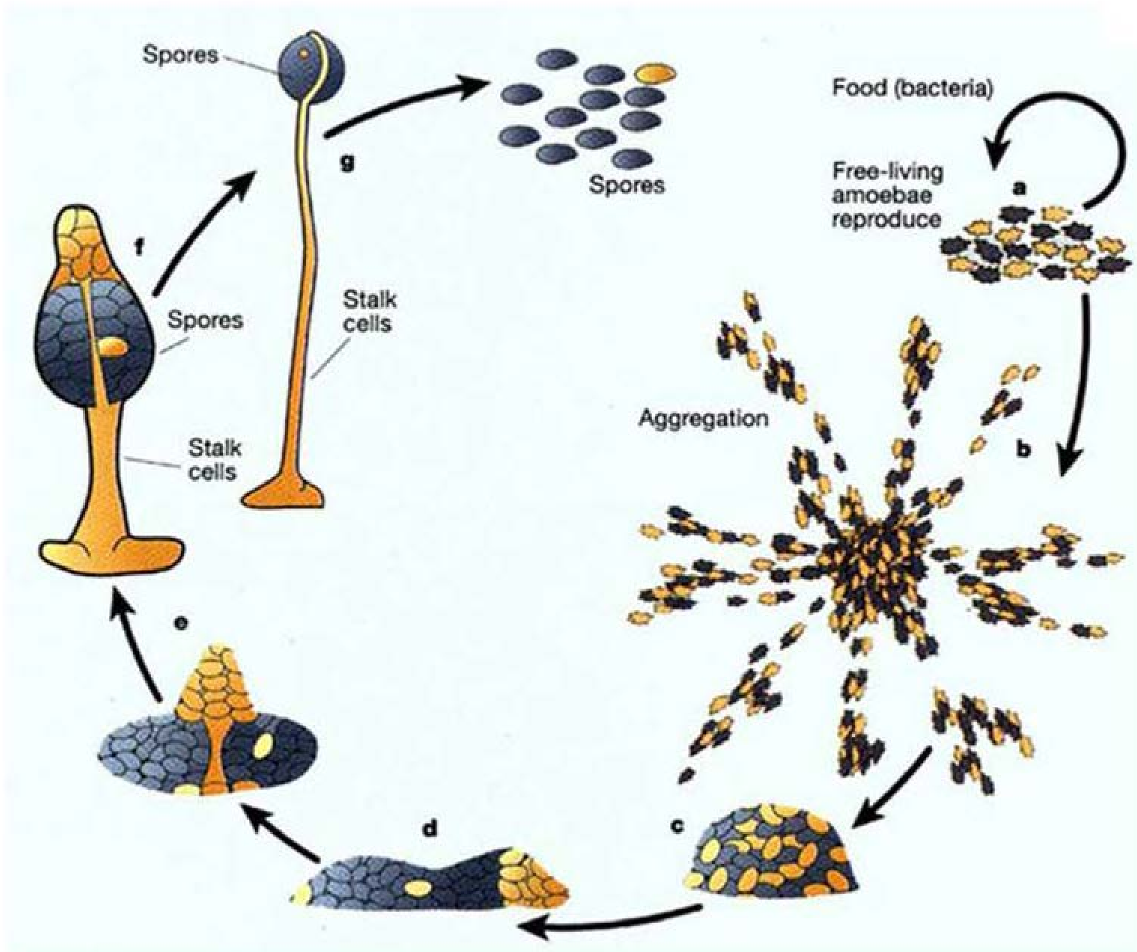

Figure 81. A CAS Example: Life Cycle of the Amoeba. Source: Wu and Kessin (2003).

CAS change by reorganizing their components to adapt themselves to the problems posed by their environment (Holland 1992). CAS have the ability to evolve, aggregate their behavior and anticipate their surroundings. A pivotal characteristic of CAS is the ability of their parts to adapt or learn. These adaptive processes are complex because they involve many parts and widely varying individual criteria for what constitutes a good outcome. Holland (1992) writes that CAS exhibit an aggregate behavior that is not simply *derived* from the actions of the parts; but that it *emerges* from the interactions of the parts. He also writes that CAS adapt to changing circumstances through their parts that develop rules that anticipate the consequences of certain responses. He gives an oil shortage as an example. "The anticipation of an oil shortage, even if it never comes to pass, can cause a sharp rise in oil prices, and a sharp increase in attempts to find alternative energy sources" (Holland 1992, 20).

CAS evolve and adapt in order to stay relevant and vital in conditions with persistent environmental effects. They achieve this adaptation without a centralized control mechanism or authority (Polacek et al. 2012). Figure 82 illustrates this point, showing birds that can produce aggregate swarming without centralized control. Holland (1992) proposes that massively parallel computation methods ae needed for modeling CAS as a distributed, many-ruled system.

Figure 82. A CAS Example: A Swarm. Source: D. Dibenski (Auklet flock in Alaska, 1986).

6. Complex Adaptive Systems of Systems

A CASoS has the characteristics of complex systems and CAS, but with the additional feature of being comprised of independent constituent systems that adapt and act in their own right. Thus, the CASoS exhibits both system level behavior and SoS level behavior.

The term, CASoS, was coined by Sandia National Laboratories. They have been studying complex systems since 2002 and initiated the Sandia Phoenix initiative in 2008 to create and evolve CASoS engineering as a discipline. They defined CASoS as vastly complex eco-socio-economical-technical systems, which must be understood to design a secure future for the world (Glass et al. 2011).

The Phoenix initiative developed the concept of aspirations, to serve as engineering goals to influence CASoS. They established categories for the aspirations: (1) to predict; prevent or cause; prepare; (2) to monitor; recover or change; and (3) to control (Glass et al. 2011). Additionally, they define three key components that must accompany each aspiration: decision, robustness of decision, and enabling resilience. Figure 83 illustrates examples of CASoS and perturbations that affect them.

