

MONTE-CARLO EVALUATION OF DIGITAL  
FILTERS FOR FIRE CONTROL SYSTEMS

Toshiaki Iida

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THESIS

MONTE-CARLO EVALUATION OF DIGITAL FILTERS  
FOR FIRE CONTROL SYSTEMS

by

Toshiaki Iida

December 1975

Thesis Advisor

D. E. Kirk

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simulation is used to compare the performance of these adaptive estimators to that obtained by using several constant-Q filters.





Monte-Carlo Evaluation of Digital Filters  
for Fire Control Systems

by

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Lieutenant (junior grade), Japanese navy

Submitted in partial fulfillment of the  
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## I. INTRODUCTION

A state estimator for a fire control system is designed to determine accurate estimates of target position , velocity and possibly acceleration for various target maneuvering levels .

Often , to simplify the state estimator , low-order linear models are used to approximate target motion . The characteristics of a Kalman filter based on these simplified models can be modified by making different selections for the assured random forcing function covariance matrix ,  $Q$  . Intuitively , "large"  $Q$ -matrices make the estimator more sensitive to maneuvers , but also more susceptible to the adverse effects of measurement noise . Thus , a tradeoff exists between having the capability of tracking maneuvering targets and degrading the filter's performance for non-maneuvering targets .

One approach for attempting to meet these conflicting objectives is to make the filter adaptive . The fundamental idea is to use low- $Q$  levels when the target is not maneuvering and high- $Q$  levels when the target maneuvers . There must also be decision logic to determine which model should be used at any given time .

In Chapter II , the theory of Kalman filters is discussed and various constant- $Q$  models are presented . Chapter III presents Monte Carlo simulation results for the constant- $Q$  state estimators . The  $Q$ -generated adaptive filter and the residual-testing adaptive filter are discussed in Chapters IV and V , respectively . Monte Carlo simulation results for each of these adaptive filters are presented and compared with the results obtained for the constant- $Q$  filters .



## II. PROBLEM DESCRIPTION

### A. KALMAN FILTER THEORY

Sequential estimation is characterized by the serial recursive processing of observations taken in time sequence. The result of every processing cycle is the current best estimate of the vector being estimated. This estimate, therefore, includes the effects of all observation data up to and including the current observation. As a new observation is made, the current estimate is updated to reflect this most recent data. In such an estimation scheme the calculations are identical in nature from cycle to cycle so they are ideally suited for implementation on a digital computer.

The Kalman filter is a recursive filter of the type applicable to a digital fire control system in which discrete observations are available from the radar or other sensors. The filter offers the capability of not only generating estimates of the observed system's states, but also of predicting future system (or plant) states.

The linear discrete model for which a Kalman filter is designed is characterized by the state and output equations.

$$\underline{X}(K+1) = \underline{\Phi} \underline{X}(K) + \underline{\Delta} \underline{U}(K) + \underline{\Gamma} \underline{W}(K) \quad (1)$$

$$\underline{Z}(K) = \underline{H} \underline{X}(K) + \underline{V}(K) \quad (2)$$

where

$\underline{X}(K)$  is the n-dimensional state vector at time  
t=KT

$\underline{U}(K)$  is the p-dimensional deterministic input  
vector at time t=KT



$\underline{z}(K)$  is the  $m$ -dimensional vector of measurements or observations taken at time  $t=KT$ .

$\underline{w}(K)$  and  $\underline{v}(K)$  are  $q$ -dimensional and  $m$ -dimensional noise processes, respectively, at time  $t=KT$ .

$\underline{\Phi}$  is the  $n \times n$  state transition matrix, which is assumed to be known.

$\underline{H}$  is the  $m \times n$  observation matrix which is assumed to be known.

$\underline{\Delta}$  and  $\underline{\Gamma}$  are  $n \times p$  and  $n \times q$  matrices, respectively, which relate the deterministic and nondeterministic forcing terms to the state vector; they are assumed to be known.

$T$  is the time period between measurements and  $K$  is a nonnegative integer.

The noise statistics are summarized below

$$E[\underline{v}(K)] = \underline{0} \quad , \quad E[\underline{v}(K) \underline{v}^T(J)] = \underline{R}(K) \underline{\delta}(K, J) \quad (3)$$

$$E[\underline{w}(K)] = \underline{0} \quad , \quad \underline{\Gamma} E[\underline{w}(K) \underline{w}^T(J)] \underline{\Gamma}^T = \underline{Q}(K) \underline{\delta}(K, J) \quad (4)$$

$$E[\underline{v}(K) \underline{w}^T(J)] = \underline{0} \quad \text{for all } K, J \quad (5)$$

$$\underline{\delta}(K, J) = \begin{cases} 0 & K \neq J \\ 1 & K = J \end{cases} \quad (6)$$

where

$E$  is the expectation operator

$\underline{\delta}(K, J)$  is the Kronecker delta function

$\underline{R}(K)$  is the  $m \times m$  covariance of measurement noise





matrix

$\underline{Q}(K)$  is the  $n \times n$  state excitation covariance matrix

It is assumed that the initial state is a random variable with known mean and covariance

$$E[\underline{X}(0)] = \bar{X}_0, E[(\underline{X}(0) - \bar{X}_0)(\underline{X}(0) - \bar{X}_0)] = \underline{P}_0 \quad (7)$$

In addition, it is assumed that the measurement noise and initial state are uncorrelated

$$E[\underline{X}(0) \underline{V}^T(K)] = \underline{0} \text{ for all } K \quad (8)$$

and that the random forcing input and the initial state are uncorrelated

$$E[\underline{X}(0) \underline{W}^T(K)] = \underline{0} \text{ for all } K. \quad (9)$$

The Kalman filter equations are summarized below

$$\underline{G}(K) = \underline{P}(K|K-1) \underline{H}^T [\underline{H} \underline{P}(K|K-1) \underline{H}^T + \underline{R}(K)]^{-1} \quad (10)$$

$$\underline{P}(K|K) = [\underline{I} - \underline{G}(K) \underline{H}] \underline{P}(K|K-1) \quad (11)$$

$$\underline{P}(K+1|K) = \underline{\Phi} \underline{P}(K|K) \underline{\Phi}^T + \underline{Q}(K) \quad (12)$$

$$\hat{\underline{X}}(K|K) = \hat{\underline{X}}(K|K-1) + \underline{G}(K) [\underline{Z}(K) - \underline{H} \hat{\underline{X}}(K|K-1)] \quad (13)$$

$$\hat{\underline{X}}(K+1|K) = \underline{\Phi} \hat{\underline{X}}(K|K) + \underline{\Delta} \underline{U}(K) \quad (14)$$

where the notation  $(K|K-1)$  is defined as a condition at time  $t=KT$  given information up to and including time  $t=(K-1)T$ .

The matrices in these equations are

$\underline{G}(K)$ :  $n \times m$  gain matrix



$\underline{P}(K|K)$ :  $n \times n$  covariance matrix of estimation error

$\underline{I}$ :  $n \times n$  identity matrix

$\underline{P}(K+1|K)$ :  $n \times n$  prediction error covariance matrix

$\underline{X}(K|K)$ :  $n \times 1$  optimal (minimum variance )  
estimate of  $X(K)$

$\underline{Z}(K)$ :  $m \times 1$  observation vector

A block diagram of the discrete plant and Kalman filter is shown in Figure 1.

The Kalman filter takes advantage of all previous state measurements along with their respective error estimates , and predicts ahead what the system states should be based on the state transition matrix  $\underline{\Phi}$  , and any known deterministic forcing input  $\underline{u}$  . When a new measurement becomes available , the filter takes the predicted state vector from the previous iteration ,  $\hat{\underline{X}}(K|K-1)$  , and corrects it by some amount depending on the difference between the predicted measurement vector and the actual measurement vector . The amount of correction is a linear function of the difference and is determined by the gain matrix,  $\underline{G}(K)$  , which has been calculated using equations (10)- (12) so that the state estimates yield minimum variance estimates.

## B. SYSTEM MODELS

In order to apply the Kalman filter to a given situation, a model for the plant must be assumed. In the case of a fire control system the type of model depends on the target. An example is the constant-velocity ( $1/S^2$ )



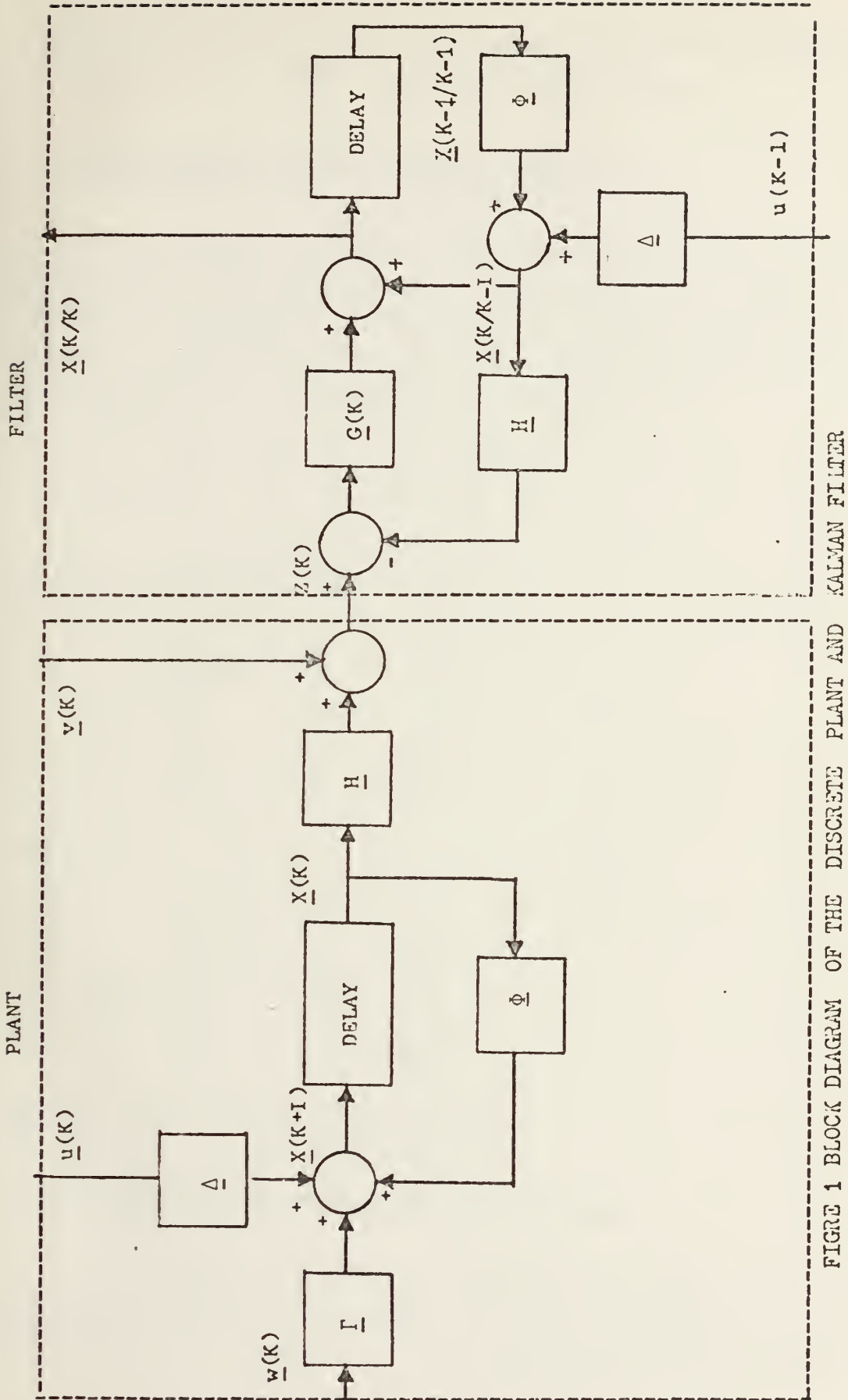


FIGURE 1 BLOCK DIAGRAM OF THE DISCRETE PLANT AND KALMAN FILTER



model which assumes that the target maintains constant velocity in all three coordinate directions.

### 1. THE CONSTANT-VELOCITY (1/S<sup>2</sup>) MODEL

This model is based on the assumption that the target maintains constant velocity in all directions and that the motion is uncoupled. The state transition matrix and the matrix  $\underline{\Lambda}$  which relates the random forcing input to the state vector for one coordinate direction are

$$\underline{\Omega}(T) = \begin{bmatrix} 1 & T \\ 0 & 1 \end{bmatrix}, \quad \underline{\Lambda}(T) = \begin{bmatrix} T^2/2 \\ T \end{bmatrix} \quad (15)$$

and for three coordinate directions

$$\underline{\Phi}(T) = \begin{bmatrix} \underline{\Omega}(T) & \underline{0} & \underline{0} \\ \underline{0} & \underline{\Omega}(T) & \underline{0} \\ \underline{0} & \underline{0} & \underline{\Omega}(T) \end{bmatrix} \quad (16)$$

and

$$\underline{\Gamma}(T) = \begin{bmatrix} \underline{\Lambda}(T) & \underline{0} & \underline{0} \\ \underline{0} & \underline{\Lambda}(T) & \underline{0} \\ \underline{0} & \underline{0} & \underline{\Lambda}(T) \end{bmatrix} \quad (17)$$

where,  $T$  is the sampling period.

### 2. THE CONSTANT-ACCELERATION (1/S<sup>3</sup>) MODEL

This model is based on the assumption that the target maintains constant acceleration in all directions and that the motion is uncoupled. The state transition matrix and





the random forcing input matrix for one direction are defined as

$$\underline{\Omega}(T) = \begin{bmatrix} 1 & T & T^2/2 \\ 0 & 1 & T \\ 0 & 0 & 1 \end{bmatrix}, \quad \underline{\Lambda}(T) = \begin{bmatrix} T^3/6 \\ T^2/2 \\ T \end{bmatrix} \quad (18)$$

For three coordinate directions

$$\underline{\Phi}(T) = \begin{bmatrix} \underline{\Omega}(T) & \underline{0} & \underline{0} \\ \underline{0} & \underline{\Omega}(T) & \underline{0} \\ \underline{0} & \underline{0} & \underline{\Omega}(T) \end{bmatrix} \quad (19)$$

$$\underline{\Gamma}(T) = \begin{bmatrix} \underline{\Lambda}(T) & \underline{0} & \underline{0} \\ \underline{0} & \underline{\Lambda}(T) & \underline{0} \\ \underline{0} & \underline{0} & \underline{\Lambda}(T) \end{bmatrix} \quad (20)$$

### 3. THE CORRELATED RANDOM ACCELERATION MODEL

One approach used to represent the effects of target motion involves introducing correlated random acceleration inputs to a  $1/s^2$  model. The correlated random accelerations are generated by an input of white noise into a coloring filter having a transfer function of  $\alpha / (s + \alpha)$ . The value of  $\alpha$  can be selected to vary the time constant of the maneuver. This results in an overall transfer function for the model of target motion of

$$T(S) = \frac{\alpha}{S^2 (S + \alpha)} \quad (21)$$

The state transition matrix and random forcing input matrix



for one direction are

$$\underline{\Omega}(T) = \begin{bmatrix} 1 & T & \frac{T}{\alpha} - \frac{1}{\alpha^2}(1 - e^{-\alpha T}) \\ 0 & 1 & \frac{1}{\alpha}(1 - e^{-\alpha T}) \\ 0 & 0 & e^{-\alpha T} \end{bmatrix} \quad (22)$$

and

$$\underline{\Lambda}(T) = \begin{bmatrix} \frac{T^2}{2} - \frac{T}{\alpha} + \frac{1}{\alpha^2}(1 - e^{-\alpha T}) \\ T - \frac{1}{\alpha}(1 - e^{-\alpha T}) \\ 1 - e^{-\alpha T} \end{bmatrix} \quad (23)$$

For a three-dimensional coordinate system, the state transition matrix and random forcing input matrix are

$$\underline{\Phi}(T) = \begin{bmatrix} \underline{\Omega}(T) & \underline{0} & \underline{0} \\ \underline{0} & \underline{\Omega}(T) & \underline{0} \\ \underline{0} & \underline{0} & \underline{\Omega}(T) \end{bmatrix} \quad (24)$$

and

$$\underline{\Gamma}(T) = \begin{bmatrix} \underline{\Lambda}(T) & \underline{0} & \underline{0} \\ \underline{0} & \underline{\Lambda}(T) & \underline{0} \\ \underline{0} & \underline{0} & \underline{\Lambda}(T) \end{bmatrix} \quad (25)$$

Here the full-order transition matrix has dimension  $9 \times 9$  and the random forcing distribution matrix  $\underline{\Gamma}$  has dimension  $9 \times 3$ .



### III. MONTE CARLO SIMULATION FOR CONSTANT-Q MODEL

The Monte Carlo simulation program described in Appendix A was used to evaluate variations of the three models described in Chapter II for various values of  $\underline{Q}$ . All Monte Carlo simulations were done for only one-dimension and used one-hundred member ensembles .

#### A. SYSTEM MATRICES

The sampling period  $T$  is selected as 1.0 and this value is also used for the adaptive filters discussed subsequently . The transition matrices for each model are calculated from equations (15), (18) and (22) . To specify the measurement noise covariance matrix ,  $R$  , the measurement noise standard deviation was selected as

$$\sigma = 5 \text{ m} \quad (26)$$

which makes

$$R(K) = 25 \quad (27)$$

In equation (4) , the state excitation matrix  $\underline{Q}$  is defined as

$$\underline{Q} = \underline{\Gamma} E [\underline{W}\underline{W}^T] \underline{\Gamma}^T \quad (28)$$

But here an additional restriction is imposed :  $\underline{Q}$  is assumed to be a diagonal matrix , that is ,  $\underline{Q}$  is represented as

$$Q = \begin{bmatrix} q & 0 & 0 \\ 0 & q & 0 \\ 0 & 0 & q \end{bmatrix} \quad (29)$$

for the constant-acceleration model and the correlated-random-acceleration model .



The adaptive filter developed from the work of Jazwinski imposes this constraint . Thus ,the assumption that  $\underline{Q}$  is diagonal is made in order to facilitate comparison among all of the adaptive filters that are considered here .

The value of  $q$  is changed and the performance of the filter is observed for various maneuvering tracks . These results are used to make comparisons with the  $Q$ -generated adaptive filter discussed subsequently and to design the Residual-testing adaptive filter discussed in Chapter V .

The Kalman filter requires that an a priori estimate of the system state vector at  $K=0$  be made . The initial state estimate vector used in all simulation runs is

$$\underline{\hat{X}}(0|-1) = \begin{bmatrix} 50000 \\ -600 \\ 0 \end{bmatrix}$$

It is desired that the initial position measurements be used as the initial position state estimates in order to have the filter track as quickly as possible. This end is accomplished quite simply by making the diagonal elements of the initial covariance of estimation error matrix very large . The effect of doing this can be seen by examining the Kalman filter gain equation in the scalar case

$$G(K) = P(K|K-1) H^T [HP(K|K-1) H^T + R(K)]^{-1} \quad (30)$$

If  $P(K|K-1)$  is made very large with respect to  $R(K)$  for  $K=0$ , then we have ,for one coordinate direction

