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**NAVAL
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MONTEREY, CALIFORNIA

THESIS

**DATA FARMING THE MARINE CORPS' READINESS
AND AVAILABILITY TOOL**

by

Kevin J. Doherty

June 2019

Thesis Advisor:
Second Reader:

Thomas W. Lucas
Mark A. Raffetto

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REPORT DOCUMENTATION PAGE			<i>Form Approved OMB No. 0704-0188</i>
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1. AGENCY USE ONLY (Leave blank)	2. REPORT DATE June 2019	3. REPORT TYPE AND DATES COVERED Master's thesis	
4. TITLE AND SUBTITLE DATA FARMING THE MARINE CORPS' READINESS AND AVAILABILITY TOOL		5. FUNDING NUMBERS NPS-19-M249	
6. AUTHOR(S) Kevin J. Doherty			
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Naval Postgraduate School Monterey, CA 93943-5000		8. PERFORMING ORGANIZATION REPORT NUMBER	
9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES) USMC Programs and Resources, Quantico, VA 22134		10. SPONSORING / MONITORING AGENCY REPORT NUMBER	
11. SUPPLEMENTARY NOTES The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government.			
12a. DISTRIBUTION / AVAILABILITY STATEMENT Approved for public release. Distribution is unlimited.		12b. DISTRIBUTION CODE A	
13. ABSTRACT (maximum 200 words) The 2018 National Defense Strategy describes the worldwide threat environment as one in which our military advantage is eroding and where interstate competition is now the most prevalent threat. Reducing the time needed to deploy forces to counter these threats is essential to national security. A key enabler of this is the operational readiness of the force. The Marine Corps' Readiness and Availability Tool (RAT) provides insight to Marine Corps leadership on the effects of readiness policies and world events on operational readiness. This thesis uses large-scale simulation and design of experiments to methodically explore the dynamic interactions of the RAT and provide insight on the key factors, critical readiness decision thresholds and model interactions. Analysis of 1200 simulated readiness timelines highlights the critical importance of not focusing on any one aspect of readiness planning, but rather considering the interactions between force structure, deployment-demand, and force-generation-timeline decisions when developing a force-wide readiness strategy for the Marine Corps. Home-station readiness levels were found to be deficient as a stand-alone metric of success for tracking the Marine Corps' readiness capacity to meet demand. The author used a multiple-objective analysis to better understand readiness capacity by exploring the trade-off between the level of home-station readiness maintained and the quantifying metric, risk of deploying non-ready forces.			
14. SUBJECT TERMS operational readiness, large-scale simulation, design of experiments		15. NUMBER OF PAGES 115	
		16. PRICE CODE	
17. SECURITY CLASSIFICATION OF REPORT Unclassified	18. SECURITY CLASSIFICATION OF THIS PAGE Unclassified	19. SECURITY CLASSIFICATION OF ABSTRACT Unclassified	20. LIMITATION OF ABSTRACT UU

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**DATA FARMING THE MARINE CORPS' READINESS AND AVAILABILITY
TOOL**

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Major, United States Marine Corps
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Submitted in partial fulfillment of the
requirements for the degree of

MASTER OF SCIENCE IN OPERATIONS RESEARCH

from the

**NAVAL POSTGRADUATE SCHOOL
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ABSTRACT

The 2018 National Defense Strategy describes the worldwide threat environment as one in which our military advantage is eroding and where interstate competition is now the most prevalent threat. Reducing the time needed to deploy forces to counter these threats is essential to national security. A key enabler of this is the operational readiness of the force. The Marine Corps' Readiness and Availability Tool (RAT) provides insight to Marine Corps leadership on the effects of readiness policies and world events on operational readiness. This thesis uses large-scale simulation and design of experiments to methodically explore the dynamic interactions of the RAT and provide insight on the key factors, critical readiness decision thresholds and model interactions. Analysis of 1200 simulated readiness timelines highlights the critical importance of not focusing on any one aspect of readiness planning, but rather considering the interactions between force structure, deployment-demand, and force-generation-timeline decisions when developing a force-wide readiness strategy for the Marine Corps. Home-station readiness levels were found to be deficient as a stand-alone metric of success for tracking the Marine Corps' readiness capacity to meet demand. The author used a multiple-objective analysis to better understand readiness capacity by exploring the trade-off between the level of home-station readiness maintained and the quantifying metric, risk of deploying non-ready forces.

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LIST OF ACRONYMS AND ABBREVIATIONS

AAV	Assault Amphibious Vehicle
ABS	Agent-Based Simulation
ATRY	Artillery
BIC	Bayesian Information Criterion
CBO	Congressional Budget Office
CLB	Combat Logistics Battalion
CLD	Casual Loop Diagrams
CNA	Center for Naval Analysis
DC	Deputy Commandant
DEP	Deployment
DRRS	Defense Readiness Reporting System
DoD	Department of Defense
DOE	Design of Experiments
DWL	Dwell
FSWG	Force Structure Working Group
FYDP	Future Year Defense Program
GAO	Government Accountability Office
GCSS-MC	Global Combat System Support – Marine Corps
GUI	Graphical User Interface
HADR	Humanitarian and Disaster Relief
HIMARS	High Mobility Artillery Rocket System
HMH	Marine Heavy Lift Helicopter
HMLA	Marine Light Attack Helicopter
HQMC	Headquarters Marine Corps
INF	Infantry
LAR	Light Armored Reconnaissance
MCO	Major Contingency Operation
MCTIMS	Marine Corps Training Information Management System
MEF	Marine Expeditionary Force
MEU	Marine Expeditionary Unit

MORS	Military Operations Research Society
NDAA	National Defense Authorization Act
NOB	Nearly Orthogonal, Nearly Balanced
NOLH	Nearly Orthogonal Latin Hypercube
NPS	Naval Postgraduate School
PA&E	Program Analysis and Evaluation
PPBE	Planning, Programming, and Budgeting Execution
PRM	Predictive Readiness Model
P&R	Programs and Resources
PTP	Pre-Deployment Training Program
P, R, S&T	Personnel, Equipment, Supply and Training Readiness
RAT	Readiness and Availability Tool
SD	System Dynamic
SEED	Simulation Experiments and Efficient Designs
SME	Subject Matter Experts
SPMAGTF	Special Purpose Marine Air Ground Task Force
TAI	Tactical Air Integration
UDP	Unit Deployment Program
USMC	United States Marine Corps
VMFA	Marine Fighter Attack
VMM	Marine Medium Tiltrotor
VVA	Verification, Validation, and Accreditation

EXECUTIVE SUMMARY

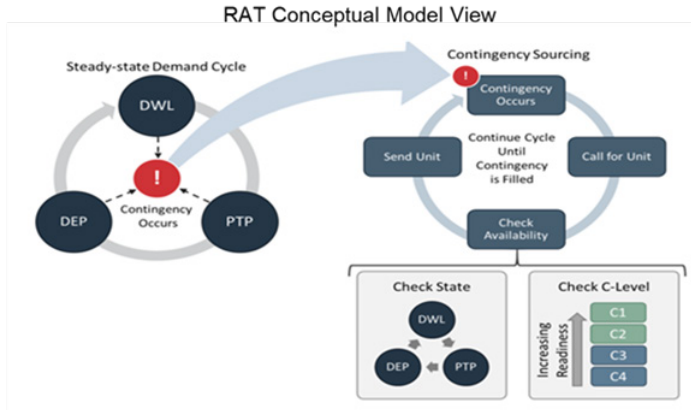
The United States' ability to rapidly deploy forces to meet emerging threats is critical to national security (Mattis 2018). The Commandant of the Marine Corps, General Robert Neller, stated that the enduring role of the Marine Corps is to be America's force in readiness, capable of operating from home-station as well as forward deployed at a moment's notice (Neller 2018). However, the Marine Corps is currently deficient in its ability to quantifiably explain and defend its ability to meet this task. In a 2016 report to Congress on the progress of the Department of Defense's (DoD's) readiness recovery plan, the Government Accountability Organization (GAO) concluded that the Marine Corps lacks an analytically informed readiness strategy and established measures of effectiveness to track the progress of its readiness recovery efforts (GAO 2016). In recognition of the risk incurred by lacking an objective, defensible, repeatable, and traceable operational readiness strategy, Headquarters Marine Corps (HQMC) Programs and Resources (P&R), has embarked on a multi-pronged readiness modeling effort led by its Program Analysis and Evaluation (PA&E) Branch working with Booz Allen Hamilton (PA&E 2018).

The Readiness and Availability Tool (RAT) is one of PA&E's readiness modeling efforts (PA&E 2018). The purpose of RAT is to provide insight to Marine Corps leadership regarding the operational readiness impacts of force structure and force employment decisions (PA&E 2018). Figure ES-1 shows a brief overview of RAT's conceptual model and intended uses. RAT's technical documentation describes the conceptual model as a process in which both force-elements and demand-nodes cyclically move through a scheduled steady state rotation of deployment, dwell, and pre-deployment training. The steady state rotation is disrupted by contingency operations that pull force-elements in order to fill pop-up needs. RAT utilizes discrete categorical input variables to facilitate the modeling of different force structures, deployment requirements, force-generation timelines, and contingency mission scenarios (Booz Allen Hamilton [Booz Allen] 2018).

Mission/Question: How do **force structure and force employment** decisions affect Marine Corps **readiness targets** over time?

Intended Uses

- To analytically inform Marine Corps readiness decisions.
- To evaluate if readiness goals support deployment and contingency requirements.



<u>Modeling Method</u>	<u>Force Elements</u>	<u>Demand Nodes</u>
Discrete Event, Agent Based Simulation	Infantry LAR	MEU
-Time Step: Month	MEU CLB VMFA	SPMAGTF
-Agents: Force Elements and Demand Nodes	Artillery VMM	UDP
-Deterministic and Stochastic	HIMARS HMLA	TAI
	AAV HMH	Contingency

Figure ES-1 RAT Modeling Overview. Adapted from Booz Allen (2018).

This thesis utilizes RAT to efficiently explore the operational readiness impacts resultant from Marine Corps force structure and force employment decisions. A joint planning effort between the research team and PA&E was conducted to develop the scope of the research design of experiments (DOE), which was implemented in a full factorial design with 1200 design points (Killian 2019). Because of the discrete nature of RAT’s input variables and the model’s fast runtime, a full factorial design was used. The primary goal of the DOE was to provide stress to the Marine Corps Readiness System in order to find breaking points in its capacity and capability to meet demand.

In order to execute the research DOE within RAT, Steve Upton of the Simulation Experiments & Efficient Designs (SEED) Center for Data Farming at the Naval Postgraduate School, enhanced RAT’s original programming to enable unrestricted simulation output (Upton 2019). As part of this research, the DOE enhanced version of RAT has been provided to PA&E to facilitate their ability to more fully study operational readiness.

Facilitated by the enhanced analytic utility of the DOE enabled RAT, the research team utilized basic summary statistics and metamodels to explore the simulation response

surface of RAT for factor significance, key decision thresholds, and variable interactions. The primary findings from this analysis are:

- The Number of Infantry Battalions is the dominant factor in determining Average Home-Station Readiness. The primary threshold to consider is whether the utilization is less than or greater than (23) battalions.
- Factor interactions are significant in each of the four metamodels developed for this research. Specifically, the Percentage of Non-Ready Units Deployed three-way interactions provide insightful thresholds that could be translated into Marine Corps policy decisions.
- At the Marine Corps' current force structure of (24) infantry battalions and deployment-demand of (≥ 7) steady state deployments, RAT displays an (11%) risk factor of deploying non-ready units even if resourcing is provided to ready units in (< 9) months. By increasing the force structure to (26), the risk can be reduced to (4.4%) and a resourcing requirement of (< 11) months.
- If the Marine Corps were to reduce its Special Purpose Marine Air Ground Task Force (SPMAGTF) deployments to only one, the risk of deploying non-ready units could be reduced below (1%) at its current force structure. However, if the Marine Corps were to also reduce its force structure to (< 23) battalions, then this risk would increase to (9.8%) with a requirement to ready units in (< 11) months.
- The multiple-objective analysis points to the need for an accompanying variable such as risk to quantify the relative value of Home-Station Readiness. In addition to utilizing risk as a quantifying metric, we recommend including cost as a third dimension. A goal of this effort would be to not only find which combinations of force structure and force employment are risk acceptable, but also those that are resource affordable.

- A potential error exists within RAT's business rules for sourcing contingency operations. It is evident that for simulation runs involving Humanitarian and Disaster Relief (HADR) operations, when RAT sourced the pop-up requirement with a deployed unit, the model counted the event as an additional deployment. This results in an inflated number of ready units deployed and an over-confident estimate of the Marine Corps' Readiness System capacity. In order to reduce the effects of model's contingency business rules, we averaged the response variables over the design points and removed HADR as a decision factor. It is recommended that the programming involved in RAT's sourcing and tracking of contingency missions be reviewed for consistency and desired effect.

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ACKNOWLEDGMENTS

I want to start by thanking my family for their love and support over the past two years. Erica, thank you for keeping me grounded, making sure I enjoy myself sometimes, and listening to my random operations research dialogues. Kaden, Levi, and Caleb, thank you for sharing your Dad with NPS and not being too difficult for your mother. I hope over the coming years to make up our lost time with many game nights, camp outs, and dirt bike rides. Professor Lucas and LtCol Raffetto, thank you both for your advice and for your mentorship during the long road to thesis completion. I look forward to continuing our relationship as I move from graduate student to operations research professional. Steve Upton, thank you for all that you do to enable students to conduct the research that we do here at NPS. To all the Operations Research faculty and staff, thank you: this is truly a word-class organization, and I have learned so much from all of you. Last but not least, it is with bitter sweetness that I thank and say goodbye to my fellow Operations Research cohort. Throughout this experience, I have come to depend on many of you for your insights and honest candor. I look forward to entering the OR workforce with you and hope that we can continue the relationships forged here at NPS.

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I. INTRODUCTION

Former Secretary of Defense James Mattis states in the 2018 National Defense Strategy:

Today, we are emerging from a period of strategic atrophy, aware that our competitive military advantage has been eroding. We are facing increased global disorder, characterized by decline in the long-standing rules-based international order—creating a security environment more complex and volatile than any we have experienced in recent memory. Inter-state strategic competition, not terrorism, is now the primary concern in U.S. national security. (Mattis 2018, p. 1)

A. BACKGROUND

What is operational readiness and why does it matter?

1. The Threat Environment of Today and How the United States Marine Corps Supports National Defense

In the environment that former Secretary of Defense Mattis describes, it is crucial that the United States be able to rapidly deploy forces to meet threats beyond its borders. It has long been the general strategy of the United States military to utilize force projection and a forward presence to deter and engage its enemies as well as to support its allies abroad.

Even from its early years, the United States Marine Corps (USMC) has served as a force in readiness. This was historically evident during the early days of the Korean War when Marine forces were deployed to support the overwhelmed Eighth Army in the defense of the Pusan Perimeter. It was the ability of the United States to quickly employ the Marines that allowed it to halt the North Korean advance. One outcome from this conflict was that, in 1952, the 82nd Congress issued a congressional mandate that the nation required an expeditionary force in readiness to be maintained and that this force would be the Marine Corps. To this day, the Marine Corps continues to faithfully carry out that mandate. In a 2018 address to the Congressional Defense Committees, General Robert Neller (2018b) stated, “We are a naval force whose mission requires us to be ready—a fight-tonight, forward deployed, Next Generation force—able to respond immediately to

emergent crises around the globe either from the sea, forward bases, or home station. While our organization, training, and equipment must continually adapt to meet changes in the operational environment, this fundamental purpose is unchanging” (p. 1).

The Marine Corps remains ready to fight its nation’s battles through the use of forward deployed forces. The Marine Expeditionary Unit (MEU) is one of the Marine Corps primary means for projecting power overseas. The MEU is an amphibious force that is anchored around a Battalion Landing Team with its own organic Aviation and Logistic forces. The MEU is organized and tasked to conduct missions that cover the full range of military operations and utilizes maneuver from the sea as a means to project its power. The MEU is a subordinate command to the Marine Expeditionary Force (MEF). The Marine Corps homeports two MEFs in the continental United States, one per coast, and one MEF overseas in Japan. To maintain near continuous forward presence, the two continental MEFs each consist of three rotating MEUs in order to allow one to be forward, one to be preparing to deploy, and one to be in a dwell period at home. The overseas MEF operates with one MEU that requires some of its forces to be sourced from continental U.S. based units. Figure 1 depicts the current force structure of the three MEFs. The investment in manpower and equipment to deploy a MEU is immense, but it is deemed essential to ensuring that the forces the Marine Corps sends forward are ready for the challenges they may face. The MEU is the typical method the Marine Corps utilizes to readily employ forces to meet the country’s enemies on a routine basis. However, having these forces forward is necessary, but not sufficient for success. In order to be able to “fight-tonight,” as the Commandant stated, the Marine Corps must be at a high state of operational readiness.

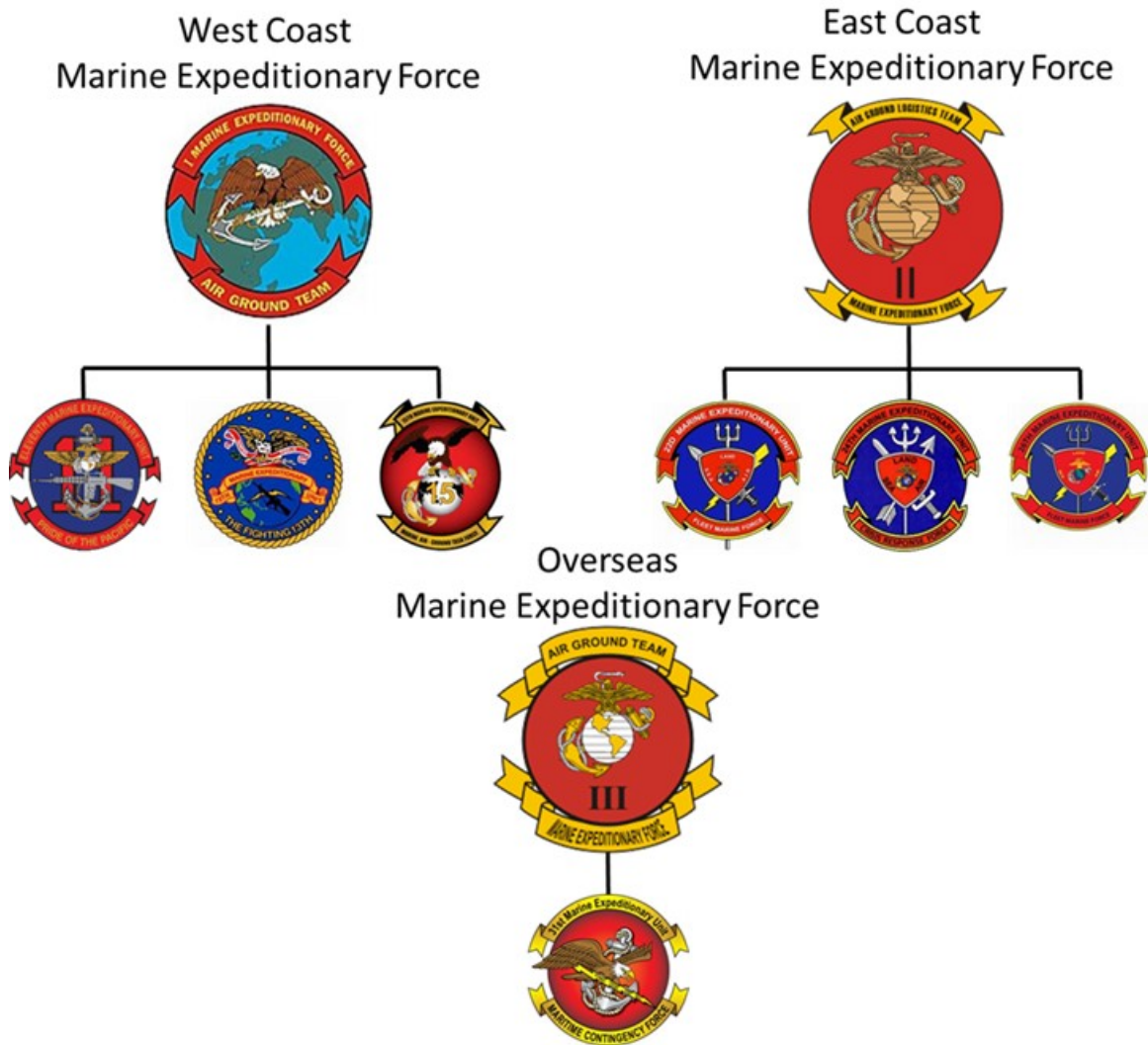


Figure 1. Marine Expeditionary Force Structure

2. Operational Readiness

Operational readiness is defined as the capability of a unit/formation, ship, weapons system, or equipment to perform the missions or functions for which it is organized or designed (DoD 2019). Under United States Code Title 10, the military service branches have the mission of ensuring operational readiness of their forces by manning, training, and equipping them. The long years of combat, both in Afghanistan and Iraq, coupled with other enduring forward deployed tasking, has degraded the overall operational readiness of the United States' forces. In 2014, the service departments were tasked by the DoD to

develop comprehensive plans to restore their forces to higher levels of operational readiness, and these plans were reported back to the DoD in 2015 (Governmental Accountability Office [GAO] 2016). Additionally, as part of the National Defense Authorization Act (NDAA) of 2016, the Congressional Defense Committees requested that an independent review of the overall plan for readiness recovery be conducted (NDAA 2016).

The GAO conducted this audit, and presented its findings to Congress, with an unclassified report titled “Military Readiness DoD’s Readiness Rebuilding Efforts May Be at Risk without a Comprehensive Plan” (GAO 2016). The report states that the DoD has identified that restoring its readiness is top priority, but that plans developed by the service departments lack the detailed strategies needed to link the planning with execution. Specifically, for the Marine Corps, the report identifies numerous shortfalls, the first of which is the lack of an overall readiness goal or strategy that can be backed up by analytic methods. According to the GAO, the Marine Corps states that its readiness is linked with five institutional pillars, “high quality people, unit readiness, capacity to meet combatant commander needs, infrastructure sustainment, and equipment modernization (GAO 2016, p. 8).” In addition to lacking a clear strategy for restoring operational readiness, the Marine Corps has not instituted measureable performance metrics to track readiness improvements. The report does state that the Marine Aviation community has instituted programs, specifically the Ready Basic Aircraft Recovery Plan, but these plans are only community centric. The ground communities have no similar plans (GAO 2016). A 2012 report by the Congressional Budget Office (CBO) regarding model usage by the DoD in planning for operational readiness similarly critiqued that the Marine Corps’ ground combat communities do not utilize models when developing their budgets for training. The Marine Corps does not utilize an analytic tool to justify the unit training plans and the resources required with the unit operational tempo requirements (CBO 2012).