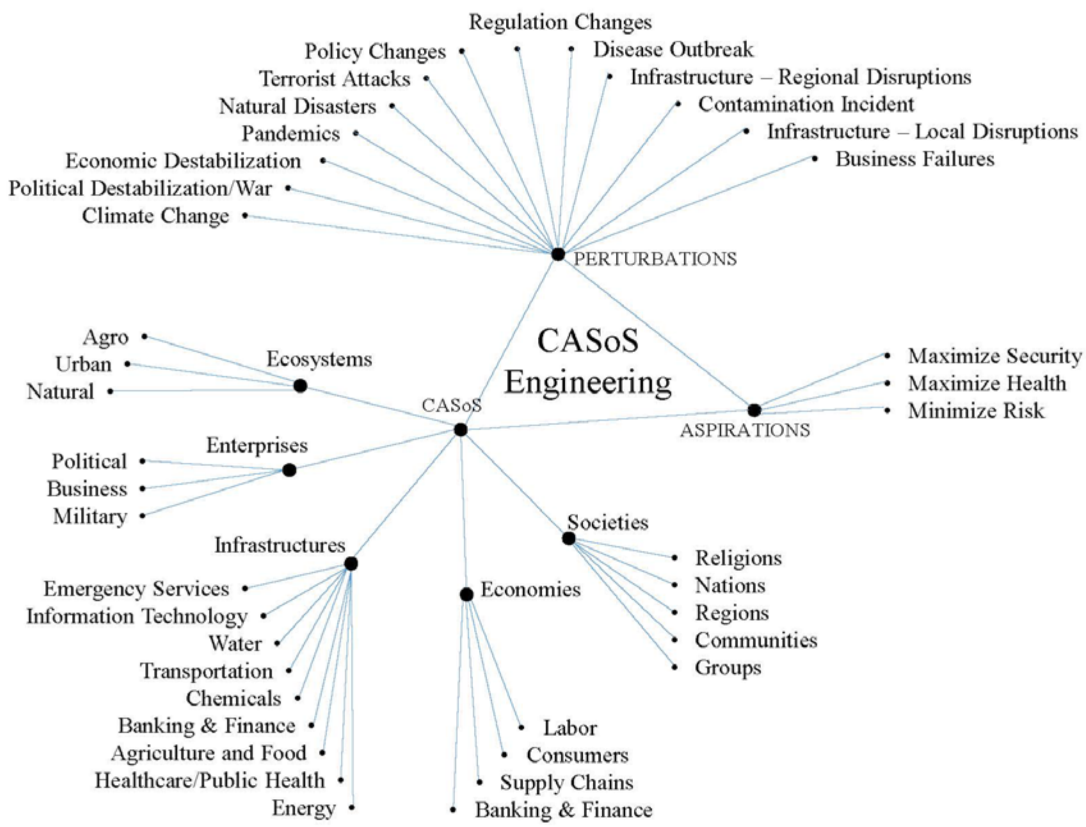

Figure 83. Engineering: CASoS, Perturbations, and Aspirations. Source: Glass et.al. (2011).

While Sandia is focused on understanding existing and observed CASoS as problem spaces, this dissertation is focused on understanding how an engineered version can be applied as a solution to complex problems. Ames et al. (2011, 14) writes, “CASoS engineering focuses almost exclusively on making changes to existing systems (i.e., retrofitting, designing, small changes), rather than designing complete systems.” This important aspect of the Phoenix initiative differentiates it from the focus of this dissertation.

While this dissertation aligns with the CASoS definition and concepts introduced by the Sandia Phoenix initiative, the focus of this dissertation differs in two ways:

This dissertation focuses on a subset of CASoS: intentionally designed (or engineered) CASoS. A primary goal of the research is to engineer human-made CASoS that are inspired by naturally occurring CASoS that the Phoenix initiative has been studying. Consequently, the first goal of this dissertation is to establish the defining characteristics of CASoS.

This dissertation focuses on engineering “intentionally designed” CASoS as a solution to address complex problems; whereas the Phoenix initiative is primarily focused on making changes to existing systems (Ames et al. 2011). Thus, the second goal of the research is to develop an engineering framework for designing and developing human-made technological CASoS solutions for addressing complex problems.

APPENDIX B. GROUNDED THEORY DATA CODING MATRIX

#	Author	Date	Source Info	Topics	Sections
1	Ackoff	1971	"Towards a System of Systems Concept," *Management Science* 17 (11): 661–671.	SoS	IV.D, IV.E.4
2	Ackoff, Emery	1972	*On Purposeful Systems*. London, England: Tavistock Publications.	Purposeful Systems	IV.E.3, IV.E.4, IV.E.5
3	Adams, Hester, Bradley, Meyers, Keating	2014	"Systems Theory as the Foundation for Understanding Systems." *Systems Engineering* 17 (1).	Systems Theory, Emergence, Self-organization, Hierarchy, Purposeful systems,	IV.E.1, IV.E.3, IV.E.4, IV.E.5, IV.F
4	Akers, Keating, Gheorghe, and Sousa-Poza	2015	"The Nature and Behaviour of Complex System Archetypes." *International Journal of System of Systems Engineering* 6 (4): 302–326.	Complex Systems, adaptation (processes for this), context—systems interaction with environment	IV.E.1, IV.E.3, IV.E.5 IV.E.6, IV.F
5	Allen	2016	"Complicated or Complex—Knowing the Difference is Important." *Learning for Sustainability*.	Complicatedness, Complexity	IV.B, IV.E.6
6	Ames, Glass, Brown, Linebarger, Beyeler, Finley, Moore	2011	"Complex Adaptive Systems of Systems (CASoS) Engineering Framework Version 1.0." *Sandia National Laboratories Report*, SAND 2011–8793.	CASoS, Complexity	IV.B, IV.C, IV.E.6
7	Ashby	1962	"Principles of the Self-Organizing System." *Transactions of the University of Illinois Symposium*. H. Von Foerster and G.W. Zoph, Jr. (eds.),	Self-organization	IV.E.4, IV.E.5, IV.F