$$G(0) = \frac{P(0|-1)}{P(0|-1) + R} = 1 \quad (31)$$

which makes the first position estimate equal to the first









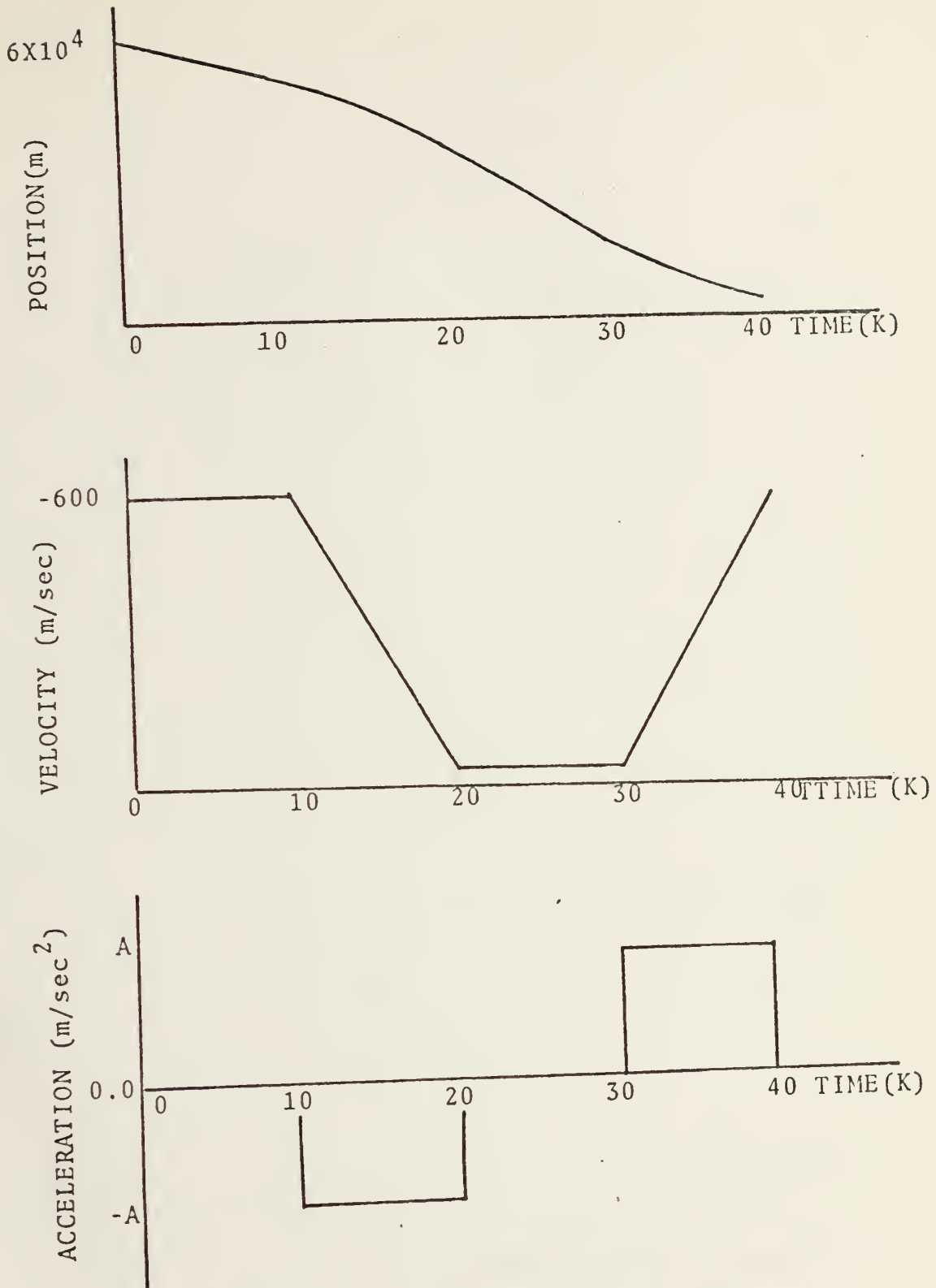


FIGURE 2 TRACK PATTERN USED FOR SIMULATION



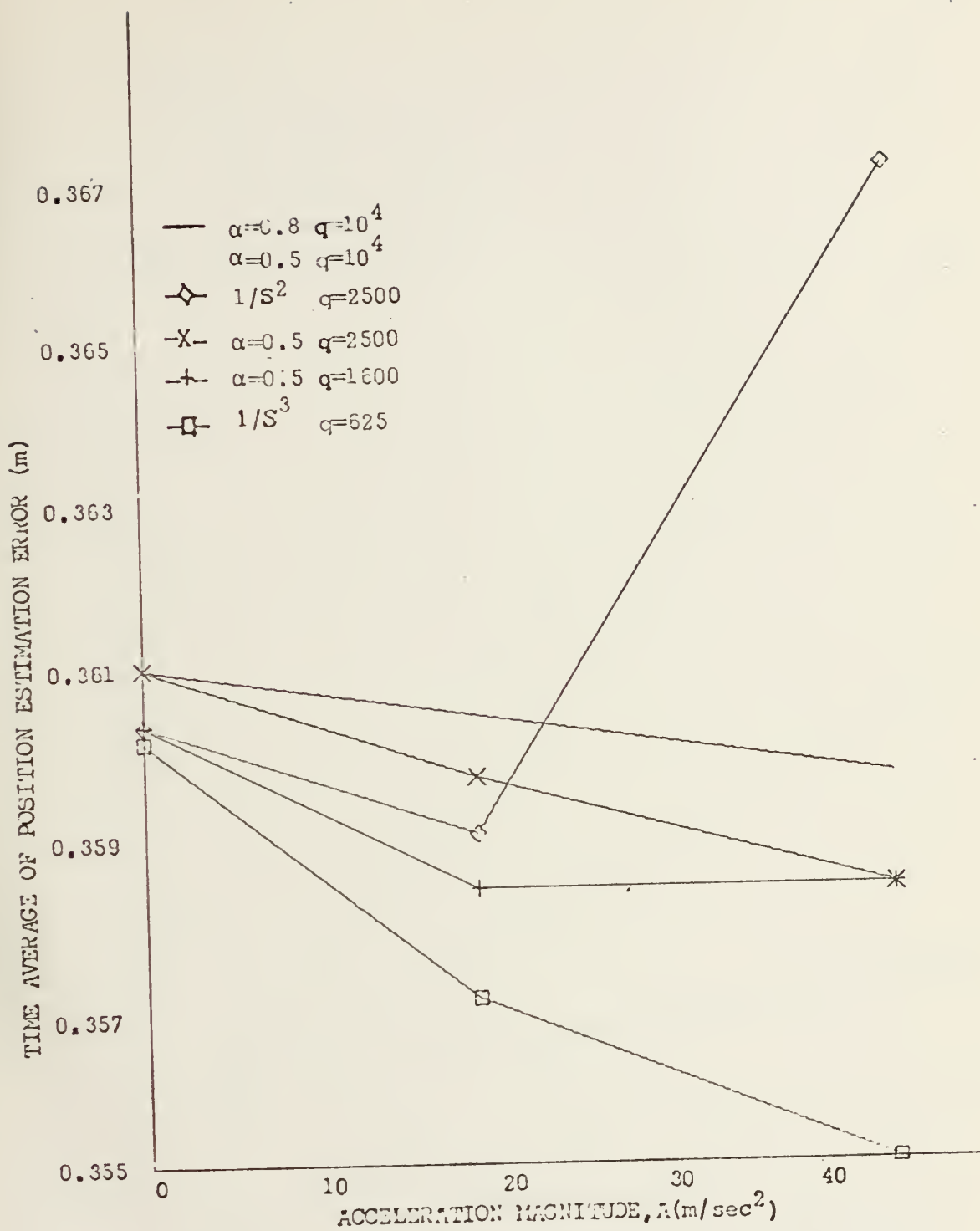


FIGURE 3 POSITION ESTIMATION ERROR FOR VARIOUS MODEL VS. MANEUVERING LEVEL FOR CONSTANT-Q FILTERS



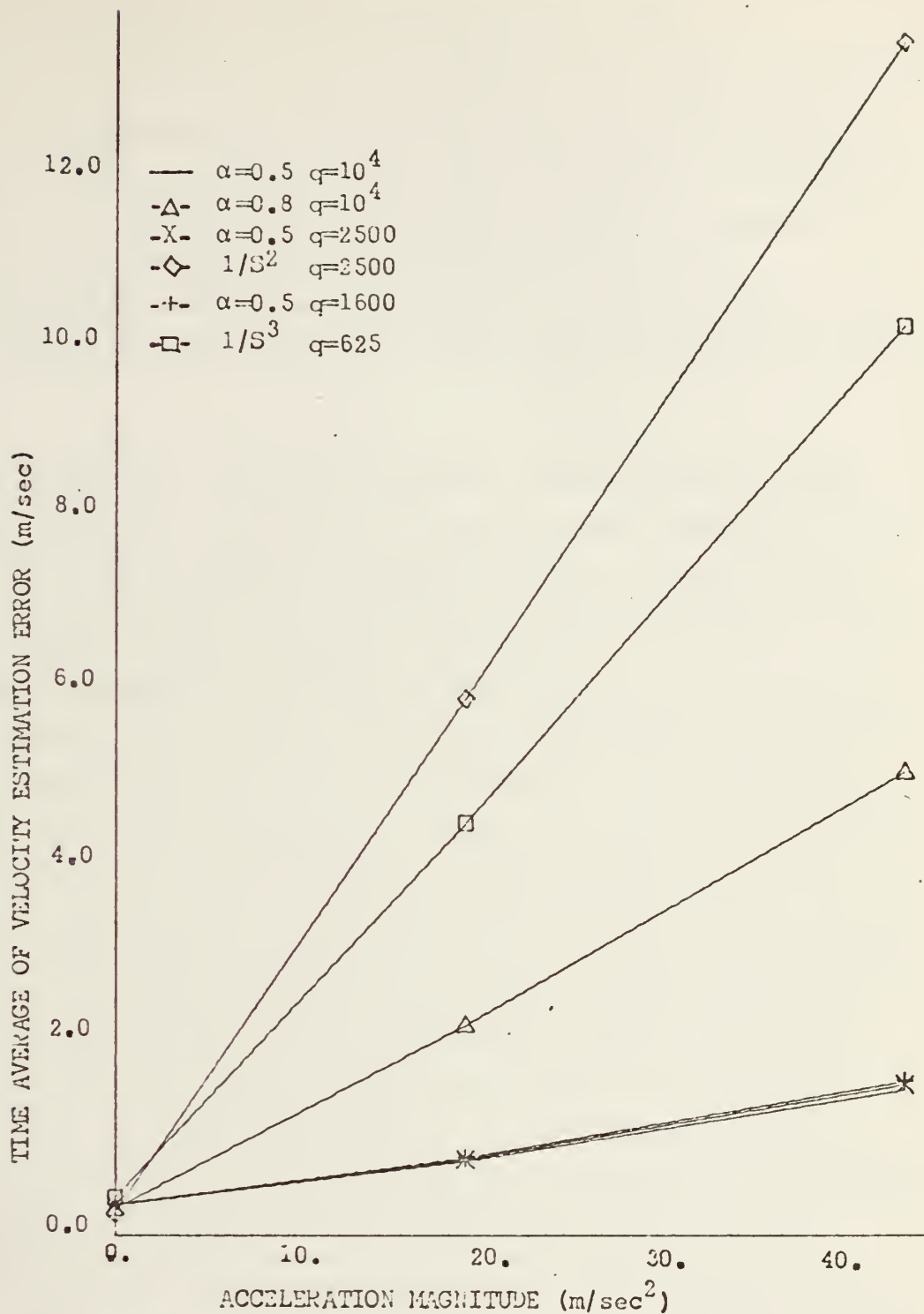


FIGURE 4 VELOCITY ESTIMATION ERROR FOR VARIOUS MODELS VS. MANEUVERING LEVEL





velocity estimation performance is poor. The correlated-constant- $Q$  filters having  $q=10000$  with  $\alpha=0.5$  and  $\alpha=0.8$  have the same position estimation error curve. The correlated models show relatively good performance for position estimation and  $\alpha=0.5$  shows excellent velocity estimation as well. The  $1/s^3$  model provides accurate estimates for position and velocity for only the nonmaneuvering track, and it has poor performance for the maneuvering tracks even if the amount of maneuvering is very small.

Comparisons were made by using time averages of the absolute values of estimation errors. When looking at the estimation errors for each sampling time, it is observed that estimation errors for constant-velocity periods are not always smaller than estimation errors for constant-acceleration periods. This means that sometimes the filter provides better estimates for the maneuvering periods than for nonmaneuvering periods. The reason is that in the constant- $Q$  model, the zero- $Q$  filter has better performance for nonmaneuvering periods than non-zero- $Q$  filters. Therefore, if we use a non-zero- $Q$  filter for the track that has both nonmaneuvering and maneuvering periods, the filter provides estimates for nonmaneuvering periods that are worse than a filter with  $q=0$  (provided that the gain schedule is prevented from reaching its steady-state value of 0). From these facts, it is evident that we have the possibility of obtaining small estimation errors by changing  $Q$ , or the gains, to match the corresponding maneuvers. The idea is to change the amount of  $Q$  as discussed in the  $Q$ -generated adaptive filter section, or to switch the gains directly for observed maneuver levels, as discussed in the section on the residual-testing adaptive filter.



#### D. CONCLUSIONS

It is important to consider whether position or velocity estimation errors are more important in comparing the filters . In this case , the differences in position estimation errors are less than 10 cm , but the differences in velocity estimation errors are greater than 3 m/sec . The velocity estimation error has more influence on prediction errors because velocity estimation errors are multiplied by elapsed time in the equation for position prediction estimation error . Therefore we can say that the filter which has the smallest velocity estimation error is the best filter in the context of fire control systems , if the position estimation error is small . From these considerations , the correlated model with  $\alpha = 0.5$  is considered to have the best performance for the tracks and estimators considered .



#### IV. THE Q-GENERATED ADAPTIVE FILTER

##### A. DEVELOPMENT

There are several methods of determining random forcing input levels as a means of compensating for model inaccuracies . Discussed in this section is a method wherein the residuals themselves determine appropriate random input levels and adapt the gains accordingly [2] , [3] , [4] . It is assumed that the residual , defined as

$$r(K+1|K) = Z(K+1) - \underline{H}\hat{\underline{X}}(K+1|K) \quad (33)$$

is a scalar and has the statistical property

$$E[r(K+1|K)] = 0 \quad (34)$$

The measurement  $Z(K)$  is known and is used to generate  $\hat{\underline{X}}(K+1|K)$  using equation (13) and (14) . It is desired to use that value of the noise variance  $Q$  which produces the most probable predicted residual  $r(K+1|K)$  , as defined in equation (33). That is , the  $Q$  value which satisfies the relationship

$$q = \max f[r(K+1|K)] \quad q > 0 \quad (35)$$

is to be found , where  $f$  is the probability density function of the residual . The restriction  $q > 0$  is consistent with the property of a variance.

The probability density in equation (35) is assumed to be zero-mean, Gaussian, with variance given by

$$\begin{aligned} Y(K+1|K) &= E[r^2(K+1|K)] \\ &= \underline{H}\underline{P}(K+1|K)\underline{H}^T + R \end{aligned} \quad (36)$$

the maximizing  $q$  is determined by



$$q = \begin{cases} \frac{r^2(K+1|K) - E[r^2(K+1|K) | \underline{Q} = 0]}{\underline{H} \underline{\Gamma} \underline{\Gamma}^T \underline{H}^T} & \text{if positive} \\ 0 & \text{otherwise} \end{cases} \quad (37)$$

and

$$\underline{Q} = \underline{\Gamma} q \underline{\Gamma}^T \quad (38)$$

where

$$r^2(K+1|K) = E[r^2(K+1|K)] \quad (39)$$

if

$$r^2(K+1|K) > \underline{H} \underline{\Phi} \underline{P}(K|K) \underline{\Phi}^T \underline{H}^T + R$$

and

$$r^2(K+1|K) = 0 \quad (40)$$

otherwise, since

$$E[r^2(K+1|K)] = \underline{H} \underline{\Phi} \underline{P}(K|K) \underline{\Phi}^T \underline{H}^T + q \underline{H} \underline{\Gamma} \underline{\Gamma}^T \underline{H}^T + R \quad (41)$$

and with abused notation

$$E[r^2(K+1|K) | \underline{Q} = 0] = \underline{H} \underline{\Phi} \underline{P}(K|K) \underline{\Phi}^T \underline{H}^T + R \quad (42)$$

then equation (37) is given from (39), (41) and (42).

The linear filter with  $q$  that is estimated in (37) is the  $Q$ -generated adaptive filter for an uncorrelated and identically distributed noise input. This adaptive filter works in the following manner: as long as the square of the residual is smaller than the variance of the residual, the filter does not generate a non-zero  $\underline{Q}$ , because the





residuals are small and consistent with small measurement noise levels . When the square of residual becomes larger than the variance of the residual , the filter is diverging and a non-zero  $\underline{Q}$  is generated . This  $\underline{Q}$  increases the value of  $P(K+1|K)$  , which increases the gains . Increasing the gains "opens " the filter to the incoming observation .

In Figure 5 the relationship among the residuals , the variance of estimation error and the generated  $q$  are plotted for 20 m/sec<sup>2</sup> acceleration with the  $\alpha=0.5$  correlated constant- $Q$  filter . Between  $K=1$  to  $K=10$  and between  $K=21$  to  $K=30$  the velocity is constant ; during the intervals  $K=11$  to 20 and  $K=31$  to 40 the acceleration is constant .

## B. SIMULATION RESULTS

For constant- $Q$  estimators , the  $Q$ -matrix was specified by Equation (29) . For the  $Q$ -generated adaptive filter , Equation (38) gives a theoretical form of the  $Q$ -matrix , but there are other  $Q$ -matrix forms , also . Jazwinski [1] represented the  $Q$ -matrix as  $\underline{Q}=q\underline{I}$  , where  $q$  is defined by Equation (37) and  $\underline{I}$  is the identity matrix . Another possible form is the diagonal matrix representation of Equation (38) .

In this Chapter , two form of  $Q$ -matrices are used to simulate the  $Q$ -generated adaptive filter . One is of the form  $\underline{Q}=q\underline{I}$  and the other is the diagonal case of Equation (38) , that is ,  $\underline{Q}=\text{diag}[\underline{\Gamma}q\underline{\Gamma}^T]$  .

In the simulation studies the correlated filter with  $\alpha=0.5$  (which had the best performance as a constant- $Q$  filter ) is used . The results are compared with



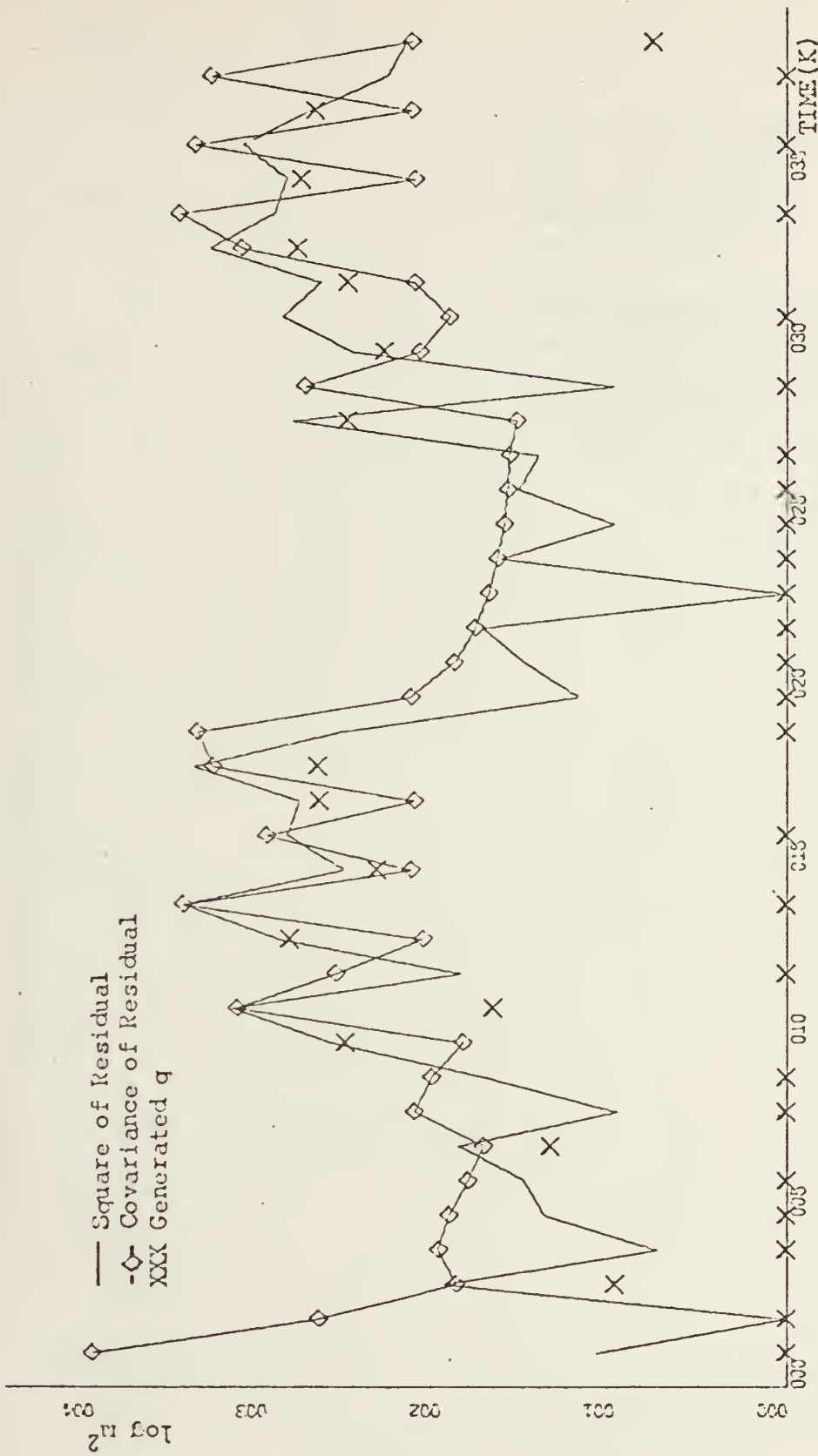


FIGURE 5 SQUARE OF RESIDUAL, COVARIANCE OF RESIDUAL AND THE RESULTING VALUE OF q GENERATED

X-SCALE=5.00E+00 UNITS INCH.  
 Y-SCALE=1.00E+00 UNITS INCH.



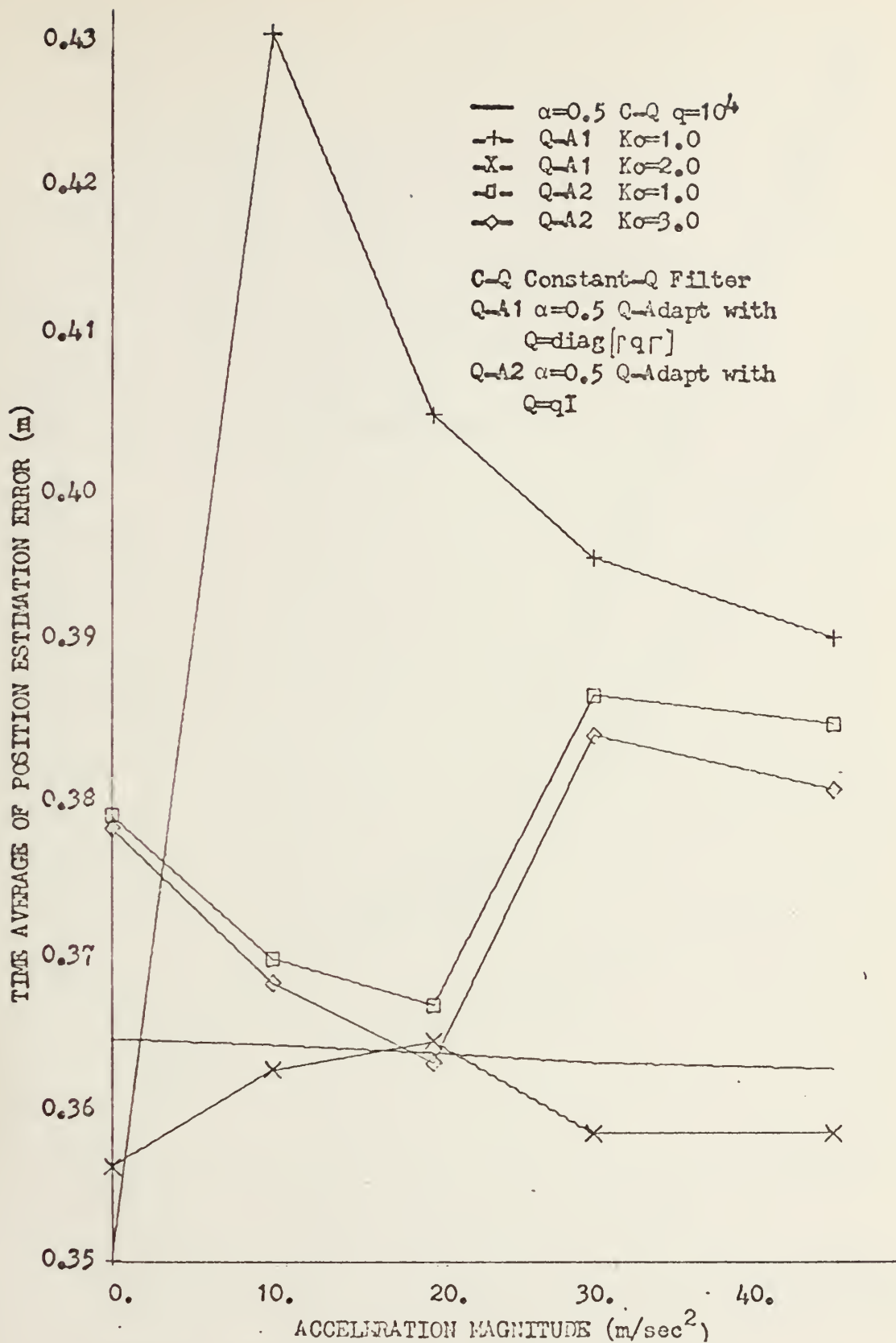


FIGURE 6 POSITION ESTIMATION ERROR FOR VARIOUS MODEL VS. MANEUVERING LEVEL FOR Q-GENERATED ADAPTIVE FILTERS



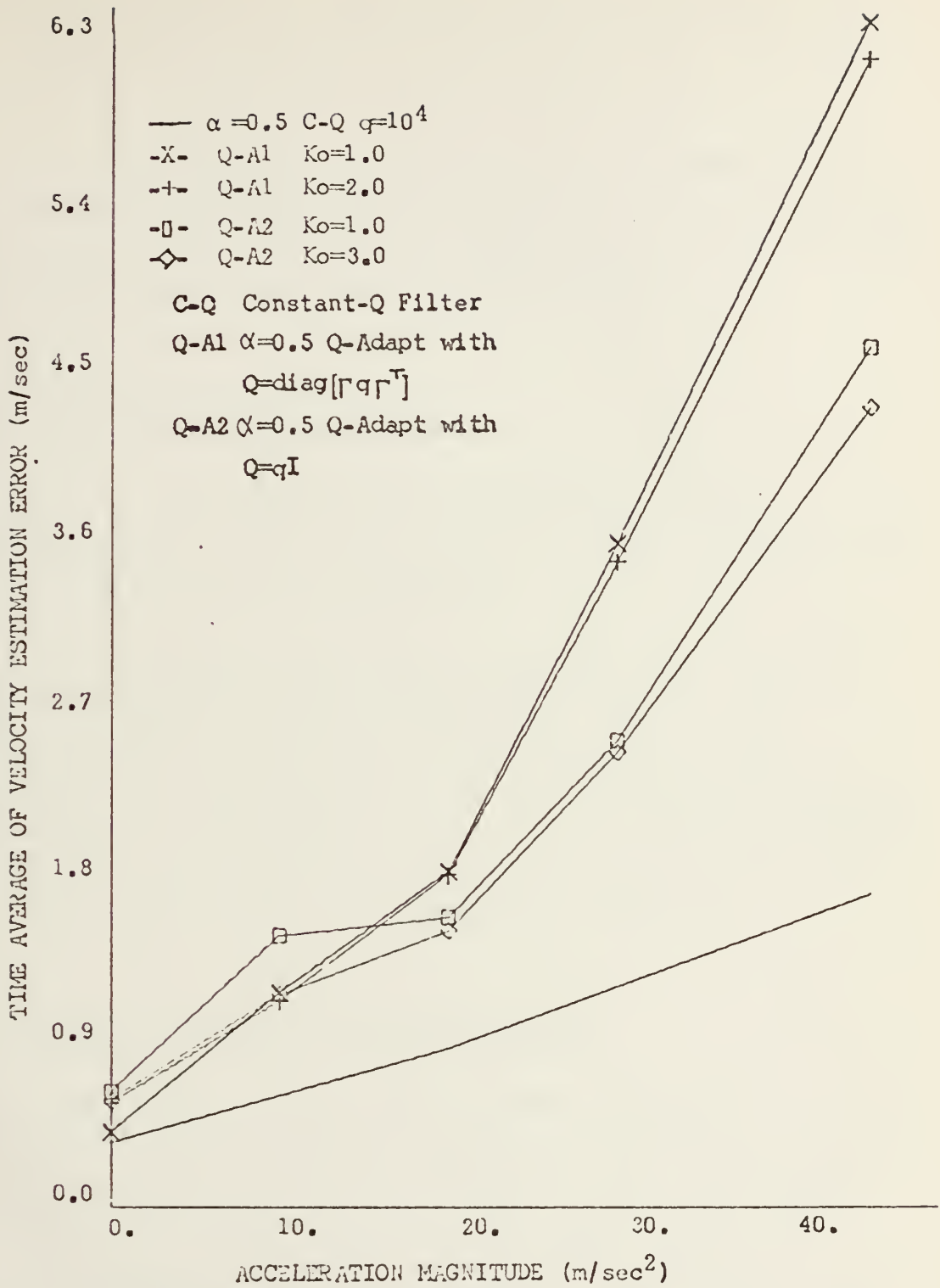


FIGURE 7 VELOCITY ESTIMATION ERRORS FOR VARIOUS MODELS VS. MANEUVERING LEVEL FOR Q-GENERATED ADAPTIVE FILTERS





constant-Q estimators , using the same track pattern , the same ensemble size and system matrices that were used for the constant-Q filter simulation in Chapter III .