Over its history, the Marine Corps has demonstrated an absolute ability to defend the United States as well as to be good stewards of the resources entrusted to it. However, in a period of constrained financial resources as well as peer adversary competition, the Marine Corps must have methods for establishing force-wide operational readiness goals

that are objective, defensible, repeatable, and traceable. Failure to do so opens the Marine Corps to outside scrutiny that it is currently not able to quantitatively refute.

3. Righting the Ship

In his address to the Congressional Defense Committees regarding the posture of the Marine Corps, Neller states that readiness is evaluated from two perspectives (Neller 2018b). The first involves having a force that is properly manned, trained, and equipped. The second perspective compares that same force against the abilities of adversaries of the United States. The Marine Corps is capable of meeting its forward deployed requirements with quality forces, but maintaining the current pace of operations is wearing down the non-deployed forces next in line to fill those overseas requirements. Additionally, the continuous pull of forces forward limits the Marine Corps' ability to respond to any pop-up threats not met by the forces already forward. By operating in this manner, the Marine Corps and the nation is operating with risk. Neller affirms that much of the Marine Corps' requested funding of the Presidential Budget Fiscal Year 2019 is planned to recover the readiness losses experienced over the preceding years. Nearly 32% of the overall Marine Corps budget is earmarked for modernization of the force (Neller 2018b). The investment of more money into the system alone will not right the ship. Decision makers need an analytical method for examining how the policies regarding operational readiness will affect the force in the long run. In a recent one-page tasking dated 16 August 2018 from the Commandant of the Marine Corps, Headquarters Marine Corps, Programs and Resources (HQMC P&R) was tasked with providing a quantitative means to account for readiness recovery (Neller 2018a).

A question that could be asked at this point is what is the current readiness tracking method and why can it not be utilized for this purpose? The existing system used to track current operational readiness is the Defense Readiness Reporting System (DRRS). DRRS starts at the tactical unit level, where commanders input readiness scores for personnel, equipment, supply and training (P, R, S&T). Much of the data for the scores is provided through the many tracking systems within the respective military service branches, such as Global Combat System Support-Marine Corps (GCSS-MC) and Marine Corps Training

Information Management System (MCTIMS). The DRRS system provides individual numeric scores for P, R, S&T as well as a combined readiness value. Tactical commanders have the ability to override the calculated score if they feel in their best judgment that it does not properly represent the unit's readiness. If the commander does utilize the override, the calculated score is still reported alongside the commander's score with comments. DRRS scores are then aggregated up through the hierarchy of the military until an overall Service score is attained, i.e., battalion, regiment, division, Marine Corps. DRRS is a sufficient tool at communicating current readiness, but lacks the ability to provide insight for long-term planning. DRRS is derived from observational data and provides a retrospective view of the effects caused by policy changes. It does not allow decision makers to experiment with potential readiness policies or resource changes to see their potential effects before implementing them.

The DoD has seen great benefit from the use of computer simulations and models in order to inform complex and otherwise costly decisions, and what was once a last resort is becoming the first horse out the gate (Lucas et al. 2015). One particular area of benefit is in the testing of weapons systems. The weapons systems of today are very expensive and field testing of new systems cannot be done in many cases to the degree that is desired. However, the requirement for dynamically testing and evaluating these systems remains, so the analyst must exploit the power of computer simulations in conjunction with small batches of live experiments. The Marine Corps needs to harness a similar process for developing and experimenting with potential operational readiness recovery profiles. In this venue, analysts would have the ability to experiment across a large spectrum of potential plans to include worst-case scenarios. Decision makers would have the ability to see the potential effect of their plans and be better able to make risk informed decisions. Models and simulations do not predict the future, but in the hands of a trained analyst, they can provide great insight.

4. Marine Corps Readiness Modeling

The Program Analysis and Evaluation (PA&E) Division is a sub-entity of HQMC P&R and has the mission of providing budgetary and program analysis. According to a

November 2015 update brief, PA&E began exploring the potential for computer simulation models to be used in modeling Marine Corps operational readiness strategic decisions in mid-2015 (Murray 2015). They began this process with Booz Allen Hamilton (Booz Allen), who had already been developing similar tools for the United States Air Force and United States Navy (Booz Allen 2018b). Two lines of effort were part of this process, each aimed at answering different readiness questions. The first line of effort was directed at the question of “how do force demands and force employment decisions impact Marine Corps readiness targets over time (Booz Allen 2018a, p. 3)?” Addressing this question will improve the Marine Corps’ understanding of what level of overall operational readiness must be maintained across the force both at home station as well as those forward deployed.

The Readiness and Availability Tool (RAT) is the out-product of this line of effort (Booz Allen 2018a). The RAT model is currently in version 2.0 and is in the verification, validation, and accreditation (VVA) phase for PA&E. The second line of effort, the Predictive Readiness Model (PRM), is aimed at connecting resource allocations and readiness policies to Marine Corps operational readiness. As described in the Current State Assessment, PRM was intended to model the complex relationships between resources and the four sub-parts of operational readiness, P, R, S & T. PA&E’s goal for PRM was to develop a tool that could provide the Marine Corps’ top leadership insight regarding budget allocation profiles. After the release of version 1.2, in June 2018, it was determined that a comprehensive review of the model was needed due to over-complexity challenges with the model. After a review of the model was complete, it was determined that a restart of the conceptual design process and a more incremental modeling process was needed (Booz Allen 2018b). The two models were designed to provide insight into different areas of operational readiness, but at the same time, they would be supportive of each other. The readiness goals found through the use of RAT are utilized as inputs as well as target values when simulating resource allocation profiles in PRM. The cancelation of the current PRM efforts does not reduce in any way the need for the insight provided by RAT.

The focus of this research and the designed experiments conducted is the Readiness and Availability Tool. Through the assistance of the Simulation Experiments and Efficient Designs (SEED) Center for Data Farming (<https://harvest.nps.edu>), we seek to leverage the

power of efficient simulation experimentation to explore the operational readiness impacts resultant from Marine Corps force structure and force employment decisions. The current framework that RAT utilizes allows for small-scale designed experiments, but nowhere in the scope of what is possible through the techniques of the SEED center. In order to make full use of RAT, an environment capable of running large-scale simulations was built around the model's existing framework. We then exercised the model across wide ranges of input values through a space-filling design in order to gain a wider understanding of the sensitivity of model outputs to model inputs. The data farming environment constructed around RAT will be given to PA&E in order to facilitate follow on operational readiness studies. Through the use of large-scale simulation PA&E will be enabled to create robust plans and policies that best prepare the Marine Corps to operate in the contested future while remaining flexible to changes that may emerge.

B. OBJECTIVES

The above discussion provides the basic context and motivation behind our research. Through the following objectives, we will set the conditions for Marine Corps' future use of RAT in making force structure and force employment decisions:

1. Improve the analytical power of RAT by enabling the use of large-scale experimentation.
2. Provide insight into the key questions asked of RAT by Marine Corps leadership specifically:
 - a. What effects do force employment and force structure decisions have on the frequency of C3 and C4 deploying units?
 - b. What effects do force employment and force structure decisions have on home-station readiness averages?
3. Assist PA&E with a sensitivity analysis that will be informative and applicable to RAT's VVA process.

C. THESIS ORGANIZATION

The focus of Chapter II is to provide an overview of Marine Corps' readiness modeling. The chapter covers the background history of PA&E and Booz Allen's projects to develop analytic readiness tools, the modeling methods utilized, the intended uses, and the internal structure of the models. Chapter III discusses the methods behind creating the design of experiments (DOE) and how the design was implemented. Chapter IV discusses data collection, post processing, the data analysis methods, and a detailed analysis of the results. Chapter V presents the findings of the research, recommendations regarding the future of the RAT, and suggested future research.

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II. USMC READINESS MODELING OVERVIEW

In this chapter, we provide an overview of the two readiness modeling tools that have been developed by Headquarters Marine Corps (HQMC), Programs and Research (P&R), Programs Analysis and Evaluation (PA&E), and Booz Allen Hamilton (Booz Allen). The primary focus of this research is on the Readiness and Availability Tool (RAT), including a detailed description of its background, intended uses, model design/implementation, and simulation execution. Although the focus of this research is not on the Predictive Readiness Model (PRM), this chapter also includes a brief overview of the background, intended uses, model design, and program issues encountered with that model as well. For further information on either RAT or PRM, see references: (Booz Allen 2018a), (Booz Allen 2018b), (Booz Allen 2018c), (PA&E 2018a).

A. READINESS AND AVAILABILITY TOOL

Understanding how force structure and force employment decisions effect operational readiness.

1. Background/Purpose: Starting with the Problem and Working Forward

In a February 2012 report, the Congressional Budget Office (CBO) concluded that the Marine Corps does not have appropriate modeling methods to link resource needs and training to be used for budget construction (CBO 2012). Additionally, the Government Accountability Office (GAO) released a 2016 report that states the Marine Corps lacks a quantitative method for determining its readiness-level goals, as well as for quantitatively determining appropriate performance metrics (GAO 2016). As a result of the 2012 CBO report, but prior to the release of the 2016 GAO report, PA&E began in early 2015 a program with Booz Allen to develop series of readiness modeling tools that would aid senior leaders within the Marine Corps in developing objective, defensible, repeatable, and traceable readiness goals (Booz Allen 2018b). RAT is one avenue of the larger readiness modeling approach adopted by PA&E. The goal of RAT is to provide insights that can aid in developing USMC force readiness levels in support of the Marine Corps'

operational requirements (PA&E 2018a). RAT helps answer the question, “how do force demands and force employment decisions affect Marine Corps [readiness] target [s] [levels] over time?” (PA&E 2018a, p. 1).

As described in a PA&E project overview from November 2015 on readiness modeling, the first iteration of RAT began in April 2015 (Murray 2015). The focus of this first model was only on the operational readiness levels of infantry battalions. The model was deterministic, and its goal was to develop the logic needed for follow-on iterations. Beginning in August 2015, a second iteration was developed using additional ground force elements, aviation elements, and infantry reserve units. Additionally, this second model had the ability to be either deterministic or stochastic (Murray 2015). RAT continued through developmental stages until its first deployable version (v1.0) release in March 2017 followed shortly by v2.0 (Booz Allen 2018a).

2. RAT Intended Uses: Understanding the Purpose behind the Model

RAT is designed to simulate combinations of force structures and force employment scenarios in order to gather insight regarding the effects of these combinations on the operational readiness levels of the Marine Corps as well as on individual units. In order to better define the purpose of RAT, PA&E developed the three intended uses depicted in Table 1.

Table 1. RAT Intended Use Cases. Adapted from PA&E (2018a).

<ol style="list-style-type: none">1) To analytically inform Marine Corps readiness decisions.2) To evaluate if readiness goals support deployment and contingency requirements.3) To generate input for the Marine Corps Predictive Readiness Model (PRM).
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PA&E further developed these use cases into key readiness questions and model applications that the Marine Corps will utilize RAT for in order to inform decisions. In this research, we focus specifically on two of these (Table 2). Further discussion into the significance of these key readiness questions is covered in Chapter III, as well as how they are captured as model output variables.

Table 2. RAT Key Readiness Questions Considered. Adapted from PA&E (2018a).

- 1) What effects do force employment and force structure decisions have on the frequency of C3 and C4 deploying units?
- 2) What effects do force employment and force structure decisions have on home-station readiness averages?

3. RAT Conceptual Model Design: Translating the Environment, the Problem, and the Purpose into a Model

A conceptual model is a description of how a real-world problem or phenomenon will be translated and represented in a simulation model. The conceptual level of design does not require discussion about implantation details; rather, the conceptual design gives the modelers a firm understanding of how they see the problem. Averill Law identifies building a conceptual design as the first step in the modeling process (Law 2013). The RAT technical documentation (Booz Allen 2018a) states that the modelers viewed the Marine Corps operational readiness process as having two primary parts: (1) the Marine Corps' ability to meet steady state demands and (2) its ability to source forces for contingency operations. In Figure 2, the Booz Allen team modeled steady state operations for force elements and deployment demands as a cyclical process of moving through the three states of dwell (DWL), pre-deployment training program (PTP), and deployment (DEP). Unplanned contingency operations alter the normal DWL-PTP-DEP cycle by pulling force element(s) in order to fulfill the pop-up requirement (Booz Allen 2018a). For more information on the RAT conceptual design, see references: (PA&E 2018b).

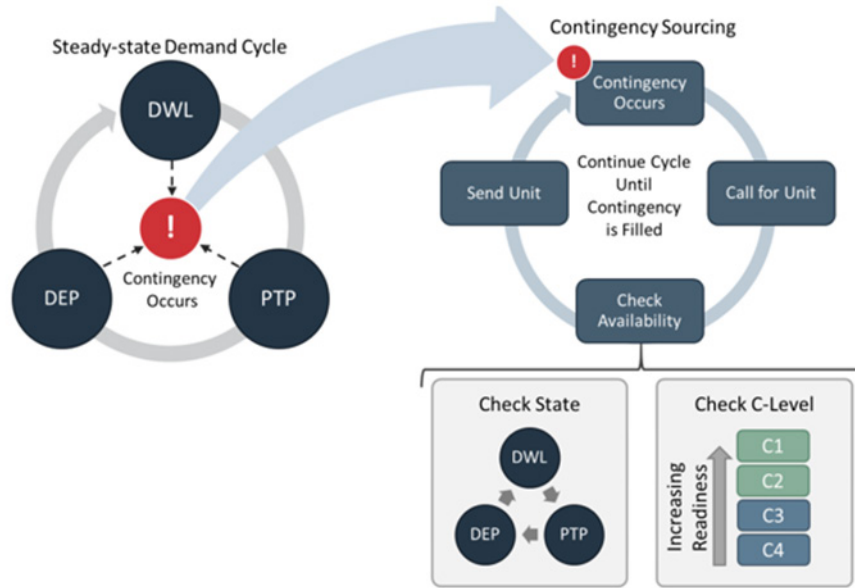


Figure 2. RAT Conceptual Design. Source: Booz Allen (2018a).

4. RAT Computational Implementation: Turning a Conceptual Model into a Computer Simulation

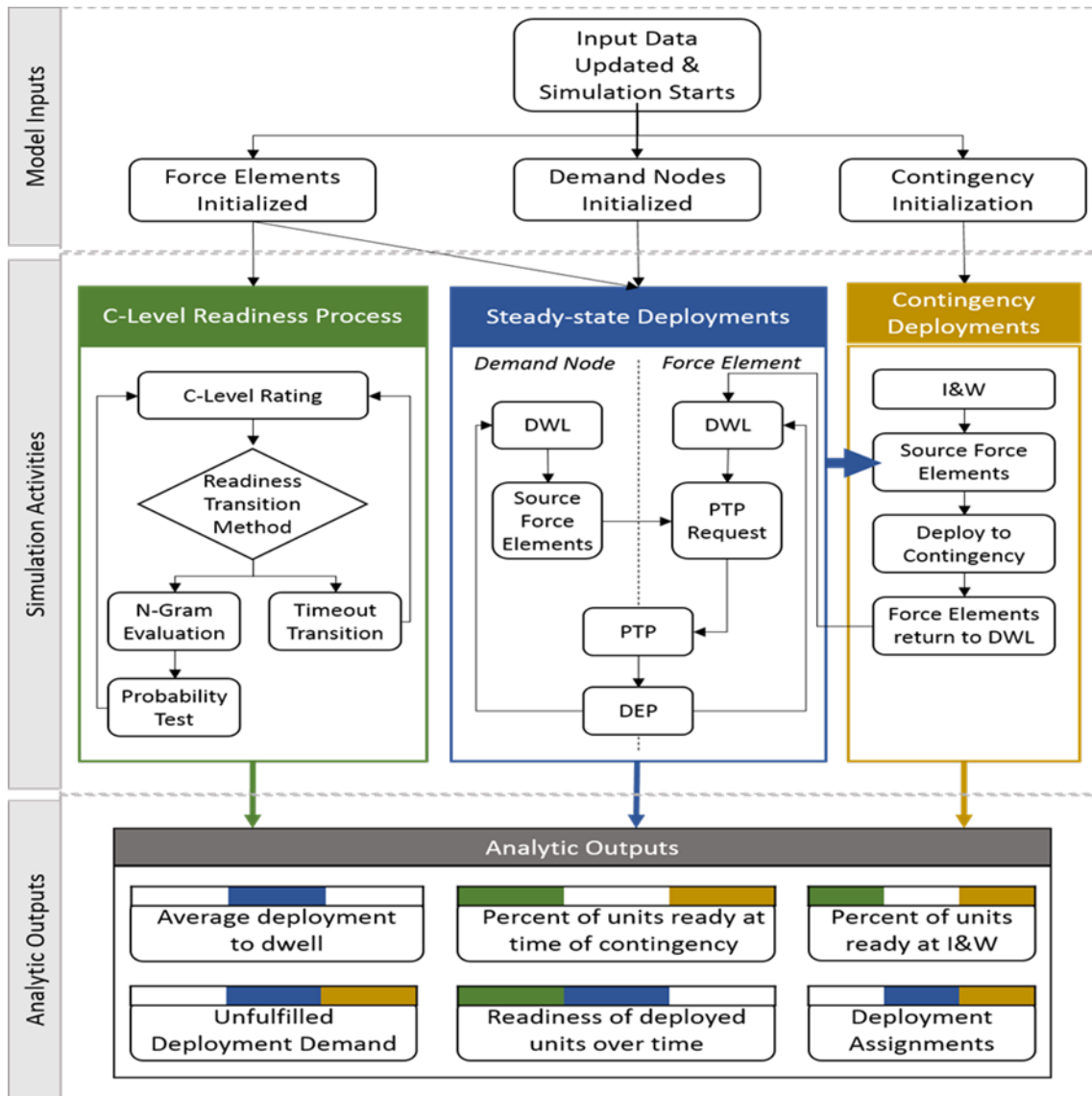
RAT is modeled as a discrete agent-based simulation (ABS). Averill Law (2013) describes ABS as a bottom-up approach that focuses on modeling the actions and states of the individual agents. In ABS, agents are the entities within the model that are given attributes and behavior characteristics. These characteristics describe how the entity will interact with other entities as well as within the overall system (Law 2013). Within RAT, force elements and deployment demands are represented by separate entities. These entities interact in order to have force elements fulfill a deployment demand need. Table 3 lists the Force Elements and Demand Nodes modeled in RAT V2.1 (Booz Allen 2018a).

Table 3. Force Elements and Demand Nodes

Force Elements	
Infantry (INF) Battalions	Marine Fighter Attack (VMFA) Squadrons
Light Armored Reconnaissance (LAR) Companies	Marine Medium Tiltrotor (VMM) Squadrons
MEU Combat Logistics Battalions (CLB)	Marine Light Attack Helicopter (HMLA) Squadrons
Assault Amphibious Vehicle (AAV) Companies	Marine Heavy Helicopter (HMH) Squadrons
Artillery (ARTY) Batteries	High Mobility Artillery Rocket System (HIMARS) Batteries
Deployment Nodes	
Marine Expeditionary Units (MEU)	Unit Deployment Program (UDP)
Special Purpose Marine Air Ground Task Force (SPMAGTF)	Tactical Air Integration (TAI)
Contingency Operations Major Contingency Operations (MCO) Humanitarian and Disaster Relief (HADR)	

In order to enact the conceptual model in a computational agent-based simulation, the RAT technical documentation (Booz Allen 2018a) states that the modeling team utilized AnyLogic modeling software. However, the user does not interact with the AnyLogic model, but rather with a Java User Interface and Microsoft Access Input Database. Additionally, the output from the model is exported from the AnyLogic model to a Microsoft Excel Output Workbook (Booz Allen 2018a).

Figure 3 depicts a top-level view of RAT’s computational modeling structure as it was implemented using the AnyLogic software. The structure comprises three separate phases: Model Inputs, Simulation Activities, and Analytic Outputs, with each phase having additional sub-processes described in follow-on sections.



Color codes found in Analytic Outputs correspond to which Simulation Activities section provides data to compute the specific output. For example, Average Deployment to Dwell only requires data from Steady State Deployments.

Figure 3. RAT Top Level Model Structure. Source: Booz Allen (2018a).

a. Model Inputs

As explained in the RAT technical documentation (Booz Allen 2018a), the data used to develop the force elements, deployment nodes, and contingency scenarios within RAT’s input database is derived from two primary sources, Defense Readiness Reporting System Marine Corps (DRRS-MC) and the USMC Playbook. The DRRS-MC data is used

to set the initial readiness level for force elements using their current or historical readiness statuses. Additionally, the DRRS-MC data was used to develop the N-gram tables that are part of the stochastic C-Level process. The Playbook data informs the analyst what deployment demands should be developed as well as what the starting DWL-PTP-DEP states should be for force elements and demand nodes. Lastly, the Playbook provides future deployment demand changes with location and time as well as Contingency planning guidance (Booz Allen 2018a). Both DRRS-MC and USMC Playbook data are classified sources, but the model is capable of using unclassified notional data as well. The model remains unclassified so long as the input data used is from unclassified sources.

Unlike some models that utilize input data throughout the simulation run, RAT's use of its input data is primarily for initializing the starting states of force elements, demand nodes, and contingency requirements (Booz Allen 2018a). This initialization occurs within the model process after the user has selected the desired simulation parameters from within the User Interface and has started the simulation run. After initialization, the model moves into the Simulation Activities phase.

b. Simulation Activities

The Simulation Activities phase has three sub-processes developed by the model designers to implement the conceptual model of how steady state and contingency demands are sourced: C-Level Readiness, Steady State Deployments, and Contingency Deployments (Booz Allen 2018a).

(1) Steady State and Contingency Sourcing Process

As the Steady State Deployment box (Figure 3, blue) shows, the demand nodes and the force elements are in separate DWL states. The force elements are called forward into PTP through a sourcing request from the demand nodes. At this point, the force elements are paired with the requesting demand through the PTP and DEP states. Following the DEP state, the force elements and demand nodes are once again separated as the process for each begins again. The RAT technical documentation (Booz Allen 2018a) states that the process for fulfilling deployment demands is governed by two separate sets of business rules (Table 4) for steady state deployments and contingency deployments. Although the specific rules

for steady state versus contingency are different, each of the business rules follows a similar algorithmic process. The first step in the algorithm is to develop a list of potential units to fill a deployment, with disqualified units removed. The second step is to sort the list based on prioritizing criteria unique to steady state or contingency operations (Booz Allen 2018a).