#	Author	Date	Source Info	Topics	Sections
			Pergamom Press: London, UK): 255–278.		
8	Azani	2009	An Open Systems Approach to System of Systems Engineering. In *System of Systems Engineering, Innovations for the 21st Century*. Ed. Mo Jamshidi, 21–43. Hoboken, NJ: John Wiley and Sons, Inc.	SoS, SoSE	IV.D
9	Barabasi	2003	*Linked*. Cambridge, MA. Plume.	Connectedness, Networks	IV.E.4
10	Bar-Yam	1997	*Dynamics of a Complex System*. Perseus Press.	Complexity	IV.B, IV.C, IV.E.5, IV.E.6
11	Bar-Yam	2003	"When Systems Engineering Fails—Toward Complex Systems Engineering." *Proceedings of the International Conference on Systems, Man, & Cybernetics*.	CSE, Complexity	IV.C, IV.E.5
12	Bar-Yam	2003	"Unifying principles in complex systems," Converging Technology (NBIC) for Improving Human Performance, (M. C. Roco and W. S. Bainbridge eds.). Kluwer Dordrecht, The Netherlands (2003).	Complexity, Complex Systems, Self-organization, evolution, architecture	IV.B, IV.C, IV.E.4, IV.E.5, IV.E.6
13	Bar-Yam	2004	*Making Things Work: Solving Complex Problems in a Complex World*, NESCI Knowledge Press.	Complex Problems	IV.B, IV.C, IV.E.5

#	Author	Date	Source Info	Topics	Sections
14	Bar-Yam	2004	"The Characteristics and Emerging Behaviors of Systems of Systems." *NECSI.*	SoS	IV.D, IV.E.4, IV.E.5
15	Bar-Yam	2004	"Multi-scale Complexity/Entropy." *Advances in Complex Systems*, 7 (1): 47–63.	Complexity, Entropy	IV.E.6
16	Bar-Yam	2004	"Multiscale Variety in Complex Systems," *Complexity* 9, No.4): 37–45.	Complex Systems, Multi-scale	IV.E.6
17	Beer	1979	*The Heart of the Enterprise*. Wiley: New York.	Viability Principle	IV.F
18	Bertalanffy	1950	"The Theory of Open Systems in Physics and Biology." *Science*. 111: 23–29.	Open systems, systems theory	IV.E.1
19	Bertalanffy	1951	"General System Theory—A New Approach to Unity of Science," *Human Biology*, Dec 1951, 23: 303–361.	Systems theory	IV.E.1, IV.E.2
20	Bertalanffy	1968	*General System Theory*. New York: George Braziller, Inc.	Systems theory	IV.E.2
21	Bertalanffy	1972	"The History and Status of General Systems Theory." *The Academy of Management Journal* 15 (4. pp. 407–426.	Systems theory	IV.E.3
	Blanchard and Fabrycky	1998	Systems Engineering and Analysis, 3rd edition. Prentice-Hall	Traditional Systems Engineering	V
22	Boulding	1956	"General Systems Theory: The Skeleton of Science," *Management Science.* 2 (3): 197–208.	Systems theory	IV.E.3, IV.E.5

#	Author	Date	Source Info	Topics	Sections
23	Braha, Minai, and Bar-Yam	2006	*Complex Engineered Systems.* Berlin: Springer-Verlag.	Complexity	IV.E.6, V
24	Carbrera and Carbrera	2015	*Systems Thinking Made Simple.* Odyssean Press.	Systems Thinking, Systems Theory	IV.E.4, IV.E.5
25	Calvano and John	2004	"Systems Engineering in an Age of Complexity." *IEEE Engineering Management Review*. 32: No 4: 29–38.	CSE, Complex Problems, Complex Solutions	IV.B, IV.E.6, V.
26	Camazine, Deneubourg, and Franks	2001	*Self Organization in Biological Systems*. Princeton University Press.	Self-organization	IV.E.3, IV.E.5
27	Checkland	1993	*Systems Thinking, Systems Practice*. West Sussex, England: John Wiley & Sons, Ltd.	Systems thinking, systems theory	IV.E.2, IV.F
28	Checkland	2000	"Soft Systems Methodology: A Thirty Year Retrospective." *Systems Research and Behavioral Science Systems Research* 17: S11-S58.	System Theory	IV.E.1, IV.E.2
29	Cilliers	1998	*Complexity and Postmodernism: Understanding Complex Systems*. London: Routledge.	Complexity, Control	IV.E.6, IV.F
30	Dagli and Kilicay-Ergink	2009	"System of Systems Architecting." *System of Systems Engineering: Innovations for the 21st Century*, edited by Mo Jamshidi, John Wiley & Sons, Inc.	SoS	IV.D, IV.E.4
31	Dahmann, Lane, Rebovich, and Baldwin	2009	"A Model of Systems Engineering in a System of Systems Context." *Proceedings*	SoS	IV.D, V

#	Author	Date	Source Info	Topics	Sections
			of the Conference on Systems Engineering Research.		
32	Dahmann, Rebovich, and Baldwin	2009	“Relationship Between SoS and Net-Centric Systems,” *7th Annual Conference on Systems Engineering Research Proceedings*.	SoS	IV.D, IV.E.4
33	Efatmaneshnik, Bradley, and Ryan	2016	“Complexity and Fragility in System of Systems.” International Journal of System of Systems Engineering. 7 (4): 294–312.	SoS, Complexity	IV.D, IV.E.5, IV.E.6
34	Emery	1969	*Systems Thinking*. Harmondsworth, England: Penguin.	Systems thinking	IV.E.3, IV.E.5
35	Fisher	2006	“An Emergent Perspective on Interoperation in Systems of Systems.” Technical Report for Carnegie Mellon Software Engineering Institute.	SoS	IV.C, IV.D
36	Fraccascia, Giannoccaro, and Albino	2018	“Resilience of Complex Systems: State of the Art and Directions for Future Research.” Complexity, 2018, Article ID 3421529.	Resilience	IV.E.6
37	Fradkov, Miroshnik, and Nikiforov	1999	*Nonlinear and Adaptive Control of Complex Systems.* Springer-Science + Business Media Dordrecht.	Nonlinearity	IV.E.6
38	Gharajedaghi	2011	*Systems Thinking: Managing Chaos and Complexity—A Platform for Designing Business Architecture,*	Systems thinking, complexity	IV.E.1