Because the levels of  $q$  generated were smaller than expected and the adaptive filter did not perform as well as anticipated , the Q-generated adaptive filters were adjusted by multiplying Equation (37) by the constant  $K_0$  .

### 1. Simulation results with $\underline{Q}=q\underline{I}$

First , the simulation was performed to find a reasonable value of  $K_0$ ; it was found by trial and error that  $K_0=3.0$  produced the best performance .

The simulation results for the Q-generated adaptive filter with  $\underline{Q}=q\underline{I}$  are shown in Figures 6 and 7 . The adaptive filters provide position estimates that are comparable to , but somewhat worse than , those provided by the constant-Q filter with  $\alpha=0.5$  . The velocity estimation performance of the adaptive filters is significantly worse than that obtained using the constant-Q estimator .

### 2. Simulation results with $\underline{Q}=\text{diag} [\underline{\Gamma} q \underline{\Gamma}^T]$ .

An appropriate value of  $K_0$  for the correlated Q-generated adaptive filter with  $\underline{Q}=\text{diag} [\underline{\Gamma} q \underline{\Gamma}^T]$  was found to be  $K_0=2.0$  . The simulation results for  $K_0=1.0$  and  $K_0=2.0$  are plotted in Figures 6 and 7 , and compared with the correlated constant-Q filter having  $\alpha=0.5$  and the Q-generated adaptive filter with  $\underline{Q}=q\underline{I}$  . For  $K_0=1.0$  , the Q-generated adaptive filter having  $\underline{Q}=\text{diag} [\underline{\Gamma} q \underline{\Gamma}^T]$  provides very poor performance compared with the  $\alpha=0.5$  correlated constant-Q filter , especially for velocity estimates . The



adaptive filter with  $K_0=2.0$  has good position estimates , but the velocity estimation error is essentially the same as with  $K_0=1.0$  . Compared with the  $Q$ -generated adaptive filter having  $\underline{Q}=\underline{q}\underline{I}$  (  $\alpha=0.5$  ) , for  $K_0=2.0$  , this filter has smaller position estimation errors , but greater velocity estimation errors .

### C. CONCLUSIONS.

The  $Q$ -generated adaptive filters were simulated with two types of  $Q$ -matrices . The choice of the form of the  $Q$ -matrix has great influence on the simulation results . As seen in Figure 6 and 7 , the adaptive filter with  $\underline{Q}=\underline{q}\underline{I}$  , gives smaller estimation errors for velocity , but greater position estimation errors than for  $\underline{Q}=\text{diag} [\underline{\Gamma} \underline{q} \underline{\Gamma}^T]$  . However , the maximum difference in position estimation was less than 5 cm , whereas the differences in velocity estimation error are more significant . From these facts , it is concluded that  $\underline{Q}=\underline{q}\underline{I}$  provides a better  $Q$ -generated adaptive filter than  $\underline{Q}=\text{diag} [\underline{\Gamma} \underline{q} \underline{\Gamma}^T]$  .

Additional simulations were done for a  $1/s^3$  model with the same  $Q$ -matrices that were used for the correlated  $Q$ -adaptive filter simulation . The  $1/s^3$   $Q$ -generated adaptive filter provided smaller position estimation errors with  $K_0=2.0$  than the  $\alpha=0.5$  correlated  $Q$ -generated adaptive filter with  $\underline{Q}=\text{diag} [\underline{\Gamma} \underline{q} \underline{\Gamma}^T]$  for  $K_0=2.0$  , but the velocity estimation errors were about seven times those of the correlated constant- $Q$  filter with  $\alpha =0.5$  . In addition , there was not any significant improvement in velocity estimation errors obtained by adjusting  $K_0$  . Therefore , the  $1/s^3$   $Q$ -generated adaptive filter does not compare favorably with the correlated constant- $Q$  filter having  $\alpha =0.5$  , the best filter discussed previously .



The difficulty with the  $Q$ -generated adaptive filters considered is their velocity estimation performance . It was anticipated that the  $Q$ -generated adaptive filters would generate the smallest estimation errors . However , the best  $Q$ 's for position estimation and velocity estimation are different . One reason for the mediocre performance may be that the  $Q$  is generated for only one residual measurement . Also , it is impossible to adjust the  $Q$  to yield optimal estimates for position , velocity , and acceleration at the same time . Another problem is computer time ; computer calculation time for the  $Q$ -generated adaptive filter is more than twice that of the constant- $Q$  model , because of the on-line gain calculation . Thus , it is difficult to find a way of obtaining accurate estimates of position , velocity and acceleration simultaneously with computation time constraints . If there is no constraint on computation time and position estimation accuracy is paramount (e.g in a satellite tracking filter ) , the adaptive- $Q$  estimator might be profitably employed . However , in the context of fire control systems , other estimators considered in this investigation are superior .



## V. THE RESIDUAL-TESTING ADAPTIVE FILTER

### A. CONSTANT-Q FILTER PERFORMANCE.

If a constant-Q filter is used to track maneuvering targets , the performance of the filter will depend on the amount of maneuvering . To some extent the estimator can be "tuned" to tracks having similar maneuvering levels by adjusting  $Q$  . However , if the tracks which the filter encounters have markedly different maneuvering levels than those for which it was designed , performance degradation results . Thus , it is virtually impossible to design a single constant-Q estimator that will perform well for tracks having a wide range of maneuvering levels . Since a constant-Q estimator can be designed to have good performance for a particular amount of maneuvering , one approach is to design several constant-Q filters and switch filters based on the size of the residual . This concept is illustrated in Figure 8.

To determine the performance of filters for various maneuvering levels , simulations were done for several constant-acceleration tracks , shown in Figure 9 , with the correlated filter having  $\alpha=0.5$  and the same system matrices that were used for the constant-Q filter simulations in Chapter III . The tracks used for the simulations all have the initial conditions of 60000 m for position , -600 m/sec for velocity , and the amount of acceleration  $B$  is constant during the run . The number of sampled points is twenty , which is long enough for the gains to have reached steady state . An ensemble size of one-hundred is used for the Monte Carlo simulations .

The results of the Monte Carlo simulations are plotted in Figures 10 and 11 . From Figure 10 , the minimizing  $q$





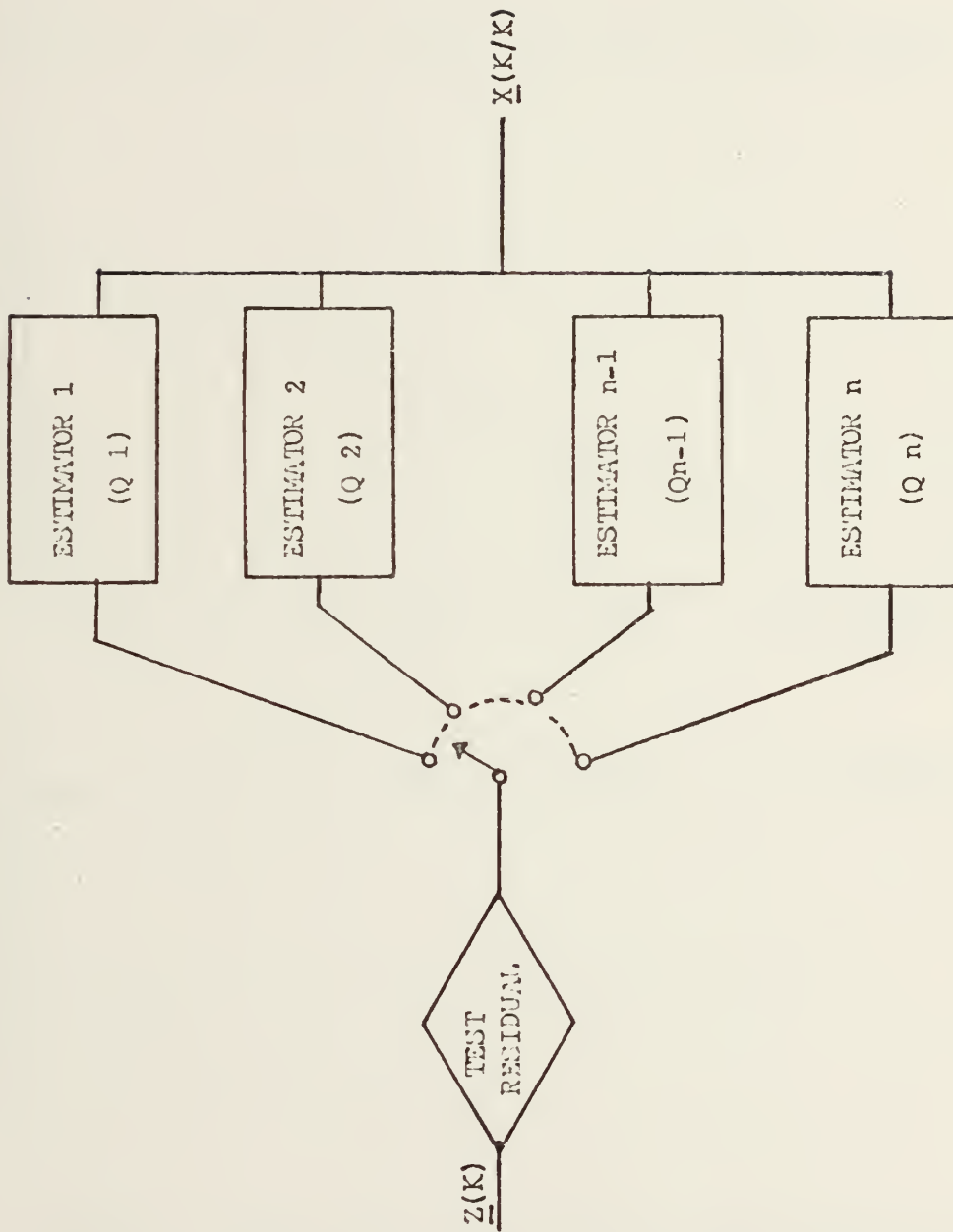


FIGURE 8 SIMPLE MODEL OF RESIDUAL-TESTING ADAPTIVE FILTER



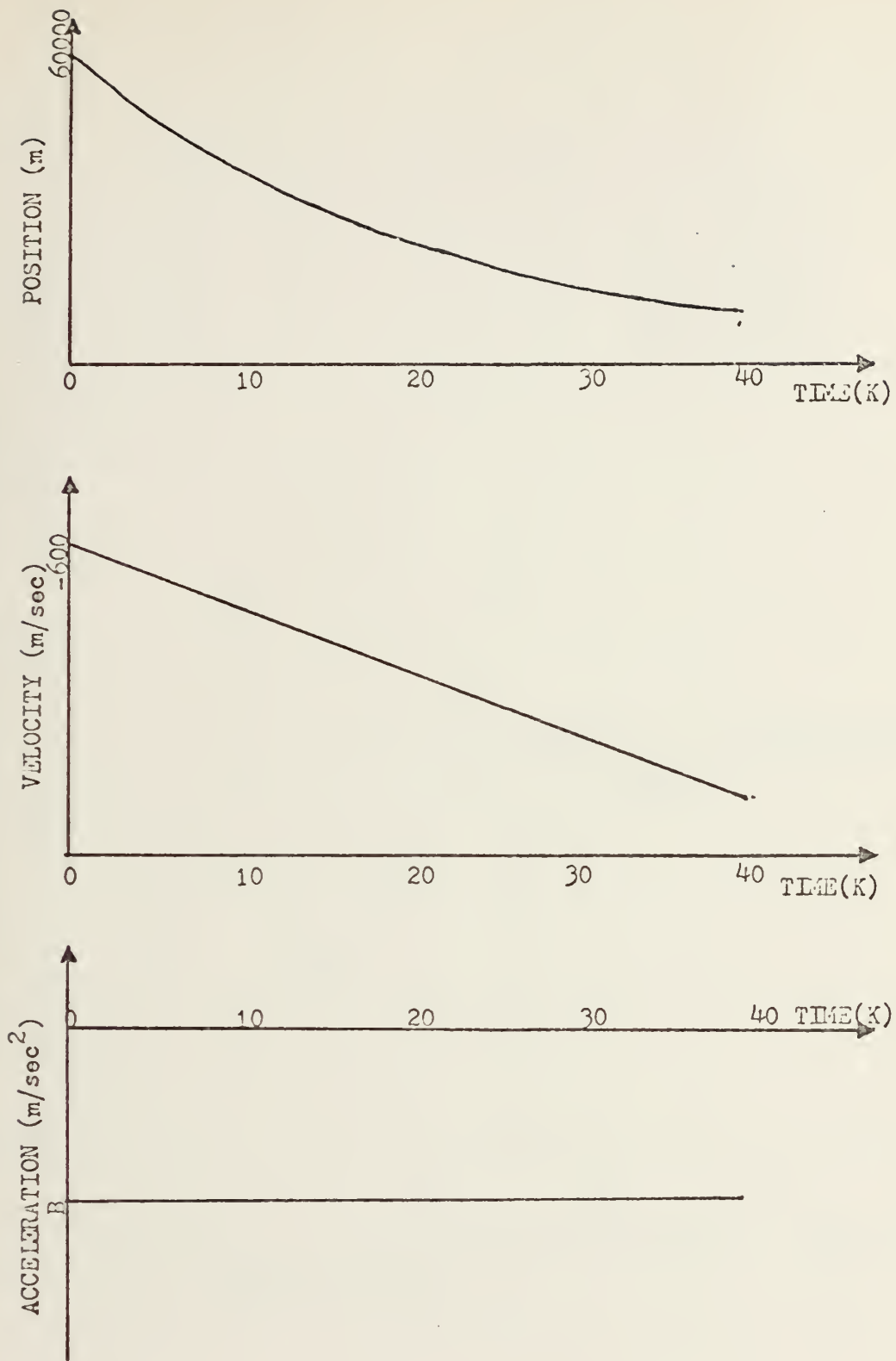


FIGURE 9 TRACK PATTERN FOR CONSTANT ACCELERATION SIMULATION



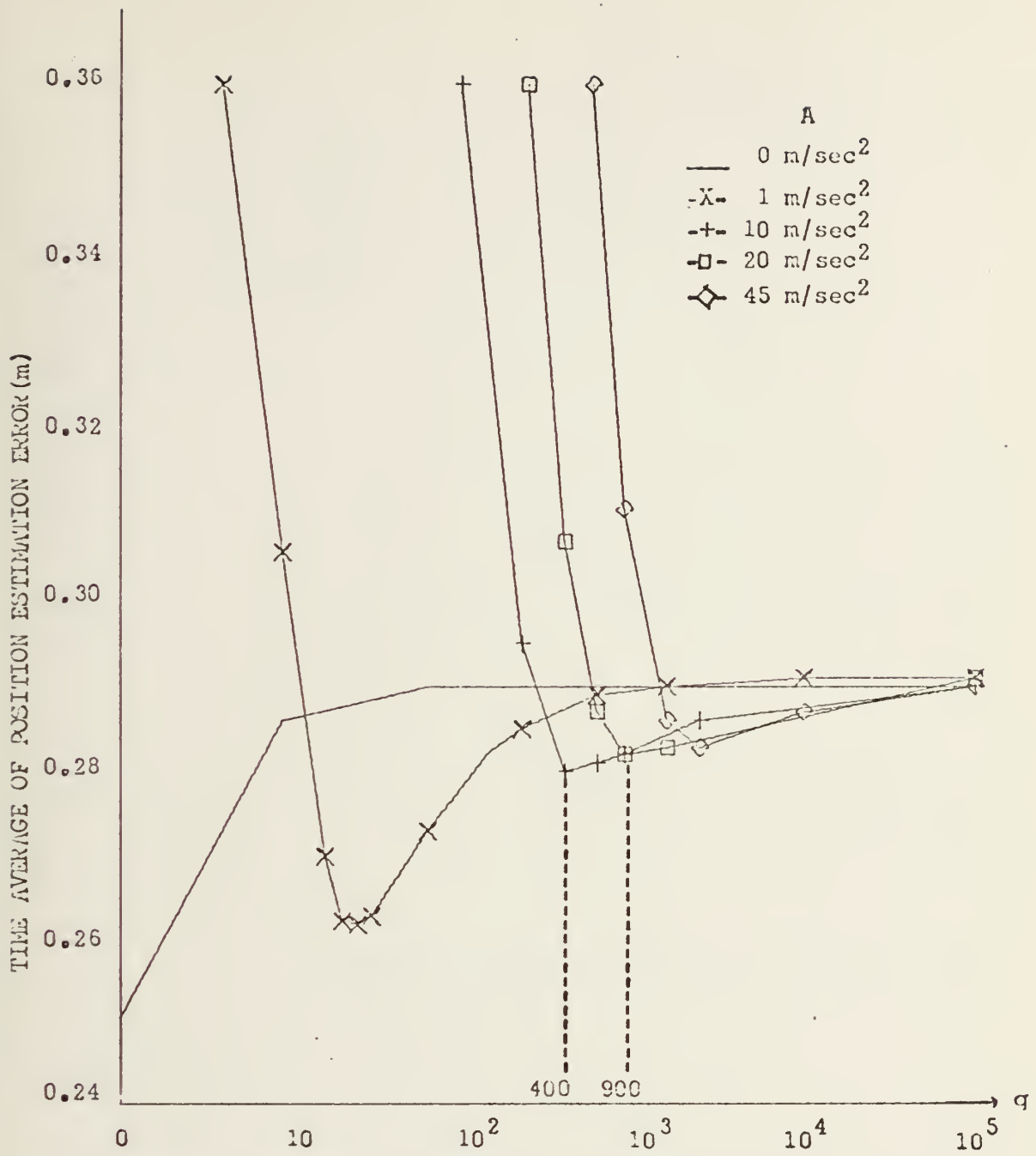


FIGURE 10 POSITION ESTIMATION ERROR DEPENDENCE ON  $q$  FOR CONSTANT MANEUVER-LEVEL,  $A$ .



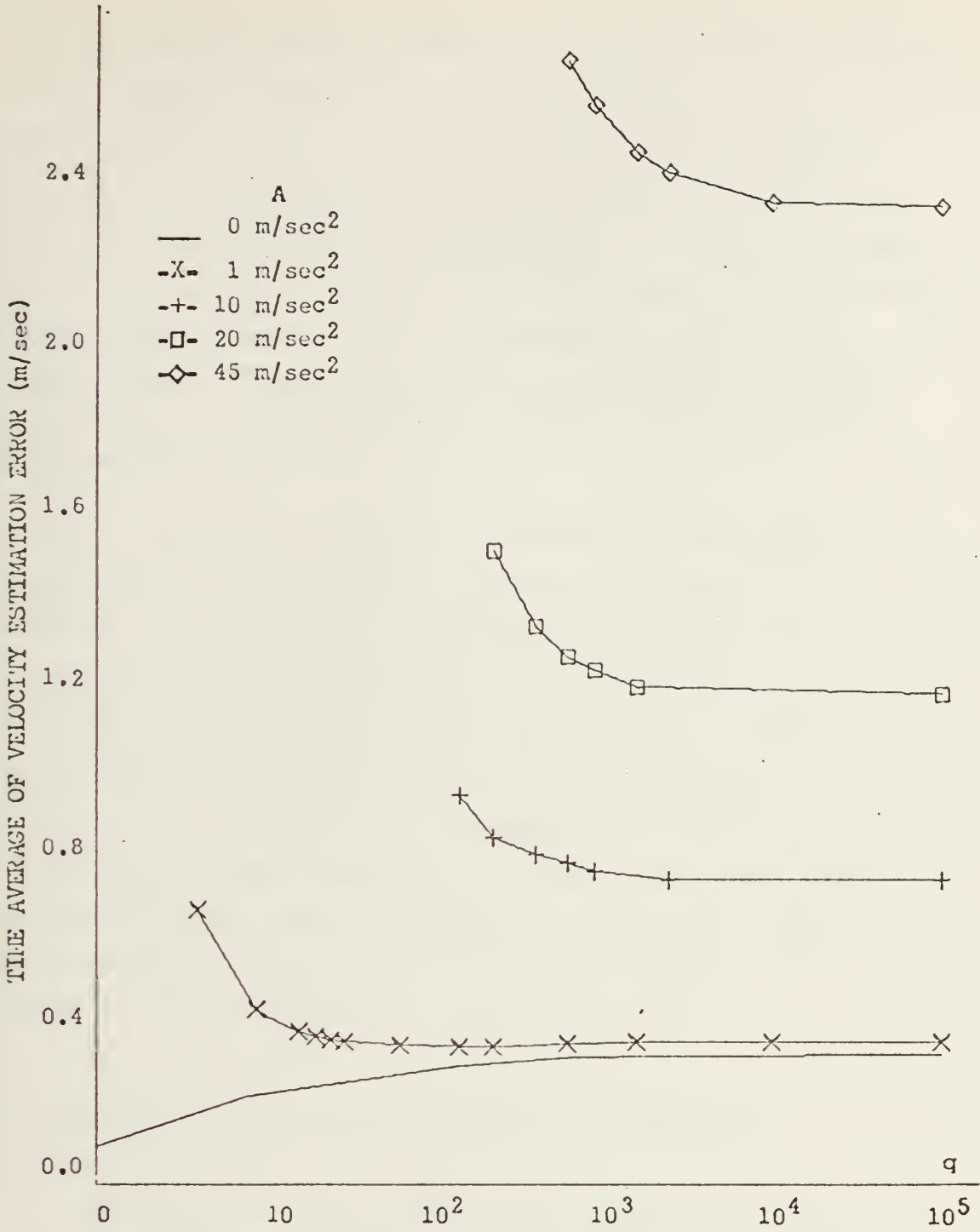


FIGURE 11 VELOCITY ESTIMATION ERROR DEPENDENCE ON  $q$  FOR  
 CONSTANT MANEUVER-LEVEL,  $A$ .





for position estimation error is observed to be  $q=400$  for the  $10 \text{ m/sec}^2$  acceleration track ,  $q=900$  for the  $20 \text{ m/sec}^2$  acceleration track and so on . For  $q$  larger than the minimizing value the position estimates are degraded slightly ; for  $q$  smaller than the minimizing value the position estimates degrade significantly . On the other hand , the velocity estimation errors monotonically decrease as  $q$  increases (except for a nonmaneuvering target ) . If the curves in Figure 11 were obtained for still larger values of  $q$  , it is anticipated that they would show a minimum eventually .

An additional factor to consider is the relative importance of position and velocity estimation errors . To predict future position , velocity errors are more important , provided the prediction time is significant . This is because position prediction errors tend to be proportional to velocity estimation errors multiplied by elapsed time . Thus , if a target is identified by some means as having an acceleration of  $20 \text{ m/sec}^2$  , Figures 10 and 11 indicate  $q=1600$  as a reasonable choice . Note that this value is slightly larger than the value of  $q=900$  which yields the minimum time -average of position estimation error for this level of maneuvering .

## B. DETECTION AND CLASSIFICATION OF RESIDUALS

The first step in designing a residual-testing adaptive filter is to provide some mechanism for determining the maneuvering level which corresponds to observed residual values . To determine a reasonable residual-testing procedure , it is necessary to investigate the characteristics of residuals .