Table 4. Business Rules for Steady State and Contingency Sourcing.
Adopted from Booz Allen (2018a)

Steady State Demand Business Rules	
List of Modeled Units (U)	
List Units Eligible for Deployment (D)	
1. Check Every Unit in (U) and Add to (D) if Eligible for Deployment	
Ineligibility Factors	<ul style="list-style-type: none"> • Not in line with Deployment Business Rule Matrix in database • East Coast/West Coast constraint for MEUs • Supporting a Contingency Operation Currently • Permanently Deployed Unit • Assigned to Another Deployment • No Available Detachments Remaining at Home Station
2. Sort Units in (D) Based on Priorities	
a. DWL Time (Highest to Lowest)	
b. C-Level Readiness (C1 to C4)	
*If units have equal value randomly sort	
Contingency (including HADR) Demand Business Rules	
List of Modeled Units (U)	
List Units Available for Contingency (C)	
1. Check Every Unit in (U) and Add to (C) if Available for Contingency Sourcing	
Unavailable Factors	Force Element Already in Support of: <ul style="list-style-type: none"> • MEU • SPMAGTF • TAI

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Contingency (including HADR) Demand Business Rules
2. Sort Units in (C) Based on Priorities a. Unit Location Relative to Contingency i. Contingency Operations: Units Already Assigned to a Combatant Command Area of Responsibility ii. HA/DR: Distance to Incident (Closest to Furthest) b. Contingencies Only: Units Deployed to UDP c. Deployment Status Units (In Order of Global Response Force, PTP, DWL) d. C-Level Readiness Rating (C1 to C4) *If units have equal value randomly sort

(2) C-Level Readiness Process

Also depicted in Figure 3 is the C-level Readiness Process (green), which occurs in parallel with the other two processes. In RAT, readiness is represented only as the combined readiness levels of C1, C2, C3, and C4 (Booz Allen 2018a). Per Marine Corps Order 3000.13A, C1 and C2 represent units that are ready for deployment. C3 and C4 represent units with degraded operational readiness that are not ready for deployment (United States Marine Corps [USMC] 2017). The change in a unit's C-level is cyclical, like the DWL-PTP-DEP cycle. Under ideal conditions, as a force element completes a DEP and moves into a DWL period, a drop in C-level from C1 to either C3 or C4 will occur. This is the normal process expected within the Marine Corps as force elements retrograde and experience both personnel and equipment turnover. As time continues, the force element will near the end of DWL and begin working up for its next deployment in the PTP phase. The purpose of the PTP phase is to ready the unit; therefore, the C-level will increase from C3 to C2 and finally to C1. Throughout the DEP phase, the force element is expected to maintain itself at C1 until its tour is completed.

The model implements a unit's transition between the different C-levels through either deterministic or stochastic means. The deterministic method is referred to in the RAT technical documentation as timeout transition (Booz Allen 2018a). Under this method, the time a unit spends in a particular C-level is set up within the input database using the Force Generation tab. In the process, the user defines how long a unit will stay in a particular C-Level and what C-Level the units will transition to next. Multiple processes can be

developed in order to test the effects of particular force generation timelines (Booz Allen 2018a).

The model has two means of stochastically executing C-level transitions. The first is referred to in the RAT technical documentation (Booz Allen 2018a) as stochastic timeout transition. In this method, which is similar to the deterministic version, a unit is in a C-level for a period of time from which a transition will occur. However, in the stochastic timeout transition, the length of time as well as the next state (C-level) is determined by a user-defined discrete probability distribution within the input database. This method allows for variability in C-level transitions and allows units to move multiple levels in one-step (Booz Allen 2018a). The other stochastic method described in the RAT technical documentation is an N-gram process, visually depicted in Figure 4 (Booz Allen 2018a). In the N-gram method, a unit has the ability to transition to a higher or lower level of readiness, or to stay at the current one, each with its own separate probability. The Roots represent the historical readiness track of the unit in question, and the Stem Candidates are the potential future states. The values depicted in the matrix are the probability values associated with transitioning from the Roots to the Stem Candidates (Booz Allen 2018a).

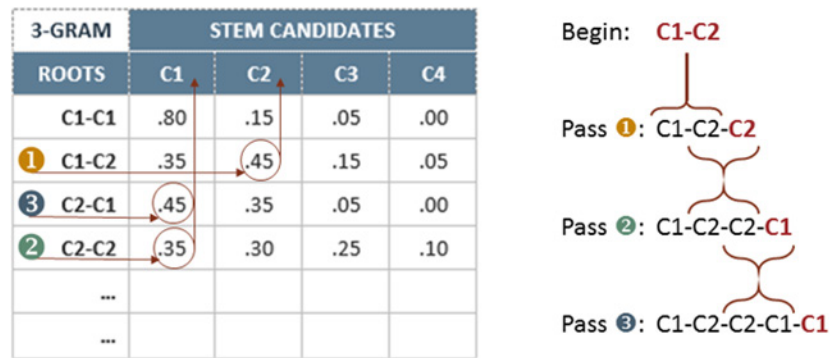


Figure 4. N-Gram Transition Matrix. Source: Booz Allen (2018a).

c. *Model Assumptions and Simplifications*

All models are wrong, but some are useful.

—British statistician George Box

A model will always be wrong to some degree because, in its very nature, it is a simplification of a real-world system and therefore cannot accurately represent every detail of that system. However, an analyst can develop insight from a model if the scope of that model's assumptions and simplifications are understood and adhered to. The key assumptions and simplifications of RAT, as described by the RAT technical documentation (Booz Allen 2018a) are as follows:

- (1) Assumptions facilitate implementation of the model in light of real-world unknown conditions (Booz Allen 2018a):
 - Demand Nodes are defined by the deployment requirements of unit types and quantities needed.
 - Decisions for determining which units will deploy for steady state and contingency operations can be made using a filtering and sorting algorithm.
 - Contingencies are a phased operation that require information regarding time of occurrence, length of operation, location, type and quantity of units needed.
- (2) Simplifications facilitate the modeling of known real-world conditions that are too complex to model exactly (Booz Allen 2018a):
 - Parent Unit readiness is not affected by readiness of detachments
 - Selection of deploying units are made only using the two business rules
 - Operational Readiness will use C-levels.
 - Demand Nodes are rotational or non-rotational:

- Rotational: UDP and SPMAGTF
- Non-rotational: MEU, TAI, Contingency
- Demand nodes and Force Elements use a supply-and-demand structure
- Demand node sourcing uses historical information as well as future plans
- The steady state cycle consists of only the three states, DWL-PTP-DEP.
- Steady state demands (MEU, UDP, TAI, SPMAGTF) must be filled even during Contingency demands
- Contingency demands have precedence over pop-up HADR missions

5. Simulation Execution and Output: Making the Model Work for You

This section will describe how the user interacts with RAT in order to conduct a simulation run as well as access the model output data.

a. User Abilities and Interactions

The model development team utilized the described use cases (Table 1) of RAT in developing the methods of user interaction with the model. The use cases were aggregated into four overall actions (Booz Allen 2018a):

- Editing Demand Node Data
- Editing Force Element Data
- Editing Scenario Data
- Running Simulation

Each of these actions have additional supporting actions, as shown in Figure 5. It can also be seen in Figure 5 that some of the supporting actions are included in more than one of the aggregated actions: for example, “Add C-state Level” is part of “Editing Demand Node Data” and “Editing Force Element Data.”

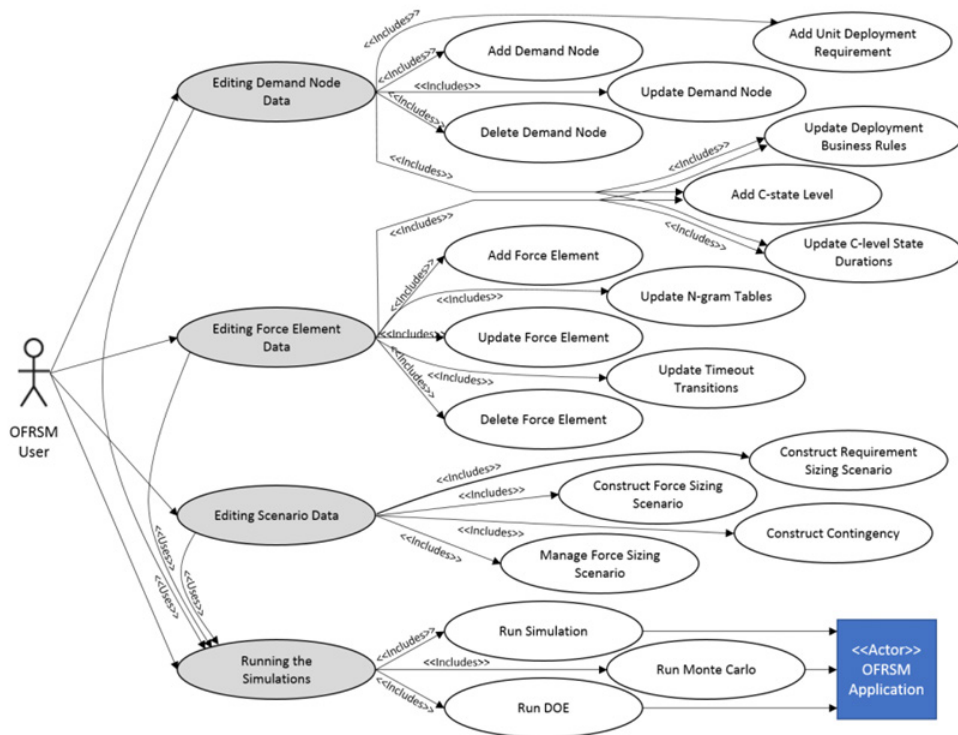


Figure 5. User Interactions with RAT. Source: Booz Allen (2018a).

The user conducts these various actions through the model’s two primary interfaces, the Java user interface and the input database. The input database is implemented using Microsoft Access and has multiple tabs that allow a user to complete the actions of editing demand nodes, force elements, and scenarios. The Java user interface is a graphical user interface (GUI) tool that allows the user to select which parameters from the input database will be used in a simulation run.

b. Running a Simulation

The analyst utilizes the GUI in order to set the parameters for a simulation run as well as execute the run itself. From the Main Inputs page (Figure 6), the analyst has multiple options for what type of simulation they intend to run. Additional model parameters can be accessed using the Advanced Inputs page (Figure 7). Details regarding the available modeling parameters are covered in Chapter III.

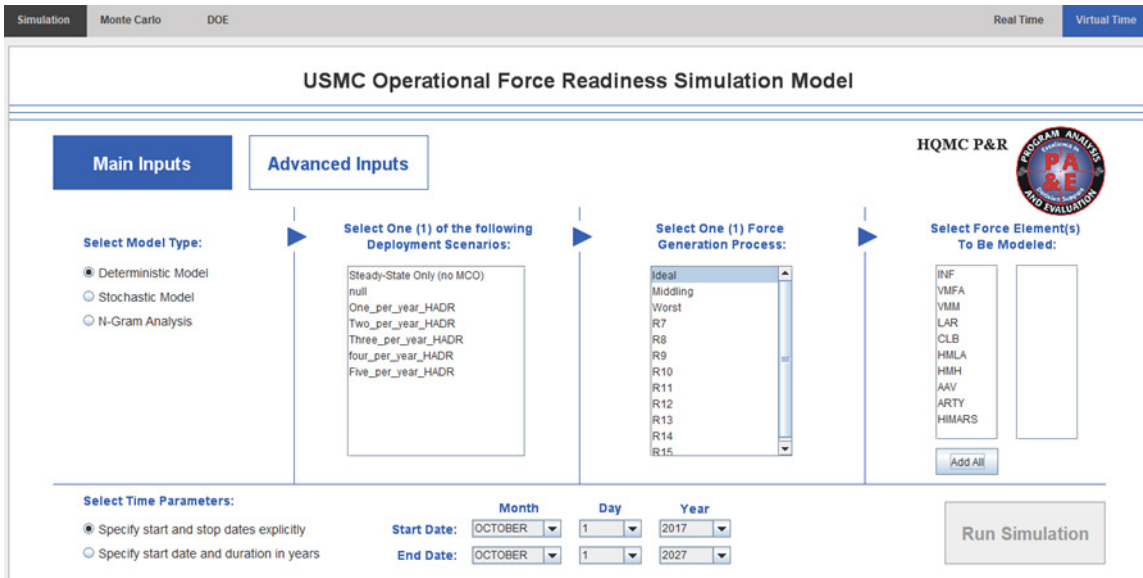


Figure 6. RAT GUI Main Inputs Page

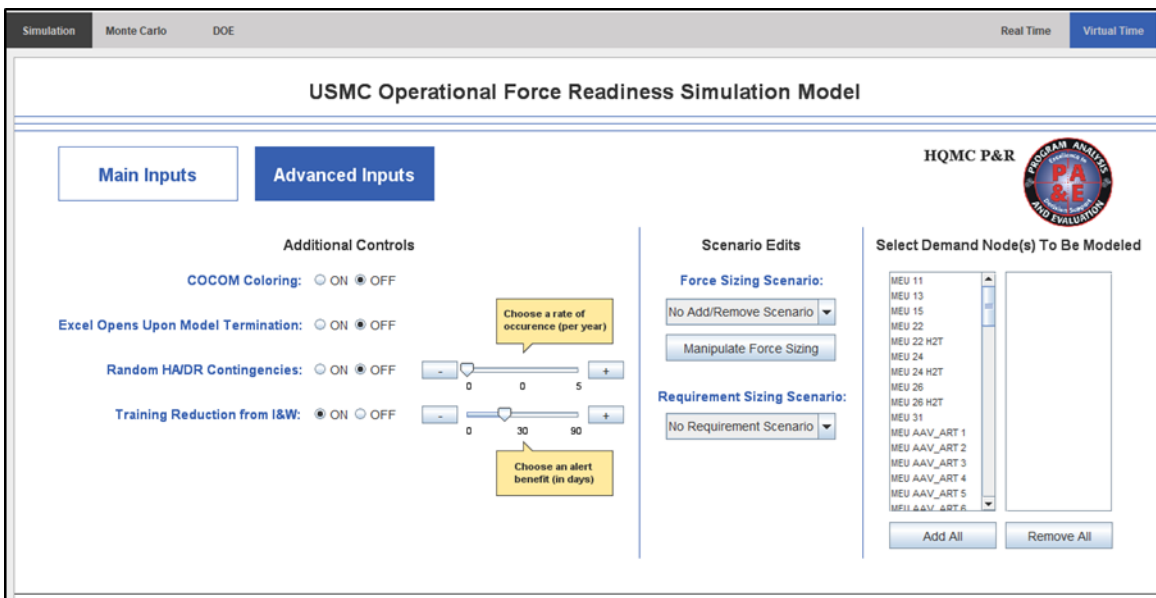


Figure 7. RAT GUI Advanced Inputs Page

c. Model Outputs

The final phase of the RAT modeling process, as shown in Figure 3, is Analytic Output. A key measure of a model's usefulness is the usability and utility of its output data

and products. At the completion of a simulation run, a multiple tab dashboard displaying the output data is presented (Figure 8).

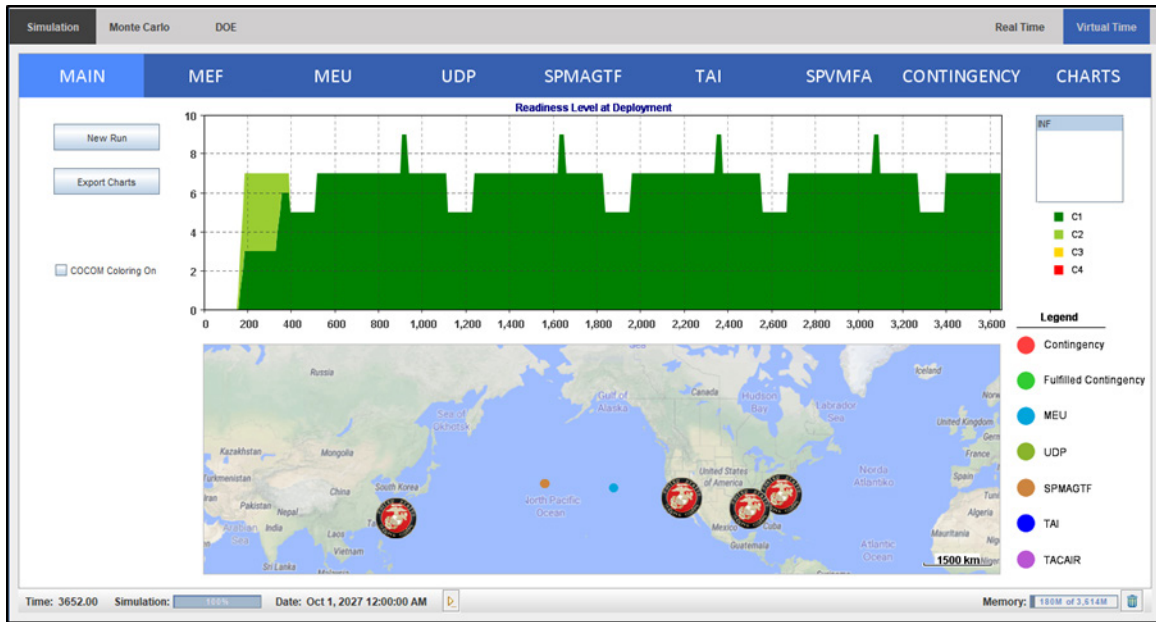


Figure 8. Simulation Output Main Dashboard

The Booz Allen team designed the output dashboard to provide both graphical and numeric information to the model user that would support the intended uses and key questions posed in Tables 1 and 2 (Booz Allen 2018a). The tab most useful for the user on the Main Dashboard (Figure 8) is the “CHARTS” tab, which allows the user to access the Executive Summary (Figure 9).

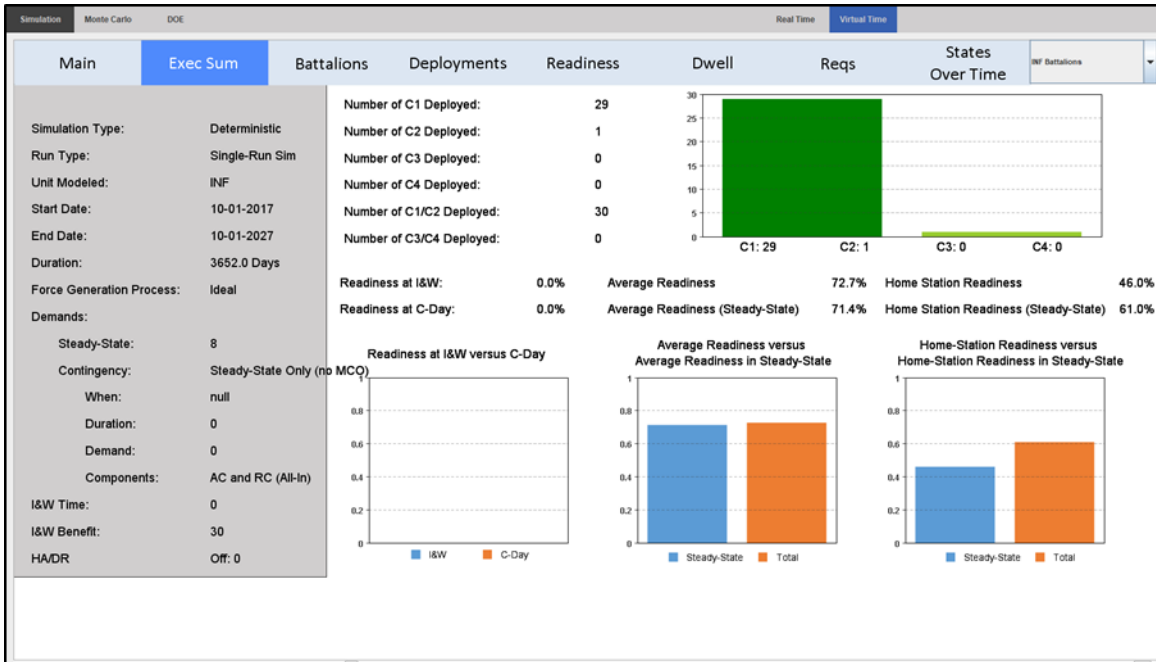


Figure 9. Simulation Executive Summary Under the CHARTS TAB

The Executive Summary provides key information regarding the number of ready and non-ready units deployed as well as the average readiness levels of both deployed and home station units. Additionally, from the Executive Summary tab the user has the ability to access more tabs that further breakdown readiness and deployment history of both force elements and demand nodes. Specifically, a visual depiction of the deployment schedule over time is shown under the “States Over Time” tab (Figure 10).

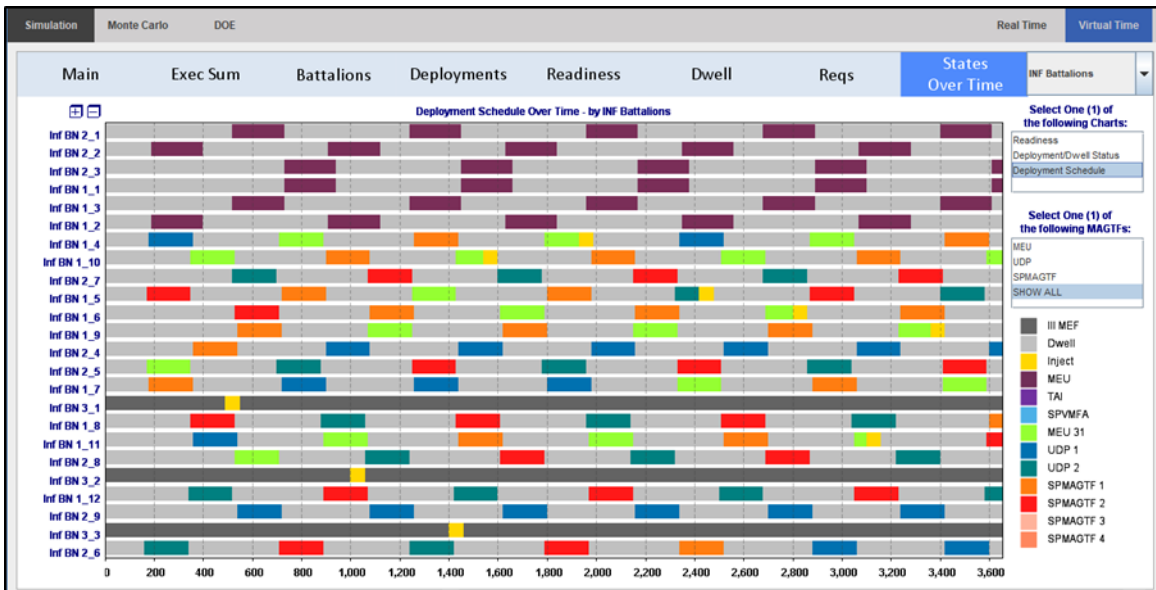


Figure 10. Deployment Schedule

To facilitate further analysis, the model outputs the same data to an external Microsoft Excel file. This file provides the user with another dashboard presentation (Figure 11), but also provides the ability to access the underlying data that created the graphic displays and summary statistics.