#	Author	Date	Source Info	Topics	Sections
			3rd edition. Morgan Kaufmann.		
39	Giammarco	2017	"Practical Modeling Concepts for Engineering Emergence in Systems of Systems." *System of Systems Engineering (SoSE), IEEE International Conference on*. (2017). IEEE.	SoS, Emergence	IV.D, IV.E.5
40	Glass, Ames, Stubblefield, Conrad, Maffitt, Malczynskki, Wilson, Carlson, Backus, Ehlen, and Vanderveen	2008	"A Roadmap for the Complex Adaptive Systems of Systems (CASoS) Engineering Initiative." *Sandia National Laboratories Report*, SAND, 4651.	CASoS	IV.B, IV.C
41	Glass, Ames, Brown, Maffitt, Beveler, Finley, Moore, Linebarger, Brodsky, Verzi, Outking	2011	"Complex Adaptive Systems of Systems (CASoS) engineering: mapping aspirations to problem solutions." In *Proceedings of the 8th International Conference on Complex Systems, Quincy, MA* (Vol. 26).	CASoS	IV.B, IV.C
42	Gould	2002	*The Structure of Evolutionary Theory*. Cambridge, MA: Belknap Press of Harvard University Press.	Evolution	IV.E.5
	Haberfellner and deWelch	2005	"Agile Systems-Engineering versus Agile-Systems Engineering." Published in *Proceedings of the*	TSE, CSE	V

#	Author	Date	Source Info	Topics	Sections
			Fifteenth Annual International Symposium of the International Council on Systems Engineering.		
43	Harney	2012	Lectures from Complex Systems Course. Naval Postgraduate School. Systems Engineering Department.	Complexity, complex systems	IV.B, IV.C, IV.E.5, IV.E.6
44	Hitch	1953	"Sub-optimization in Operations Problems." *Journal of the Operations Research Society of America* 1 (3): 87–99.	Sub-optimization principle	IV.F
45	Hitchins	1992	*Putting Systems to Work*. John Wiley & Sons	Systems theory	IV.C, IV.E.1, IV.E.2, IV.E.5
46	Hitchins	1996	"Getting to grips with complexity." In *proceedings of the 2nd annual conference of the INCOSE–UK*.	Complexity	IV.C, IV.E.5, IV.E.6
47	Hitchins	2003	*Advanced systems thinking, engineering, and management*. Artech House.	Systems thinking, systems theory	IV.C, IV.E.5
48	Hitchins	2007	"What's in a System of Systems?"	SoS	IV.C, IV.E.2, IV.E.5
49	Ho, Richards, and Gonsalves	2006	*"Complex Adaptive Systems-based Toolkit for Dynamic Plan Assessment."* Charles River Analytics, Cambridge, Massachusetts.	Complexity, Adaptive	IV.E.5, IV.E.6
50	Holland	1992	"Complex Adaptive Systems." *The MIT*	Complexity, Adaptation, Anticipation	IV.C, IV.E.3, IV.E.4,

#	Author	Date	Source Info	Topics	Sections
			Press Daedalus 121 (1): 17–30.	(Prediction), Aggregate Behavior, Evolution, Internal Models	IV.E.5, IV.E.6, IV.F
51	Holland	1995	*Hidden Order: How Adaptation Builds Complexity*. Reading, MA: Helix Books.	Adaptation, complexity	IV.E.3, IV.E.4, IV.E.5, IV.E.6, IV.F
52	Honour	2006	"Systems Engineering and Complexity." *Conference on Systems Engineering Research*, Los Angeles, CA.	CSE. Complexity	V
53	Hooper	2009	"*Intelligent Strategies for Secure Complex Systems Integration and Design, Effective Risk Management, and Privacy*." Proceedings of the IEEE Systems Conference, Vancouver, CA.	CSE	IV.E.6, V
54	Jackson and Keys	1984	"Towards a System of Systems Methodologies," *The Journal of Operational Research Society* 35 (6): 473–486.	SoS	IV.D
55	Keating	2009	"Emergence in Systems of Systems." Chapter 7 in *System of Systems Engineering: Innovations for the 21st Century*, Edited by Mo Jamshidi. John Wiley & Sons, Inc.	SoS, Emergence	IV.D, IV.E.3, IV.E.4, IV.E.5
56	Korzybski	1994	*Science and Sanity: An Introduction to Non-Aristotelian Systems and General Semantics*. Wiley: New York.	Circular Causality	IV.F.3

#	Author	Date	Source Info	Topics	Sections
57	Langford	2017	"The Making of a System of Systems: Ontology Reveals the True Nature of Emergence." *System of Systems Engineering (SoSE), IEEE International Conference on*. (2017). IEEE.	SoS, Emergence	IV.D, IV.E.5
58	Levin	2002	"Complex Adaptive Systems: Exploring the Known, the Unknown, and the Unknowable." *Bulletin of the American Mathematical Society*, 40 (1): 3–19.	Complexity, Adaptive, Variety, Evolution	IV.C, IV.E.3, IV.E.5, IV.E.6
59	Levy	2000	Applications and Limitations of Complexity Theory in Organizational Theory and Strategy, Handbook of Strategic Management Marcel Decker, NY): 67–87.	Complexity	IV.E.6
60	Lowe and Ng	2006	"The Implications of Complex Adaptive Systems Thinking on Future Command and Control." *Proceedings of the 11th International Command and Control Research and Technology Symposium*.	Complexity, Adaptive	IV.E.5, IV.E.6
61	Maier	1998	"Architecting Principles for Systems-of-Systems." *Systems Engineering* 1 (4. (pp 267–284).	SoS	IV.D, IV.E.4

#	Author	Date	Source Info	Topics	Sections
62	Maier and Rechtin	2000	*The Art of Systems Architecting, 2^{nd} edition.* CRC Press.	Systems Theory	IV.E.4
63	Marsh	2009	"The Demystification of Emergent Behavior." arXiv preprint *arXiv*: 0907.1117.	Emergence	IV.E.5
64	Miettinen	2008	"The Ontology of Systems." Proceedings of the Third International Ontology for the Intelligence Community Conference (OIC-2008), Fairfax, VA.	Systems theory	V
65	Miller and Page	2007	*Complex Adaptive Systems*. Princeton: Princeton University Press.	Complexity, Adaptive	IV.B, IV.C, IV.E.3, IV.E.4, IV.E.5, IV.E.6
66	Mitchell	2009	*Complexity: A Guided Tour*. New York: Oxford University Press.	Complexity	IV.B, IV.C, IV.E.3, IV.E.6
67	Moffat	2003	*Complexity Theory and Network Centric Warfare*. CCRP Publication Series.	Complexity	IV.E.4, IV.E.5, IV.E.6
	Ncube	2011	*"On the Engineering of Systems of Systems: Key Challenges for the Requirements Engineering Community." IEEE): 70–73.*	TSE, SoSE	V.
	Neill	2010		TSE	V
68	Nichols and Dove	2011	"Architectural Patterns for Self-Organizing Systems of Systems," *Proceedings of the INCOSE International Symposium.*	Self-organization, SoS	IV.D, IV.E.4, IV.E.5