## 1. Investigation of the characteristics of residuals .

As a mechanism to accomplish the detection and classification of residuals , it is reasonable to use the time average of residual absolute values . Using the minimizing values of  $q$  for position estimation error , the time averages of residual absolute values were computed in the constant-acceleration track simulation described in Section A . The results are plotted in Figure 12 . Based on the curve in Figure 12 , a residual-testing adaptive filter (Filter-0) was synthesized and simulated . The filter was the correlated  $\alpha = 0.5$  estimator , the system matrices and tracks used for the simulation were the same as for the constant- $Q$  filter simulation in Chapter III . Figure 13 illustrates the use of the data in Figure 12 in designing an adaptive filter . The information in Figure 13 is used in the following manner : a calculated residual value at time  $K$  is used to enter the graph on the ordinate and the corresponding  $q$  value is read from the abscissa . For example , if the residual is 32.0 , the value of  $q$  used to determine the next gain value is  $q=900$  . The level settings for the residuals and the specified  $q$  values shown in Figure 13 were obtained by subjective evaluation of the information in Figures 10-12 .

The simulation results for this filter were poor , but it was helpful in observing the characteristics of residuals . As seen in Figure 12 , the time average of the residual absolute value for a nonmaneuvering target is 6.15 . Thus , Filter-0 assumes that the track is in a nonmaneuvering period whenever the residual is less than 6.15 , and provides the gains which correspond to zero- $Q$  to the system . However , frequently residuals were observed to be less than 6.15 , even if the track was maneuvering . It is apparent from Figure 10 and 11 , that the zero- $Q$



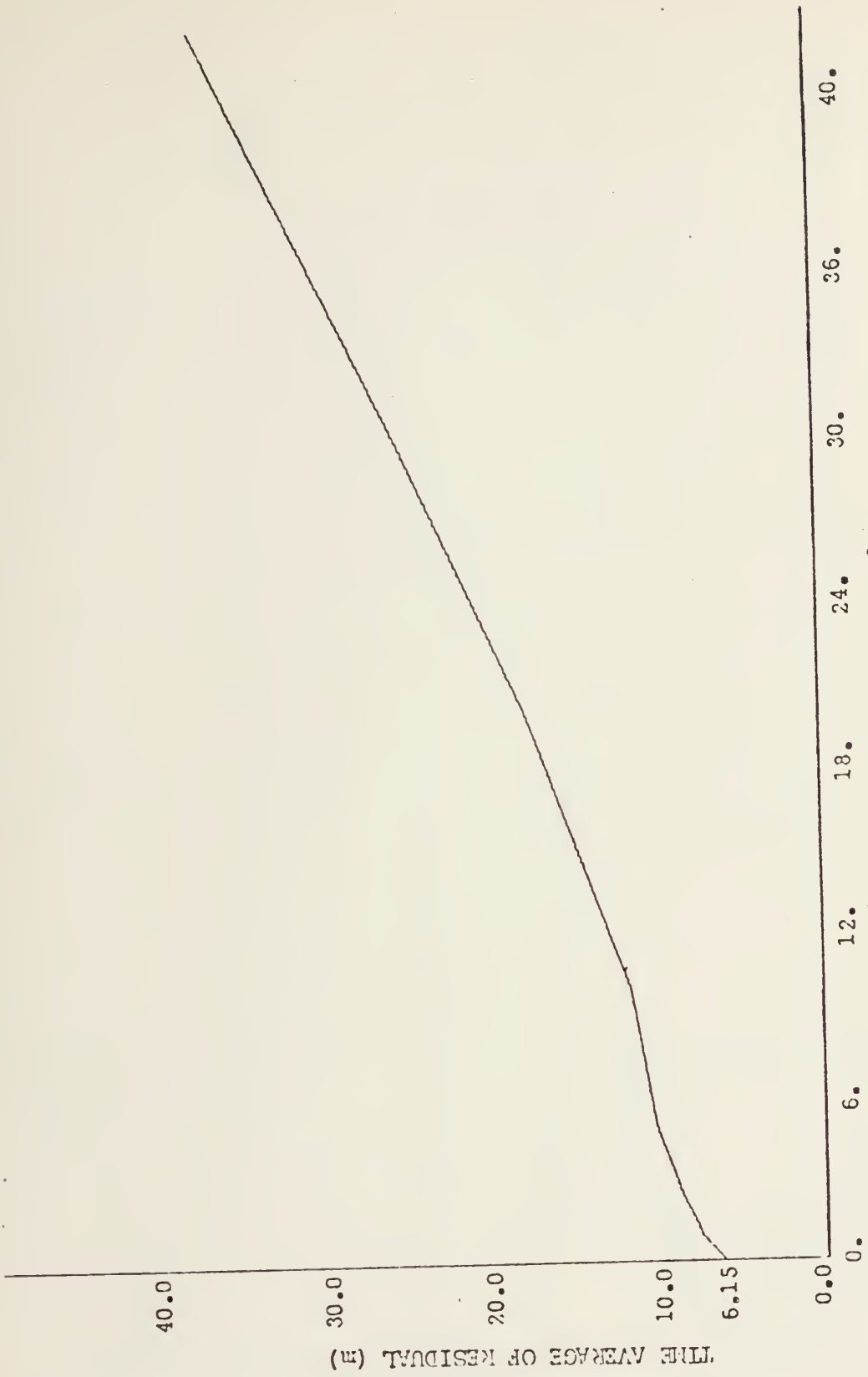


FIGURE 12 THE TIME AVERAGE OF RESIDUALS VS. MANEUVERING LEVEL



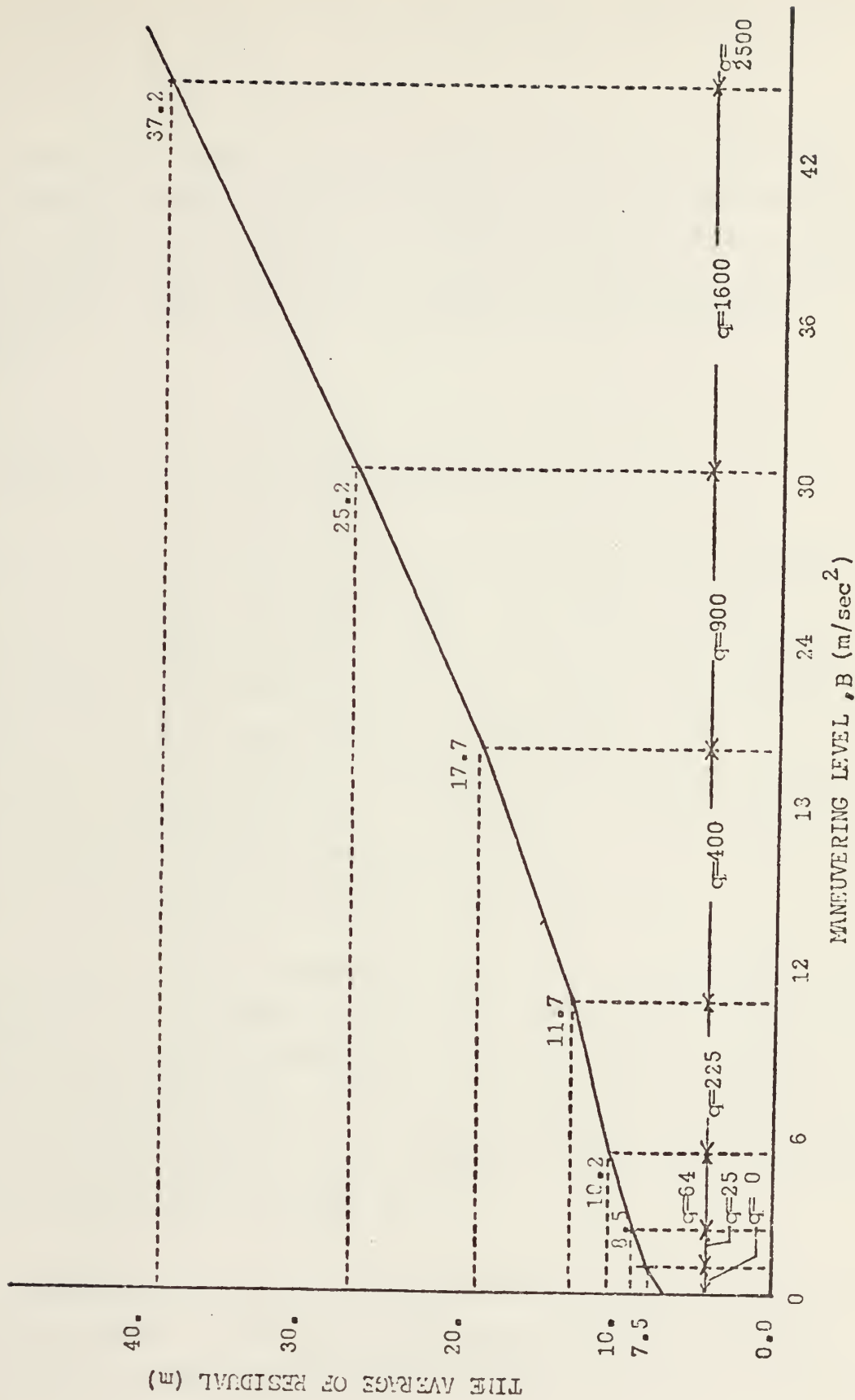


FIGURE 13 LEVEL SETTING FOR RESIDUAL AND  $q$  SELECTION FOR FILTER-0





gains generate large position and velocity estimation errors for maneuvering tracks ; this is the reason that Filter-0 provided such poor performance .

From the simulation for Filter-0 , it was found that the residuals cannot be detected and classified sufficiently well by using only the current value of the residual . Thus the residual testing mechanism tested in Filter-0 , required improvement . This point is addressed in the following section .

## 2. Residuals and acceleration estimation error.

In the previous section , it was found that the residuals are often less than the measurement noise level , even if the target is maneuvering , and that the time averages of residual absolute value do not provide enough information to adequately detect and classify the residuals . Thus , for the numerical values used here , the measurement noise does not influence the residuals as much as target acceleration does . Because of this observation , the acceleration estimation error for the constant-acceleration track was next considered .

For the constant-acceleration track simulations in Section A , it was observed that the acceleration estimation error for a constant-acceleration track reached constant values (the steady-state values of acceleration estimation error ) as  $K$  becomes large . These steady-state acceleration values were computed in the simulation described in Section A , and are shown in Figure 14 .

The steady-state acceleration estimation error curve is almost parallel to the time average of residual absolute value curve , and the difference between these two curves is



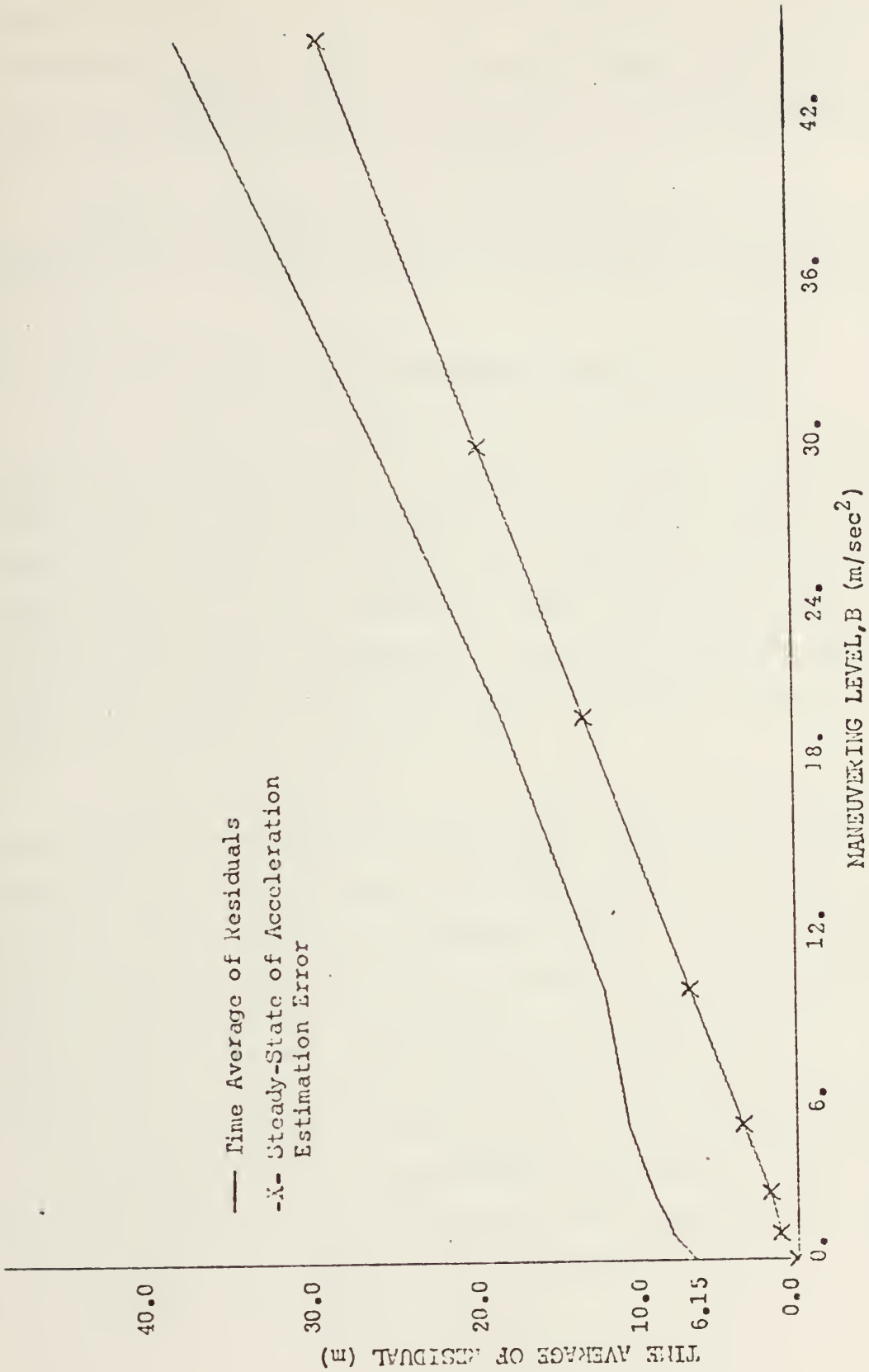


FIGURE 14 THE STEADY-STATE OF ACCELERATION ESTIMATION ERROR AND THE TIME AVERAGE OF RESIDUALS VS. MANEUVERING LEVEL



close to the value of the standard deviation of measurement noise level (5 m) . From this , it can be inferred that the steady-state acceleration estimation error can be obtained by subtracting the standard deviation of measurement noise from the time-average of residuals .

Thus the steady-state values of acceleration estimation errors can be used to detect and classify the residuals .

### 3. A modification of the Residual-Testing Filter

In Sections B.1 and B.2 , two viewpoints concerning residuals were examined . The first approach assumes that the residuals are significantly influenced by measurement noise and attempts to classify the residuals by using the time average of their absolute values (see Figure 14) . A second possibility is ignore the effects of measurement noise on residuals and attribute the residual values entirely to target acceleration .

One way to incorporate both of these observations in the filter is to utilize an adaptive switching scheme <sup>5</sup> which operates as follows : if two consecutive residuals are less than a selected threshold level , the gains are set to the zero-Q gains and it is assumed that the track is in a nonmaneuvering period ; otherwise , the residuals are equated to the steady-state values of acceleration estimation errors shown in Figure 14 (by assuming that the residual is negligibly influenced by the measurement noise ) and the values of  $q$  are determined accordingly . The switching level threshold used for this scheme , 7.0 , is obtained from the time average of residuals for zero-acceleration in Figure 12 .



### C. THE SELECTION OF Q.

The second step in designing the residual-testing adaptive filter is to select an appropriate value of  $Q$  for each acceleration level . To simplify the implementation of the filters , the steady-state gain values were used . Two sets of threshold selections were made by arbitrarily quantizing the steady-state acceleration dependence on  $q$  illustrated in Figure 14 .

### D. FILTER A

Filter A uses the threshold levels given below . Two consecutive residuals having absolute values of less than 7.0 causes the zero- $Q$  gains to be selected . Otherwise , the gains corresponding to the  $q$  values below are used .

Filter A

Acceleration ( $m/sec^2$ )	Residual value (m)	Selected $q$
0.0 - 1.0	0.00 - 1.00	0
1.0 - 2.5	1.00 - 1.67	64
2.5 - 5.0	1.67 - 3.25	144
5.0 - 10.0	3.25 - 6.41	400
10.0 - 20.0	6.41 - 12.75	625
20.0 - 30.0	12.75 - 19.08	1600
Above 30.0	Above 19.08	10000

All  $q$  values were selected to be slightly greater than the position estimation error minimizing  $q$  values .





## E. FILTER B

Filter B has the following thresholds and corresponding values of  $q$  . Again 7.0 was used as the threshold for examining two consecutive residuals . Notice that the quantization levels for acceleration and residual values are the same as for Filter A .

Filter B						
Acceleration (m/sec <sup>2</sup> )			Residual value (m)		Selected $q$	
0.0	-	1.0	0.00	-	1.00	0
1.0	-	2.5	1.00	-	1.67	64
2.5	-	5.0	1.67	-	3.25	625
5.0	-	10.0	3.25	-	6.41	1600
10.0	-	20.0	6.41	-	12.75	2500
20.0	-	30.0	12.75	-	19.08	10000
Above 30.0			Above 19.08			100000

Filter B utilizes generally higher  $q$  values than Filter A . As seen in Figures 10 and 11 , the estimation errors for position and velocity have very flat characteristics . Therefore , if  $q$  values are selected to be much greater than the minimizing  $q$  values for position estimation error , Filter B should generate larger position estimation errors , but smaller velocity estimation errors . Also , Filter B is expected to be more capable than Filter A of following large maneuvering levels .



## F. PERFORMANCE RESULTS.

The simulation of the residual-testing adaptive filter was done with the same system matrices , the same ensemble size for Monte Carlo simulations and using the same track as for the constant-Q estimator simulation in Chapter III .

The performance results are shown in Figures 15 and 16 . Compared with the constant-Q filters , the residual-testing adaptive filters have smaller position and velocity estimation errors . The position estimation error for an acceleration of  $10 \text{ m/sec}^2$  is excellent for both adaptive filters . Compared with the Q-generated adaptive filter , the residual-testing adaptive filters have relatively large position estimation errors for a nonmaneuvering track , but overall , they have smaller position estimation errors for the range of tracks tested . The velocity estimates are considerably better than those provided by the Q-generated adaptive filter and are very similar to those provided by the constant-Q estimator .

Comparing the two residual-testing filters , Filter A and Filter B have almost the same velocity estimation performance , and slightly different position estimation performance .

## G. CONCLUSIONS

The residual-testing adaptive filters were developed from the considerations described in Section V.B . From simulation results , the assumptions used appear to be very reasonable because the residual-testing adaptive filters provide better performance than the constant-Q filters investigated .



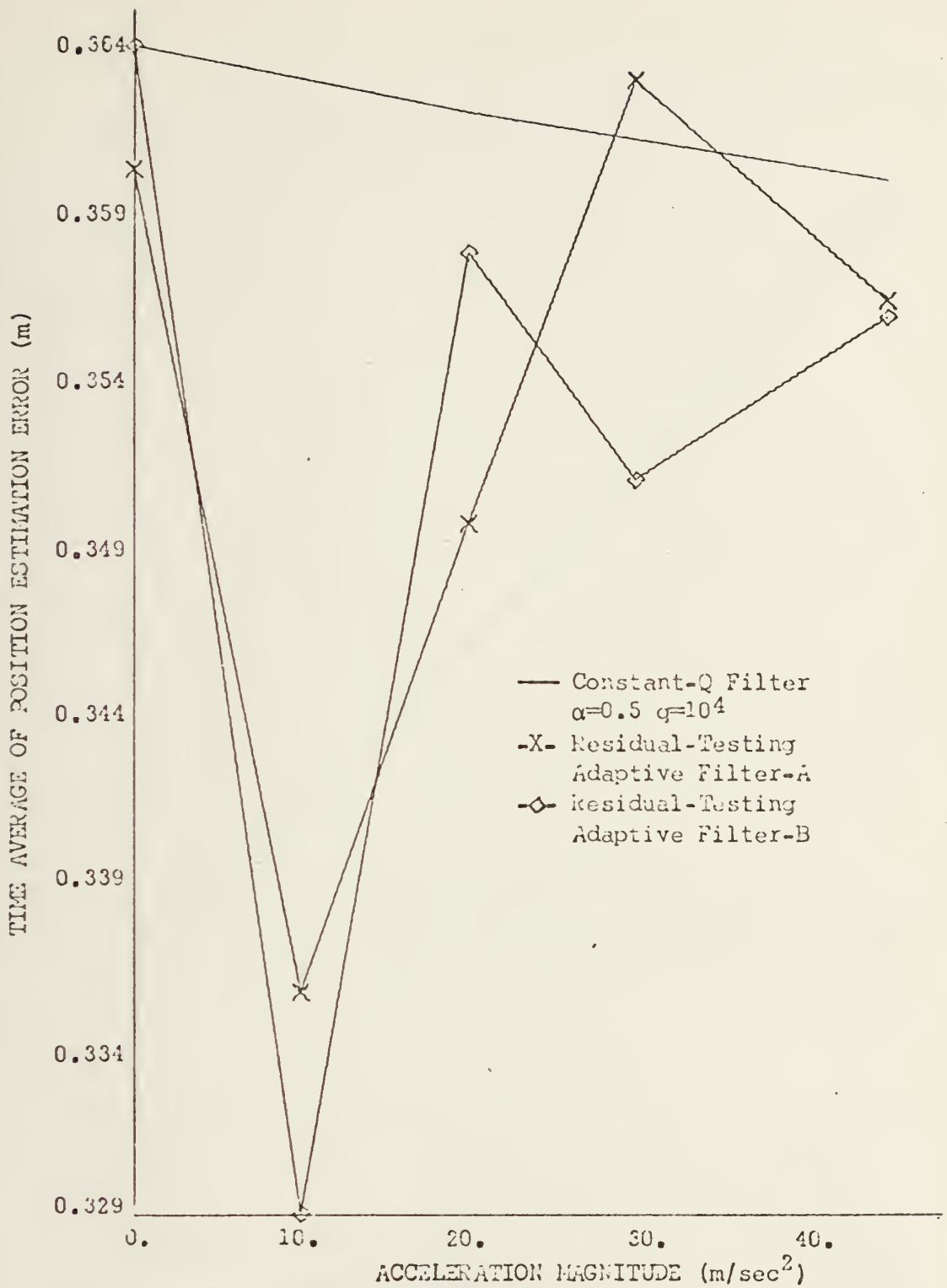


FIGURE 15 POSITION ESTIMATION ERRORS FOR TWO RESIDUAL-TESTING ADAPTIVE FILTER VS. MANEUVERING LEVEL



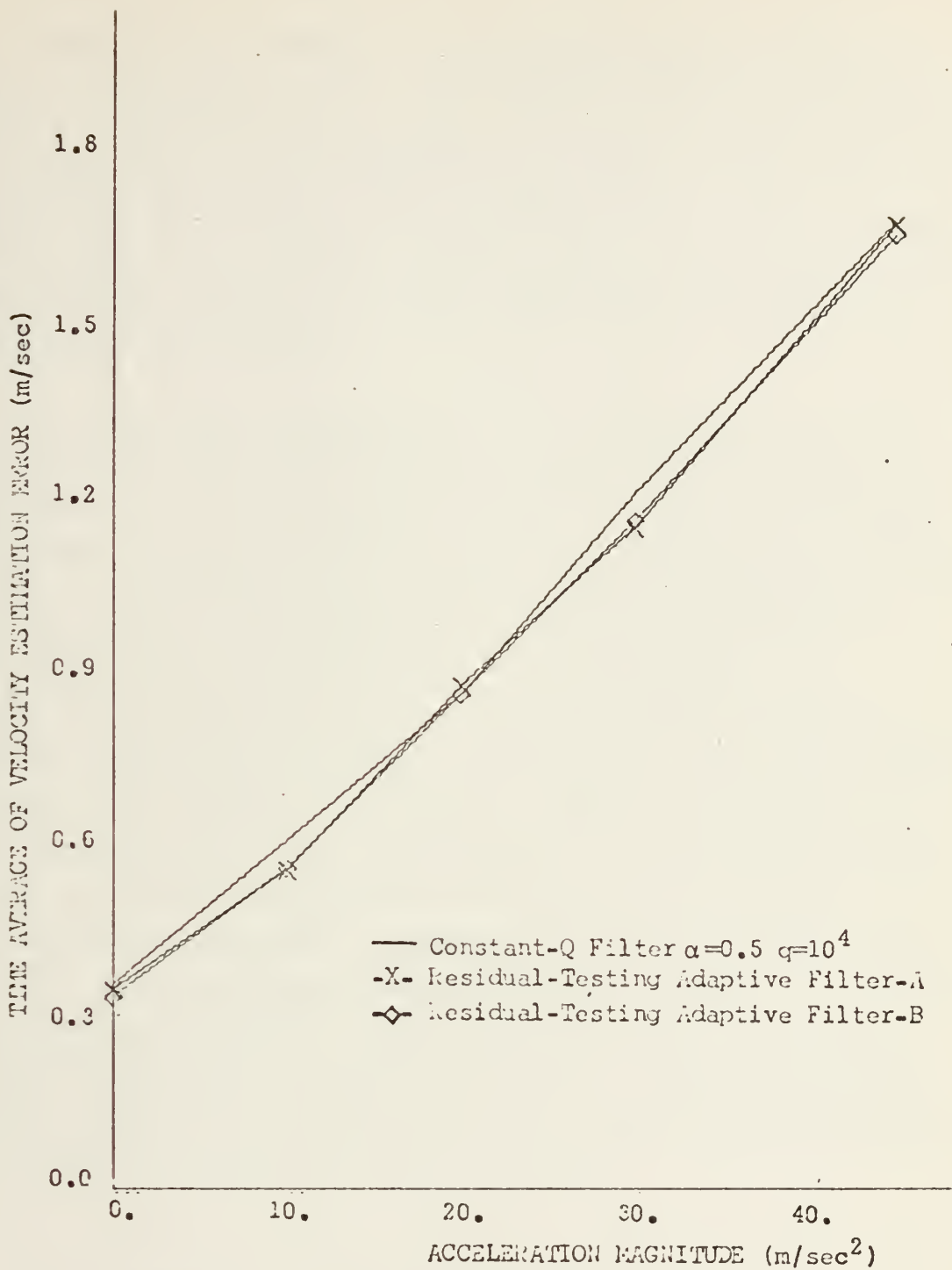


FIGURE 16 VELOCITY ESTIMATION ERRORS FOR TWO RESIDUAL-TESTING ADAPTIVE FILTER VS. MANEUVERING LEVEL





When the two residual-testing adaptive filters are compared with each other , the velocity estimates are very similar , even if the gains are different . This might be explained from the characteristics of the velocity estimation error curves shown in Figure 11 . The curves are almost flat in the high-Q region , thus , differences in the gains are not expected to give significant differences in the simulation results .