Figure 11. Microsoft Excel Output Dashboard

6. RAT Summary

RAT is one of two readiness modeling projects underway within HQMC P&R in conjunction with Booz Allen. The purpose of RAT is to explore questions regarding the effects of Marine Corps force structure and force employment decisions on operational readiness. RAT is a discrete-event, agent-based simulation that is modeled using AnyLogic software. Model users interact with RAT through a JAVA user interface and Microsoft Access input database. Output from the model is presented within the user interface as well as through an external Microsoft Excel workbook. RAT is currently going through its VVA process. Figure 12 graphically displays the implementation structure of RAT described in this section.

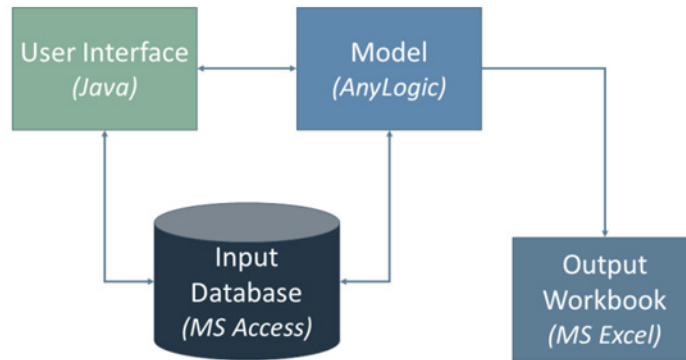


Figure 12. RAT Implementation Structure. Source: Booz Allen (2018a).

B. PREDICTIVE READINESS MODEL

For too long the Marine Corps has been unable to trace resources to readiness or predict changes in unit readiness due to programmatic or force management decisions made today. Given advances in technology that enable the implementation of time-tested mathematical and simulation techniques the institution can no longer continue to provide our senior leaders with less-than-the-best possible analysis. (Booz Allen 2018b, 12)

1. Background

The Predictive Readiness Model (PRM) is the second step in PA&E’s readiness modeling program. PRM sets out to provide insight for Marine Corps decision makers on how resource funding decisions and strategic policies influence the operational readiness of the force (Booz Allen 2018b). PRM is designed to work in concert with RAT in order to understand what resourcing is needed to maintain the home-station and deployed readiness goals found through RAT.

As discussed in the Current State Assessment (Booz Allen 2018b), in the summer of 2015, PA&E began initial exploration into modeling how resources allocation profiles effect operational readiness. At the time, Booz Allen was working with PA&E on RAT as well as working with the United States Air Force and Navy on resource readiness models. A pilot program began between PA&E and Booz Allen in September 2015 that modeled equipment readiness for VMFA Squadrons and AAV Battalions. The pilot study successfully demonstrated to the Marine Corps the importance of having a resource modeling technique (Booz Allen 2018b).

Following the pilot program, PA&E began the PRM program in August 2016 with the desired end state of “a Government owned/Government operated predictive readiness model for select force elements that provides sufficient analytically-based decision support that is clearly defensible when faced with making programmatic and force management choices” (Booz Allen 2018b, 11). It was decided in August 2016 that modeling the infantry battalion force element would be the initial production goal, with follow on versions including additional force elements to be delivered over a multiple year period. Booz Allen released PRM version 1.0 in March 2018, followed closely by versions 1.1 and 1.2 in April and June, respectively (Booz Allen 2018b).

2. Intended Uses: Defining the Purpose of PRM

The intended use of PRM as articulated in the end-state goal of the Deputy Commandant (DC) of P&R is to inform leaders about the impact of potential budget, program, and force structure decisions, as well as provide quantitative defense of those decisions throughout the budget review process. In application, PRM is a tool that will inform the Marine Corps on how to make defensible decisions throughout the Planning, Programming, and Budgeting Execution (PPBE) process (Booz Allen 2018b). Figure 13 graphically shows how PRM fits in throughout the PPBE process and where its impacts can be made.

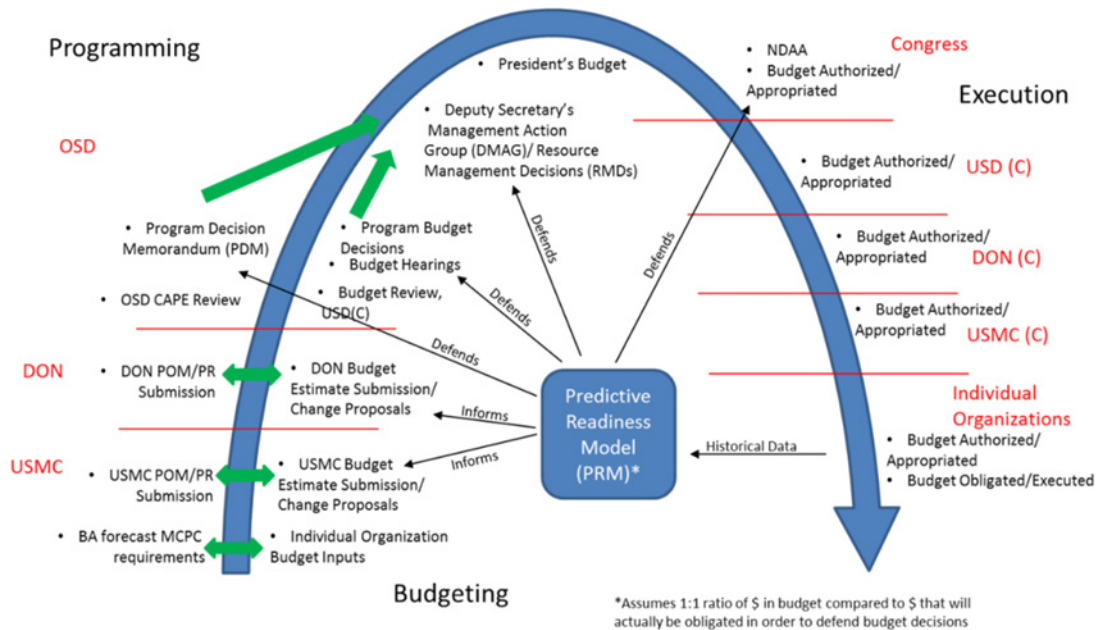


Figure 13. PRM’s Applications within PPBE Process. Source: Booz Allen (2018b).

In addition to these areas of application, the PA&E team developed six use cases (Table 5) that further help define the specific intended purpose of the model.

Table 5. PRM Intended Uses, June 2018. Adapted from Booz Allen (2018b).

- | |
|--|
| <ol style="list-style-type: none"> 1. Modify funding profiles to see changes in readiness over the Future Years Defense Program (FYDP). 2. Understand the effect that across-the-board cuts (salami slices) have on readiness over the FYDP. 3. Compare/contrast two different funding profiles to see readiness over the FYDP. 4. Understand the effect of force employment changes on readiness over the FYDP. 5. Understand the effect of USMC end strength changes on readiness over the FYDP. 6. Quantify the effects of Continuing Resolutions on readiness over the FYDP. |
|--|

3. PRM Model Design

How do you Translate Operational Readiness into Modeling and Simulation?

a. Modeling Method

The current state assessment (Booz Allen 2018b) indicates that the modeling team viewed operational readiness as a process driven heavily by the flow of resources within a connected network of nodes. These resources could be physical, such as the number of Marines or vehicles provided to a unit, or less tangible, like the amount of training time allotted to a unit for PTP. This vision of resources flowing within a network unfolded in the selection of an overall System Dynamic (SD) modeling method (Booz Allen 2018b).

Averill Law discusses in his book *Simulation Modeling and Analysis*, that SD models have two primary components, stocks and flows. Stocks represent quantities of resources, and flows represent the movement of those resources into or out of a stock. These two primary components are combined within a stock and flow diagram. The diagram itself is the visual representation of the SD model and explains the different variables and relationships within (Law 2013).

The current state assessment (Booz Allen 2018b) informs us that the modeling team implemented the SD stock and flow diagrams for PRM in is referred to as Causal Loop Diagrams (CLDs). Within the CLDs there exist a hierarchy of key variables (Global, First-Order, Middle-Order, Final-Order) that represent the independent factors driving readiness. Model inputs enter the CLDs through the Global variables and drive the values of the subsequent levels of key variables through causal links. Causal links connect key variables and contain the algorithms used to calculate how the value of one variable drives the value of another. At the completion of a simulation, the Final-Order variables of personnel, supply, equipment, and training (P, R, S&T) readiness levels are calculated (Booz Allen 2018b).

In addition to PRM being a SD model, it was desired by the Marine Corps that PRM have the ability to capture both the top-level view of Marine Corps-wide force readiness and unit-level readiness over time. To achieve this, the modeling team additionally utilized

agent-based modeling within the SD framework to capture the hierarchy of the Marine Corps (Booz Allen 2018b).

In summary, the overall modeling method utilized for PRM is discrete event, system dynamic (SD), and agent-based. Figure 14 displays the high-level modeling structure that was implemented in the creation of PRM.

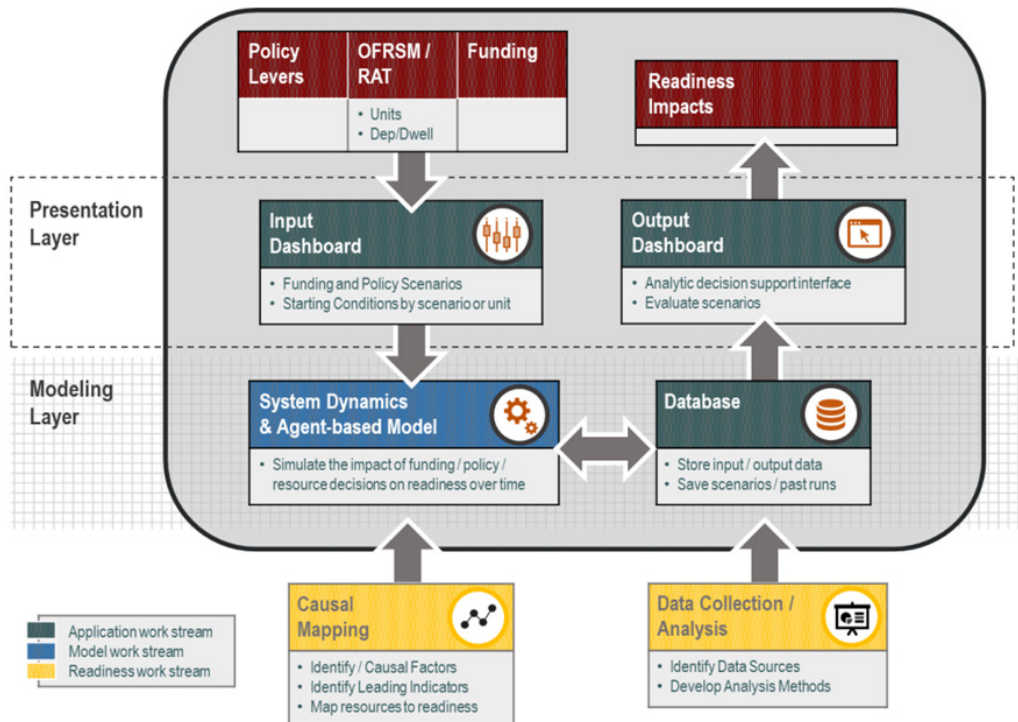


Figure 14. High-Level Modeling Structure. Source: Booz Allen (2018b).

4. Challenges in Execution

During the first few months with the early versions of PRM, challenges were experienced using the model resulting in PA&E’s request for a comprehensive review of the current PRM model to be completed by Booz Allen (Booz Allen 2018b). In September 2018, Booz Allen released the findings of this review in the Predictive Readiness Model Current State Assessment. Among many other challenges, Booz Allen identifies two overarching issues: over-complexity and lack of data-driven relationships (Booz Allen 2018b).

The challenge of over-complexity is a function of trying to model a difficult target such as tying resources and policies to operational readiness generation. The CLDs that were developed highlighted the vast number of causal factors involved in this process. The current state assessment indicates that it was believed that the complexity of the CLDs was a positive aspect of the model, however, they proved to be unwieldy to implement in a model (Booz Allen 2018b).

The difficulties with data-driven relationships in PRM is a further offshoot of the complexity of the CLDs. A key aspect to SD modeling is having functions that map the causal relationships between the variables in the model to enact the flow of resources (Booz Allen 2018b). Because of the complex causal relationships, the model requires a vast amount of data to develop the quantitative functions between the PRM key variables. In a discussion with the PA&E team in September 2018, it was stated that only 65 of the key variables used in PRM v1.2 were data developed, with 79 utilizing notional values (Cinotti 2018). Although these values allowed the model to run, they presented major problems with the verification and validation process (Booz Allen 2018b).

The comprehensive review performed by Booz Allen clearly states that the Marine Corps will benefit greatly from a model that can link resource allocations and strategic policies to operational readiness. The review further recommended to conduct a ground-up restart of the PRM project focused on an incremental model-building approach and to reuse previously built model structure where able (Booz Allen 2018b).

5. Model Summary

PRM is one of two readiness modeling projects underway within USMC P&R in conjunction with Booz Allen. The purpose of PRM is to explore the questions regarding the effects of USMC resource allocation and strategic policy decisions on operational readiness. PRM is a discrete-event, system dynamic, and agent-based simulation. Due to the issues found in PRM Version 1.2, the project is currently on hold. However, the need for such a capability still exists.

III. EXPERIMENTAL DESIGN

This chapter discusses the design approach taken for exploring the model factors that impact the Readiness and Availability Tool (RAT) and the Marine Corps Readiness System. Section 3A provides a brief overview of the art and science associated with the field of Design of Experiments (DOE), as well as its contribution to simulation analysis. Section 3B focuses on the output response variables selected to facilitate analysis of the Marine Corps' readiness questions. Section 3C provides an overview of the design factors and initialization parameters utilized in the DOE. Lastly, section 3D covers the final design selected.

A. DESIGN OF EXPERIMENTS: HOW BEST TO HARVEST YOUR DATA FARMING EFFORTS.

Design of Experiments is a computationally efficient methodology for determining which model factors have an important impact on a response, taking into account interactions that may occur between factors (Law 2017, Tutorial, p 563).

DOE is a field of study that has its roots in the early 1900s with physical experimentations, but due to recent research into advanced methodologies, DOE has been effectively adapted to conduct large-scale computer simulations involving highly complex systems (Vieira et al. 2011). DOE for modeling and simulation focuses on efficiently utilizing the inputs of a model to gain the most analytical benefit and insight from the model's output variables. Developing a DOE and implementing it for a simulation is a combination of art and science. The analyst must be able to dissect the model to properly frame the problem. They must utilize the advice of subject matter experts (SMEs) to compile the distributions associated with potential input and output variables to be explored. Lastly, the analyst must properly scope their analysis through the use of assumptions. All of these can be classified under the art of designing an experiment. The science behind a DOE is the alignment and spacing of the design factor levels in such a manner that the design space is efficiently explored without the introduction of confounding effects. A DOE built with only consideration given to the science of development will efficiently explore the design space, but may fall short of providing

insight to the problem at hand. Conversely, a design that properly employs art with no adherence to science may find its output data unusable due to the entanglements of confounded factors. By harnessing both the art and science of DOE development, an analyst can leverage the full effects of a simulation and perform detailed and relevant analysis on the problem at hand.

B. RAT RESPONSE VARIABLES: SYMPTOMS OF THE HEALTH OF THE OPERATIONAL READINESS SYSTEM

In this research, we utilize response variables as symptoms of a readiness system's health similar to the way a doctor would view symptoms presented by a sick patient. RAT, like most models, has the ability to present many different response variables for analysis. In order to derive which response variables from the model will be of importance to our research, we utilize the common military method of backwards planning, in backwards planning, we examine the desired end state of a mission and plan backward in order to develop enabling conditions to reach that end state. The same idea can be effectively implemented for a simulation by focusing on the model's intended uses. Through examination of the model's intended uses and key questions asked by the Marine Corps (Tables 1 and 2), we focus our efforts on the following two response variables.

1. Percentage of Non-Ready Units Deployed

The deployment of non-ready (C3 or C4) units imparts considerable risk on the military force. As former Secretary of Defense Donald Rumsfeld stated in 2004, "You go to war with the Army you have, not the Army you might want or wish to have at a later time."

2. Average Home-Station Readiness

Determining the level of home station readiness to be maintained is a question of both risk as well as cost. As the Commandant of the Marine Corps discusses in the Marine Operating Concept, the Marine Corps must be ready to deploy forces from the United States to meet unforeseen threats (USMC 2016). In order to fill these unforeseen missions, the Marine Corps must maintain ready units. These ready units, however, cannot be those units currently in pre-deployment training for a steady state requirement. Utilizing these

forces would have compounding readiness issues and effectively be an instance of robbing Peter to pay Paul. Rather, the Marine Corps needs to establish and maintain a ready bench. How many units should be ready? A balance must be struck between readiness and risk to ensure that the cost of maintaining this bench is sustainable.

It is a logical expectation that home-station readiness levels will contribute to the number of non-ready units deployed. An additional goal of this analysis is to examine the trade-offs between these two response variables.

C. MODEL INPUTS

This section will discuss the primary model inputs that set the conditions for the system to operate within.

1. Decision Factors: The Root Causes to your Readiness Health

Continuing the medical analogy used in 3.B, the connection between response variables and decision factors is comparable to symptoms and the root causes of an illness. Although symptoms (response variables) provide evidence of a potential problem, they are merely a manifestation of the root causes (decision factors). The true value of a simulation analysis is not in simply reporting the response variable values, but rather in the ability to understand the interactions between decision factors and the casual relationships that result in the observed system responses. Determining the level of significance or impact that a decision factor has on the model's output is often the analyst's primary objective (Sanchez, Sanchez, and Wan 2018).

Decision factors are the independent variables of the model, and as the term decision implies, they are generally the variables that the modeler has some degree of control over. They are grouped into quantitative (numerical in nature) and qualitative (categorical in nature) factors. Qualitative factors can be further broken down into being ordinal (assigned order) or nominal (no assigned order) categories. Levels of a decision factor refer to the range of values, continuous or discrete for a quantitative variable or the number of categories for a qualitative variable.

In the context of the RAT input database, the four primary qualitative (ordinal categories) decision factors are Force Generation Timelines, Requirement Sizing Scenarios, Force Sizing Scenarios, and Contingency Operation Scenarios. Table 6 highlights these decision factors. RAT’s decision factors should be considered qualitative in nature with each level being a discrete scenario programmed into the input database. Further explanation of the exact levels utilized for these decision factors is covered in section 3.D. Design Methodology.

Table 6. RAT Categorical Decision Factors

Force Generation Timelines
<p>Purpose: These timelines represent Marine Corps polices regarding the readiness progression of units. Within the model, these timelines are utilized as the deterministic C-level state transition matrices for each of the demand node type. The state transitions are between the different C-levels (C4-C3, C3-C2, C2-C1, C4-C1) with a time duration in days. Force elements do not have their own force generation timelines. Rather, force elements are associated with a primary demand node and utilize its force generation timeline. *Stochastic C-Level Transition utilizes a different input method.</p> <p>User Abilities: The model user sets the force generation process name, selects the demand node type, selects the starting C-level state, sets the time duration in the current state, and sets the next state to transition to.</p>
Requirement Sizing Scenarios
<p>Purpose: These scenarios represent Marine Corps force employment plans as they relate to steady state deployments. The user is able to add or subtract the types and quantities of force elements required by a specific steady state demand node that has previously been built in the database. During a simulation run, demand nodes cannot be created or removed, but through the use of a requirement sizing scenario, the demand nodes can be rendered on or off by adding or removing the number of force elements assigned.</p> <p>User Abilities: The user sets the scenario name, selects the existing demand node to modified, the number and type of force element to be adjusted, and the model time of the requirement modification to take place. Additional requirement modifications can be completed within a named scenario.</p>
Force Sizing Scenarios
<p>Purpose: The end strength of the Marine Corps is a topic that receives a lot of attention and, over the Marine Corps’ history, this number has increased and decreased as national security situations dictated. These scenarios allow a model user to explore varying Marine Corps end strengths by the addition or subtraction of individual force element units.</p> <p>User Abilities: The user sets the scenario name, the force element type to be modified, if the change will be an add or remove, and the name of the existing unit (removal) or new unit name. Lastly, the model execution time for the modification is selected. Within a force sizing scenario, multiple units can be added or removed.</p>

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Contingency Operation Scenarios

Purpose: An enduring message of the Commandant in the Marine Operating Concept is the need for ready to deploy forces (USMC 2016). These forces are needed to meet emerging and unplanned threats as well as provide relief forces during disasters. One of the key questions asked of RAT is how well does the Marine Corps recover from disruptions in the steady state deployment cycles (Booz Allen 2018a). These scenarios allow the model user to inject unplanned contingency operations that could be a single pulse of forces or consist of many phased deployments over time.

User Abilities: The user provides a scenario name, but also what event (phase) to create. By adding additional events, the user can create a phased deployment operation. Within each event, the user further specifies at what time in the model the event will occur, the duration in days, the locations in Latitude and Longitude, and the type and quantity of force elements required.

The user abilities described in Table 6 for each of the decision factors provide numerous continuous value input possibilities, but the manipulation of these values cannot be done in real time. Only the values entered in the pre-developed scenarios within the input database prior to a simulation run can be modeled. This process does allow for a wide range of values to be explored, but with the cost in time of developing each unique scenario.