#	Author	Date	Source Info	Topics	Sections
69	Norman and Kuras	2006	"Engineering Complex Systems." In: Braha D., Minai A., Bar-Yam Y. (eds) *Complex Engineered Systems. Understanding Complex Systems*. Springer, Berlin, Heidelberg. pp. 206–245.	Complexity, CSE	V
70	Oliver, Kelliher, and Keegan	1997	*Engineering Complex Systems with Models and Objects*. McGraw-Hill.	CSE, Complexity	IV.E.5, IV.E.6
71	Ottino	2003	"Complex Systems." *American Institute of Chemical Engineers, AIChE Journal.* February 2003: 49, 2): 292–299.	Complex Systems, Complicated, adaptability, robustness, aggregation, self-organization	IV.B, IV.C, IV.E.3, IV.E.4, IV.E.5, IV.E.6
72	Ottino	2004	"Engineering Complex Systems." *Nature* 427, January 2004, 399.	CSE	IV.E.6, V
73	Page	2011	*Diversity and Complexity*. Princeton University Press. Princeton, NJ.	Complexity, Diversity	IV.B, IV.E.3, IV.E.6
74	Paul, Beitz, Feldhusen, and Grote	2011	*Engineering Design: a Systematic Approach*. (K. Wallace and LTM Blessing, Trans. 3rd ed.), Springer, Berlin.	Redundancy of Resources, Reliability, TSE	IV.F, V
75	Petrov	2002	"The Laws of System Evolution." *The TRIZ Journal*, March 2002.	System theory, evolution	IV.E.3, IV.E.5, IV.E.6, IV.F
76	Phelan	1999	"A Note on the Correspondence Between Complexity and Systems Theory." Systemic Practice and Action Research 12, No.3.	Systems theory and complexity	IV.F

#	Author	Date	Source Info	Topics	Sections
77	Polacek, Giannetto, Khashanah, and Verma	2012	"On Principles and Rules in Complex Adaptive Systems: A Financial System Case Study." *Systems Engineering* 15(4): 433–447.	Complex systems	IV.E.5, IV.E.6
78	Rapoport	1966	"Mathematical aspects of general systems analysis." General Systems 11.3 (1966): 1–28.	Systems Theory	V
79	Rasch and Knodt	1994	"*Systems Theory and the System of Theory*." New German Critique (61), Special Issue on Niklas Luhmann (Winter, 1994): 3–7.	Systems Theory	IV.F
80	Richardson	2004	"Systems Theory and Complexity: Part 1." *Emergence: Complexity and Organization Journal (E:CO) Issue* 6 (3): 75–79.	Systems Theory, Complexity	IV.E.3, IV.4, IV.E.5, IV.E.6, IV.F
81	Richardson	2004	"Systems Theory and Complexity: Part 2." *Emergence: Complexity and Organization Journal (E:CO) Issue* 6 (4): 77–82.	Systems Theory, Complexity	IV.E.3, IV.4, IV.E.5, IV.E.6, IV.F
82	Richardson	2005	"Systems Theory and Complexity: Part 3." *Emergence: Complexity and Organization Journal (E:CO) Issue* 7 (3): 104–114.	Systems Theory, Complexity	IV.E.3, IV.4, IV.E.5, IV.E.6, IV.F
83	Richardson	2007	"Systems Theory and Complexity: Part 4." *Emergence: Complexity and Organization Journal*	Systems Theory, Complexity	IV.E.3, IV.4, IV.E.5, IV.E.6, IV.F

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			(E:CO) Issue 9, Nos. 1–2, p.166.		
84	Ryan	2006	"About the Bears and the Bees: Adaptive Responses to Asymmetric Warfare." Interjournal (2006).	Adaptation, CSE	IV.E.4, IV.E.5
85	Senge	2006	*The Fifth Discipline: The Art and Practice of the Learning Organization*. New York: Crown Business.	Complexity	IV.E.6
86	Sheard	2007	"Complex adaptive systems in systems engineering and management." In W.B. Rouse & A.P. Sage (Eds), *Handbook of systems engineering and management*, 2nd edition. Wiley, NY): 1283–1318.	Complexity, Adaptation	IV.E.5, IV.E.6
87	Simon	1955	"A Behavioral Model of Rational Choice." *Quarterly Journal of Economics*. 69 (1): 99–118.	Principle of Satisficing	IV.F.5
88	Simon	1956	"Rational Choice and the Structure of the Environment." *Psychological Review*. 64 (2): 129–138.	Principle of Satisficing	IV.F.5
89	Skyttner	2001	*General Systems Theory: Ideas and Applications*. World Scientific Publishing Company Inc.	Systems Theory	IV.E.2, IV.E.3, IV.E.4, IV.E.5, IV.F
90	Smuts	1926	*Holism and Evolution.* Greenwood Press, New York.	Holism, Evolution	IV.F
91	Sousa-Poza	2015	"Mission Engineering." *International Journal*	Systems Theory	V

#	Author	Date	Source Info	Topics	Sections
			of Systems Engineering 6 (3): 161–185.		
92	Stacey	1995	"The Science of Complexity: An Alternative Perspective for Strategic Change Processes." *Strategic Management Journal* 16): 477–495.	Complexity	IV.E.5, IV.E.6
93	Sterman	2000	*Business Dynamics: Systems Thinking and Modeling for a Complex World*. Boston, MA. Irwin McGraw-Hill.	Systems Thinking, Complexity	IV.E.5, IV.E.6
94	Stevens	2008	"Profiling Complex Systems." 2008. *Proceedings of the IEEE International Systems Conference*, April 7–10, 2008.	Complexity, Complex Systems	IV.B, IV.E.5, IV.E.6
95	Suh, Furst, Mihalvov, and deWeck	2010	"Technology Infusion for Complex Systems: A Framework and Case Study." *Systems Engineering*. 13 (2): 186–203.	Complex Systems	IV.E.6, V
96	Svetinovic	2013	"Strategic Requirements Engineering for Complex Sustainable Systems." *Systems Engineering*. 16 (2): 165–174.	Complex Systems	V
97	Vakili, Tabatabaee, and Khorsandi	2012	"Emergence of Cooperation in Peer-to-Peer Systems: A Complex Adaptive System Approach." *Systems Engineering*. 16 (2): 2013.	Complex Systems, Distributed architecture, adaptive architecture, CSE (bottom up & top down), Self-organization	IV.E.4, IV.E.5, IV.E.6, V
98	Wang	2005	"Toward a Paradigm Shift in Social	Complex Systems	V