For low-level maneuvering , it is difficult for the estimator to detect the maneuver because it is "hidden" to some extent in the measurement noise . Even for low-level maneuvers , however , the residuals will eventually tend to increase , thus signaling the presence of the maneuver . The statistical characteristics of these errors are completely different from those errors that are mainly caused by measurement noise . The adaptive-switching scheme detects nonmaneuvering periods very well . In Figure 17 , a typical gain schedule is plotted . There are effects of measurement noise , but the detection of the nonmaneuvering period is clearly seen (K=1 to 10 and k=21 to 30 are nonmaneuvering periods) . Notice that in the interval from K=1 to 5 , the residual-testing adaptive filter is operated as a constant-Q filter . When Filters A and B were used without the adaptive switching feature , estimation errors for position and velocity were three times as large as when the adaptive switching scheme was added .



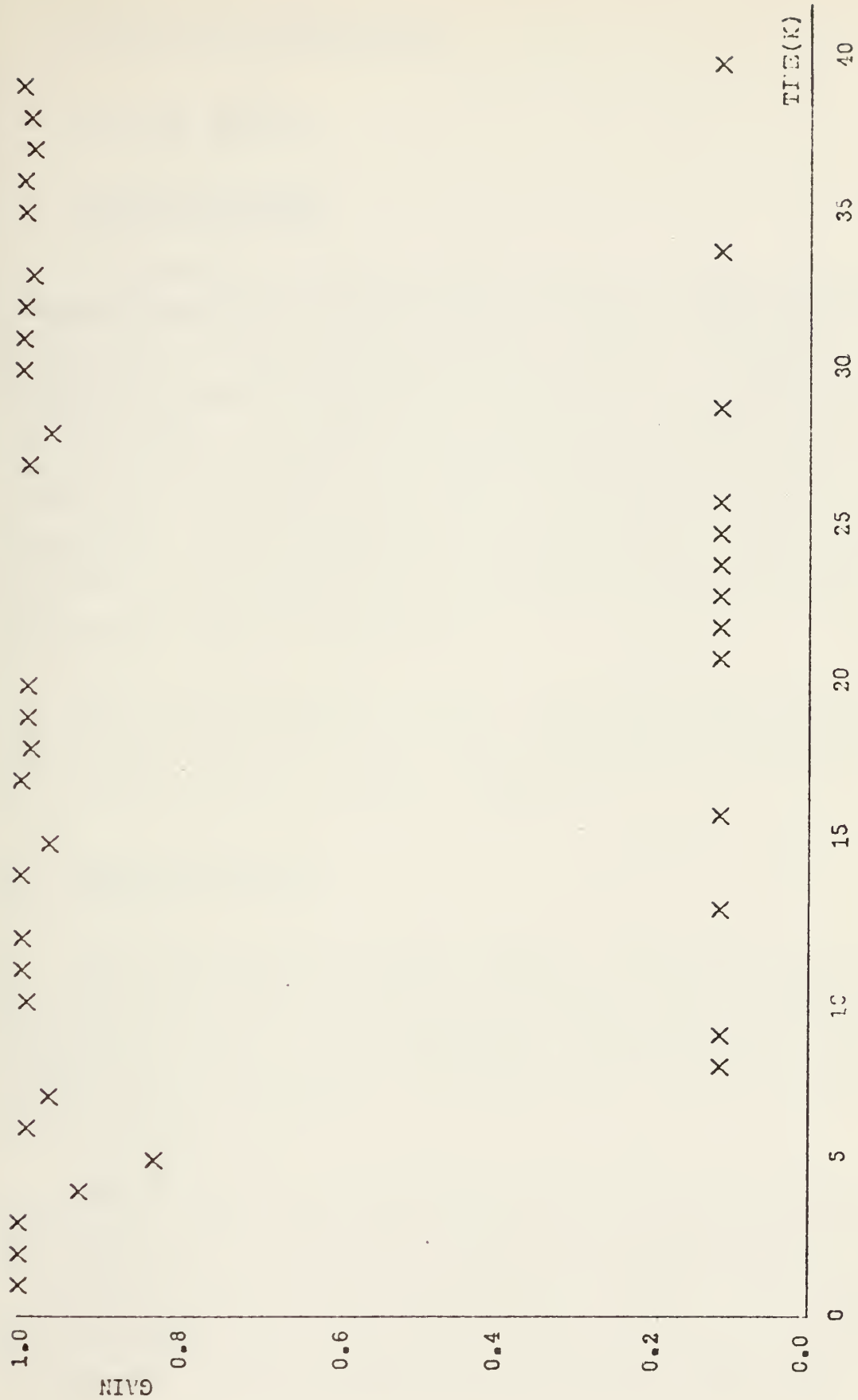


FIGURE 17 GAINS IN RESIDUAL-TESTING ADAPTIVE FILTER AND DETECTION OF NONMANEUVERING PERIOD



## VI. SUMMARY AND CONCLUSIONS

### A. THE TEST RESULTS

#### 1. Constant-Q model

Simulation of the Constant-Q model was done to obtain knowledge about the performance of various models and to have data to compare with adaptive filters . However , the assumption that the Q-matrix is diagonal as expressed by Equation (29) may limit the conclusions that can be drawn . In the various models the correlated-constant-Q model with  $\alpha=0.5$  had excellent performance for position and velocity estimation over the simulated maneuver range . The adaptive filters were compared with this filter to see if better performance could be achieved .

For the simulation studies , only one track pattern was used ; the amount of maneuvering was varied by adjusting the acceleration level A shown in Figure 2 .

#### 2. Adaptive filters

The Q-generated adaptive filter , discussed in Chapter IV , provided generally poor performance over the simulated maneuvering range . The adjustment for generating q gave improvement for position estimates , but did not provide good velocity estimates .

The Residual-testing adaptive filter design was done in Chapter V . The design was based on the simulation results for the performance of the correlated constant-Q model with  $\alpha=0.5$  against constant-acceleration tracks . The results were compared with the original correlated-constant-Q model (  $\alpha=0.5$  ) . The residual-testing adaptive filter had



slightly better performance for position and velocity estimates than the correlated-constant-Q model .

## B. SUGGESTIONS FOR FUTURE INVESTIGATION

The most significant assumption for the filters was the form of the Q-matrix . In Chapter III the Q-matrix was specified by Equation (29) . The same assumption was made for the Residual-testing adaptive filter . There was no strong reason for making this assumption , but this form of the Q-matrix gave monotonically decreasing velocity estimation errors as functions of  $q$  , over the simulated range of maneuver levels . It was desired to select the switching levels for residuals and gains to provide accurate estimates for position and velocity simultaneously . The properties and effects of the form of the Q-matrix should be investigated further , and the design procedure for the Residual-testing adaptive filter should be refined .

In the Residual-testing adaptive filter , the residual switching levels were determined by trial and error . To reduce uncertainty in the design , the characteristics of the residual should be analyzed more carefully .

In this thesis , adaptive filters were compared with constant-Q filters by using simplified tracks with medium-level maneuvering . It may be possible that the adaptive filters will perform better for particular tracks , for example , such as missile tracks , high-speed and high-level-maneuver attacking tracks .

For digital fire control systems , computation time is an important factor . For this reason , the Q-generated adaptive filter is not a good filter , especially when a





higher-order model is required , because the computation time requirement is extremely large compared with the constant-Q model .

### C. CONCLUSIONS

The Residual-testing adaptive filter did not have remarkable improvement over the best correlated-constant-Q filter . The design of the Residual-testing adaptive filter is developed from a particular constant-Q filter and is based on the constant-acceleration track performance of this filter . In our case , as seen in Figures 9 and 10 , the correlated-constant-Q estimator with  $\alpha=0.5$  had relatively the same performance for a wide range of maneuvering levels for  $q$  greater than 900 . Even though the position estimation error has minimizing points , the biggest difference in position estimation error between the minimum point and the estimation error at  $q=10^5$  , was less than 2 cm . The velocity estimation error performance is monotonically decreasing with very small rates and has an almost flat characteristic over the simulated  $q$  range . Therefore , the Residual-testing filter could not have much improvement over the correlated-constant-Q filter . However , if the constant-Q estimator has sharper minimizing points for position and velocity estimation errors , and if it is possible to select  $q$ 's that simultaneously provide small estimation errors for position , velocity and acceleration , the Residual-testing filter might give much improvement over the constant-Q filter .



## APPENDIX A

### THE MONTE-CARLO SIMULATION PROGRAM

#### A.1 Program description

An addition to the original Monte-Carlo simulation program that was developed by Prof . d . e . kirk of the Naval Postgraduate School is a new flag IQQ that is employed to implement the Residual-testing adaptive filter . Details of Subroutine QON and RETAD that perform the Q-generated adaptive scheme and the Residual-testing adaptive technique are described in Appendices B and C .

Input description and various options are explained by comments at the beginning of the program .



A.2 COMPUTER PROGRAM FOR MONTE-CARLO SIMULATION

```

C      THIS PROGRAM PERFORMS MONTE CARLO SIMULATION OF STATE ESTIMATORS
C      OF WHICH THE KALMAN FILTER IS ONE EXAMPLE. THERE ARE SEVERAL
C      OPTIONS AVAILABLE AS INDICATED IN THE DETAILED COMMENTS BELOW.
C      IT SHOULD BE NOTED THAT ALL COMPUTATIONS OF GAINS USING THE
C      SUBROUTINE GAIN ARE PERFORMED IN DOUBLE PRECISION. THUS ALL
C      ARRAYS FOR USE IN "GAIN" MUST BE PREPARED ACCORDINGLY.
C      REAL*8 GAMMA, COVW, R, PHI, H, TEMP, TEMPI, TEMP2, PKKM1, G, PKK, Q, EI
C      COMMON EI(4,4), Q(4,4), G(4,4), PKK(4,4), GAMMA(4,4), COVW(4,4),
C      TEMP(4,4), TEMPI(4,4), TEMP2(4,4), H(4,4), PKKM1(4,4), R(4,4), PHI(4,4),
C      VAR(4,4,60), GKS(4,4,60), PKKS(4,4,60), XM(4,60), ERR(4,60),
C      GAMMAS(4,4), PHIS(4,4), XS(4,60), HS(4,4), GK(4,4), SIGW(4), X(4),
C      SIGXZ(4), XZMEAN(4), XHKK(4), XHKKM1(4), VIMP(4), Z(4), V(4), SIGV(4),
C      XHATZ(4),
C      N, NSAM, IQ, M, ITER, ITRK, IN, ISTAT, K, ITRO, IXZ, IV, IW, IEST, ND
C      DIMENSION XP(80), YP(80)
C      DIMENSION PKKM2(4,4)
C      DIMENSION AVEE(4), AVEV(4), SUME(4), SUMV(4)
C
C      N=ORDER OF SYSTEM MODEL AND FILTER (DIMENSION OF X, XHAT)
C      M=NUMBER OF MEASUREMENTS (DIMENSION OF THE VECTOR Z)
C      IN=NUMBER OF INPUT RANDOM FORCING FCNS (=DIMENSION OF W)
C      NSAM=NUMBER OF TIME SAMPLES
C      NENS=NUMBER OF MEMBERS IN ENSEMBLE
C      READ(5, I00) N, M, IN, NSAM, NENS
C      FORMAT(5, I10)
C
C      THE VALUE OF ND READ IN MUST EQUAL THE ROW (AND COLUMN) DIMENSION
C      SPECIFIED FOR THE SQUARE MATRIX "TEMPI", E.G. IF TEMPI(3,3) IS
C      SPECIFIED IN THE COMMON STATEMENT "ND" MUST BE EQUAL TO 3.
C      READ(5, I20) ND
C      FORMAT(I2)
    
```

MCSPO010  
 MCSPO020  
 MCSPO030  
 MCSPO040  
 MCSPO050  
 MCSPO060  
 MCSPO070  
 MCSPO080  
 MCSPO090  
 MCSPO100  
 MCSPO110  
 MCSPO120  
 MCSPO130  
 MCSPO140  
 MCSPO150  
 MCSPO160  
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 MCSPO380  
 MCSPO390  
 MCSPO400  
 MCSPO410  
 MCSPO420  
 MCSPO430



```

CC      IG=-1  -- GAINS COMPUTED OFF-LINE AND READ IN          MCSPO440
CC      0      -- GAINS COMPUTED ONLY ONCE BEFORE STARTING MONTE CARLO MCSPO450
CC      1      -- GAINS COMPUTED FOR EACH MEMBER OF ENSEMBLE    MCSPO460
CC      IFLR=0  -- R IS READ IN                                MCSPO470
CC      IFLR.NE.0 -- R IS COMPUTED ON-LINE AT EACH TIME SAMPLE MCSPO480
CC      IEST=0  -- STANDARD KALMAN FILTER EQUATION IS USED      MCSPO490
CC      IEST.NE.0 -- STD. KALMAN FILTER EQ. NOT USED          MCSPO500
CC      ITRK= 0  -- SEVERAL TRACKS GENERATED FROM STD LINEAR EQS MCSPO510
CC      ITRK= 1  -- ONLY ONE TRACK IS USED                     MCSPO520
CC      ITRK.NE.0 -- SEVERAL TRACKS GENERATED BUT NOT FROM STD. MCSPO530
CC      LINEAR DIFFERENCE EQUATIONS                          MCSPO540
CC      ISTAT=0  -- MEAN OF TRACK, MEAN & VARIANCE OF EST. ERROR COMPUTED MCSPO550
CC      ISTAT.NE.0 -- SAME AS ISTAT=0 BUT OFF-DIAGONAL TERMS IN COVARIANCE MCSPO560
CC      MATRIX ARE ALSO COMPUTED                             MCSPO570
CC      READ(5,101) IG,IFLR,IEST,ITRK,ISTAT,IQ,ITRO          MCSPO580
CC      FORMAT(7(I10))                                       MCSPO590
CC      IQ=-1  -- Q IS COMPUTED ON-LINE AT EACH SAMPLE BY "QQN" MCSPO600
CC      0      -- Q MATRIX IS READ IN                          MCSPO610
CC      1      -- COVARIANCE OF W READ IN AND Q IS COMPUTED ONCE BEFORE MCSPO620
CC      MONTE CARLO BEGINS BY CALLING "QMAT"                 MCSPO630
CC      ITRO=0  -- ONLY USED IF ONE TRACK; ITRO=0 INDICATES THE MCSPO640
CC      TRACK IS READ IN (S.P.), OTHERWISE THE TRACK        MCSPO650
CC      IS GENERATED BY A SINGLE CALL OF SUBROUTINE         MCSPO660
CC      TRACK.                                                MCSPO670
CC      IPRT=0  -- SOME OR ALL OUTPUT DATA IS PRINTED        MCSPO680
CC      IPLT=0  -- SOME OR ALL OUTPUT DATA IS PLOTTED        MCSPO690
CC      READ(5,110) IPRT,IPLT                                MCSPO700
CC      FORMAT(2(I5))                                         MCSPO710
CC      IGPLT,ITHVPL,IMTPLT,ISMPLT,ISVPLT ARE PLOTTING INDICATORS MCSPO720
CC      IF THE INDICATOR IS EQUAL TO 1 PLOTS ARE GENERATED. THE INDICATORS MCSPO730
CC      CORRESPOND TO THE FOLLOWING QUANTITIES               MCSPO740
CC      IGPLT(GAIN VS K),ITHVPL (THEORETICAL COVARIANCE MATRIX VS K), MCSPO750
CC      IMTPLT (SAMPLE MEAN OF TRACK=TRACK IF ONLY ONE TRACK), MCSPO760
CC      ISMPLT (SAMPLE MEAN OF EST. ERROR VS K), ISVPLT (SAMPLE VARIANCE MCSPO770
CC      OF EST. ERROR VS K)                                  MCSPO780
CC      IF(IPLT.EQ.0) READ(5,111) IGPLT,ITHVPL,IMTPLT,ISMPLT,ISVPLT MCSPO790
CC      FCRMAT(5(I10))                                        MCSPO800
CC      111

```





CC

MC SP0920  
MC SP0930  
MC SP0940  
MC SP0950  
MC SP0960  
MC SP0970  
MC SP0980  
MC SP0990  
MC SP1000  
MC SP1010  
MC SP1020  
MC SP1030  
MC SP1040  
MC SP1050  
MC SP1060  
MC SP1070  
MC SP1080  
MC SP1090  
MC SP1100  
MC SP1110  
MC SP1120  
MC SP1130  
MC SP1140  
MC SP1150  
MC SP1160  
MC SP1170  
MC SP1180  
MC SP1190  
MC SP1200  
MC SP1210  
MC SP1220  
MC SP1230  
MC SP1240  
MC SP1250  
MC SP1260  
MC SP1270  
MC SP1280  
MC SP1290  
MC SP1300  
MC SP1310  
MC SP1320  
MC SP1330  
MC SP1340  
MC SP1350  
MC SP1360  
MC SP1370  
MC SP1380  
MC SP1390

```

IPHI=0 -- PHI MATRIX TO BE READ IN (IN DOUBLE PREC)
IPHI.NE.0 -- PHI MATRIX NOT TO BE READ
IH=0 -- H MATRIX TO BE READ IN (IN D.P.)
IR=0 -- R MATRIX IS READ IN
IPKKM1=0 -- THE STARTING VALUE FOR THE MATRIX P(K/K-1) IS TO
          BE READ IN (D.P.)
IGAM=0 -- GAMMA MATRIX TO BE READ IN (D.P.)
ISIGV=0 -- STD. DEVIATIONS OF MEASUREMENT NCISE TO BE READ IN (SP)
ISIGW=0 -- STD. DEVIATIONS OF RANDOM INPUTS TO BE READ IN (SP)
IXHZ=0 -- INITIAL VALUE OF THE PREDICTED VALUE XH(O/-1) TO
          BE READ IN (S.P.)
IC=1 -- ONE INITIAL CONDITION VALUE USED FOR THE STATE
        OTHERWISE THE VALUE OF X(O) IS GENERATED BY A RANDOM
        NUMBER GENERATOR CALLED BY "XZERO"

          READ(5,103) IPHI,IH,IR,IPKKM1,IGAM,ISIGV,ISIGW,IXHZ,IC
          FCRMAT(915)

          IF THE IG=1 FOLLOWING FLAGS MUST BE SPECIFIED
          IFLQ=1 -- SUBROUTINE QON IS CALLED FOR ON LINE Q CALCULATION
                 AND GAIN IS CALCULATED ON-LINE
                 0 -- QON IS NOT CALLED
          IQQ=1 -- SUBROUTINE QON CALLED BUT GAIN IS NOT CALCULATED
                 ON-LINE
                 WHEN IQQ=1, IFLQ MUST BE 1.

          READ(5,103) IFLQ ,IQQ
          CALL QVFLOW
          IN=6395217

```

103

CC



IV=1936748  
IXZ=135769

THE FOLLOWING SECTION PRINTS OUT A DESCRIPTION OF THE RUN AS  
SPECIFIED BY THE USER'S FLAGS

```
WRITE(6,250)
FORMAT(20X,'DESCRIPTION OF RUN',/)
202 IF(IG.EQ.0) GO TO 300
   IF(IJ.EQ.1) GO TO 301
240 WRITE(6,240)
   FORMAT(10X,'GAINS COMPUTED OFF-LINE AND READ IN',/)
   GO TO 302
300 WRITE(6,241)
241 FORMAT(10X,'GAINS COMPUTED ONCE IN "GAIN" BEFORE STARTING MONTE CAR
   . . . . . GO TO 302
301 WRITE(6,242)
242 FORMAT(10X,'GAINS COMPUTED FOR EACH MEMBER OF ENSEMBLE',/)
   IF(1FLQ.EQ.1.AND.IQQ.EQ.1) WRITE(6,666)
666 FORMAT(10X,'GAINS SWITCHED BY SUBROUTINE QON',/)
302 IF(1EST.EQ.0) GO TO 303
243 WRITE(6,243)
   FORMAT(10X,'THE STANDARD LINEAR EQS. DO NOT CHARACTERIZE THE FILTE
   . . . . . R',/)
   GO TO 304
303 WRITE(6,244)
244 FORMAT(10X,'THE STD. KALMAN EQS. CHARACTERIZE THE LINEAR FILTER',/)
304 IF(ITRK.EQ.0) GO TO 305
   IF(ITRK.EQ.-1) GO TO 306
   IF(ITRO.EQ.0) GO TO 307
245 WRITE(6,245)
   FORMAT(10X,'ONLY ONE TRACK IS USED AND IT IS GENERATED BY SUBROUTI
   . . . . . NE TRACK',/)
   GO TO 308
307 WRITE(6,246)
246 FORMAT(10X,'ONLY ONE TRACK IS USED AND IT IS READ IN',/)
   GO TO 308
306 WRITE(6,247)
247 FORMAT(10X,'SEVERAL TRACKS USED BUT NOT GENERATED FROM STD. LINEAR
   . . . . . DIFFERENCE EQS.',/)
   GO TO 308
305 WRITE(6,248)
```

MCSP1400  
MCSP1410  
MCSP1420  
MCSP1430  
MCSP1440  
MCSP1450  
MCSP1460  
MCSP1470  
MCSP1480  
MCSP1490  
MCSP1500  
MCSP1510  
MCSP1520  
MCSP1530  
MCSP1540  
MCSP1550  
MCSP1560  
MCSP1570  
MCSP1580  
MCSP1590  
MCSP1600  
MCSP1610  
MCSP1620  
MCSP1630  
MCSP1640  
MCSP1650  
MCSP1660  
MCSP1670  
MCSP1680  
MCSP1690  
MCSP1700  
MCSP1710  
MCSP1720  
MCSP1730  
MCSP1740  
MCSP1750  
MCSP1760  
MCSP1770  
MCSP1780  
MCSP1790  
MCSP1800  
MCSP1810  
MCSP1820  
MCSP1830  
MCSP1840  
MCSP1850  
MCSP1860  
MCSP1870