2. Model Initialization: Developing the Baseline Starting Conditions

Not all model inputs to RAT were treated as decision factors in this research. Many inputs are needed to initialize the model and are held constant across all simulations runs. For RAT, these inputs represent the baseline force structure and steady state deployment demands from which the decision factors will deviate from.

a. Steady State Demand

As mentioned in Chapter II, RAT is capable of modeling Marine Expeditionary Units (MEUs), Special Purpose Marine Air Ground Task Forces (SPMAGTFs), Unit Deployment Programs (UDPs), and Tactical Aviation Integrations (TAIs). The baseline deployment demand was established at eleven nodes; six continental based MEUs, one overseas MEU, two SPMAGTFs, and two UDPs. These demands were evenly divided between I Marine Expeditionary Force (MEF) and II MEF, excluding the Overseas MEU which was assigned to I MEF. Two additional SPMAGTF nodes were created, but not assigned any requirements in order to utilize them within requirement sizing scenarios.

b. Force Structure

In this study, we focus on the infantry force element only and will utilize the current force structure of the Marine Corps, which consists of a total of (24) battalions, (12) assigned to I MEF, nine assigned to II MEF, and three assigned to III MEF. In addition to developing force-elements, deployment-business-rules were established to determine what primary and secondary demand node type (MEU, SPMAGTF, UDP) each infantry battalion would fulfill. The baseline deployment-business-rules provided I MEF and II MEF with three dedicated MEU infantry battalions and the remainder of their battalions assigned to fill both SPMAGTFs and UDPs. III MEF units are considered in RAT to be permanently deployed forward and are not associated with a specific primary or secondary demand node.

c. Deployment Schedule

The last major initialization steps are to assign the demand nodes to the starting deployment schedule and to align specific force elements to demand nodes. In order to remain unclassified, the deployment schedule for this study utilized the Marine Corps Deployed Unit Database supplied by the Center for Naval Analysis (Center for Naval Analysis [CNA] 2019). In this data set, CNA captures historical unit deployments, allowing the study to develop a deployment schedule that properly aligns with Marine Corps planning. The unit deployment schedule utilized for this study is from the Marine Corps' unit deployment picture on 1 October 2016.

3. Scenario Assumptions

Just as assumptions must be made when developing a model in order to scope reality, assumptions had to be made regarding the baseline scenario.

a. Deployment Business Rules Remain Constant

The internal rules for which type of deployment an individual force element can fulfill is assumed to remain constant over the simulated ten-year period.

b. Starting Readiness Levels

In this research, we are assuming that readiness system at day zero was functioning properly and had been sufficient to meet the demand requirements prior to the simulation start. This decision was made in order to examine the effects of our implemented force employment and force structure decisions over a 10-year period without adding any bias from an already insufficient readiness system. Therefore, at the initialization of the model, we assume that any unit in either DEP or PTP is at a readiness level of C2, with all others at C3.

c. Force Sizing and Requirement Sizing Scenario Start Times

All decisions involving force structure and demand node requirements are made at the beginning of the simulation run.

D. DESIGN METHODOLOGY

1. Decision Factor Level Selection

In December 2018, a research-design planning meeting was held between the research team and the operations research section within PA&E. The goal of this meeting was to establish the scope of the overarching research scenario and to determine the range of levels to explore within the decision factors. It was decided that the research scenario would focus on the current infantry battalion force structure and major deployment demand nodes of MEUs, SPMAGTFs, and UDPs (Killian 2019). Table 7 lists the desired number of levels for each of the decision factors. Detailed discussion of what each level represents is described later in this section.

Table 7. Decision Factor Levels

Decision Factor	Number of Levels
Force Generation Timelines	10
Requirement Sizing Scenarios	5
Force Sizing Scenarios	6
Contingency Scenarios	4

a. Force Generations Timelines: Six to 15 Months to Reach C2 Readiness

The goal of PA&E and the research team in the development of the Force Generation Timelines was to explore the effects of units taking increased time progression from unready to ready (C4/C3 to C2). Once a unit reaches the C2 level of readiness, they are considered ready. Ten different Force Generation Timelines were developed with readiness progression periods ranging from six to (15) months.

b. Requirement Sizing Scenarios: Five to Nine Steady State Deployment Demands

The goal of PA&E and the research team in the development of requirement sizing scenarios was to apply stress to the Marine Corps' readiness system and gain insight to its force deployment capacity. PA&E, along with the research team, decided that varying the number of SPMAGTFs would be the most appropriate way to implement various stress levels. Unlike increasing the number of MEUs, which would require the United States Navy to also expand its amphibious fleet, adding a SPMAGTF is relatively straightforward. Additionally, SPMAGTFs are rotational, meaning that the deployment presence itself is continuous, with new units conducting reliefs in place at specific time intervals. Requirement sizing scenarios represent the implementation of the Marine Corps' plans for force employment over a period of time. The research team, in conjunction with PA&E, decided to utilize the two major SPMAGTF deployments as the baseline point from which to deviate from. Two additional scenarios were developed to add permanent SPMAGTFs to both Europe and South America as well as one scenario that divests the Marine Corps from all SPMAGTF requirements. The results of these SPMAGTF scenarios along with the other steady state demands not adjusted (MEUs and UDPs) models the Marine Corps as having from (5) to (9) deployed units at a time.

c. Force Sizing Scenarios: 150k, 165k, 174k 182k, 198k, and 207k

The goal of PA&E and the research team in using the Force Sizing Scenarios was to explore a wide range of potential Marine Corps end strengths represented by the number of infantry battalions that would be fielded at each strength level. In order to develop credible force structure scenarios, we utilized the 2013 Marine Corps' Force Structure

Working Group (FSWG) report, “The Prime Force, Force Design in Fiscal Austerity.” The report states that the FSWG was stood up by then Commandant of the Marine Corps General Amos to develop potential force structure designs that would allow the Marine Corps to remain a force in readiness, balanced against the fiscal constraints of sequestration. The working group concluded that a three-tiered approach to force structure with end strengths of 174,000, 165,000, and 150,000 should be pursued. The report additionally highlighted the expected steady state and crisis response capabilities with the associated risk to the institution and its readiness at each level (USMC 2014). Utilizing the force diagrams depicted in the report for each of the force levels, we developed three force sizing scenarios within the RAT input database. Additionally, we developed two scenarios that increased the Marine Corps end strength. To develop these two scenarios, we utilized the number of forces lost in both the 174k and 165k Prime Force structures and added those forces to the baseline structure. This allowed for end strengths of approximately 198k and 207k.

d. HADR Contingency Operations: Zero to Three per year from Six Regions

The strategic competition discussed by Mattis (2018) in the National Defense Strategy will increase the world’s degree of instability. Much like during the Cold War, these areas of instability and crisis will be unconventional battlegrounds where our military forces will be in close proximity with other peer state forces potentially in opposition to our national will. Additionally, U.S. forces have been committed to provide relief to major disasters and human crises ranging from extreme weather phenomena to the outbreak of highly contagious diseases like Ebola. The nature of these contingencies, whether due to political instability or natural disasters, will make them difficult to predict and to plan steady state deployment rotations around. They therefore have the potential to provide considerable stress to the Marine Corps’ readiness system. To implement this stress, four scenarios were developed that inject HADR missions into the steady state demand cycle at rates of occurrences ranging from zero to three per year. When creating these scenarios in the RAT input database, in order to not introduce bias regarding when or where these contingencies occur, an R script was utilized that randomly generated the appropriate start day for each

scenario as well as selected the region of the conflict from six possible areas of the world (Table 8). The script did not allow the same region to be selected within the same calendar year, but did allow for repeat issues to occur over time. The duration of each contingency was held constant at (60) days with a single infantry battalion being assigned.

Table 8. HADR Scenario Regions

Northern Africa	Horn of Africa	Southeast Asia
Northwest Asia	Caribbean Islands	Northern South America

2. Design Implementation

This section discusses the method chosen to explore the design space as well as the process used to enhance RAT analytic utility.

a. Full Factorial Design

Two key factors that must be considered when implementing a design are the design space coverage and the computational size or time needed to complete a run. The most basic design implementation often considered is the full factorial design. In this method, every potential combination of the decision factors is explored, which in turn explores 100% of the design space. Although a full factorial design has good coverage, they are not often used in simulation models because they grow exponentially large as the range of factors and levels expands, specifically with continuous variables.

Because RAT utilizes discrete scenarios as decision factors programed within its input database, it does not suffer from the same degree of rapid growth often seen in simulation models. As such, we have developed a full factorial implementation of the scenario levels listed in Table 7, resulting in 1200 design points. Each individual design point represents the decision factor settings for a single run of the model. Taken as a collective whole, they represent the full design. In Figure 15, the space-filling properties of the design as well as the column correlations are shown. The design has zero correlation between columns and 100% of the decision factors combinations are covered. RAT as a

simulation runs in relatively short time, with single simulation run taking roughly two seconds on the author’s personal laptop. The time to implement this full factorial design is (40) minutes.

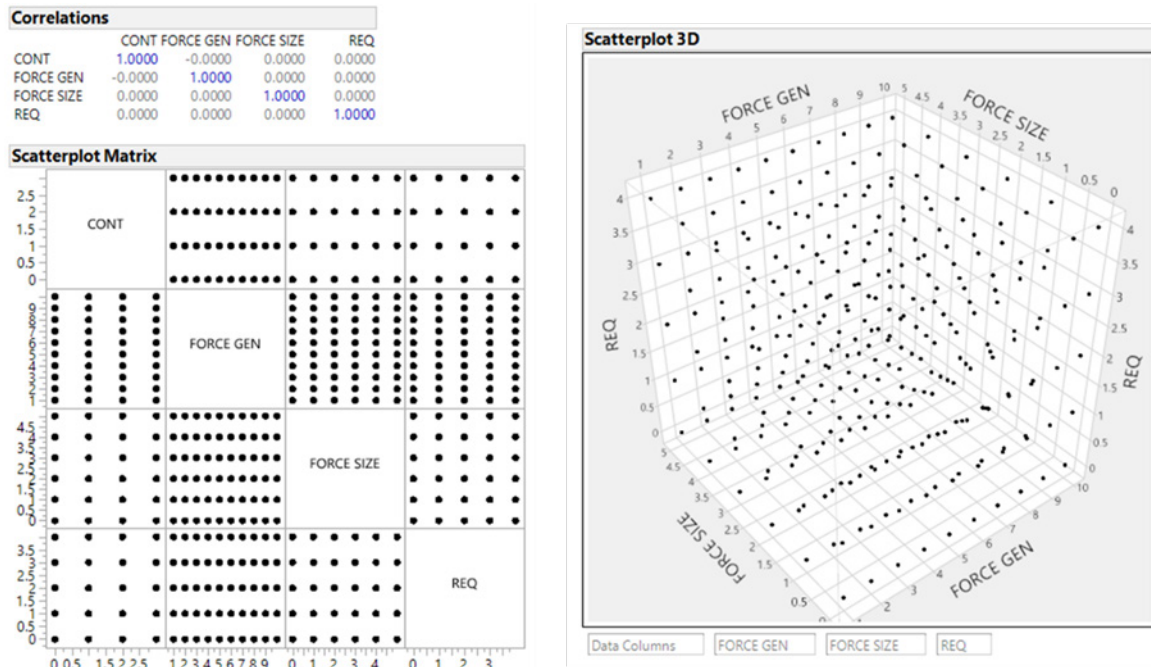


Figure 15. Full Factorial Space-Filling Properties

b. Making RAT Data Farmable

Once the DOE has been developed, it is crucial that the simulation itself is capable of automated execution of the DOE in order to improve the analytic utility of RAT (Research Objective 1). This process is known as data farming. Data farming differs from today’s commonly used term of data mining. As Sanchez discusses in Simulation Experiments, Better Data, Not Just Big Data (2015), data mining is a process of digging through large data sets for nuggets of valuable information. In this context, the data itself is already present and the miner’s job is to sift through it. Data farming on the other hand is associated with enabling a simulation to receive large scale DOEs and to produce output data that can then be analyzed to determine trends in system behavior. In this context, data

farmers cultivate the simulation environment to maximize the analytic potential (Sanchez 2015).

RAT was originally designed with small-scale data farming in mind. The technical documentation (Booz Allen 2018a) states that RAT was designed with a DOE module that allows for full factorial designs to be run, however this basic capability was not maximized. Due to system limitations, only the output data from a maximum of five runs was designed to be exported, therefore leaving the vast majority of usable information uncultivated (Booz Allen 2018a). It was at this point that the SEED center began its manipulation of RAT's DOE environment in order to better farm its output. Steve Upton, SEED center research associate, was the main effort for making RAT more data-farmable.

The primary line of effort for Steve Upton was in removing the run export limit of the basic RAT full factorial module, thereby allowing it to run larger designs (Upton 2019). In order to make the required changes, Upton had to modify two of the core Anylogic Model files utilizing Anylogic Professional version 8.2.3. Upton changed the method of data exportation so that each simulation run, i.e., design point, produces its own output file, which receives a unique file name. Additionally, the original code activated multiple information dialogue boxes throughout a simulation run that would pause the simulation until the user acknowledges the message. Upton removed these pop-up dialogue boxes in order to allow the simulation uninterrupted run time. With these changes in place, Upton was able to compile the new Anylogic files and replace them within the basic RAT simulation (Upton 2019). In this data farmable version of RAT, the user continues to interact with the standard graphical user interface (GUI), but now has the ability to cultivate the data generated from the DOE.

The output from the modified RAT simulation is a single Microsoft Excel file for each design point. In order to organize the data into a single file for analysis, Steve Upton created an R Script file that compiles all of the key response variable information while still preserving the original data in the individual files. By preserving the original data, follow-on analysis, such as PA&E's VVA, can be conducted on different response variables without having to rerun the model.

E. DESIGN SUMMARY

The developed DOE seeks to stress the Marine Corps' Readiness System as it is modeled in RAT through the exploration of the decision factors Force Generation Timelines, Force Sizing and Requirement Sizing Scenarios, and Contingency Operations. We analyze how these decision factors affect our model's response variables, Average Home Station Readiness and the Percentage of Non-Ready to Ready Units Deployed. The work by SEED research associate Steve Upton was critical to enabling the exploration of the design space. This work has enabled RAT to conduct large-scale simulation, which is directly in line with Objective 1 for this research.

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IV. SIMULATION ANALYSIS

This chapter discusses the data analysis conducted on the Readiness and Availability (RAT) simulation experiments executed as designed in Chapter III. Section 4.A. provides a brief overview of the analytic method and tools utilized. Sections 4.B. and 4.C., respectively, cover the results found from analyses of the two response variables, Percentage of Non-Ready Units Deployed and Average Home-Station Readiness. Section 4.D. is a multiple-objective analysis examining the potential trade-offs between the two response variables. The overall objective of this chapter is to provide analytic results to Program Analysis and Evaluation (PA&E) regarding the effects force employment and force structure decisions could have on the percentage of non-ready units being deployed and average home-station readiness.

A. ANALYTIC METHOD

In this section, we first discuss the simulation analysis process followed for analyzing the output data from the full factorial design of experiments (DOE). Secondly, we discuss the statistical software tools utilized to implement the analysis.

1. Simulation Analysis Process

The analysis process utilized in this research is adapted from what Sanchez et al. (2018) refer to as the Top Ten Questions to Ask During Analysis (Table 9) as presented in their tutorial on data farming at the 2018 Military Operations Research Society (MORS) Symposium. As the directors and primary research affiliates of the Simulation Experiments and Efficient Design (SEED) Center for Data Farming at the Naval Postgraduate School (NPS), Sanchez et al. stress the importance of simple statistical graphics, linear regression models, and partition trees in providing usable insight to decision-makers from simulation experiments (Sanchez et al. 2018).

Table 9. Top Ten Questions to Ask During Analysis. Adapted from Sanchez et al. (2018).

Q1: What was the spread of the response [variables] over the entire experiment?
Q2: How much random variation was observed just over the random replications?
Q3: Were there any outliers?
Q4: Were the responses correlated?
Q5: Which factors were most influential?
Q6: Were there any significant interactions?
Q7: What were the interesting regions and threshold values?
Q8: Are any of your results counter-intuitive?
Q9: Which configurations were most robust?
Q10: Are there any configurations which satisfy multiple objectives?

By following this basic framework for analysis, we intend to create a flow that conveys key insights readily and derive conclusions logically. When considering Q1-Q8, we will conduct individual analysis on the response variables. We will explore the potential trade-offs between the two response variables in Q10.

a. Metamodels Using Multiple Regression and Partition Trees to Explore Factor Significance, Interactions, and Threshold Values

In simulation analysis, the output data that we utilize in our statistical model building is not the result of real-world data-gathering efforts but rather the output from our simulation, which itself is a model of a real-world phenomenon. As such, we use the term “metamodel” (i.e., model of a model) when referring to the statistical models we develop for analysis (Sanchez 2018). Our goal in developing metamodels for simulation analysis is to fit the mathematical metamodel (or response surface) as closely as possible to the simulation output. By doing so, we can use the metamodel as a surrogate for the true model, so long as we remain within the bounds of our experiment. Additionally, these metamodels can identify critical information regarding variable importance and variable interactions. Two of the metamodel methods discussed by Sanchez et al. (2018) are partition trees and multiple regression.

(1) Partition Trees

In this research, partition trees have been utilized as a key analysis method because of how decision factor thresholds and interactions naturally identify themselves within the

model and convey a straightforward picture of how the response depends on factor settings. Partition tree models are a method in which the data is split into groups based on decision factors with the intent of predicting the response variable. As the data is continually split from its original state, it begins to develop into a decision tree (SAS 2018b). The fit of the metamodel is highly dependent on the number of splits and the relative importance between variables utilized. It is the analyst's job to balance the tree between, on the one hand, over-splitting to create a good fit at the cost of making the model less understandable and, on the other hand, failing to explain the variance by under-splitting the model. This method is particularly useful for identifying the most significant factors affecting the response variable and their relative importance in an understandable way.

(2) Multiple Regression using a Linear Model

In this research, we have selected to utilize the linear model as the basis for our multiple regression metamodel due to its ease of interpretation when providing insight to decision makers. However, this choice can raise a red flag because the two response variables considered in this study are bounded between (0 and 1) and the linear model has the potential to predict values outside of these bounded ranges. However, as Hellevik (2009) argues in his paper, "Linear Versus Logistic Regression When the Dependent Variable is a Dichotomy," the common belief that linear regression is not applicable for these types of response variables is not valid. Hellevik demonstrates that the two main arguments against linear regression, risk of meaningless prediction results and inappropriate linear significance tests, can be overcome and do not significantly affect the overall analysis. Hellevik does not discount the appropriateness of logistic regression when performing predictive analysis. However, for causal analysis, Hellevik states that the linear model is the best at answering causal relationship questions and provides the most intuitive and communicable insights (Hellevik 2009).

b. Representing the Decision Factors as Numeric versus Ordinal in Order to Improve the Interpretability of the Output

As is discussed in Chapter III, the experimental design was generated from the four ordinal decision factors with their individual levels, listed in Table 7. Although each level

of the decision factors represents a discrete scenario in the database, they additionally have a corresponding numerical interpretation. For example, the Force Generation Scenarios can be transformed to a numeric variable describing the number of months a unit takes to reach a C2 readiness level. Table 10 shows the transformations from ordinal to numeric for each of the variables.

Table 10. Ordinal to Numeric Decision Factor Transformations

<u>Ordinal Representation</u>	<u>Numeric Representation</u>	<u>Range</u>
Force Generation Scenario	Number of Months to C2	6-15
Force Sizing Scenario	Number of Infantry Battalions	17-28*
Requirement Sizing Scenario	Number of Steady State Deployments	5-9
Contingency Operations	Number of Humanitarian and Disaster Relief (HADR) Missions per Year	0-3

*Values for the Number of Infantry Battalions was discretely sampled at (17, 20, 23, 24, 26, 28) based on the suggested force structures of the 2013 Force Structure Working Group (USMC 2014).

The ranges listed in Table 10 are not truly continuous variables, but rather they are discrete points sampled from a possible continuous range. As such, caution should be used when extrapolating new values far outside those listed in the table. Regardless of this issue, the choice to represent the decision factors as numeric rather than ordinal greatly enhances the interpretability of the variables and allows the potential for better insight to be gained from the metamodels.

2. Statistical Analysis Software Tool

The primary statistical analysis tool utilized to execute the analytic process described in Table 9 is JMP Pro 14, developed by SAS. The JMP website describes it as a statistical discovery software tool that goes to the next level by offering all the capabilities of standard JMP plus advanced features including predictive modeling and cross-validation techniques, which allows the analyst to explore data efficiently and effectively. JMP Pro 14's capabilities include, but are not limited to, basic exploratory analysis, linear regression

model building, predictive and specialized modeling methods, dynamically linked data, and professional visualization graphics (JMP 2019). The partition platform and the stepwise regression capability are two of the primary statistic capabilities utilized in this research.

a. Partition Platform

The JMP partition tree platform allows the user to select the desired response variable as well as all of the decision factors to explore. Which variable is used for the splits and where each split occurs can be decided manually by the analyst or automatically by JMP based on recursive partitioning of the data across each factor for the optimal split at each level (SAS 2018b). In this research, we explored the data by both manual and automatic methods in order to find interesting thresholds and interactions. Specifically, manual splitting was used to prevent the same variable from appearing in consecutive splits. Lastly, the user has the ability to watch the split history to see the degree of fit over time and to discover at which point adding more splits provides no appreciable improvement in the model fit.

b. Stepwise Regression

In order to implement the RAT simulation output data into a linear regression metamodel, we turned to the stepwise regression capability of JMP Pro 14. The stepwise regression capability of JMP allows the user to automate the metamodel building process while exploring potential main effects, interactions, and polynomial factor transformations. The user has the ability to control the stopping method utilized (P-value Threshold, Minimum Bayesian Information Criterion [BIC], etc.). When the user initiates the building process, JMP iterates through potential model variants until reaching the desired stopping case and then provides the user with a potential metamodel solution. JMP also provides the significance levels for each of the factors and allows the user to modify the proposed selected subset as deemed appropriate. Once all final manipulations to the metamodel have been completed, the user implements the selected model parameters to build a linear model (SAS 2018a).

B. INDIVIDUAL ANALYSIS OF THE PERCENTAGE OF NON-READY UNITS DEPLOYED

The first response variable we analyze is the Percentage of Non-Ready Units Deployed. In many regions of the world, the most forward United States military unit is a Marine Corps deployed element. These forces must be ready to conduct their mission immediately upon assuming their area of responsibility. The deployment of non-ready units (C3 and C4) presents a critical risk to the Marine Corps and the United States. Managing this risk requires a knowledge of how force structure and force employment decisions effect the Percentage of Non-Ready Units Deployed.