#	Author	Date	Source Info	Topics	Sections
			Computing: The ACP Approach." *IEEE Intelligent Systems*. (September/October 2007): 65–67.		
99	Wang	2008	"Toward a Revolution in Transportation Operations: AI for Complex Systems." *IEEE Intelligent Systems*. (November/ December 2008): 8–13.	Complex Systems	V
100	Weinberg	1975	*An Introduction to General Systems Thinking*. New York: Wiley.	Systems Thinking, Systems Theory	IV.F
101	White	2005	"Perspectives on Complex-System Engineering." MITRE Systems Engineering Process Office (SEPO) Collaborations Publication 3 (2), June 2005.	CSE	V
102	Whitney, Bradley, Baugh, and Chesterman	2015	"Systems Theory as a Foundation for Governance of Complex Systems." *International Journal of System of Systems Engineering*. 6, 1/2.	Complex Systems, Systems Theory	V
103	Wiener	1948	*Cybernetics: Or Control and Communication in the Animal and the Machine*. MIT Press: Cambridge, MA.	Principle of Feedback	IV.E.4, IV.F.3
104	Wiener	1961	*Cybernetics, 2nd ed*. New York: John Wiley & Sons.	Systems Theory	IV.E.4, IV.F
105	Zandi	2000	"Science and Engineering in the Age of Systems."	Systems Theory	V

#	Author	Date	Source Info	Topics	Sections
			Proceedings of the International Council of Systems Engineering (INCOSE).		
106	Zhang, Huang, Zhang, and Liu	2006	"Research on Parallel Decision Analyzing for Complex System of Systems." *Proceedings of the IEEE 5th International Conference on Machine Learning and Cybernetics*. Dalian): 1812–1817.	Complex SoS	IV.D

APPENDIX C. ADVANCED CODING: SYSTEMS ENGINEERING APPROACHES

A. INTRODUCTION

> If a "system" is defined as a set of interacting elements exhibiting an overall behavior beyond those of its individual parts, then engineers have been designing systems for many years, although the scope of such engineered systems has changed dramatically. (Calvano and John 2004, 30)

This phase of the advanced coding process focused on gathering, coding, and analyzing data concerning systems engineering methods and practices that have been developed and continue to be developed to engineer human-made systems. Blanchard and Fabrycky (1998, xi) write that "systems may be classified as either natural or human-made. Natural systems come into existence by natural processes. Human-made systems, or technical systems, come into being by human intervention in the natural order utilizing pervasive technologies through system components, attributes, and relationships."

This appendix presents how the engineering of systems is changing as technology and complexity are evolving. Three codes or types of systems engineering approaches were identified: traditional systems engineering (TSE), systems of systems engineering (SoSE), and complex systems engineering (CSE). This appendix is organized into three sections based on the three codes. The first subsection discusses traditional or classical systems engineering which refers to the engineering of systems whose boundaries, behaviors, and interfaces can be understood and are well-defined. These systems may be large in scale, span multiple disciplines, and address highly critical problems. Examples include aircraft, spacecraft, weapon systems, submarines and many other high technology systems. The second subsection discusses the engineering of SoS that exhibit "emergent" or "meta-level" behavior based on the collaboration of component or constituent systems. SoSE has been recognized as a distinct approach that faces a number of technical, acquisition, and management challenges. The third subsection discusses the engineering of complex systems. This is a relatively new field with the goal of engineering highly complex systems with emergent behaviors that are not apparent from the analysis of the component parts and their summations (Calvano and John 2004).

B. TRADITIONAL SYSTEMS ENGINEERING (TSE)

Traditional systems engineering focuses on how to design systems to meet a set of well-specified requirements. Kossiakoff and Sweet (1998, 3) write that "No particular date can be associated with the origins of systems engineering. SE principles have been practiced at some level since the building of the pyramids and probably before. (The Bible records that Noah's Ark was built to a system specification)." SE began to be recognized as a distinct activity following World War II. A number of textbooks were published in the 1950s and 1960s that identified SE as a distinct discipline and defined its place in the engineering of systems. Since this time, many SE methods, concepts, organizational structures, and modeling techniques have been developed to support the better understanding of systems and the design, development, test, evaluation, production, and operation of systems as they grow in scale and complexity.

Calvano and John (2004) discuss the evolution of systems engineering: that early-on, systems were considered engineered products—an idea that evolved from the simpler machines that existed. The early systems were based on well-defined architectures and they evolved as new technology was integrated into these architectures. They described TSE as being based on system architectures with clearly defined relationships and well-defined functions. TSE design concepts and associated efforts could be partitioned easily and with confidence and system architectures were well-defined and well-understood mechanical interfaces.

TSE is described as a "closed system" philosophy by Hitchins (1992). He explains that although TSE is holistic, encompasses all the aspects of the system life cycle, and considers interfaces with other systems, it does not allow for adaptation. As an example, he writes that in classical SE, interfaces "tend to be fixed, once chosen, and the concept of the future system within the interface boundary adapting form and function in response to interchanges across the interfaces is quite alien" (Hitchins 1992, 265–266). Another example of the TSE "closed system" philosophy is the standard practice of developing a fixed system according to a set of fixed requirements. Hitchins (1992) also describes the engineers' philosophy in which systems engineers cannot operate without fixed requirements and specifications.

The failure of TSE lies in the fact that many engineered systems are open systems. Hitchins (1992) explains that SE has unfortunately evolved from conventional hard engineering and classical science, which inhibit an “open system” attitude. He explains that this has resulted in TSE concentrating on producing fixed technological solutions to a continually moving problem. He proposes an “open system” philosophy for systems engineering with an understanding that most systems are open and need to adapt to changing environments.