C  
C  
C  
C  
C  
C

C



```

248 FORMAT(10X,'SEVERAL TRACKS GENERATED BY USING THE STD. LINEAR DIFF',MCSP1880
ERRENCE EQS.',/)
308 IF(ISTAT.EQ.0) GO TO 309
WRITE(6,249)
249 FORMAT(10X,'MEAN OF TRACK, MEAN OF EST. ERROR AND COVARIANCE OF EST. ERROR ARE
T. ERROR ARE COMPUTED',/)
GO TO 310
309 WRITE(6,251)
251 FORMAT(10X,'MEAN OF TRACK, MEAN AND VARIANCES OF EST. ERROR ARE
COMPUTED',/)
310 IF(IQ.EQ.0) GO TO 311
GO TO 312
252 FORMAT(10X,'THE Q MATRIX IS COMPUTED ON-LINE AT EACH SAMPLE BY "Q"',/)
GO TO 313
312 WRITE(6,253)
253 FORMAT(10X,'THE COVARIANCE OF W IS READ IN AND Q IS COMPUTED BY "Q
MAT" BEFORE STARTING MONTE CARLO',/)
GO TO 313
311 WRITE(6,254)
254 IF(IFLR.EQ.0) GO TO 314
WRITE(6,255)
255 FORMAT(10X,'R IS COMPUTED ON-LINE AT EACH SAMPLE BY "RON"',/)
GO TO 315
314 WRITE(6,256)
256 FORMAT(10X,'R IS READ IN',/)
315 WRITE(6,257)
257 FORMAT(//),20X,'INPUT DATA CALLED FOR',/)
IF(IPHI.EQ.0) WRITE(6,258)
FCRMA(10X,'PHI MATRIX',/)
IF(IH.EQ.0) WRITE(6,259)
FCRMA(10X,'H MATRIX',/)
IF(IFLR.EQ.0) WRITE(6,260)
FCRMA(10X,'R MATRIX',/)
GO TO 316
IF(IQ.EQ.0) GO TO 317
IF(IQ.EQ.-1) GO TO 317
WRITE(6,261)
261 FORMAT(10X,'COVARIANCE OF W',/)
GO TO 317
316 WRITE(6,262)
262 FORMAT(10X,'Q MATRIX',/)
317 IF(ICGM.EQ.0) WRITE(6,282)
282 FORMAT(10X,'GAMMA MATRIX',/)
IF(ISIGV.EQ.0) WRITE(6,263)
263 FORMAT(10X,'STANDARD DEVIATIONS OF MEASUREMENT NOISE',/)
IF(ISIGW.EQ.0) WRITE(6,264)

```



```

264 FORMAT(10X,'STANDARD DEVIATIONS OF INPUT FORCING W',/)
    IF(IXHZ.EQ.0) WRITE(6,265)
265 FORMAT(10X,'XHAT(0/-1)',/)
    IF(IC.NE.1) WRITE(6,268)
268 FORMAT(10X,'MEANS AND VARIANCES OF X(0)',/)
    IF(IPKKML.EQ.0) WRITE(6,267)
267 FORMAT(10X,'P(0/-1)',/)

    C
    C
    C
    C
    C
    C
    C

    THE FOLLOWING SECTION PRINTS OUT A DESCRIPTION OF THE OUTPUT
    DATA CALLED FOR

269 WRITE(6,269)
    FORMAT(777,20X,'OUTPUT CALLED FOR',/)
    IF(IPRT.NE.0) GO TO 320
    WRITE(6,270)
270 FORMAT(10X,'PRINTED OUTPUT OF THE FOLLOWING DATA',/)
    IF(IG.EQ.0) WRITE(6,271)
271 FORMAT(15X,'GAIN MATRICES AND THEORETICAL COVARIANCE OF EST. ERROR
    MATRICES',/)
    WRITE(6,272)
272 FORMAT(15X,'SAMPLE MEANS OF TRACK AND ESTIMATION ERROR, SAMPLE VAR
    IANCES OF EST. ERROR',/)
    IF(ISTAT.NE.0) WRITE(6,273)
273 FORMAT(15X,'COVARIANCE OF ESTIMATION ERROR MATRIX',/)
    GO TO 321
320 WRITE(6,274)
274 FORMAT(10X,'NO PRINTED OUTPUT CALLED FOR',/)
321 IF(IPLT.NE.0) GO TO 322
    WRITE(6,275)
275 FORMAT(10X,'THE FOLLOWING PLOTS ARE CALLED FOR',/)
276 IF(IGPLT.EQ.1) WRITE(6,276)
    FORMAT(15X,'G(K) VS. K',/)
277 IF(ITHVPL.EQ.1) WRITE(6,277)
    FORMAT(15X,'P(K/K) THEORETICAL VS. K',/)
278 IF(IMPLT.EQ.1) WRITE(6,278)
    FORMAT(15X,'MEAN OF TRACK VS. K',/)
279 IF(ISMPLT.EQ.1) WRITE(6,279)
    FORMAT(15X,'SAMPLE MEANS OF ESTIMATION ERROR VS. K',/)
280 IF(ISVPLT.EQ.1) WRITE(6,280)
    FORMAT(15X,'SAMPLE VARIANCES OF ESTIMATION ERROR VS. K',/)
    GO TO 323
322 WRITE(6,281)
281 FORMAT(10X,'NO PLOTS CALLED FOR',/)
323

```

C  
C  
C  
C  
C  
C  
C





```

WRITE(S,250)
WRITE(6,201)
FORMAT(20X,'INPUT DATA',//)
WRITE(6,200) N,M,IN,NSAM,NENS
FORMAT(4X,'N=',I2,4X,'IN=',I2,4X,'NSAM=',I3,4X,'NENS=',I5
.,//)
C
C
C
C
THE FOLLOWING SECTION READS THE SPECIFIED INPUT MATRICES
IF(IPHI.NE.0) GO TO 61
CALL MREAD(PHI,N,N)
DO 60 I=1,N
DO 60 J=1,N
PHIS(I,J)=PHI(I,J)
WRITE(6,204)
FORMAT(//,10X,'THE PHI MATRIX IS',/)
CALL MWRITE(PHI,N,N)
C
C
61 IF(IH.NE.0) GO TO 63
CALL MREAD(H,M,N)
DO 62 I=1,M
DO 62 J=1,N
HS(I,J)=H(I,J)
WRITE(6,205)
FORMAT(//,10X,'THE H MATRIX IS',/)
CALL MWRITE(H,M,N)
C
C
63 IF(IR.NE.0) GO TO 66
CALL MREAD(R,M,M)
WRITE(6,206)
FORMAT(//,10X,'THE R MATRIX IS',/)
CALL MWRITE(R,M,M)
C
C
66 IF(IQ.NE.1) GO TO 59
CALL MREAD(COVW,IN,IN)
WRITE(6,207)
FORMAT(//,10X,'THE COVARIANCE OF W MATRIX IS',/)
CALL MWRITE(COVW,IN,IN)
GO TO 68
59 IF(IQ.NE.0) GO TO 68
CALL MREAD(Q,N,N)
WRITE(6,203)
FORMAT(//,10X,'THE Q MATRIX IS',/)
CALL MWRITE(Q,N,N)

```

```

MC SP2840
MC SP2850
MC SP2860
MC SP2870
MC SP2880
MC SP2890
MC SP2900
MC SP2910
MC SP2920
MC SP2930
MC SP2940
MC SP2950
MC SP2960
MC SP2970
MC SP2980
MC SP2990
MC SP3000
MC SP3010
MC SP3020
MC SP3030
MC SP3040
MC SP3050
MC SP3060
MC SP3070
MC SP3080
MC SP3090
MC SP3100
MC SP3110
MC SP3120
MC SP3130
MC SP3140
MC SP3150
MC SP3160
MC SP3170
MC SP3180
MC SP3190
MC SP3200
MC SP3210
MC SP3220
MC SP3230
MC SP3240
MC SP3250
MC SP3260
MC SP3270
MC SP3280
MC SP3290
MC SP3300
MC SP3310

```



```

C C      68 IF(IGAM.NE.0) GO TO 65
      CALL MREAD(GAMMA,N,IN)
      DO 64 I=1,N
      DO 64 J=1,IN
      64 GAMMA(S(I,J))=GAMMA(I,J)
      208 WRITE(6,208)
      FORMAT(/,IOX,'THE GAMMA MATRIX IS',/)
      CALL MWRITE(GAMMA,N,IN)
C C
      65 IF(IPKKM1.NE.0) GO TO 67
      CALL MKEAD(PKKM1,N,N)
      WRITE(6,209)
      209 FORMAT(/,IOX,'THE MATRIX P(0/-1) IS',/)
      CALL MWRITE(PKKM1,N,N)
      DO 1500 I=1,N
      DO 1500 J=1,N
      1500 PKKM2(I,J)=PKKM1(I,J)
C C
      67 IF(ISIGV.NE.0) GO TO 69
      CALL VREAD(SIGV,M)
      WRITE(6,210)
      210 FORMAT(/,IOX,'THE STD. DEVIATIONS OF MEASUREMENT NOISE ARE',/)
      CALL VWRITE(SIGV,M)
C C
      69 IF(ISIGW.NE.0) GO TO 71
      CALL VREAD(SIGW,IN)
      WRITE(6,211)
      211 FORMAT(/,IOX,'THE STD. DEVIATIONS OF INPUT FORCING W ARE',/)
      CALL VWRITE(SIGW,IN)
C C
      71 IF(IXHZ.NE.0) GO TO 73
      CALL VREAD(XHATZ,N)
      WRITE(6,212)
      212 FORMAT(/,IOX,'THE VECTOR XHAT(0/-1) IS',/)
      CALL VWRITE(XHATZ,N)
C C
      73 IF(IC.EG.1) GO TO 75
      IC.NE.1 MEANS THAT MEANS AND STD. DEVIATIONS OF THE INITIAL STATE
      VALUE MUST BE READ IN. OTHERWISE NOT READ IN.
      CALL VREAD(XZMEAN,N)
      WRITE(6,213)

```



```

213 FCRMAT(//,10X,'THE MEAN OF THE VECTOR X(0) IS',/)
C CALL VWRITE(XZMEAN,N)
C
C CALL VREAD(SIGXZ,N)
C WRITE(6,214)
214 FCRMAT(//,10X,'THE STANDARD DEVIATIONS OF THE VECTOR X(0) ARE',/)
C CALL VWRITE(SIGXZ,N)
C GO TO 90
C
C 75 READ(5,105) (XS(I,1),I=1,N)
C INITIAL CONDITION HAS BEEN READ
C WRITE(6,219)
C 219 FCRMAT(//,10X,'THE INITIAL STATE IS',/)
C WRITE(6,221) (XS(I,1),I=1,N)
C IF(ITRK.NE.1) GO TO 90
C IF(ITRO.NE.0) GO TO 85
C DC 81 K=2,NSAM
C 81 READ(5,105) (XS(I,K),I=1,N)
C 105 FORMAT(4F20.0)
C GO TO 86
C 85 CALL TRACK
C IF TRACK CALLED HERE IT SHOULD BE WRITTEN TO GENERATE AND
C STORE THE TRACK IN XS(N,K) FOR K=2(NSAM),NSAM
C
C 86 WRITE(6,220)
C 220 FCRMAT(//,10X,'THE FIRST AND LAST POINTS ON THE SINGLE TRACK TO BE
C USED ARE',/)
C WRITE(6,221) (XS(I,1),I=1,N)
C WRITE(6,221) (XS(I,NSAM),I=1,N)
C 221 FCRMAT(9(2X,1PE12.5),/)
C 90 CONTINUE
C
C THE FOLLOWING SECTION PREPARES FOR THE MONTE CARLC LOOP
C
C FCRM NXN IDENTITY MATRIX IN DOUBLE PRECISION
C DO 30 I=1,N
C DC 30 J=1,N
C EI(I,J)=0.DO
C IF(I.EQ.J) EI(I,J)=1.DO
C 30 GIVEN THE MATRIX GAMMA AND THE COVARIANCE OF W COMPUTE Q
C USING DOUBLE PRECISION ARITHMETIC
C IF(IQ.NE.1) GO TO 4
C CALL QMAT

```

```

MCSP3800
MCSP3810
MCSP3820
MCSP3830
MCSP3840
MCSP3850
MCSP3860
MCSP3870
MCSP3880
MCSP3890
MCSP3900
MCSP3910
MCSP3920
MCSP3930
MCSP3940
MCSP3950
MCSP3960
MCSP3970
MCSP3980
MCSP3990
MCSP4000
MCSP4010
MCSP4020
MCSP4030
MCSP4040
MCSP4050
MCSP4060
MCSP4070
MCSP4080
MCSP4090
MCSP4100
MCSP4110
MCSP4120
MCSP4130
MCSP4140
MCSP4150
MCSP4160
MCSP4170
MCSP4180
MCSP4190
MCSP4200
MCSP4210
MCSP4220
MCSP4230
MCSP4240
MCSP4250
MCSP4260
MCSP4270

```









```

C CALL MEAS
C GAIN IS NOT TO BE COMPUTED ON-LINE IF IG.NE.1
C IF (IG.NE.1) GO TO 70
C IF(IQ.EQ.1.AND.K.LE.5) GO TO 70
C IF(IFLQ.EQ.1.AND.K.EQ.1) GO TO 999
C
C Q IS TO BE COMPUTED ON-LINE IF IFLQ.NE.0
C
C IF(IQ.EQ.1) GO TO 994
C CALL PEST(A1,A2,A3)
C IF (IFLQ.NE.0) CALL QON(A1,A2,A5)
C
C R TO BE COMPUTED ON-LINE IF IFLR.NE.0
C
C IF(IFLR.NE.0) CALL RON
C GO TO 999
C
C RESIDUAL TESTING ADAPTIVE FILTER PERFORMED IN "RETAD"
C
C 994 CALL RETAD
C GO TO 991
C
C 999 CALL GAIN(IG,IQQ)
C DO 996 I=1,N
C DO 996 L=1,N
C 996 PKK(I,L,K)=PKK(I,L)
C 991 DO 3 I=1,N
C DO 3 J=1,M
C 3 GK(I,J,K)=G(I,J)
C
C UPDATE THE STATE ESTIMATE
C
C 70 CALL ESTIM
C
C UPDATE RUNNING SUMS USED IN COMPUTING STATISTICS
C CALL STAT
C IF(K.EQ.NSAM) GO TO 1000
C
C UPDATE TRACK BY COMPUTING X(K+1)
C IF(ITRK.NE.1) CALL TRACK
C
C 1000 CONTINUE
C
C DIVIDE RUNNING SUMS COMPUTED BY SUBROUTINE STAT BY ENSEMBLE
C SIZE TO COMPUTE STATISTICS
C ENS=NENS
C DO 2 K=1,NSAM
C DO 2 J=1,N

```

```

MC SP4760
MC SP4770
MC SP4780
MC SP4790
MC SP4800
MC SP4810
MC SP4820
MC SP4830
MC SP4840
MC SP4850
MC SP4860
MC SP4870
MC SP4880
MC SP4890
MC SP4900
MC SP4910
MC SP4920
MC SP4930
MC SP4940
MC SP4950
MC SP4960
MC SP4970
MC SP4980
MC SP4990
MC SP5000
MC SP5010
MC SP5020
MC SP5030
MC SP5040
MC SP5050
MC SP5060
MC SP5070
MC SP5080
MC SP5090
MC SP5100
MC SP5110
MC SP5120
MC SP5130
MC SP5140
MC SP5150
MC SP5160
MC SP5170
MC SP5180
MC SP5190
MC SP5200
MC SP5210
MC SP5220
MC SP5230

```



```

        IF(ITRK.EQ.1) GO TO 6
        XM(J,K)=XM(J,K)/ENS
        ERR(J,K)=ERR(J,K)/ENS
        VAR(J,J,K)=VAR(J,J,K)/ENS-ERR(J,K)**2
        IF(ISTAT.EQ.0) GO TO 80
C
C COMPUTE OFF-DIAGONAL TERMS IN COVARIANCE OF ESTIMATION
C ERROR MATRIX IF ISTAT.NE.0
DC 5 K=1,NSAM
DC 5 L=2,N
LM1=L-1
DC 5 J=1,LM1
5 VAR(L,J,K)=VAR(L,J,K)/ENS-ERR(L,K)*ERR(J,K)
80 CONTINUE
C
C IF(IPRT.NE.0) GO TO 600
WRITE(6,230)
FORMAT('I,20X,'OUTPUT DATA',//)
230 WRITE GAINS, 'THEORETICAL COVARIANCES OF ESTIMATION ERROR
IF ONE SET OF GAINS HAS BEEN USED.'
WRITE(6,222)
FCRMT(10X,'THE GAIN MATRICES ARE',/)
DO 425 K=1,NSAM
WRITE(6,223) K
FORMAT(5X,'K=',I3,/,10X,'G(K)=' ,/)
425 WRITE(6,221) (GKS(I,J,K),J=1,M)
IF(IG.NE.0) GO TO 450
WRITE(6,224)
FCRMT(1X,/,10X,'THE THEORETICAL COVARIANCE MATRIX IS',/)
DO 426 K=1,NSAM
WRITE(6,225) K
FORMAT(5X,'K=',I3,/,10X,'P(K/K)=' ,/)
426 WRITE(6,221) (PKKS(I,J,K) ,J=1,N)
C
C WRITE(6,250)
WRITE(6,226)
WRITE(6,227)
FCRMT(15,'TIME',T16,'VECTOR COM-',T34,'SAMPLE MEAN',
T51,'SAMPLE MEAN OF',T71,'SAMPLE VARIANCE OF')
226 T51,'SAMPLE INDEX',T16,'COMPONENT INDEX',T34,'OF TRACK',
227 T51,'ESTIMATION ERROR',T71,'ESTIMATION ERROR')
228 FCRMT(6X,I3,I3X,I1,10X,1PE14.7,2(6X,1PE14.7))
229 FCRMT(//)
DC 696 I=1,N

```

```

MC SP5240
MC SP5250
MC SP5260
MC SP5270
MC SP5280
MC SP5290
MC SP5300
MC SP5310
MC SP5320
MC SP5330
MC SP5340
MC SP5350
MC SP5360
MC SP5370
MC SP5380
MC SP5390
MC SP5400
MC SP5410
MC SP5420
MC SP5430
MC SP5440
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MC SP5470
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MC SP5590
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MC SP5620
MC SP5630
MC SP5640
MC SP5650
MC SP5660
MC SP5670
MC SP5680
MC SP5690
MC SP5700
MC SP5710

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MC SP5720  
 MC SP5730  
 MC SP5740  
 MC SP5750  
 MC SP5760  
 MC SP5770  
 MC SP5780  
 MC SP5790  
 MC SP5800  
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 MC SP5960  
 MC SP5970  
 MC SP5980  
 MC SP5990  
 MC SP6000  
 MC SP6010  
 MC SP6020  
 MC SP6030  
 MC SP6040  
 MC SP6050  
 MC SP6060  
 MC SP6070  
 MC SP6080  
 MC SP6090  
 MC SP6100  
 MC SP6110  
 MC SP6120  
 MC SP6130  
 MC SP6140  
 MC SP6150  
 MC SP6160  
 MC SP6170  
 MC SP6180  
 MC SP6190

```

SUME(I)=0.0
SUMV(I)=0.0
AVEE(I)=0.0
AVEV(I)=0.0
CONTINUE
DO 451 K=1, NSAM
  WRITE(6,229)
DO 451 I=1,N
  SUME(I)=SUME(I)+ABS(ERR(I,K))
  SUMV(I)=SUMV(I)+VAR(I,I,K)
  SUMV(I)=SUMV(I)+XM(I,K),ERR(I,K),VAR(I,I,K)
DO 697 I=1,N
  AVEE(I)=SUME(I)/NSAM
  AVEV(I)=SUMV(I)/NSAM
  WRITE(6,470) AVEE(I),AVEV(I)
CONTINUE
FORMAT(//53X,E14.7,6X,E14.7)
WRITE(6,250)
IF(ISTAT.EQ.0) GO TO 600
FCRMAT(1)
WRITE(6,290)
FCRMAT(10X,'THE SAMPLE COVARIANCE OF EST. ERROR MATRIX IS',//)
DO 452 K=1,NSAM
  DO 452 I=1,N
    WKRITE(5,221) ( VAR(I,L,K),L=1,I)
  FORMAT(//2X,'K=',I3,/)
  WRITE(6,250)
  IF(IPLT.NE.0) GO TO 650
  DO 603 K=1,NSAM
    XP(K)=K
    IF(IGPLT.NE.1) GO TO 610
  DC 601 I=1,N
  DC 601 J=1,M,NSAM
  DO 602 K=1,NSAM
    YP(K)=GKS(I,J,K)
  WRITE(6,250)
  CALL PLOTP(XP,YP,NSAM,0)
  WRITE(6,232) I,J
  FORMAT(12X,'G(',I1,',',I1,',',I1,',') VS. K')
  IF(ITHVPL.NE.1) GO TO 620
  DC 611 I=1,N
  DC 612 K=1,NSAM
  YP(K)=PKKS(I,I,K)
  WRITE(6,250)
  CALL PLOTP(XP,YP,NSAM,0)
  WRITE(5,233) I,I
  FORMAT(12X,'PKK(',I1,',',I1,',',I1,',') VS. K')
  
```



```

620 IF (IMTPLT.NE.1) GO TO 630
    DO 621 I=1,NSAM
    DO 622 K=1,NSAM
    YP(K)=XM(I,K)
622 WRITE(6,2250)
    CALL PLOTP(XP,YP,NSAM,0)
621 WRITE(6,234) I
234 FCFMAT(12X,'MEAN OF X(',I1,') VS. K')
630 IF (ISMPLT.NE.1) GO TO 640
    DC 631 I=1,NSAM
    DO 632 K=1,NSAM
    YP(K)=ERR(I,K)
632 WRITE(6,2250)
    CALL PLOTP(XP,YP,NSAM,0)
631 WRITE(6,235) I,I
235 FCFMAT(12X,'XHATKK(',I1,') -X(',I1,') VS. K')
640 IF (ISVPLT.NE.1) GO TO 650
    DC 641 I=1,NSAM
    DO 642 K=1,NSAM
    YP(K)=VAP(I,I,K)
642 WRITE(6,2250)
    CALL PLOTP(XP,YP,NSAM,0)
641 WRITE(6,236) I
236 FCFMAT(12X,'ERROR VARIANCE(',I1,') VS.. K')
650 WRITE(6,250)
    CCNTINUE
    STOP
    END

```

```

MCSP6200
MCSP6210
MCSP6220
MCSP6230
MCSP6240
MCSP6250
MCSP6260
MCSP6270
MCSP6280
MCSP6290
MCSP6300
MCSP6310
MCSP6320
MCSP6330
MCSP6340
MCSP6350
MCSP635U
MCSP6370
MCSP6380
MCSP6390
MCSP6400
MCSP6410
MCSP6420
MCSP6430
MCSP6440
MCSP6450
MCSP6460
MCSP6470

```

```

SUBROUTINE ESTIM
THIS SUBROUTINE UPDATES THE STATE ESTIMATE. IN THE DEFAULT
CONDITION (IEST.EQ.0) THE STANDARD EQUATIONS
XHAT(K/)=XHAT(K/K-1)+G(K)*(Z(K)-H(K)*XHAT(K/K-1))
XFAT(K+1/K)=PHI*XHAT(K/K)
ARE EVALUATED
REAL*8 GAMMA,COVW,R,PHI,H,TEMP,TEMP1,TEMP2,PKKM1,G,PKK,Q,EI
COMMON EI(4,4),Q(4,4),PKK(4,4),GAMMA(4,4),COVW(4,4),
TEMP(4,4),TEMP1(4,4),H(4,4),PKKM1(4,4),OR(4,4),PHI(4,4),
VAR(4,4,60),GKS(4,4,60),PKKS(4,4,60),XM(4,60),ERR(4,60),
GAMMAS(4,4),PHIS(4,4),XS(4,60),HS(4,4),GK(4,4),X(4),
SIGXZ(4),XZMEAN(4),XHKK(4),XHKKM1(4),VTMP(4),Z(4),V(4),SIGV(4),
C C C C C C C C

```

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MCSP0010
MCSP0020
MCSP0030
MCSP0040
MCSP0050
MCSP0060
MCSP0070
MCSP0080
MCSP0090
MCSP0100
MCSP0110
MCSP0120
MCSP0130
MCSP0140
MCSP0150