1. Exploratory Analysis into the Spread of the Response Surface and Outlier Regions (Q1, Q3)

When examining the distribution of a response variable, our goal is often to gain insight into the amount of internal random variance within the simulation. However, this research however utilizes a deterministic version of RAT. As such, the response variable distribution does not capture any random variability, but we can still gain an appreciation for the amount of spread over the set if outcomes. Figure 16 displays the spread of the response variable Percentage of Non-Ready Units Deployed graphically using a histogram as well as numeric summaries.

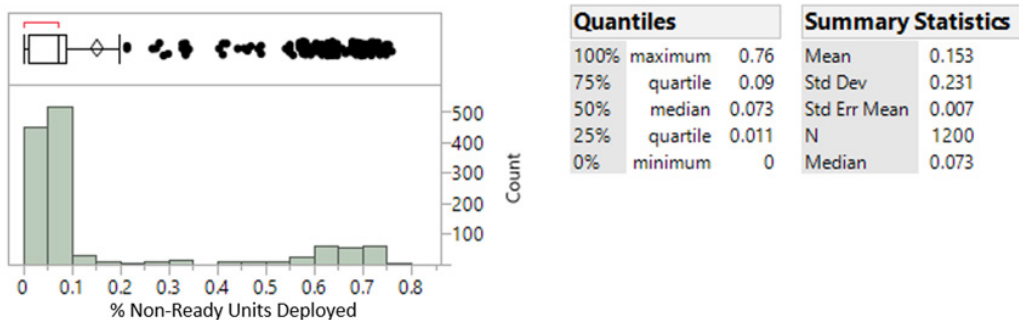


Figure 16. Distribution of the Percentage on Non-Ready Units Deployed

When we examine Figure 16, it is seen that the preponderance of observations (75%) are contained at or below (0.09), with over (80%) of the data below (0.2). Additionally, (25%) of the observations show a value of (1%) or less, with (173) instances (14%) of those having a value of (0%). From a risk perspective, this information demonstrates that the Marine Corps Readiness Systems is able to keep relatively low percentages of non-ready units from deploying over a wide range of force structure and force employment scenarios. That being said, roughly (20%) of the data has a value exceeding (0.2), with a maximum of (0.76). These data points represent combinations of scenarios in which the Marine Corps Readiness System is insufficient in maintaining ready units for deployments. To examine these data points more closely, we isolated them from the remainder of the data using JMP's lasso function. Figure 17 displays these outlier data points alongside the decision factors that contribute to them.

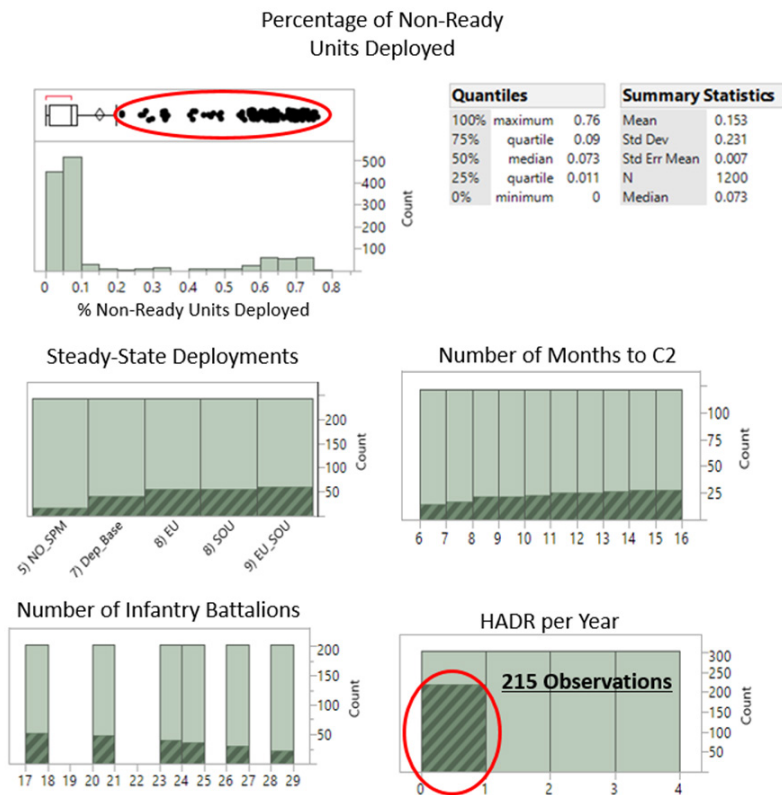


Figure 17. Outlier Analysis of the Percentage of Non-Ready Units Deployed

In Figure 17, we can see a slight increasing trend within the variables Months to C2 and Steady State Deployments. These trends suggest that as the number of months for a unit to become ready or the number of steady state deployments increase the Percentage of Non-Ready Units Deployed increases as well. We see a decreasing trend in the concentration of outlier observations within our variable Number of Infantry Battalions. This suggests that as the number of infantry battalions increase, more units are available for the model to task, and therefore, fewer of them are deploying in a non-ready status. With each of these three variables, we detect slight trends, but overall, there is no significant concentration of outlier values. However, the linked data displays that for the Number of HADRs per Year, all (215) outliers exist within simulations runs with no HADR missions (zero per year). This result runs counter to our initial thoughts that pop-up HADR missions would lead to more frequent non-ready units being deployed.

Through exploration of the raw simulation data, it was discovered that the main contributor for the disparity between simulation runs that have no HADR missions and those that do is the business rules RAT utilizes to fill contingency operations. The RAT contingency business rules allow the model to utilize Unit Deployment Program (UDP) units to source the contingency requirements before looking to utilize a home-station unit. Furthermore, the method for tracking the number of deployments in the simulation counts all HADR missions as new deployments regardless of how they were sourced. This creates a situation where UDP units being utilized for pop-up mission support are counted as an additional deployment. These units tend to be C1 status (2700 instances of C1 units deploying for HADRs) as well. The increased number of C1 units deployed combined with the increased number of overall deployments, results in the lowering of the percentage of non-ready units deployed for simulations runs that involved HADR missions.

Although the use of forward deployed units to meet pop-up contingencies is directly in line with the role of the Marine Corps as America's Force in Readiness, the method by which contingency missions are currently tracked within RAT provides an overly optimistic upper bound on the effectiveness of the Marine Corps Readiness System in meeting demand. In order to reduce the effects caused by the contingency business rules in the model, we decided to summarize the results by using the Tables Summary function

within JMP. We grouped our data on the remaining three decision variables (reducing total observations from 1200 to 300 and removed HADR as a decision factor) and calculated the mean and standard deviation of the response variables. Although this decision lowered the number of observations available, it in turn reduces the effect of the model's contingency business rules. Figure 18 displays the spread of the summarized data. There still exist a sizable portion (32%) of observations with values below (0.1) and (14%) with values of (0.0), demonstrating the relative sufficiency of the Marine Corps Readiness System. However, the data does show a more realistic distribution with a fair sized concentration of values located at or above (0.2). The deployment of non-ready units at over (20%) is a significantly troubling state to avoid. Figure 18 displays where the concentration of high response values (>0.2) exists within the decision variables in order to better understand this region of the response surface. These higher levels of non-ready units being deployed are combinations of high months to reach C2, high numbers of steady state deployments, and low numbers of infantry battalions. More on this will be drawn out as we examine the pairwise relationships and develop metamodels.

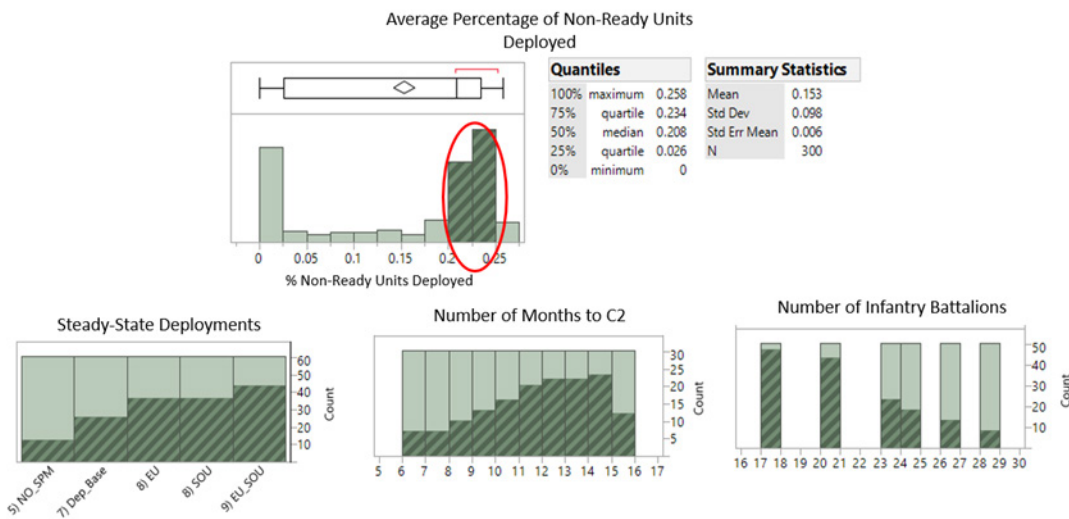


Figure 18. Percentage of Non-Ready Units Deployed (Summarized)

2. Model Variable Correlation: Examining Relationship Trends (Q4)

Continuing the analysis of the response surface spread, our goal in examining pairwise relationships between the model variables is to begin the process of identifying relational trends and to gain insight into which variables may be significant and have interactions. Figure 19 displays a correlation matrix with the associated scatterplot matrix for Percentage of Non-Ready Units Deployed versus the decision factors.

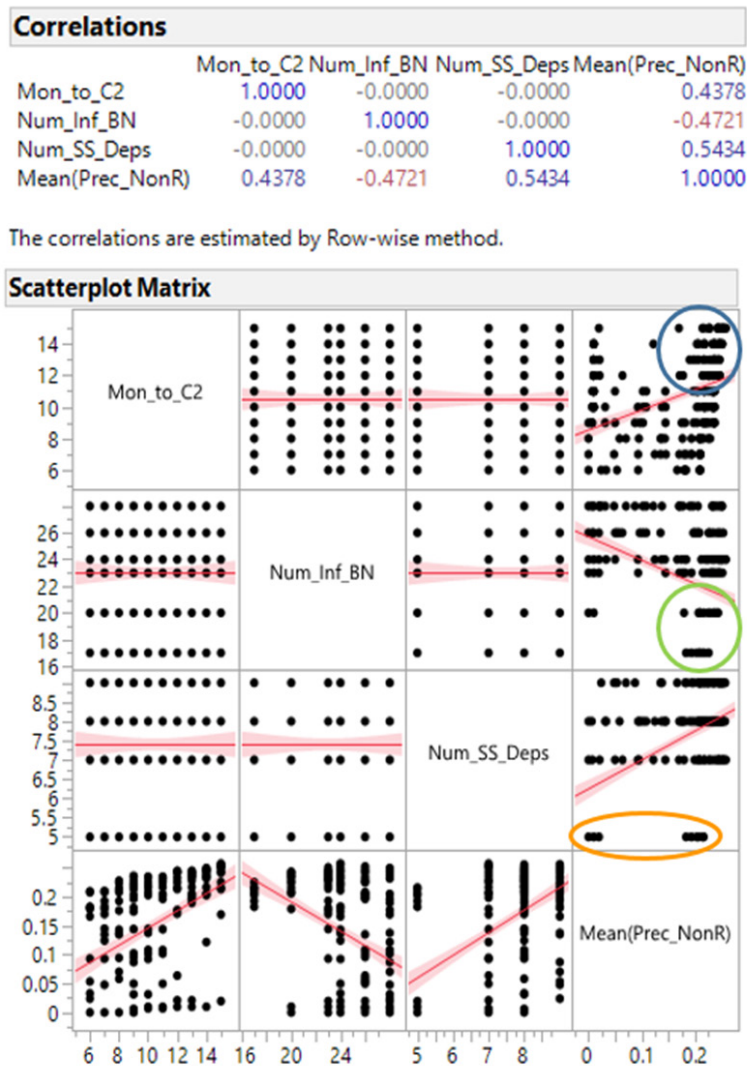


Figure 19. Correlation and Scatterplot Matrices for Percentage of Non-Ready Units Deployed

The relational trends seen in Figure 19 coincide with those seen when we examined the spread of our response variable in Figure 18. The Months to C2 and Steady State Deployments both exhibit moderate positive correlation with the response variable, while the Number of Infantry Battalions shows a moderate negative correlation. The scatterplot matrix additionally provides visual information on where potential threshold values exist for the decision factors. Examining the Number of Infantry Battalions, we see a concentration of high response variable values (green circle) once we have (23) battalions or less. Similarly, we see a concentration of higher response values (blue circle) when the number of Months to C2 exceeds (11). The Number of Steady State Deployments show a segregation of high and low values (orange circle) once below seven deployment nodes. In Figure 19, we have begun to visually detect the underlying model variable relationship trends as well as where potential thresholds exist. Our next step is to develop metamodels in order to fit the response surface and further explore the simulation's output data.

3. Metamodels: Fitting a Response Surface

In this section, we fit the response surface in order to examine variable importance, interactions, and threshold values (Q5-Q7). We will utilize both multiple regression and partition trees as metamodeling methods.

a. Multiple Regression

JMP's Stepwise Regression platform was used to build the linear regression metamodel examining potential two- and three-way interactions as well as second-degree polynomial transformations of the decision variables (ten potential model parameters). The resultant model included eight highly significant model parameters including a three-way interaction and one polynomial (Number of Infantry Battalions). Figure 20 displays the key regression model information.

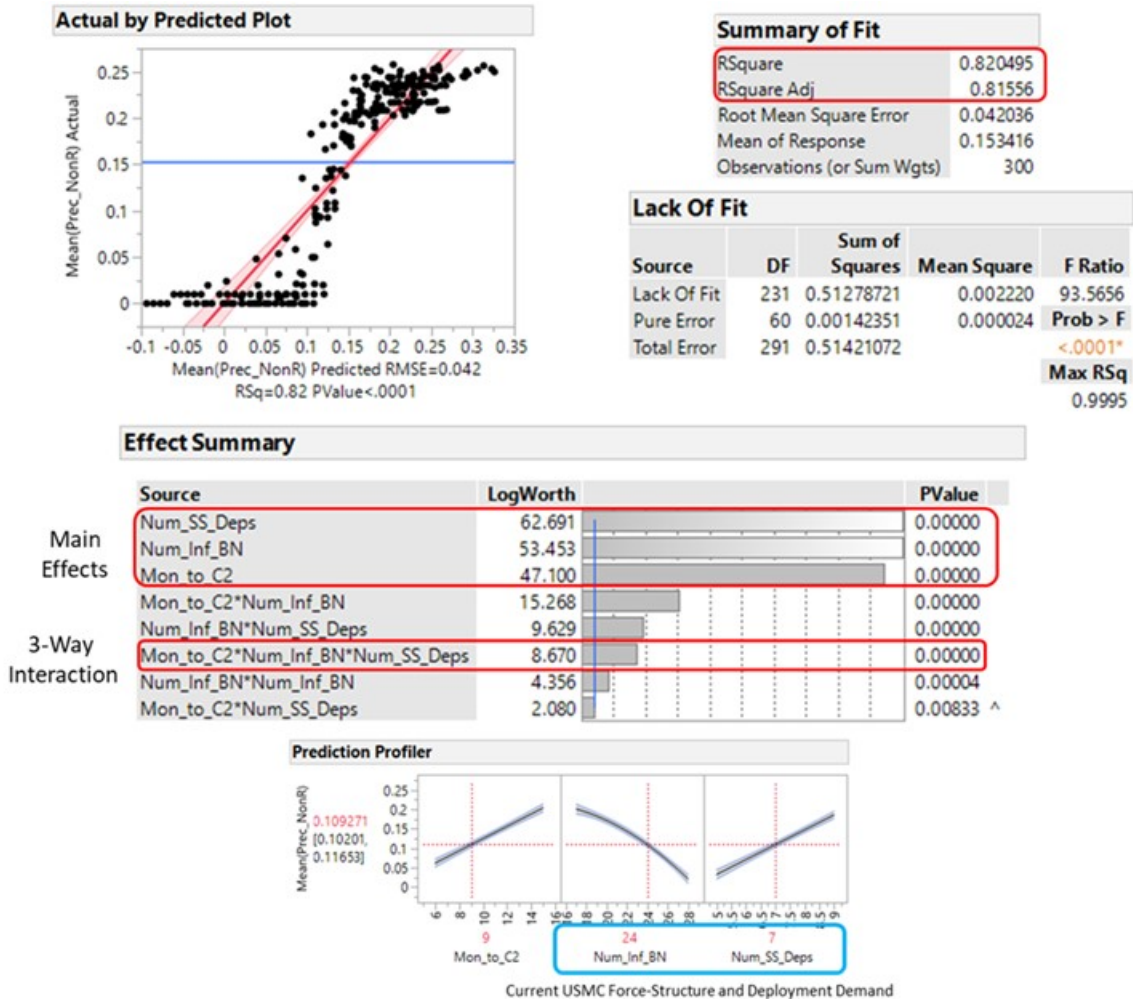
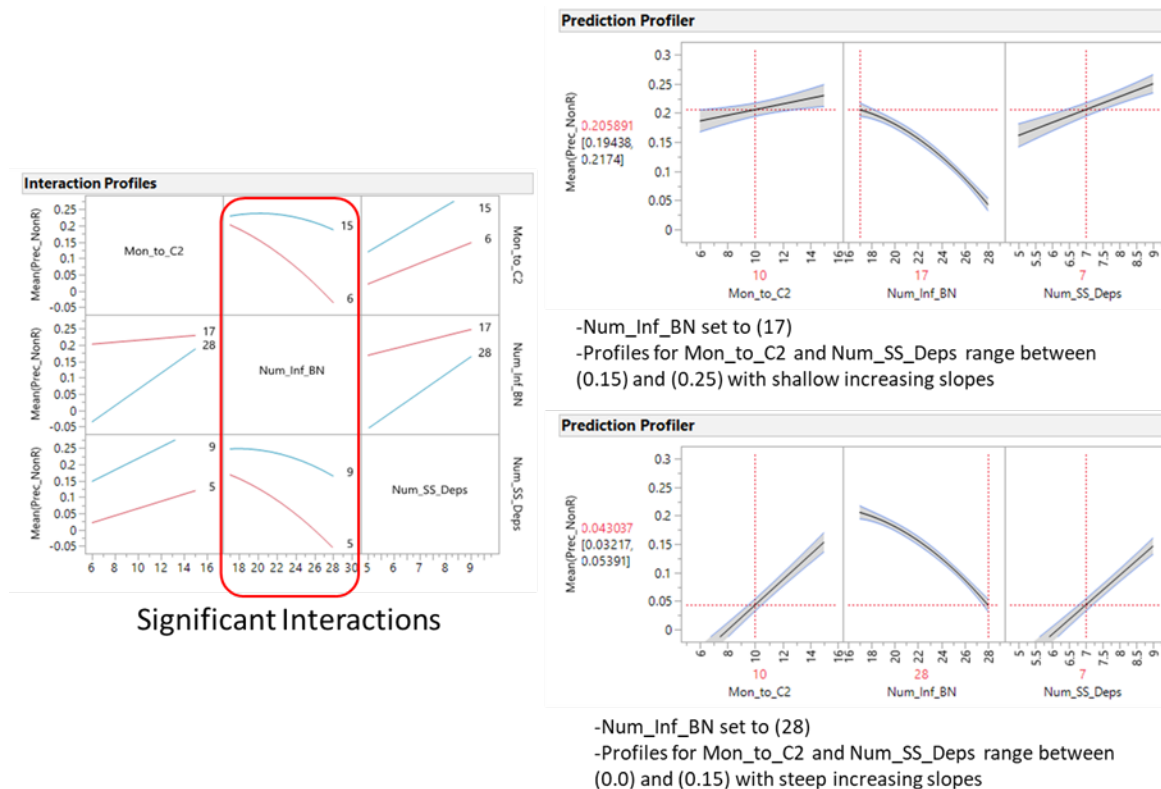


Figure 20. Linear Regression Metamodel for Percentage of Non-Ready Units Deployed

The model demonstrates a good fit to the simulation response surface, with an adjusted RSquare of (0.816). The model’s main effects are found to be the top three most significant parameters, with Steady State Deployments most significant, followed by the Number of Infantry Battalions and Months to C2, respectively. The direction of influence for each parameter visually shown in the Prediction Profiler confirms the relational trends that we have already seen. As the Number of Months to C2 and the Number of Steady State Deployments increase, our response variable linearly increases. The Number of Infantry Battalions has a decreasing effect on the response variable, but we see the effect is not purely linear due to a quadratic effect.

As seen in the Effect Summary of Figure 20, the two- and three-way interactions of the model are highly significant, which is visually confirmed in Figure 21. To dynamically explore the interaction effects of the model, we utilized the Prediction Profiler and adjusted the Number of Infantry Battalions while holding the remaining variables constant. We see that with (17) battalions both Months to C2 and the Steady State Deployments have shallow increasing slopes with response variable values ranging between (0.15) and (0.25). When we change to (28) battalions the slopes of both other variables become steeply increasing with an overall downward shift in the range of response variable values. Because of the significant effects that factor interactions have on the response variable, the natural next step is to continue our analysis to explore partition trees.



b. Partition Tree: Developing a Logical Decision Support Tool

A key attribute of the partition tree that makes it a primary simulation analysis tool is the natural way that interactions and threshold values show up. Figure 22 displays the partition tree developed for the Percentage of Non-Ready Units Deployed using JMP's Predictive Modeling Partition platform.