C. SYSTEMS OF SYSTEMS ENGINEERING (SOSE)

> Traditional systems engineering approaches have proven effective in addressing complex systems problems where technical aspects dominate the solution space and boundaries are clearly discernable. However, a new class of complex systems problems has begun to emerge. This class of systems is referred to as a system of systems. (Keating 2009, 169)

A significant body of knowledge has been developed and accumulated for SoSE. The Department of Defense (DoD) defines a SoS as a “set or arrangement of systems that results when independent and useful systems are integrated into a larger system that delivers unique capabilities” (OUSD AT&L 2008, 4). Dahmann et.al. (2008) write that the main challenge of engineering SoS is having to use existing systems as components to meet stakeholder needs. They point out that the constituent systems have their own management and budgets and therefore the SoS engineers have no control over their development. Thus, a bottom-up SoSE process to integrate and interoperate existing systems has generated much industry, government, and academic attention. Significant effort has focused on addressing the technical challenges of interoperability; however, an equal, if not greater, effort has focused on overcoming the acquisition, management, and governance challenges. In fact, the OUSD AT&L guide to SoS (2008) cites Maier (1998) and Dahmann (2008) in its definition of four types of SoS, based on their type of management:

- **Virtual**—Virtual SoS lack a central management authority and a centrally agreed upon purpose for the SoS. Large-scale behavior emerges—and may be desirable—but this type of SoS must rely upon relatively invisible mechanisms to maintain it.

- **Collaborative—**In collaborative SoS the component systems interact more or less voluntarily to fulfill agreed upon central purposes. The Internet is a collaborative system. The Internet Engineering Task Force works out standards but has no power to enforce them. The central players collectively decide how to provide or deny service, thereby providing some means of enforcing and maintaining standards.

- **Acknowledged—**Acknowledged SoS have recognized objectives, a designated manager, and resources for the SoS; however, the constituent systems retain their independent ownership, objectives, funding, and development and sustainment approaches. Changes in the systems are based on collaboration between the SoS and the system.

- **Directed—**Directed SoS are built and managed to fulfill specific purposes. They are centrally managed during long-term operation to continue to fulfill those purposes as well as any new ones the system owners might wish to address. The component systems maintain an ability to operate independently, but their normal operational mode is subordinated to the centrally managed purpose.

A problem with classifying SoS in this manner—according to how the SoS will be managed rather than basing it on their principal characteristics of multi-level systemic behavior and emergence resulting from collaboration—is that it is derived from a reductionist view and presupposes a set of design solutions. The “directed” category allows for SoS to be designed and built with the SoS in mind (as opposed to the other three categories which indicate the integration of existing systems). However, it specifies that the SoS be centrally managed; which prevents a holistic systems approach. In contrast to the DoD approach to SoSE, this dissertation proposes an additional category of SoS with a purely top-down system approach that doesn’t prescribe a management style and is based on the level of collaborative emergence achieved and the ability to exhibit multi-level systemic behavior.

Hitchins (2009) criticizes SoSE in general as being misconceived, as he contends that SoS are really just systems. He writes, "while we may need to continue developing and evolving SE, the idea that there is a new subject called 'SoSE' seems to me to be arrant nonsense: a 'SoS' is a system, so SoSE simply reverts to SE (Hitchins 2005, 4)." He criticizes a bottom-up SoSE approach as "reductionist" and argues that thee reductionist methods do not accommodate complexity, but actually make it worse. He describes bottom-up SoSE practices as a "Lego building block approach to systems. Join the blocks together in the right way, it proposes, and you can construct whatever you want from the bottom up" (Hitchins 2005, 4–5). He explains that the problem with this approach is that it does not accommodate systems with people in them because people are flexible and adaptable. This would also apply to adaptive technology systems.

Hitchins (2005) advocates a top-down approach for SoSE: "In designing the whole system, then, it is necessary to start at the top and work down." He proposes that SoSE focus on the whole system of systems in terms of function management, form management, and concept of operations. Operationally, the SoS will function as a whole with no aspects in isolation, so SoSE must be performed holistically from the top down. The subsystems are the constituent systems of the SoS. Hitchins proposes that they be viewed as a substrate upon which to lay the whole system (SoS) functions and behavioral features. He explains that the whole system functions exchanged information upwards and downwards with the constituent systems, and therefore, the couplings between the constituent systems should be loose. Giammarco (2017) writes about engineering a system with a goal of steering its emergent behavior. She presents the idea of using engineering design to suppress undesired emergent behavior and support desired emergent behavior. Thus, Hitchins and Giammarco are paving the way for a shift in the focus of SoSE to a top-down intentionally designed systems approach rather than a bottom-up integration of existing systems.

D. COMPLEX SYSTEMS ENGINEERING (CSE)

Bar-Yam (2004) asserts that high complexity tasks require system solutions that are sufficiently complex to perform them. Engineered (human-made) systems become necessarily complex when they must perform effectively and function in response to highly uncertain environments. Designing a system to respond appropriately and effectively to unpredictable situations is challenging. As engineered systems become more complex, TSE methods no longer apply (Calvano and John 2004). CSE does not "…primarily seek to produce predictable, stable behavior within carefully constrained situations, but rather to obtain systems capable of adaptation, change, and novelty—even surprise" (Braha, Minai, and Bar-Yam 2006, 9).

Advances are being made in the science of complexity based on the study of complexity found in natural and social systems (Ames 2011). These are leading to novel approaches to designing and developing complex human-made systems (Bar-Yam 2003). A central tenet of complex systems is the principle of emergence: that the whole is greater than the sum of its parts. This implies potential advantages for higher-level functionality emerging from engineered elements comprising a system. According to John Holland (1992), it is this aggregate behavior that is of interest. Another implication is that unpredictable emergent behavior can arise. When the principle of emergence is applied to complex engineered systems, these human-made systems may behave in unexpected ways (Bar-Yam 2004). CSE is attempting to address this question by exploring methods to best engineer complex systems by taking advantage of their complexity while managing unpredictability (Calvano and John 2004).

1. TSE Limits for Complex Systems

TSE methods do not work for engineering complex systems. The TSE method, according to Bar-Yam (2003), is basically to design by decomposition. He writes that the TSE method begins with a high-level description which is then decomposed into components and then further decomposed. Neill et al. (2010, 11) explain that TSE methods are appropriate for less complex, hardware dominated systems, with relatively stable, long planning cycles." White (2005) explains that TSE can serve two roles: (1) to design systems that are not overly complex and (2) to design the interactions among components of complex systems.