```





```

      XHATZ(4), M, ITER, ITRK, IN, ISTAT, K, ITRO, IXZ, IV, IW, IEST, ND
      TAKE THE APPROPRIATE GAIN AND STORE IN THE ARRAY GK
      DO 1 I=1, N
      DO 1 J=1, M
      1 GK(I, J)=GKS(I, J, K)
      IF(IEST.NE.0) GO TO 100
      CALL VPROD(HS, XHKKM1, M, N, VTMP)
      CALL VSUB(Z, VTMP, M, VTMP)
      CALL VPROD(GK, VTMP, N, XHKK)
      CALL VADD(XHKKM1, VTMP, N, XHKK)
      C XHAT(K/K) HAS BEEN COMPUTED AND STORED IN THE ARRAY XHKK
      C CALL VPROD(PHIS, XHKK, N, N, XHKKM1)
      C XHAT(K+1/K) HAS BEEN COMPUTED AND STORED IN THE ARRAY XHKKM1
      RETURN
      C CONTINUE
      C 100 IF STANDARD EQUATIONS ARE NOT TO BE USED, THE APPROPRIATE
      C EQUATIONS MUST BE INSERTED HERE BY THE USER.
      RETURN
      END
      SUBROUTINE GAIN(IG, IQQ)
      REAL*8 GAMMA, COVW, R, PHI, H, TEMP, TEMP1, TEMP2, PKKM1, G, PKK, Q, EI
      COMMON EI(4,4), Q(4,4), PKK(4,4), GAMMA(4,4), COVW(4,4),
      . VAR(4,4,60), TEMPI(4,4,60), PKKS(4,4,60), ERR(4,60),
      . GAMMAS(4,4), PHIS(4,4), XS(4,60), HS(4,4), GK(4,4), X(4),
      . SIGXZ(4), XZMEAN(4), XHKK(4), XHKKM1(4), VTMP(4), Z(4), V(4), SIGV(4),
      . XHATZ(4)
      C XHATZ(4)
      C N, NSAM, IQ, M, ITER, ITRK, IN, ISTAT, K, ITRO, IXZ, IV, IW, IEST, ND
      G(K) = P(K/K-1)*HT*(H*P(K/K-1)*HT + R)
      CALL TRANS(H, M, N, TEMP2)
      CALL PROD(PKKM1, TEMP2, N, N, M, TEMP)
      CALL PROD(H, TEMP, M, N, M, TEMP1)
      CALL ADD(TEMP1, R, M, M, TEMP1)
      IF(M.EQ.1) GO TO 1
      MC=ND
      CALL GAUSS3(M, EPS, TEMP1, TEMP2, KER, MD)
      CALL PROD(TEMP, TEMP2, N, M, M, G)
      C NOTE HERE PKK(I, J) = P(K/K) WHERE

```

```

MC SP0160
MC SP0170
MC SP0180
MC SP0190
MC SP0200
MC SP0210
MC SP0220
MC SP0230
MC SP0240
MC SP0250
MC SP0260
MC SP0270
MC SP0280
MC SP0290
MC SP0300
MC SP0310
MC SP0320
MC SP0330
MC SP0340
MC SP0350
MC SP0360
MC SP0370

```

```

MC SP0010
MC SP0020
MC SP0030
MC SP0040
MC SP0050
MC SP0060
MC SP0070
MC SP0080
MC SP0090
MC SP0100
MC SP0110
MC SP0120
MC SP0130
MC SP0140
MC SP0150
MC SP0160
MC SP0170
MC SP0180
MC SP0190
MC SP0200
MC SP0210

```



MCSP0220  
 MCSP0230  
 MCSP0240  
 MCSP0250  
 MCSP0260  
 MCSP0270  
 MCSP0280  
 MCSP0290  
 MCSP0300  
 MCSP0310  
 MCSP0320  
 MCSP0330  
 MCSP0340  
 MCSP0350  
 MCSP0360

```

C      P(K/K) = (I-G(K)*H)*P(K/K-I)
      2  CALL PROD(G,H,N,M,N,TEMP)
        CALL SUB(EI,TEMP,N,N,TEMP2)
        CALL PKCD(TEMP2,PKKM1,N,N,N,PKK)
        IF(IQ.EQ.1) GO TO 30
        IF (IG.EQ.1) RETURN
      30 CALL TRANS(PHI,N,N,TEMP2)
        CALL PROD(PKK,TEMP2,N,N,TEMP)
        CALL PROD(PHI,TEMP,N,N,TEMP1)
        CALL ADD(TEMP1,Q,N,N,PKKM1)
        RETURN
      1  DC 3 I=1,N
      3  G(I,1)=TEMP(I,1)/TEMP1(I,1)
        GO TO 2
        END
  
```

MCSP0010  
 MCSP0020  
 MCSP0030  
 MCSP0040  
 MCSP0050  
 MCSP0060  
 MCSP0070  
 MCSP0080  
 MCSP0090  
 MCSP0100  
 MCSP0110  
 MCSP0120  
 MCSP0130  
 MCSP0140  
 MCSP0150  
 MCSP0160  
 MCSP0170  
 MCSP0180  
 MCSP0190  
 MCSP0200

```

SUBROUTINE MEAS
THIS SUBROUTINE STARTS WITH THE TRUE STATE VALUE XS
AND ADDS ZERO-MEAN WHITE GAUSSIAN NOISE TO H*XS TO
GENERATE A NOISY VECTOR OF MEASUREMENTS Z.

REAL*8 GAMMA,COVW,R,PHI,H,TEMP,TEMP1,TEMP2,PKKM1,G,PKK,Q,EI
COMMON EI(4,4),Q(4,4),G(4,4),PKK(4,4),COVW(4,4),
TEMP(4,4),TEMP1(4,4),TEMP2(4,4),H(4,4),PKKM1(4,4),PHI(4,4),
VAR(4,4,60),GKS(4,4,60),PKKS(4,4,60),XM(4,60),ERR(4,60),
GAMMAS(4,4),PHIS(4,4),XS(4,60),HS(4,4),GK(4,4),X(4),
SIGXZ(4),XZMEAN(4),XHKK(4),XHKKM1(4),VTMP(4),Z(4),V(4),SIGV(4),
XHSATZ(4),
N,NSAM,IQ,M,ITER,ITRK,IN,ISTAT,K,ITRO,IXZ,IV,IW,IEST,ND
DO 1 I=1,M
CALL SNORM(IV,V,M)
1  V(I)=SIGV(I)*V(I)
Z(I)=XS(I,K)+V(I)
RETURN
END
  
```

MCSP0010  
 MCSP0020  
 MCSP0030

```

SUBROUTINE PEST(A1,A2,A3)
REAL*8 GAMMA,COVW,R,PHI,H,TEMP,TEMP1,TEMP2,PKKM1,G,PKK,Q,EI
COMMON EI(4,4),Q(4,4),G(4,4),PKK(4,4),COVW(4,4),
  
```



```

      TEMP(4,4),TEMP1(4,4),TEMP2(4,4),H(4,4),PKKMI(4,4),R(4,4),PHI(4,4),
      VAR(4,4,60),GKS(4,4,60),PKKS(4,4,60),XM(4,60),ERR(4,60),
      GAMMAS(4,4),PHIS(4,4),XS(4,60),HS(4,4),GK(4,4),SIGW(4),X(4),
      SIGXZ(4),XZMEAN(4),XHKK(4),XHKKMI(4),VTMP(4),V(4),SIGV(4),
      XHATZ(4),
      N,NSAM,IQ,M,ITER,ITRK,IN,ISTAT,K,ITRO,IXZ,IV,IW,IEST,ND
    THIS SUBROUTINE CALCULATE THE COVARIANCE OF RESIDUAL
    WITH ASSUMING Q=0 ,FOR SUBROUTINE QON
    CALL PROD (H,PHI,M,N,N,TEMP)
    CALL TRANS (TEMP,M,N,TEMP1)
    CALL PRCD (PKK,TEMP1,N,M,TEMP1)
    CALL PRCD (TEMP,TEMP1,M,N,M,TEMP)
    CALL ADD (TEMP,R,M,M,TEMP)
    AI=TEMP(1,1)
    RETURN
  END

```

CCCCC

```

SUBROUTINE QMAT
  THIS SUBROUTINE COMPUTES THE MATRIX Q FROM THE EQUATION
      Q=GAMMA* E(W*WT) * GAMMAT
  DOUBLE PRECISION ARITHMETIC IS USED
  REAL*8 GAMMA,COVW,R,PHI,H,TEMP,TEMP1,TEMP2,PKKMI,G,PKK,Q,EI
  COMMON EI(4,4),Q(4,4),G(4,4),PKK(4,4),GAMMA(4,4),COVW(4,4),
  TEMP(4,4),TEMP1(4,4),TEMP2(4,4),H(4,4),PKKMI(4,4),R(4,4),PHI(4,4),
  VAR(4,4,60),GKS(4,4,60),PKKS(4,4,60),XM(4,60),ERR(4,60),
  GAMMAS(4,4),PHIS(4,4),XS(4,60),HS(4,4),GK(4,4),SIGW(4),X(4),
  SIGXZ(4),XZMEAN(4),XHKK(4),XHKKMI(4),VTMP(4),V(4),SIGV(4),
  XHATZ(4),
  N,NSAM,IQ,M,ITER,ITRK,IN,ISTAT,K,ITRO,IXZ,IV,IW,IEST,ND
  CALL PROD(GAMMA,COVW,N,IN,IN,TEMP)
  CALL TRANS(GAMMA,N,IN,TEMP1)
  CALL PRCD(TEMP,TEMP1,N,IN,N,Q)
  SUBROUTINE QON(A1,A2,A3)

```

CCCCCCC

CC



MCSP0240  
 MCSP0250  
 MCSP0260  
 MCSP0270  
 MCSP0280  
 MCSP0290  
 MCSP0300  
 MCSP0310  
 MCSP0320  
 MCSP0330  
 MCSP0340  
 MCSP0350  
 MCSP0360  
 MCSP0370  
 MCSP0380  
 MCSP0390  
 MCSP0400  
 MCSP0410  
 MCSP0420  
 MCSP0430

IF Q IS TO BE COMPUTED ON-LINE (IFLQ.NE.0) IT IS DONE  
 IN THIS SUBROUTINE

REAL\*8 GAMMA,COVW,R,PHI,H,TEMP,TEMPI,TEMP2,PKKM1,G,PKK,Q,EI  
 COMMON EI(4,4),Q(4,4),PKK(4,4),GAMMA(4,4),COVW(4,4),  
 TEMP(4,4),TEMPI(4,4),TEMP2(4,4),H(4,4),PKKM1(4,4),R(4,4),PHI(4,4),  
 VAR(4,4,60),GKS(4,4,60),PKKS(4,4,60),XM(4,60),ERR(4,60),  
 GAMMAS(4,4),PHIS(4,4),XS(4,60),HS(4,4),GK(4,4),SIGW(4),X(4),  
 SIGXZ(4),XZMEAN(4),XHKK(4),XHKKM1(4),VTMP(4),Z(4),V(4),SIGV(4),  
 SHATZ(4),  
 N,NSAM,IQ,M,ITER,ITRK,IN,ISTAT,K,ITRO,IXZ,IV,IW,IEST,ND

THE APPROPRIATE STATEMENTS FOR COMPUTING Q ON-LINE MUST  
 BE INSERTED HERE BY THE USER

RETURN  
 END  
 RETURN  
 END

MCSP0010  
 MCSP0020  
 MCSP0030  
 MCSP0040  
 MCSP0050  
 MCSP0060  
 MCSP0070  
 MCSP0080  
 MCSP0090  
 MCSP0100  
 MCSP0110  
 MCSP0120  
 MCSP0130  
 MCSP0140  
 MCSP0150  
 MCSP0160  
 MCSP0170  
 MCSP0180

SUBROUTINE RETAD  
 "RETAD" CALLED IF IFLQ AND IQQ EQ TO 1

REAL\*8 GAMMA,COVW,R,PHI,H,TEMP,TEMPI,TEMP2,PKKM1,G,PKK,Q,EI  
 COMMON EI(4,4),Q(4,4),PKK(4,4),GAMMA(4,4),COVW(4,4),  
 TEMP(4,4),TEMPI(4,4),TEMP2(4,4),H(4,4),PKKM1(4,4),R(4,4),PHI(4,4),  
 VAR(4,4,60),GKS(4,4,60),PKKS(4,4,60),XM(4,60),ERR(4,60),  
 GAMMAS(4,4),PHIS(4,4),XS(4,60),HS(4,4),GK(4,4),SIGW(4),X(4),  
 SIGXZ(4),XZMEAN(4),XHKK(4),XHKKM1(4),VTMP(4),Z(4),V(4),SIGV(4),  
 SHATZ(4),  
 N,NSAM,IQ,M,ITER,ITRK,IN,ISTAT,K,ITRO,IXZ,IV,IW,IESF,ND

GAIN IS COMPUTED IN THIS PROGRAM BY RESIDUAL TESTING  
 ADAPTIVE SCHEME  
 RETURN  
 END





MCSP0010  
 MCSP0020  
 MCSP0030  
 MCSP0040  
 MCSP0050  
 MCSP0060  
 MCSP0070  
 MCSP0080  
 MCSP0090  
 MCSP0100  
 MCSP0110  
 MCSP0120  
 MCSP0130  
 MCSP0140  
 MCSP0150  
 MCSP0160  
 MCSP0170  
 MCSP0180  
 MCSP0190

```

SUBROUTINE RON
  IF R IS TO BE COMPUTED CN-LINE (IFLR.NE.0) IT IS DONE
  IN THIS SUBROUTINE
  REAL*8 GAMMA,COVW,R,PHI,H,TEMP,TEMP1,TEMP2,PKKM1,G,PKK,Q,EI
  COMMON EI(4,4),Q(4,4),G(4,4),PKK(4,4),GAMMA(4,4),COVW(4,4),
  .TEMP(4,4),TEMP1(4,4),TEMP2(4,4),H(4,4),PKKM1(4,4),R(4,4),PHI(4,4),
  .VAR(4,4,60),GKS(4,4,60),PKKS(4,4,60),XM(4,60),ERR(4,60),
  .GAMMAS(4,4),PHIS(4,4),XS(4,60),HS(4,4),GK(4,4),SIGW(4),X(4),
  .SIGXZ(4),XZMEAN(4),XHKK(4),XHKKM1(4),VTMP(4),Z(4),V(4),SIGV(4),
  .XHATZ(4),
  .N,NSAM,IQ,M,ITER,ITRK,IN,ISTAT,K,ITRO,IXZ,IV,IW,IEST,ND
  THE APPROPRIATE STATEMENTS FOR COMPUTING R CN-LINE MUST
  BE INSERTED HFRE BY THE USER
  RETURN
  END
  
```

MCSP0010  
 MCSP0020  
 MCSP0030  
 MCSP0040  
 MCSP0050  
 MCSP0060  
 MCSP0070  
 MCSP0080  
 MCSP0090  
 MCSP0100  
 MCSP0110  
 MCSP0120  
 MCSP0130  
 MCSP0140  
 MCSP0150  
 MCSP0160  
 MCSP0170  
 MCSP0180  
 MCSP0190  
 MCSP0200  
 MCSP0210  
 MCSP0220  
 MCSP0230  
 MCSP0240

```

SUBROUTINE STAT
  THIS SUBROUTINE COMPUTES RUNNING SUMS USED IN DETERMINING THE
  SAMPLE STATISTICS OF TRACK AND ESTIMATION ERRORS. IN THE DEFAULT
  OPTION (ISTAT.EQ.0) THE STATISTICS TO BE COMPUTED ARE MEAN OF
  TRACK, MEAN OF ESTIMATION ERROR AND VARIANCE OF ESTIMATION
  ERROR. IF(ISTAT.NE.0) THE OFF-DIAGONAL TERMS IN THE COVARIANCE OF
  ESTIMATION ERROR MATRIX ARE ALSO COMPUTED.
  REAL*8 GAMMA,COVW,R,PHI,H,TEMP,TEMP1,TEMP2,PKKM1,G,PKK,Q,EI
  COMMON EI(4,4),Q(4,4),G(4,4),PKK(4,4),GAMMA(4,4),COVW(4,4),
  .TEMP(4,4),TEMP1(4,4),TEMP2(4,4),H(4,4),PKKM1(4,4),R(4,4),PHI(4,4),
  .VAR(4,4,60),GKS(4,4,60),PKKS(4,4,60),XM(4,60),ERR(4,60),
  .GAMMAS(4,4),PHIS(4,4),XS(4,60),HS(4,4),GK(4,4),SIGW(4),X(4),
  .SIGXZ(4),XZMEAN(4),XHKK(4),XHKKM1(4),VTMP(4),Z(4),V(4),SIGV(4),
  .XHATZ(4),
  .N,NSAM,IQ,M,ITER,ITRK,IN,ISTAT,K,ITRO,IXZ,IV,IW,IEST,ND
  DIMENSIONION EXH(3)
  IF(ITRK.NE.1) GO TO 3
  IF(ITER.NE.1) GO TO 3
  DO 4 J=1,N
    XM(J,K)=XS(J,K)
  4 GO TO 3
  2 CCNTINUE
  DO 6 J=1,N
    XM(J,K)=XM(J,K)+XS(J,K)
  6
  
```



MCSP0250  
 MCSP0260  
 MCSP0270  
 MCSP0280  
 MCSP0290  
 MCSP0300  
 MCSP0310  
 MCSP0320  
 MCSP0330  
 MCSP0340  
 MCSP0350  
 MCSP0360

```

3 CCNTINUE
  DO 1 J=1,N
    EXH(J)=XHKK(J)-XS(J,K)
    ERR(J,K)=ERR(J,K)+EXH(J)
  1 VAR(J,J,K)=VAR(J,J,K)+EXH(J)**2
    IF(ISTAT.EQ.0) RETURN
  DO 5 L=2,N
    LM1=L-1
  DO 5 J=1,LM1
    VAR(L,J,K)=VAR(L,J,K)+EXH(L)*EXH(J)
  RETURN
END
  
```

MCSP0010  
 MCSP0020  
 MCSP0030  
 MCSP0040  
 MCSP0050  
 MCSP0060  
 MCSP0070  
 MCSP0080  
 MCSP0090  
 MCSP0100  
 MCSP0110  
 MCSP0120  
 MCSP0130  
 MCSP0140  
 MCSP0150  
 MCSP0160  
 MCSP0170  
 MCSP0180  
 MCSP0190  
 MCSP0200  
 MCSP0210  
 MCSP0220  
 MCSP0230  
 MCSP0240  
 MCSP0250  
 MCSP0260  
 MCSP0270  
 MCSP0280  
 MCSP0290  
 MCSP0300  
 MCSP0310

SUBROUTINE TRACK  
 IF TRACK IS TO BE GENERATED ON-LINE IT IS DONE IN THIS SUBROUTINE  
 IN THE DEFAULT OPTION (ITRK.EQ.0) THE TRACK IS GENERATED  
 FROM THE STANDARD LINEAR DIFFERENCE EQUATION

$$X(K+1) = \text{PHI} * X(K) + \text{GAMMA} * W(K)$$

```

REAL*8 GAMMA,COVW,R,PHI,H,TEMP,TEMP1,TEMP2,PKKMI,G,PKK,Q,EI
COMMON EI(4,4),Q(4,4),G(4,4),PKK(4,4),GAMMA(4,4),COVW(4,4),
TEMP(4,4),TEMP1(4,4),TEMP2(4,4),H(4,4),PKKMI(4,4),R(4,4),PHI(4,4),
VAR(4,4,60),GKS(4,4,60),PKKS(4,4,60),XM(4,4,60),ERR(4,60),X(4),
GAMMAS(4,4),PHIS(4,4),XS(4,60),HS(4,4),GK(4,4),SIGW(4),X(4),
SIGXZ(4),XZMEAN(4),XHKK(4),XHKKMI(4),VTMP(4),Z(4),V(4),SIGV(4),
XHATZ(4),
N,NSAM,IQ,M,ITER,ITRK,IN,ISTAT,K,ITRO,IXZ,IV,IW,IESI,ND
DIMENSION W(3)
ITRK NE.0 OR 1 -- SEVERAL TRACKS GENERATED, BUT NCT FROM STD.
LINEAR EQS.
= 0 -- SEVERAL TRACKS GENERATED FROM STD LINEAR EQS
= 1 -- ONLY ONE TRACK IS USED
IF(ITRK.NE.0) GO TO 100
CALL SNORM(IW,W,IN)
CCONVERT EACH N(O,1) R.V. TO N(O,SIGW(I)) R.V.
DO 1 I=1,IN
  W(I)=SIGW(I)*W(I)
DC 3 I=1,N
  X(I)=XS(I,K)
CALL VPROD(GAMMAS,W,N,IN,W)
CALL VPROD(PHIS,X,N,N,VTMP)
CALL VADD(VTMP,W,N,VTMP)
DO 2 I=1,N
  
```

MCSP0010  
 MCSP0020  
 MCSP0030  
 MCSP0040  
 MCSP0050  
 MCSP0060  
 MCSP0070  
 MCSP0080  
 MCSP0090  
 MCSP0100  
 MCSP0110  
 MCSP0120  
 MCSP0130  
 MCSP0140  
 MCSP0150  
 MCSP0160  
 MCSP0170  
 MCSP0180  
 MCSP0190  
 MCSP0200  
 MCSP0210  
 MCSP0220  
 MCSP0230  
 MCSP0240  
 MCSP0250  
 MCSP0260  
 MCSP0270  
 MCSP0280  
 MCSP0290  
 MCSP0300  
 MCSP0310

```

1 W(I)=SIGW(I)*W(I)
DC 3 I=1,N
  X(I)=XS(I,K)
CALL VPROD(GAMMAS,W,N,IN,W)
CALL VPROD(PHIS,X,N,N,VTMP)
CALL VADD(VTMP,W,N,VTMP)
DO 2 I=1,N
  
```



MCSPO0320  
 MCSPO0330  
 MCSPO0340  
 MCSPO0350  
 MCSPO0360  
 MCSPO0370  
 MCSPO0380  
 MCSPO0390  
 MCSPO0400  
 MCSPO0410  
 MCSPO0420  
 MCSPO0430  
 MCSPO0440  
 MCSPO0450  
 MCSPO0460  
 MCSPO0470  
 MCSPO0480  
 MCSPO0490  
 MCSPO0500  
 MCSPO0510  
 MCSPO0520  
 MCSPO0530  
 MCSPO0540  
 MCSPO0550  
 MCSPO0560  
 MCSPO0570  
 MCSPO0580  
 MCSPO0590  
 MCSPO0600  
 MCSPO0610  
 MCSPO0620  
 MCSPO0630  
 MCSPO0640  
 MCSPO0650  
 MCSPO0660  
 MCSPO0670

```

2 XS(I,K+1)=VTMP(I)
C NEW VALUE OF X HAS BEEN COMPUTED AND STORED IN THE ARRAY XS
RETURN
100 IF(ITRK.NE.1) GO TO 200
C IF(ITRK.EQ.1) THE USER MUST INSERT HERE THE STATEMENTS REQUIRED
C TO GENERATE A SINGLE TRAJECTORY AND STORE IT IN THE ARRAY
C XS(I,K), I=1,N,K=2,NSAM (NOTE THAT IF A SINGLE TRAJECTORY IS TO BE
C GENERATED, THE INITIAL CONDITION HAS BEEN READ IN AND STORED
DO 40 K=2,NSAM
IF (K.GT.10) GO TO 10
XS(3,K)=0.0
XS(2,K)=-600.0
XS(1,K)=60000.0-600.0*(K-1)
GO TO 40
10 IF(K.GT.20) GO TO 20
XS(3,K)=-20.0
XS(2,K)=-600.0+XS(3,K)*(K-10)
XS(1,K)=XS(1,K-1)+XS(2,K)
GO TO 40
20 IF(K.GT.30) GO TO 30
XS(3,K)=0.0
XS(2,K)=XS(2,20)
XS(1,K)=XS(1,K-1)+XS(2,K)
GO TO 40
30 XS(3,K)=20.0
XS(2,K)=XS(2,30)+XS(3,K)*(K-30)
XS(1,K)=XS(1,K-1)+XS(2,K)
40 CONTINUE
RETURN
200 CONTINUE
C IF THIS POINT IS REACHED, ITRK NOT EQUAL 0 OR 1 INDICATING THAT
C SEVERAL TRACKS ARE TO BE GENERATED, BUT NOT BY USING THE STD.
C LINEAR DIFFERENCE EQS..THE USER MUST SUPPLY THE APPROPRIATE
C STATEMENTS HERE.
RETURN
END
  
```

MCSPO0010  
 MCSPO0020  
 MCSPO0030  
 MCSPO0040  
 MCSPO0050  
 MCSPO0060  
 MCSPO0070

```

SUBROUTINE XZERO
THIS SUBROUTINE GENERATES THE INITIAL STATE VALUE FROM A NORMAL
RANDOM NUMBER GENERATOR. IT IS ASSUMED THAT THE INITIAL STATE
HAS COMPONENTS THAT ARE INDEPENDENT
REAL*8 GAMMA,COVM,R,PHI,H,TEMP,TEMP1,TEMP2,PKKM1,G,PKK,Q,EI
COMMON EI(4,4),Q(4,4),G(4,4),PKK(4,4),GAMMA(4,4),COVM(4,4),
TEMP(4,4),TEMP1(4,4),TEMP2(4,4),H(4,4),PKKM1(4,4),R(4,4),PHI(4,4),
.
  