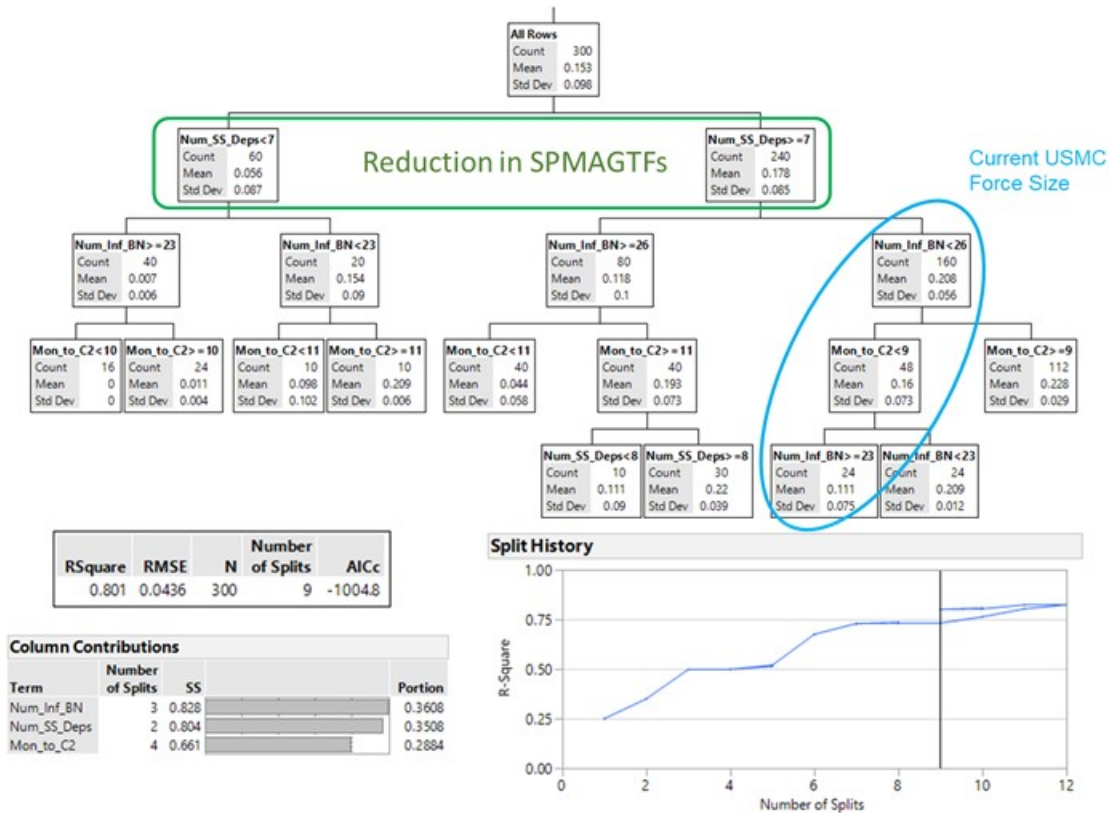


Figure 22. Partition Tree for the Percentage of Non-Ready Units Deployed

At nine splits of the data, we obtain an RSquare of (0.801), which is comparable to the response surface fit achieved with the multiple regression model. With only three factors considered, it is not surprising that all three had high column contribution portions. It is interesting that Months to C2 has the highest number of splits (four), but the lowest portion of contribution at (0.288).

Examining the thresholds and interactions present in Figure 22, we see that the first split occurs at (7) Steady State Deployments. This split results in a large separation of the risk incurred by the percentage of non-ready units being deployed, (0.056) compared to (0.178). With regard to a Marine Corps Readiness System decision, this split represents the continued utilization of two or more Special Marine Air Ground Task Forces (SPMAGTFs) in conjunction with Marine Expeditionary Units (MEUs) and UDPs, or reducing the use of SPMAGTFs.

The incurred risk of deploying non-ready units while utilizing two or more SPMAGTFs (0.178), right side of the tree, can be reduced by maintaining (26) or more infantry battalions. This threshold, however, constitutes two more battalions than is currently fielded by the Marine Corps. If the Marine Corps is capable of fielding (26) battalions and can resource its units to reach a C2 readiness status in less than (11) months, then the probability of deploying non-ready units is reduced to (0.044). However, if (11) months or greater is needed to reach C2, then maintaining a maximum of (7) steady state deployments can keep the level of risk at (0.111) compared to (0.22).

If the Marine Corps is unable to increase the number of infantry battalions from its current (24) to (26), then it must resource its units to reach a C2 readiness status in less than (9) months in order to reduce the probability of deploying non-ready units to (0.16). Continuing further down this branch, we see that if the Marine Corps can maintain at least (23) battalions the probability can be further reduced to (0.111).

Returning to the first split, we are able to explore scenarios involving less than (7) steady state demand nodes. In regard to Marine Corps force employment decisions, this would involve maintaining all current MEUs, two UDPs, and at most one SPMAGTF. Continuing down the left side of the tree, we see that our next split anchors around having (23) infantry battalions. If the Marine Corps maintains (23) or greater battalions, then it can effectively reduce its risk for deploying non-ready units to ($< 1\%$). However, if less than (23) battalions are field, then the best risk value that can be achieved is (0.098), which requires units to be C2 in (< 11) months.

4. Summary of Individual Analysis for the Percentage of Non-Ready Units Deployed

The initial spread of the data for the Percentage of Non-Ready Units Deployed (Figure 17) shows some counter-intuitive results regarding the effects of the HADR variable. The primary cause of these effects are the business rules implemented within RAT for sourcing and tracking contingency missions. Although modeling pop-up contingency mission such as HADRs is important, the current method for doing so within RAT produces over-confident results. To reduce the over-confidence effects, we summarized the data points and utilized the average Percentage of Non-Ready Units Deployed (Figure 18) as our response variable moving forward.

The correlation and scatterplot matrices (Figure 19) identified moderately increasing relational trends between the response variable and both the Number of Months to C2 as well as the Number of Steady State Deployments. The Number of Infantry Battalions has a moderately decreasing trend with the response variable.

The linear regression metamodel (Figures 20 and 21) identified that each of the three main effects are highly significant, but more importantly it identified the significance of the variable interactions. Specifically, the linear model identified the three-way interaction between all of the variables as significant. This three-way interaction was explored further within the partition tree (Figure 22), tying it as well to key threshold values. Significant thresholds identified by the partition tree involved the effect of having (≥ 7) steady state deployments. The second tier of the partition tree centers on force structure decisions involving either (23) or (26) infantry battalions. The third tier of the tree provides the appropriate force-generation-timeline dependent on the respective deployment demand and force structure decisions chosen. The partition tree in Figure 22 naturally demonstrates the threshold level interactions between the different decision variables providing Marine Corps leaders an easily adaptable decision support tool.

C. INDIVIDUAL ANALYSIS OF AVERAGE HOME-STATION READINESS

In this section, we shift our analysis to the response variable Average Home-Station Readiness. The amount of home-station readiness maintained by the United States is a

question of both resource management as well as deployment capability options. Maintaining a high level of home-station readiness (healthy ready bench) allows the Marine Corps and the United States to have dynamic options when considering military force responses. However, an over-sized ready bench comes at a high fiscal cost, which in the current resource constrained environment cannot be maintained without due cause.

1. Exploratory Analysis into the Spread of the Response Surface and Outlier Regions (Q1, Q3)

Figure 23 displays the spread of the response variable Average Home-Station Readiness. The shape of the response surface is fairly symmetric, with a mean of (0.504) and a median of (0.519).

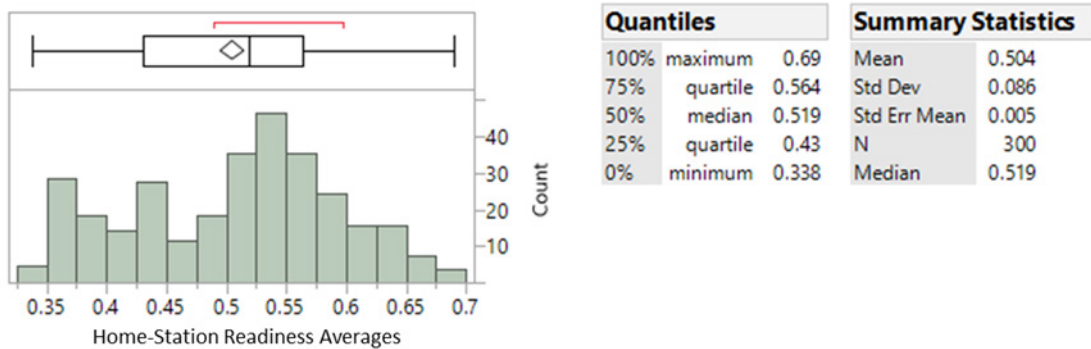


Figure 23. Distribution of Average Home-Station Readiness

The data is, however, multi-modal, with the largest of these modes at (0.53). The two smaller modes located near (0.35) and (0.42) represent concentrations of relatively low readiness levels for the Marine Corps. Figure 24 utilizes the linked data functionality of JMP in order to highlight these two smaller modes and look for trends in their corresponding decision variable levels.

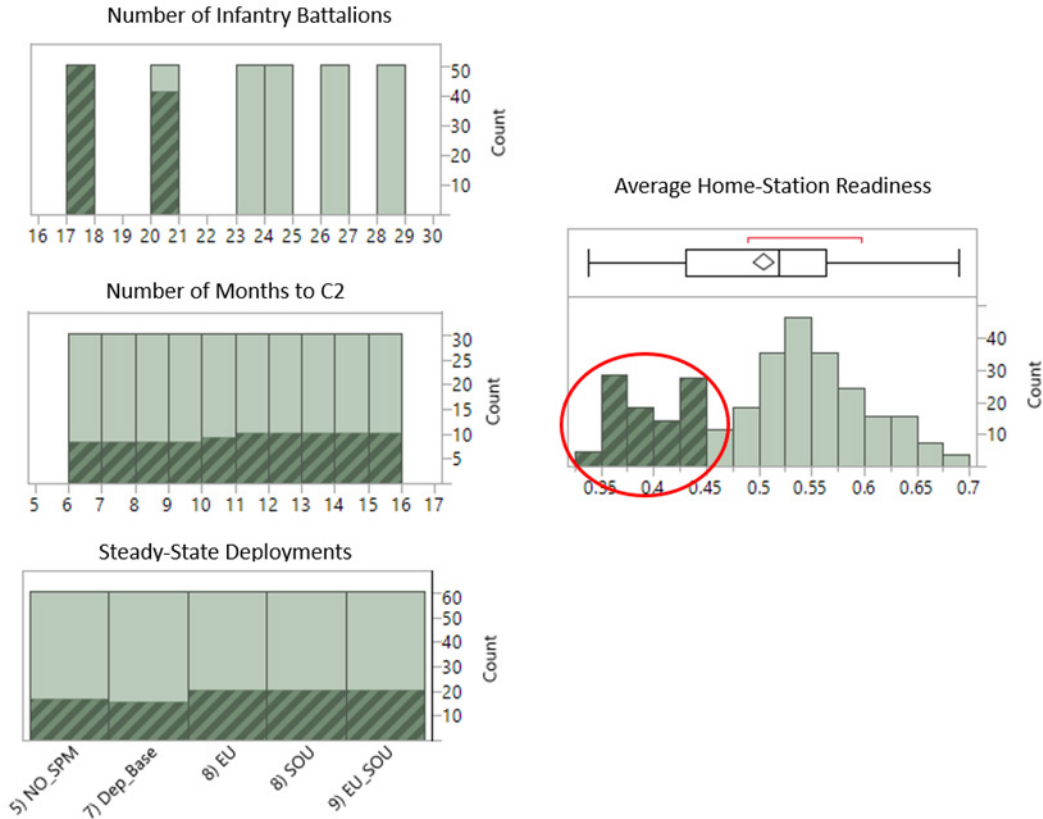


Figure 24. Low Home-Station Readiness Concentrations

Both the Number of Steady State Deployments and Number of Months to C2 display very slight increasing trends, but overall a fairly uniform spread of the low readiness observations. On the contrary, the Number of Infantry Battalions has all of its observations concentrated at both (17) and (20). At this point, we can start to detect that the Number of Infantry Battalions is highly influential in determining our Average Home-Station Readiness. To explore the initial insights found in the spread of our response, we will conduct a pairwise analysis between the decisions factors and the response variable.

2. Model Variable Correlation: Examining Relationship Trends (Q4)

The goal of examining pairwise relationships between the model variables is to begin the process of identifying relational trends and to gain insight on which variables

may be significant. Figure 25 displays a correlation matrix with the associated scatterplot matrix for Average Home-Station Readiness versus the decision factors.

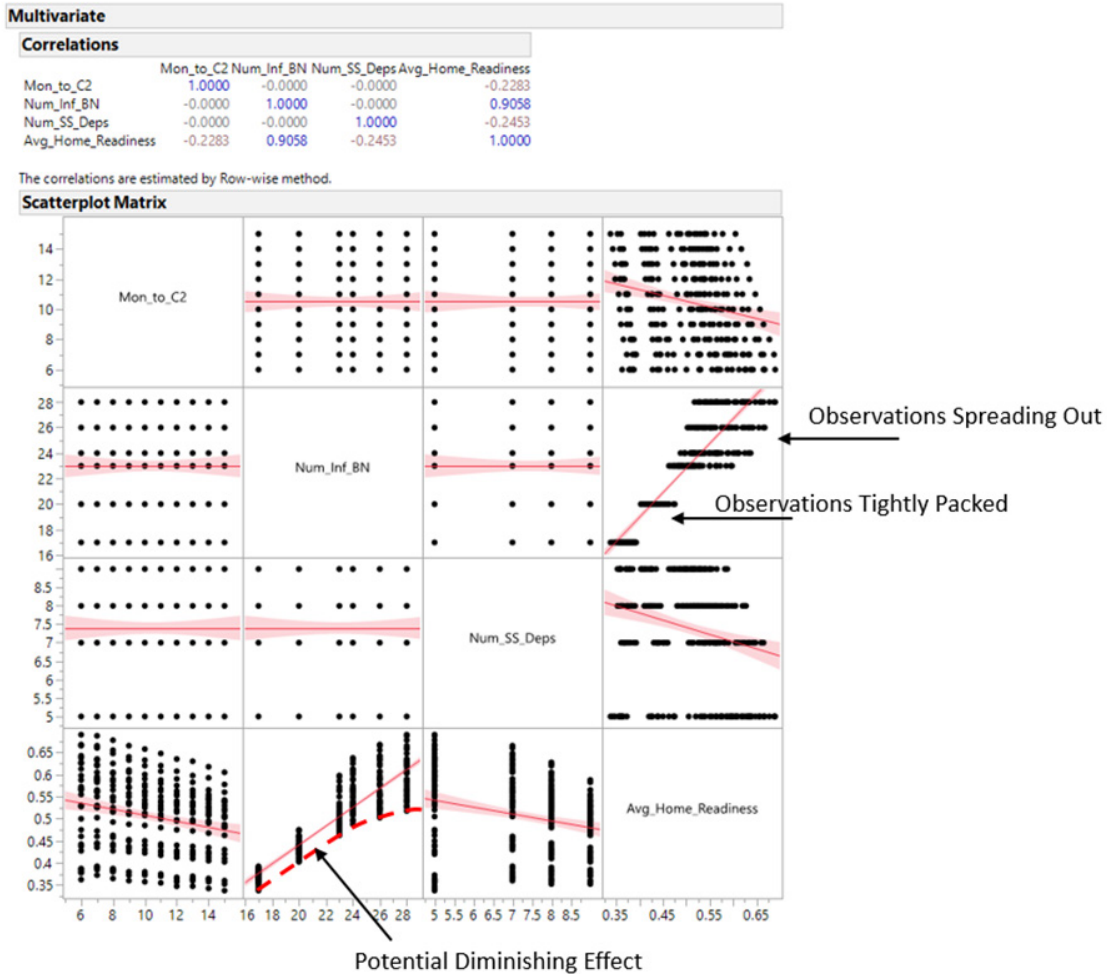


Figure 25. Correlation and Scatterplot Matrices for Average Home-Station Readiness

In Figure 25, the strong positive relationship between the Number of Infantry Battalions that was suspected in Figure 24 is confirmed with a correlation value of (0.9508). It is interesting how densely concentrated the observations are at the (17) and (20) battalions, but as the number of battalions increases the internal spread for each level increases as well. Additionally, the improvement in the average readiness for each level appears to decrease for (24) battalions and above. This gives the impression of a non-linear

relationship between Average Home-Station Readiness and the Number of Infantry Battalions. The other decision factors, Number of Months to C2 and the Number of Steady State Deployments, each have weak negative correlations at (-0.228) and (-0.245). The potential causal relationships found here are further explored through our metamodel development.

3. Metamodels: Fitting a Response Surface

In this section, we fit the response surface in order to examine variable importance, interactions, and threshold values (Q5-Q7). We will utilize both multiple regression and partition trees as metamodeling methods.

a. Multiple Regression

Stepwise Regression was utilized again to develop the linear regression metamodel for the Average Home-Station Readiness considering the potential for up to three-way interactions and second order polynomial transformations, for a total of (10) potential terms. Figure 26 displays the resultant model with eight significant factors developed through the Stepwise platform utilizing minimum BIC as the stopping criteria.

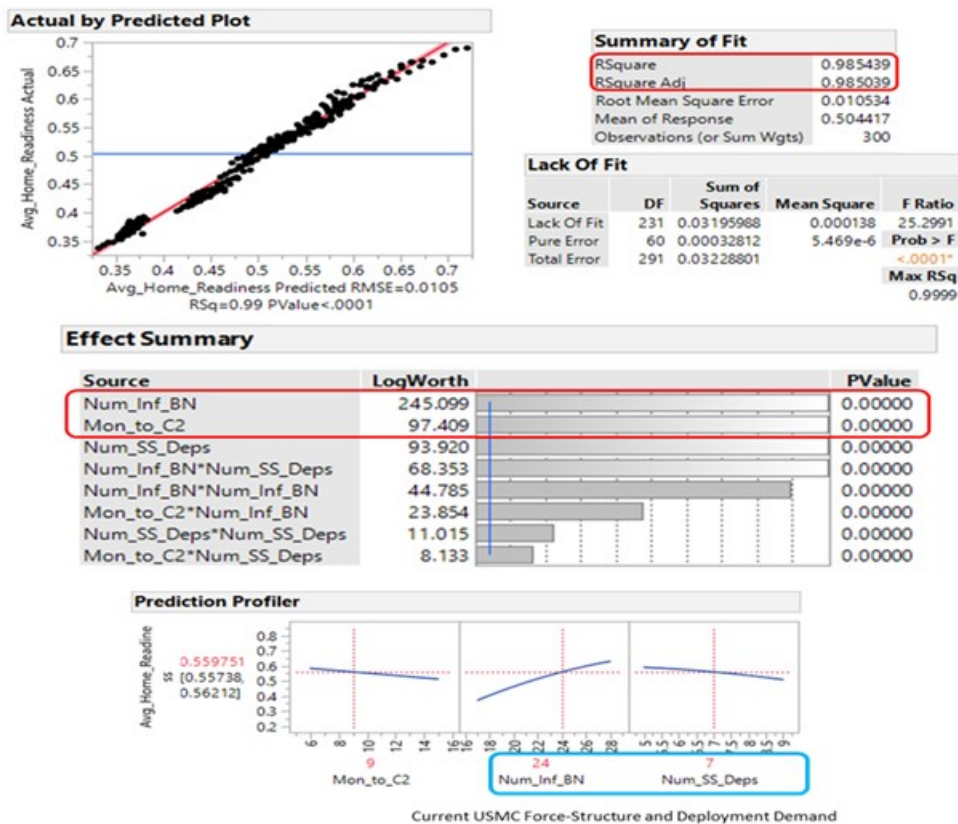


Figure 26. Average Home-Station Readiness Linear Regression Metamodel

The Adjusted RSquare at (0.985) gives an excellent indication of the goodness of the model fit. The included factors for the resultant model contains each of the two-way interactions as well as two of the second order polynomial transformations (Number of Infantry Battalions and Number of Steady State Deployments). Examining the Effects Summary listed in Figure 26, we see that the Number of Infantry Battalions is by far the most influential factor, with (2.5) times as much worth as that of the next factor’s level of worth. Additionally, the Number of Infantry Battalions is the only factor with positive contribution as seen in the Prediction Profiler. This evidence further confirms what was seen in the correlation matrix and scatterplot (Figure 25) regarding factor relationships with the response variable. The non-linear relationship between the Number of Infantry Battalions and the response variable is found to be significant in the metamodel. This suggests that although increasing the number of battalions improves readiness it does so with diminishing returns.

As was seen with the previous response variable, Percentage of Non-Ready Units Deployed factor interactions are found to be significant, specifically those involving the Number of Infantry Battalions. In Figure 27, we see visually how these interactions effect the response variable values. Exploring the effects of changing the Number of Infantry Battalions, we see that at (17) battalions both Months to C2 and Steady State Deployments have near flat slopes with response variable values ranging from (0.4) to (0.37). With an increase in battalions to (28), we see the profile slopes changing to a decreasing profile with an upward shift in the range of response variable values. Although the relative degree of interaction effects found in this regression model is considerably less than those seen with Percentage of Non-Ready Units Deployed (Figure 21), it still demonstrates the importance of all of the decision factors in the response.

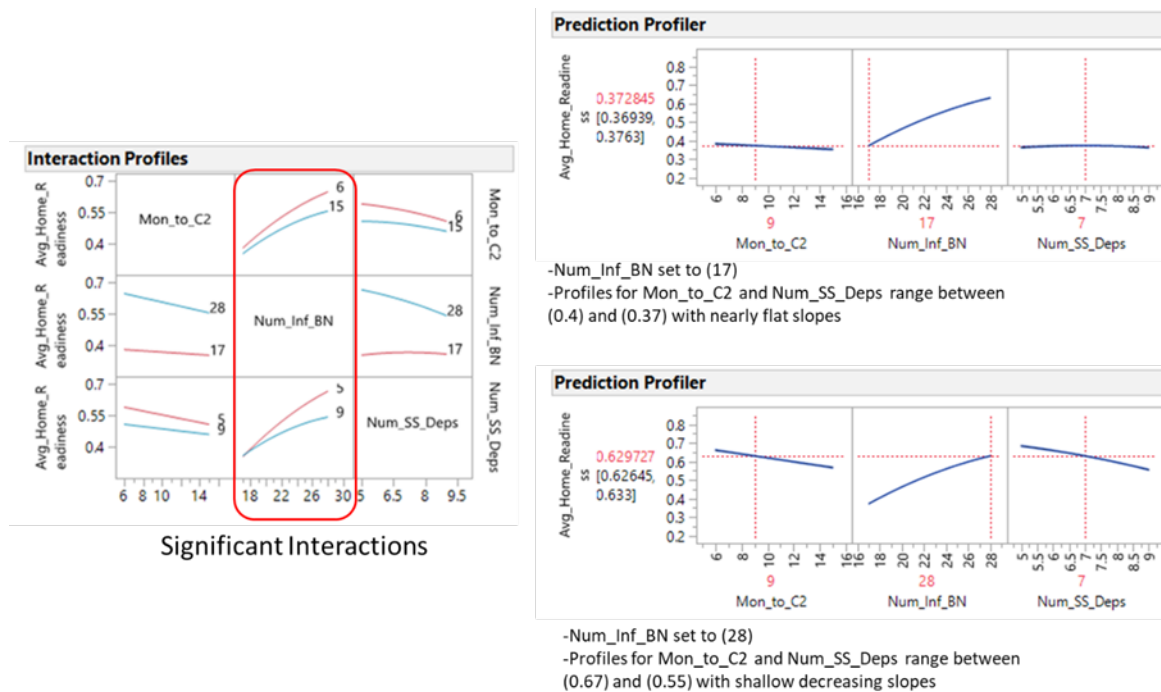


Figure 27. Interaction Effects of the Number of Infantry Battalions

b. Partition Tree: Developing a Natural Decision Support Tool

In Figure 28, we see the partition tree developed for the response variable Average Home-Station Readiness. Utilizing only (7) splits we were able to achieve a response

surface fit with an RSquare of (0.886). The Column Contributions chart clearly shows the overwhelming influence of the Number of Infantry Battalions. Additionally, the Number of Infantry Battalions is the variable utilized for the first split, accounting for (0.724) of the overall metamodel's RSquare. In developing this tree, we reach diminishing returns on RSquare improvement at (5) splits, but decided to continue to (7) splits in order to explore additional variable interactions.