A number of CSE practitioners write about the inability of TSE to produce adaptive or agile systems. Haberfellner and deWech (2005, 7) caution that installing intentional and purposeful agility into a systems using the TSE process, requires more effort in "thinking, planning, rethinking, and modifying." Polacek et al. (2012) explain that TSE focuses on attaining ideal requirements that are complete, unambiguous, and testable. Well-defined hierarchies of requirements are decomposed from the ideal requirements. However, by designing systems to meet the ideal requirements, they limit the systems from addressing unforeseen situations.

The main challenge for CSE lies in the difficulties of engineering complex systems that can handle uncertain and unpredictable situations (Polacek et al. 2012). Uncertainty and unpredictability cause poor assumptions and uninformed decisions during the design process (Beckerman 2000). Developing more detail to address increasing complexity can cause a new kind of complexity within the system's design. This can lead to a system whose possible states and behaviors become unknowable which can lead to undesired behavior. This results in an impractical and unachievable system.

2. CSE Approaches

a. Design the Environment

Bar Yam (2003) proposes a CSE approach focused on creating an environment or process instead of an end product. He writes that the TSE process has the objective of designing a system, while CSE should create processes or environments by which the system will appear and evolve over time. He uses manufacturing processes as an example of designing a process instead of a system. His other example is the Internet, which was designed as an environment for applications created by users. White (2005) proposes the CSE idea of designing the environment and processes by which the system is going to be created, instead of designing the system itself.

b. Principles-Oriented

A principles-oriented CSE approach is proposed as a method for handling system risk in complex systems. Polacek et al., (2012) propose a method of exerting external influence on complex systems as a way of controlling behavior and avoiding risks of undesired behavior. They write about intra-system and inter-system leverage points for managing this external influence. They discuss differences between rules-oriented systems (which control processes and behavior) and principles-oriented systems (which indirectly control systems). Using a principles-oriented methodology may be effective for complex systems that are too detailed and unpredictable for a rules-oriented approach.

c. Distributed Peers

Vakili, Tabatabaee, and Khorsandi (2012) describe a CSE approach based on designing "distributed peers" that act as "autonomous machines." They envision a peer-to-peer architecture that provides constituent systems in the form of a "large pool of resources." They recommend using cooperation policies between the peers to establish how resources are contributed and coordinated. They identify the need for an overall performance utility that incentivizes the distributed peers to participate and contribute resources while also meeting individual peer goals. Figure 84 is an illustration of their CSE approach.

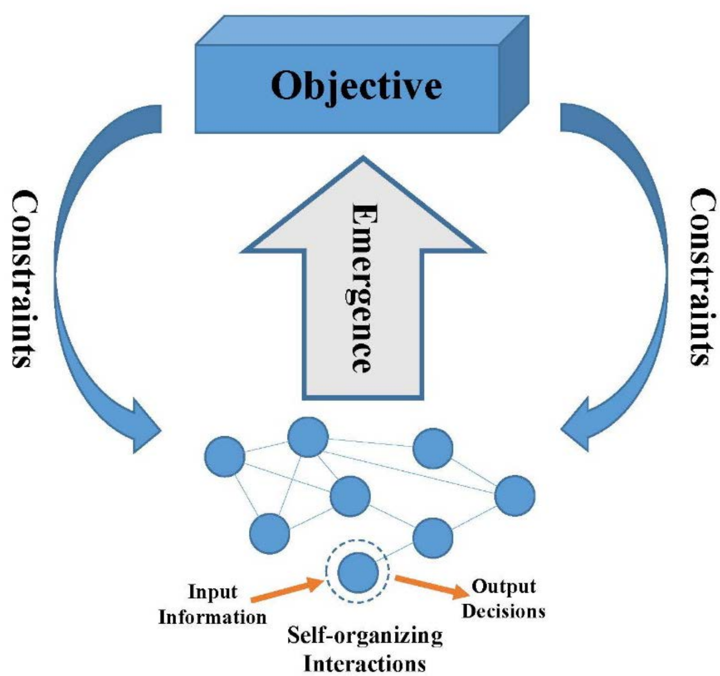

Figure 84. Peer-to-Peer Cooperative Design Approach. Source: Vakili et al. (2012).

d. A Balance of Top Down and Bottom Up

Vakili et al. (2012)'s proposed CSE method includes top down and bottom up systems engineering methods. They point out that the top-down method requires knowledge of all possible system states which is not possible in peer-to-peer systems. They also point out that a strictly bottom-up peer-to-peer system will self-organize and produce emergent behavior, but the behavior will not meet overall objectives. Therefore, they propose a balance between the top-down and bottom-up methods. The recommend starting with a top-down approach that establishes the intended overall behavior, and then developing peers and their interactions to meet these behavioral goals.

e. Local Behavior and Emergence

Fisher (2006) proposes a CSE method that focuses on local actions and interactions of constituent systems with a goal of gaining an understanding of emergent processes. He bases his method on a study of natural systems to provide insight into the nature of complexity in SoS. He observes that automated systems, like natural systems, are often highly complex in terms of large numbers of constituents and interconnections, dynamic interactions, unexpected external influences, and unpredictable behavior. He also observes that the local behaviors and neighbor interactions are relatively simple. As a result, he recommends a focus on understanding what types of emergent behaviors are possible from the simple local actions and interactions of the constituent systems. He contends that this method will overcome the perceived challenges of engineering a complex system and can predictably produce desired emergent behavior.

E. CSE CONCLUSION

This literature review concludes with an observation from Sheard (2007, 296): "What is needed in these cases is CSE, but to date, hardly anyone knows what that is, or even that it is needed. Some people deny that there is anything different about CSE; many of them will have to be convinced, or will retire, before the industry fundamentally improves its ability to engineer complex adaptive systems." In any case, current complex systems practitioners share many of the original goals of the general systems movement, such as the need for multi-disciplinary contributions and CSE methods to address a growing increase in complexity. This dissertation aims to extend the study of CSE to include the engineering of systems that are complex, adaptive, and exhibit multi-level behavior and collaborative-based emergence.

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