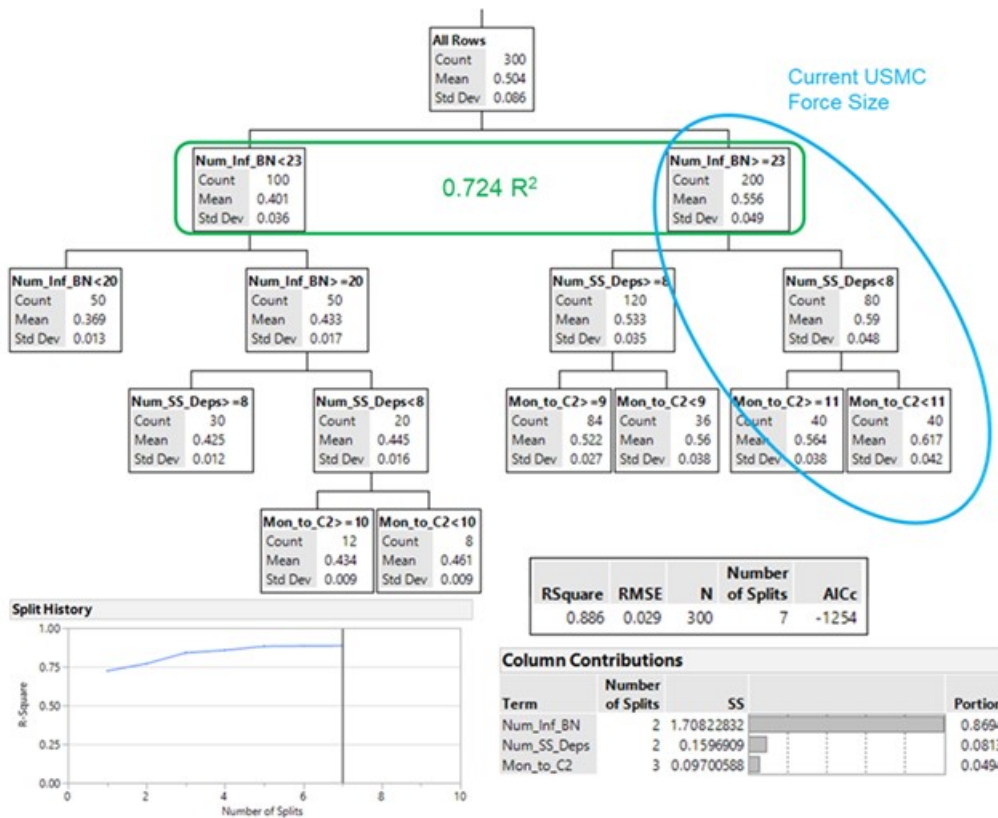


Figure 28. Average Home-Station Readiness Partition Tree

Exploring the partition tree, we see that the first split is anchored around having (23) infantry battalions. This threshold divides the potential Average Home-Station Readiness from (0.401) to (0.556). Continuing down the (≥ 23) branch, we begin exploring a Marine Corps force structure not unlike the one employed today. We see that on this side of the tree our next threshold level pivots around (8) steady state deployments. For force employment decisions involving (≥ 8) steady state deployments, resourcing must be

provided to Marine Corps units in order to reach C2 status in (< 9) months in order to maximize the home-station readiness potential at (0.56). On the contrary, if (< 8) steady state deployments are employed, then Marine Corps units can be resourced to C2 (< 11) months and maintain a home-station readiness potential of (0.617).

Moving back up the tree to the initial split, we see that if the Marine Corps has (< 23) infantry battalions, but (≥ 20) it can maintain a home-station readiness potential of (0.433). The splitting performed below the (≥ 20), partition provide only (0.004) improvement in RSquare, but allow us to explore the thresholds of Steady State Deployments and Months to C2.

4. Summary of the Individual Analysis of Average Home-Station Readiness

The spread of the Average Home-Station Readiness response variable (Figure 23) is relatively symmetric with its mean and median near (0.5). The response distribution is multi-modal (Figure 24), with its largest peak at (0.53), and two smaller peaks at (0.35) and (0.42). These smaller peaks contained observations highly concentrated at (17) and (20) infantry battalions. This was our first indication of the overall significance of the Number of Infantry Battalions as a model variable. The correlation and scatterplot matrices (Figure 25) further showed this significance by identifying a strong positive correlation between the Number of Infantry Battalions and the Average Home-Station Readiness. In the linear regression metamodel (Figure 26), we discovered that not only is the Number of Infantry Battalions significant as a main effect, so too are its interactions (Figure 27). We continued our exploration of metamodels by developing a seven split partition tree (Figure 28). It is interesting that the first split involving the Number of Infantry Battalions accounts for (0.724) of the total (0.886) RSquare. The key threshold discovered is the significance of (23) or more battalions, which divide the home-station readiness maintained between (0.401) and (0.556).

D. MULTIPLE-OBJECTIVE ANALYSIS: QUANTIFYING HOME-STATION READINESS LEVELS THROUGH RISK

In the individual analysis for Average Home-Station Readiness, we focused on significant thresholds aimed at maintaining high levels of readiness, but what is the correct level to maintain? It is intuitive that extreme low levels of readiness are undesirable, but what about the other end of the spectrum? How much readiness is enough? In order to examining the relative benefit of different levels of home-station readiness, we conducted a multi-objective analysis comparing the Percentage of Non-Ready Units Deployed, i.e., risk, with Average Home-Station Readiness maintained. By linking these two response variables, decision-makers can now see the trade-off in risk versus readiness in order to make informed decisions. Figure 29 depicts a two-dimensional plot of risk versus readiness.

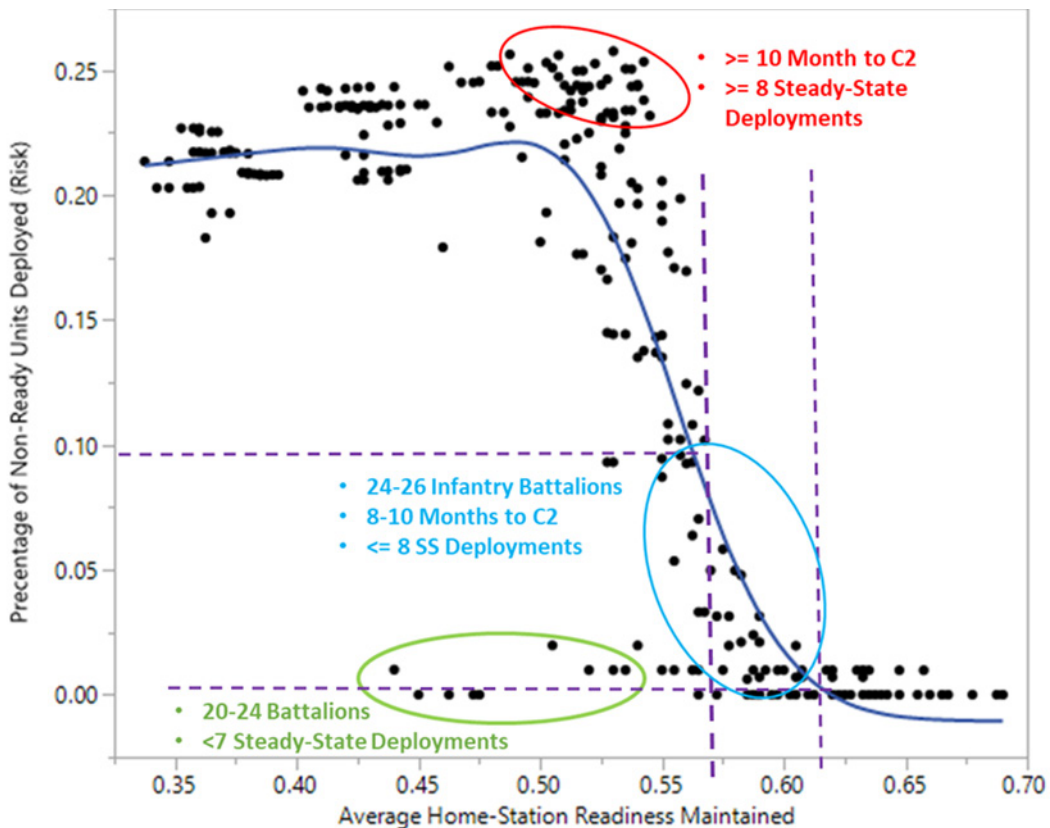


Figure 29. Risk versus Home-Station Readiness

The blue smoother line in Figure 29 is provided to assist in detecting trends within the data. Examining the relationship between risk and readiness, we see that at low levels of readiness (< 0.5) the preponderance of risk is between (0.2) and (0.25). This level of risk demonstrates an insufficiency in the Marine Corps Readiness System. At the point where home-station readiness begins to exceed (0.5), a sharp downward trend in the degree of risk develops. This trend of risk reduction becomes very steep as home-station readiness approaches (0.52) and maintains this downward trend until approximately (0.6). With an approximate (7%) increase in home-station readiness, we observe an approximately (20%) decrease in risk. The observed reduction in risk trend displays diminishing returns as the home-station readiness passes (0.6).

Utilizing a target risk level of (10%), we see that the range of home-station readiness to maintain is between (0.56) and (0.61). Highlighted in blue are those observations found within this risk reduction range. Using linked data, we found that the preponderance of these points shared the characteristics of between (24) and (26) infantry battalions, (8) to (10) months to reach C2, and (≤ 8) steady state deployments.

Amplifying the need to quantify readiness with risk, we have highlighted in red a region of observations in which readiness is maintained above (0.5), but there is no corresponding reduction in the amount of non-ready units deployed. We found that these observations all have the characteristics of (≥ 8) steady state deployments with (≥ 10) Months to C2. In these situations, the relatively high level of readiness is not sufficient to deploy enough ready units. This demonstrates the importance of interactions within readiness and how a seemingly good home-station readiness value could be meaningless without an additional metric like risk to quantify what “good” really is.

On the other side of the situation, we highlight in green a section of observations with seemingly low readiness, but yet almost no risk. We found that these observations had the common characteristics of (< 7) steady state deployments and between (20) and (24) battalions. In this combination, we find that the deployment demand is low enough because of the reduction in SPMAGTFs that the force structure can achieve low risk with a reduced home-station readiness requirement. Important to this finding is our assumption that the deployment demand signal remained the same over the ten-year simulation period. If the

deployment demand were to increase due to worldwide events, the low home-station readiness level could become a liability.

In summary, it should be understood that home-station readiness by itself is not a strong indicator of the Marine Corps Readiness Systems' health. This metric must be coupled with some quantifying metric such as risk. In this research, we utilized the Percentage of Non-Ready Units Deployed as our risk factor. The goal of this multiple-objective analysis was to develop an easily interruptible tool that senior leaders can use to make risk informed decisions. It was discovered through this analysis that to maintain a risk level of ($< 10\%$) home-station readiness should optimally be maintained between (0.56) and (0.61). In regard to readiness decisions, the number of infantry battalions should be between (24) and (26), steady state deployments (≤ 8), and resourcing established for units to reach a C2 status between (8) and (10) months.

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V. CONCLUSIONS AND RECOMMENDATIONS

In the current threat environment dominated by strategic peer level competition described by Former Secretary of Defense James Mattis in the 2018 Nation Defense Strategy, the United States' ability to rapidly deploy forces to meet emerging threats is critical to national security (Mattis 2018). Maintaining an operationally ready force at home and overseas is a key enabler of the Department of Defense (DoD) in supporting the nation's security. The Commandant of the Marine Corps, General Robert Neller, states clearly in a 2018 address to the Congressional Defense Committees that the role of the Marine Corps is to be a force in readiness capable of operating from home-station as well as forward deployed at a moment's notice (Neller 2018b). However, the Marine Corps is currently deficient in its ability to quantifiably defend its capacity and capability to meet this task. In a 2012 report, the Congressional Budget Office (CBO) determined that the Marine Corps lacks appropriate budget development models that account for the resources needed and training requirements for its ground forces (CBO 2012). Furthermore, the Government Accountability Organization (GAO) reported in 2016 that the Marine Corps lacks an analytically informed readiness strategy as well as established measures of effectiveness to track the progress of its readiness recovery efforts (GAO 2016). In recognition of the risk incurred by lacking an objective, defensible, repeatable, and traceable operational readiness strategy, Headquarters Marine Corps (HQMC) Programs and Resources (P&R) has embarked on a multi-pronged readiness modeling effort lead by its Program Analysis and Evaluation (PA&E) Branch (PA&E 2018a). The Readiness and Availability Tool (RAT) is one avenue of PA&E's readiness modeling effort. RAT focuses on providing insight for Marine Corps leadership regarding the operational readiness impacts of force structure and force employment decisions (PA&E 2018a).

A. RESEARCH FOCUS

The focus of this research was to utilize RAT to efficiently explore the operational readiness impacts that result from Marine Corps force structure and force employment decisions using large-scale simulation. The Design of Experiments (DOE) developed for

this research was a joint effort between the research team and PA&E's operations research section. A goal of the DOE was to provide stress to the Marine Corps Readiness System in order to find breaking points in its capacity and capability to meet demand.

B. RESULTS AND FINDINGS BY RESEARCH OBJECTIVES

This section highlights the research results and findings as they relate to each of the research objectives stated in Chapter I.

1. Objective 1: Improve the Analytical Power of RAT by Enabling the Use of Large-scale Experimentation

Although RAT was designed with a limited DOE module, it is currently severely limited its ability to conduct a large-scale DOE (Booz Allen 2018a). As one of the first steps in this research, Steve Upton, research associate with the Simulation Experiments & Efficient Design (SEED) Center for Data Farming at the Naval Postgraduate School, modified the DOE module of RAT to no longer be limited in its experimental size (Upton 2019). As part of this research, the DOE enhanced version of RAT has been provided to PA&E to facilitate their further study of operational readiness.

2. Objective 2: Provide Insight into the Key Questions asked of RAT by Marine Corps Leadership

This research focused on asking what effects do force structure and force employment decisions have on the frequency of C3 and C4 deploying units (assessed as risk in this study) and on the average home-station readiness level maintained? The insight derived from these two questions is intended to inform Marine Corps leadership in the development of an objective and defensible Marine Corps Readiness Strategy. The results of this effort were the formulation of five primary findings.

- The Number of Infantry Battalions is found to be the dominant factor in determining Average Home-Station Readiness. The primary threshold to consider is the utilization of less than or greater than (23) battalions. This split accounts for (0.724) of the partition tree's RSquare (Figure 28).

- Factor interactions are found to be significant in each of the four metamodels developed for this research. In the Percentage of Non-Ready Units Deployed multiple regression model (Figure 20), the three-way interaction is significant, highlighting the importance of all three main effects in readiness planning.
- At the Marine Corps' current force structure of (24) infantry battalions and deployment-demand of (≥ 7) steady state deployment, RAT displays an (11%) risk factor of deploying non-ready units even if resourcing is provided to ready units in (< 9) months. By increasing the force structure to (26), the risk can be reduced to (4.4%) and a resourcing requirement of (< 11) months compared to the previous (< 9) months.
- If the Marine Corps were to reduce its SPMAGTF deployments to only one, the risk of deploying non-ready units can be reduced below (1%) at its current force structure. However, if the Marine Corps were to also reduce its force structure to (< 23) battalions, then this risk would increase to (9.8%) with a requirement to ready units in (< 11) months.
- The multiple-objective analysis points to the need for an accompanying variable such as risk to quantify the relative value of Home-Station Readiness.

Although Force Sizing (the Number of Infantry Battalions) is found to be dominant in determining Average Home-Station Readiness, all four of the metamodels developed for this research (Figures 20, 22, 26, 28) show the importance of factor interactions. The importance of the factor interactions within RAT amplifies the point that the development of a Marine Corps Readiness Strategy must spread its focus across the three factors of Force Sizing, Requirement Sizing, and Force Generation Timelines. As a visual confirmation, we see in Figure 22 (Percentage of Non-Ready Units Deployed Partition Tree) how thresholds of one factor have rippling down effects for force sizing and force generation thresholds needed to reduce the Marine Corps risk of deploying non-ready units.

Lastly, we find through a multiple-objective analysis that home-station readiness must be quantified with an external factor such as risk in order to be a useful measure of success for a readiness strategy. Failure to account for risk could result in a readiness strategy that gives a false impression of its capacity to meet demand. This was most evident in the Risk versus Home-Station Readiness Plot, Figure 29, where over 50 points were identified (red circle) in which between 50–55% average home-station readiness was maintained, but over 20% of the units deployed were non-ready.

3. Objective 3: Assist PA&E with a Sensitivity Analysis that Will Be Informative and Applicable to the Verification, Validation, and Accreditation (VVA) Process.

By enabling RAT to be executed over an extensive design space, the research team was able to assist PA&E in examining the logical functionality and operation of RAT as part of their VVA process. Within a VV&A, verification is used to determine that a model operates as the designers intended in their conceptual design (Department of the Navy 2019). While exploring the 1200 design point DOE, many of the trends found between the decision factors and response variables were intuitive and in agreement with the conceptual model described by both Booz Allen (Booz Allen 2018a) and PA&E (PA&E 2018b). However, the research team located a potential error (or source of confusion) in the way that RAT tracks contingency operations, resulting in an inflation of the number of ready units deployed (Section 4.B.1). RAT’s business rules for sourcing contingency operations place priority on utilizing Unit Deployment Program units when possible (Table 4). When RAT tasks an already deployed unit with a contingency, it was evident that RAT counts it as an additional deployment. By doing so, the research team found that for simulation runs involving HADR missions the number of deployed units, specifically C1 units, was inflated due to this additional counting. The use of forward deployed units to fill contingency needs is in line with the purpose of Marine Corps, but the method for tracking these deployments within RAT results in an over-confident picture of the readiness system’s capacity. It is recommended that the programming involved in RAT’s sourcing and tracking of contingency missions be reviewed for consistency and desired effect. RAT should maintain

a capability to track and record all sourced contingencies, but a different counting method should be employed for already deployed units versus those sourcing from home-station.

The research team additionally recommends the following three minor improvements be made to the contingency scenario functionality of RAT.

- Random HADR injects: In the technical documentation it was discussed that RAT has the ability to inject random HADR mission to a simulation run (Booz Allen 2018a). It was determined by both the research team and Booz Allen that this functionality was not completed due to other design priorities within the model (Hatfield 2018). The lack of the random HADR capability requires the analyst to program in every desired instance of a HADR mission, which can become quite tedious over a long simulation time period. Additionally, real-world HADR missions tend to come with limited warning and the random injection within the model would add a degree of realism. It is recommended that the random HADR functionality be fully incorporated into RAT.
- Source Contingencies from all Deployed Units: In its current state, RAT only considers UDPs to fill contingency operations and the other deployment demand node types are excluded. This is contrary to the purpose of Marine forward deployed elements, which is to be the United States' first response forces when contingencies occur, specifically Marine Expeditionary Units. It is recommended that the contingency business rules be modified to utilize all types of deployed units located within the same combatant command as the contingency for potential sourcing.
- Investigate the potential limit in the number of contingency injects per simulation run: It was found during this research that RAT has a limit in the number of contingency missions that it will inject into a single simulation run. This was discovered while conducting test runs of the developed HADR scenarios with high rates of occurrence per year (>3 per year), in which cases the model would cease adding injects after reaching

approximately (18) injects even if the input data base called for them. To confirm this situation, the research team conferred with PA&E and Booz Allen. It was determined by Booz Allen that there is no visible error within the input database programming, but RAT still limits the number of injects (Hatfield 2019). It is recommended that the contingency injection portion of RAT's programming be examined to locate the cause of this limit.

C. FUTURE RESEARCH

- Further Enhancing the Analytic Utility of RAT: The design method utilized by the enhanced RAT still remains full factorial. The full factorial design does not currently present a significant limit to the research potential of RAT due to the quick simulation speed (2 secs) and discrete nature of the input database. As research continues with RAT, specifically with the exploration of continuous variables, the full factorial design will no longer be tenable. It is suggested that further work be done in enhancing the analytic utility of RAT by expanding its capabilities to use efficient design methods, such as the nearly orthogonal Latin hypercube (NOLH) (Cioppa and Lucas 2007) and the nearly orthogonal and nearly balanced (NOB) (Vieira Jr et al. 2011) design.
- Stochastic force generation: In this research, only deterministic force generation timelines were utilized in order to give insight for Marine Corps leadership regarding potential policies or resourcing plans for the operating forces. However, the realistic time that a unit takes to transition between readiness levels is by no means deterministic. Future research should be conducted using RAT's stochastic force generation methods in order to better understand the interval variance of the Marine Corps readiness process.
- Link resource costs with readiness and risk: In this research, we discovered that home-station readiness levels alone are not sufficient to

determining the relative health of the readiness system without an accompanying metric such as risk. Due to the high resource costs of sustaining a ready Marine Corps, future research endeavor to add cost as a third dimension to the readiness and risk equation. A goal of this effort would be to not only find which combinations of force structure and force employment are risk acceptable, but also those that are resource affordable.

- Assess Marine Corps readiness utilizing Defense Planning Scenarios: The scenarios utilized within this research were derived from the current operating picture as well as notional alternate Marine Corps configurations. Future research should be directed at exploring the Marine Corps' capacity and capability to sustain its readiness system under actual Defense Planning Scenarios.

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