```



MCSPO0080  
 MCSPO0090  
 MCSPO0100  
 MCSPO0110  
 MCSPO0120  
 MCSPO0130  
 MCSPO0140  
 MCSPO0150  
 MCSPO0160  
 MCSPO0170

```

    .VAR(4,4,60),GKS(4,4,60),PKKS(4,4,60),XM(4,60),ERR(4,60),
    .GAMMAS(4,4),PHIS(4,4),XS(4,60),HS(4,4),GK(4,4),SIGW(4),X(4),
    .SIGXZ(4),XZMEAN(4),XHKK(4),XHKKMI(4),VIMP(4),Z(4),V(4),SIGV(4),
    .XHATZ(4),
    .N,NSAM,IQ,M,ITER,ITRK,IN,ISTAT,K,ITRO,IXZ,IV,IW,IEST,ND
    CALL SNORM(IXZ,X,N)
    DO I=1,N
      1 XS(I,1)=SIGXZ(I)*X(I)+XZMEAN(I)
    RETURN
  END
  
```

MCSPO0010  
 MCSPO0020  
 MCSPO0030  
 MCSPO0040  
 MCSPO0050  
 MCSPO0060  
 MCSPO0070  
 MCSPO0080  
 MCSPO0090  
 MCSPO0100

```

    SUBROUTINE ADD (A,B,N,M,C)
    THIS SUBROUTINE ADDS THE NXM MATRICES A AND B, STORING THE
    RESULT IN C
    REAL*8 A,B,C
    DIMENSION A(4,4),B(4,4),C(4,4)
    DO 152 I=1,N
      DO 152 J=1,M
        C(I,J) = A(I,J) + B(I,J)
    152 RETURN
  END
  
```

MCSPO0010  
 MCSPO0020  
 MCSPO0030  
 MCSPO0040  
 MCSPO0050  
 MCSPO0060  
 MCSPO0070  
 MCSPO0080  
 MCSPO0090  
 MCSPO0100  
 MCSPO0110

```

    SUBROUTINE MREAD(A,N,M)
    THIS SUBROUTINE READS AN NXM MATRIX A ACCORDING TO THE FORMAT
    8D10.5. THE ENTRIES IN THE FIRST ROW OF A ARE READ FIRST, THEN
    THE ENTRIES IN THE SECOND ROW, AND SO ON.
    REAL*8 A(4,4)
    DIMENSION A(4,4)
    DO 10 I=1,N
      READ(5,20) (A(I,J),J=1,M)
    10 FORMAT(8F10.0)
    RETURN
  END
  
```

MCSPO0010  
 MCSPO0020

```

    SUBROUTINE MWRITE(A,N,M)
    THIS SUBROUTINE WRITES THE ENTRIES OF THE NXM MATRIX A
  
```





MC SP0030  
 MC SP0040  
 MC SP0050  
 MC SP0060  
 MC SP0070  
 MC SP0080  
 MC SP0090

```

REAL*8 A
DIMENSION A(4,4)
DO 10 I=1,N
WRITE(6,20) (A(I,J),J=1,M)
FORMAT(9(2X,1PE12.5))
20 RETURN
END
10
20

```

MC SP0010  
 MC SP0020  
 MC SP0030  
 MC SP0040  
 MC SP0050  
 MC SP0060  
 MC SP0070  
 MC SP0080  
 MC SP0090  
 MC SP0100  
 MC SP0110  
 MC SP0120  
 MC SP0130  
 MC SP0140  
 MC SP0150  
 MC SP0160  
 MC SP0170  
 MC SP0180

```

SUBROUTINE PROD (A,B,N,M,L,C)
THIS SUBROUTINE COMPUTES THE MATRIX PRODUCT AB AND STORES THE
C RESULT IN C
C
C A = NXM, B = MXL, C = NXL
REAL*8 A,B,C,T
DIMENSION A(4,4),B(4,4),C(4,4),T(4,4)
DO 1 I=1,N
DO 1 J=1,L
T(I,J)=0.0
151 DO 2 I=1,N
DO 151 J=1,L
DO 151 K=1,M
T(I,J) = T(I,J) + A(I,K)*B(K,J)
2 RETURN
END
C
C

```

MC SP0010  
 MC SP0020  
 MC SP0030  
 MC SP0040  
 MC SP0050  
 MC SP0060  
 MC SP0070  
 MC SP0080  
 MC SP0090  
 MC SP0100

```

SUBROUTINE SUB (A,B,N,M,C)
THIS SUBROUTINE SUBTRACTS THE NXM MATRIX B FROM THE NXM MATRIX
C A AND STORES THE RESULT IN C
C
C REAL*8 A,B,C
DIMENSION A(4,4),B(4,4),C(4,4)
DO 152 I=1,N
DO 152 J=1,M
152 C(I,J) = A(I,J) - B(I,J)
RETURN
END
C
C

```



MCSPO010  
 MCSPO020  
 MCSPO030  
 MCSPO040  
 MCSPO050  
 MCSPO060  
 MCSPO070  
 MCSPO080  
 MCSPO090  
 MCSPO100  
 MCSPO110

```

C C
C SUBROUTINE TRANS(A,N,M,C)
C THIS SUBROUTINE FORMS THE MATRIX TRANSPOSE OF A STORING THE
C RESULT IN C
C A = NXM, C = MXN
C REAL*8 A,C
C DIMENSION A(4,4),C(4,4)
C DO 153 I = 1,N
C DO 153 J = 1,M
C C(J,I) = A(I,J)
C RETURN
C END
153
  
```

MCSPO010  
 MCSPO020  
 MCSPO030  
 MCSPO040  
 MCSPO050  
 MCSPO060  
 MCSPO070  
 MCSPO080  
 MCSPO090

```

C C
C SUBROUTINE VADD(X,Y,N,Z)
C THIS SUBROUTINE COMPUTES THE SUM OF THE N-VECTORS X AND
C Y AND STORES THE RESULT IN THE N-VECTOR Z
C REAL*4 X(4),Y(4),Z(4)
C DO 1 I = 1,N
C Z(I) = X(I) + Y(I)
C RETURN
C END
1
  
```

MCSPO010  
 MCSPO020  
 MCSPO030  
 MCSPO040  
 MCSPO050  
 MCSPO060  
 MCSPO070  
 MCSPO080  
 MCSPO090  
 MCSPO100  
 MCSPO110  
 MCSPO120  
 MCSPO130  
 MCSPO140  
 MCSPO150

```

C C
C SUBROUTINE VPROD(A,X,M,N,Y)
C THIS SUBROUTINE COMPUTES THE PRODUCT OF THE MXN MATRIX
C A AND THE N-VECTOR X AND STORES THE RESULT IN THE
C M-VECTOR Y
C REAL*4 A(4,4),X(4),Y(4),T(4)
C DO 1 I = 1,M
C T(I) = 0.00
C DO 1 J = 1,N
C T(I) = T(I) + A(I,J)*X(J)
C DC 2 I = 1,M
C Y(I) = T(I)
C RETURN
C END
1
2
  
```



MC SP0010  
MC SP0020  
MC SP0030  
MC SP0040  
MC SP0050  
MC SP0060  
MC SP0070  
MC SP0080  
MC SP0090

```
      SUBROUTINE VREAD(V,N)
      THIS SUBROUTINE READS THE N-DIMENSIONAL S.P. VECTOR V
      DIMENSION V(4)
      READ(5,10) (V(I), I=1,N)
      FORMAT(8F10.0)
      RETURN
      END
10
```

C  
C  
C

MC SP0010  
MC SP0020  
MC SP0030  
MC SP0040  
MC SP0050  
MC SP0060  
MC SP0070  
MC SP0080  
MC SP0090

```
      SUBROUTINE VSUB(X,Y,N,Z)
      THIS SUBROUTINE COMPUTES THE DIFFERENCE X-Y OF THE TWO
      N-VECTORS X & Y AND STORES THE RESULT IN THE N-VECTOR Z
      REAL*4 X(4),Y(4),Z(4)
      DO 1 I=1,N
      Z(I)=X(I)-Y(I)
      RETURN
      END
1
```

C  
C  
C

MC SP0010  
MC SP0020  
MC SP0030  
MC SP0040  
MC SP0050  
MC SP0060  
MC SP0070  
MC SP0080  
MC SP0090

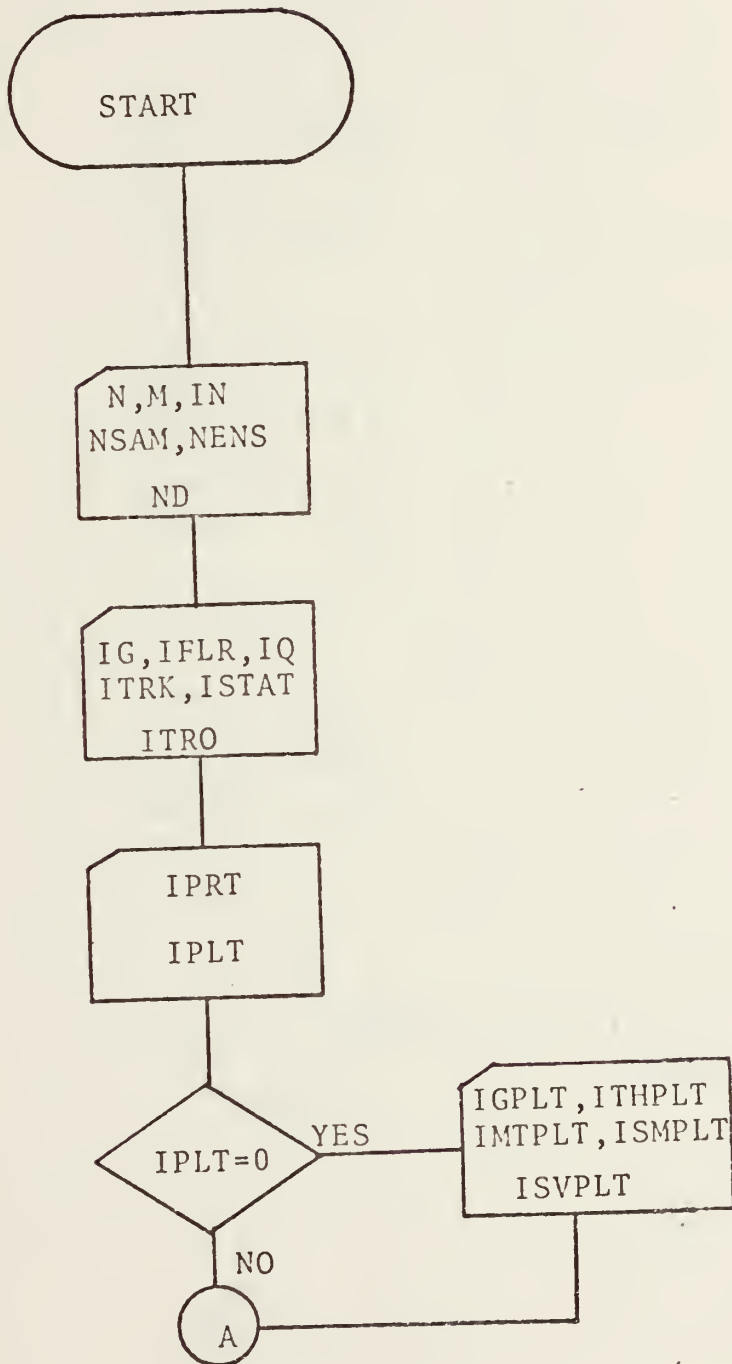
```
      SUBROUTINE VWRITE(V,N)
      THIS SUBROUTINE WRITES THE N-DIMENSIONAL S.P. VECTOR V
      DIMENSION V(4)
      WRITE(6,10) (V(I), I=1,N)
      FORMAT(9(2X,1PE12.5))
      RETURN
      END
10
```

C  
C  
C



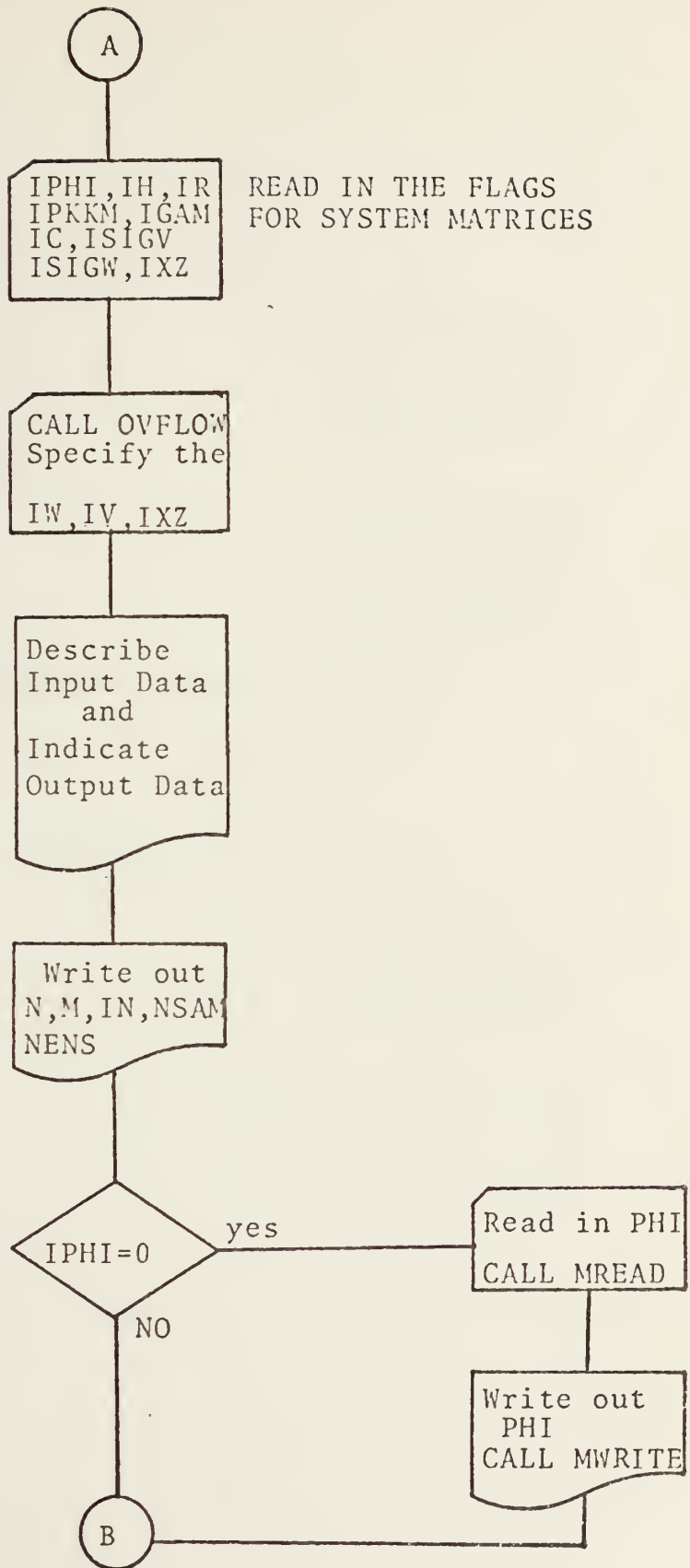
### A.3 Flowchart of the Monte Carlo Simulation Program

#### 1. Main Flowchart

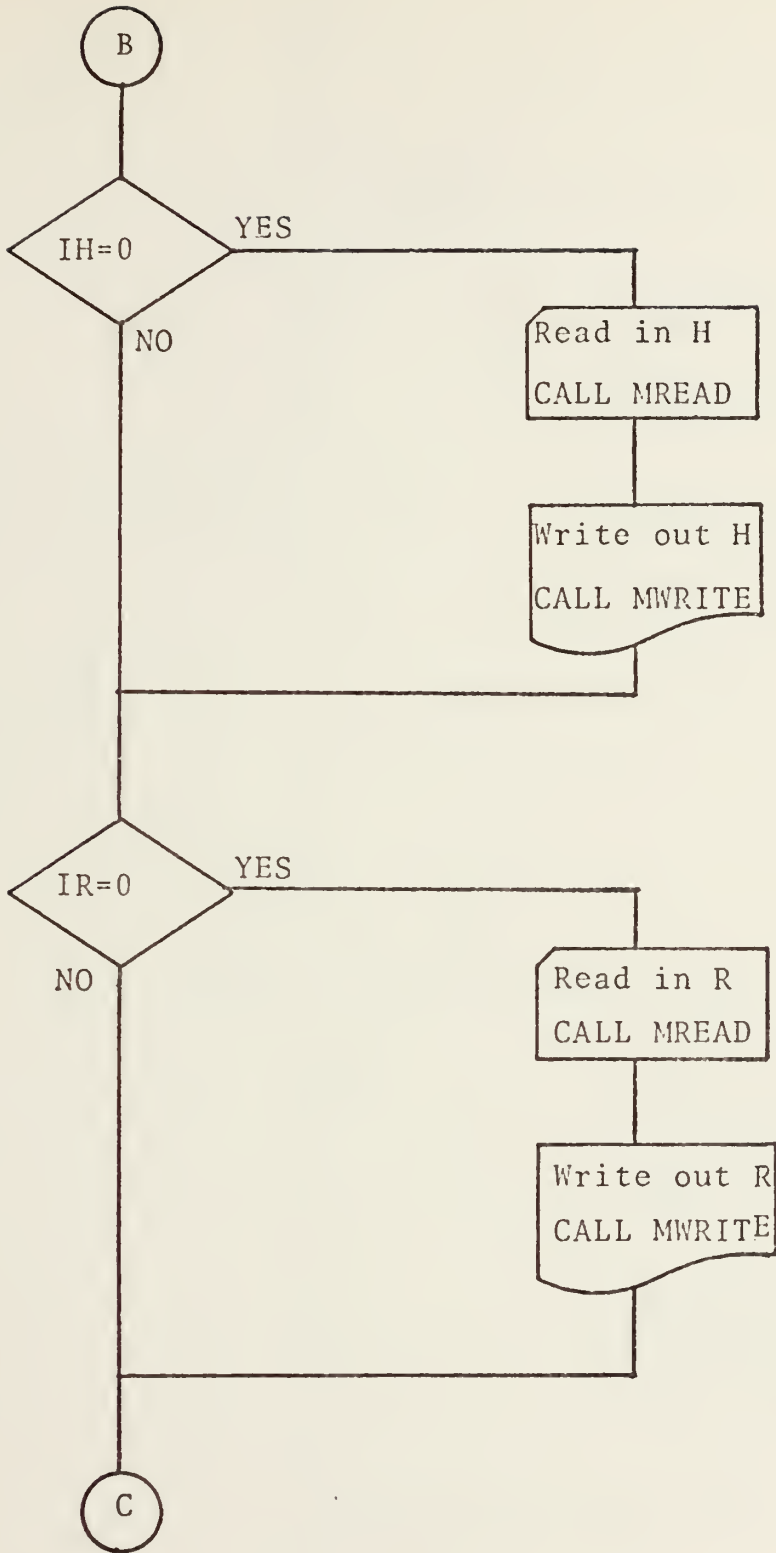




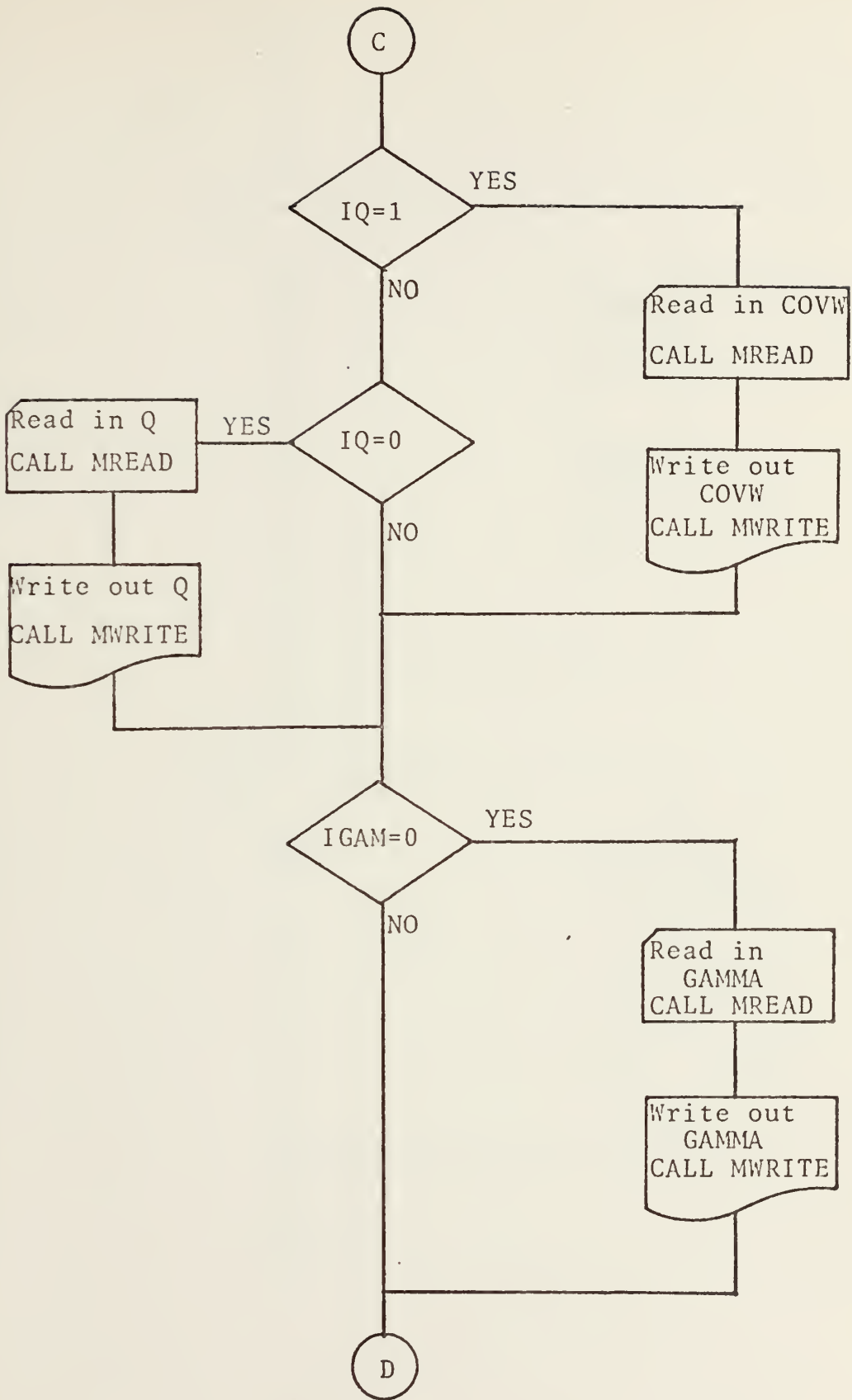




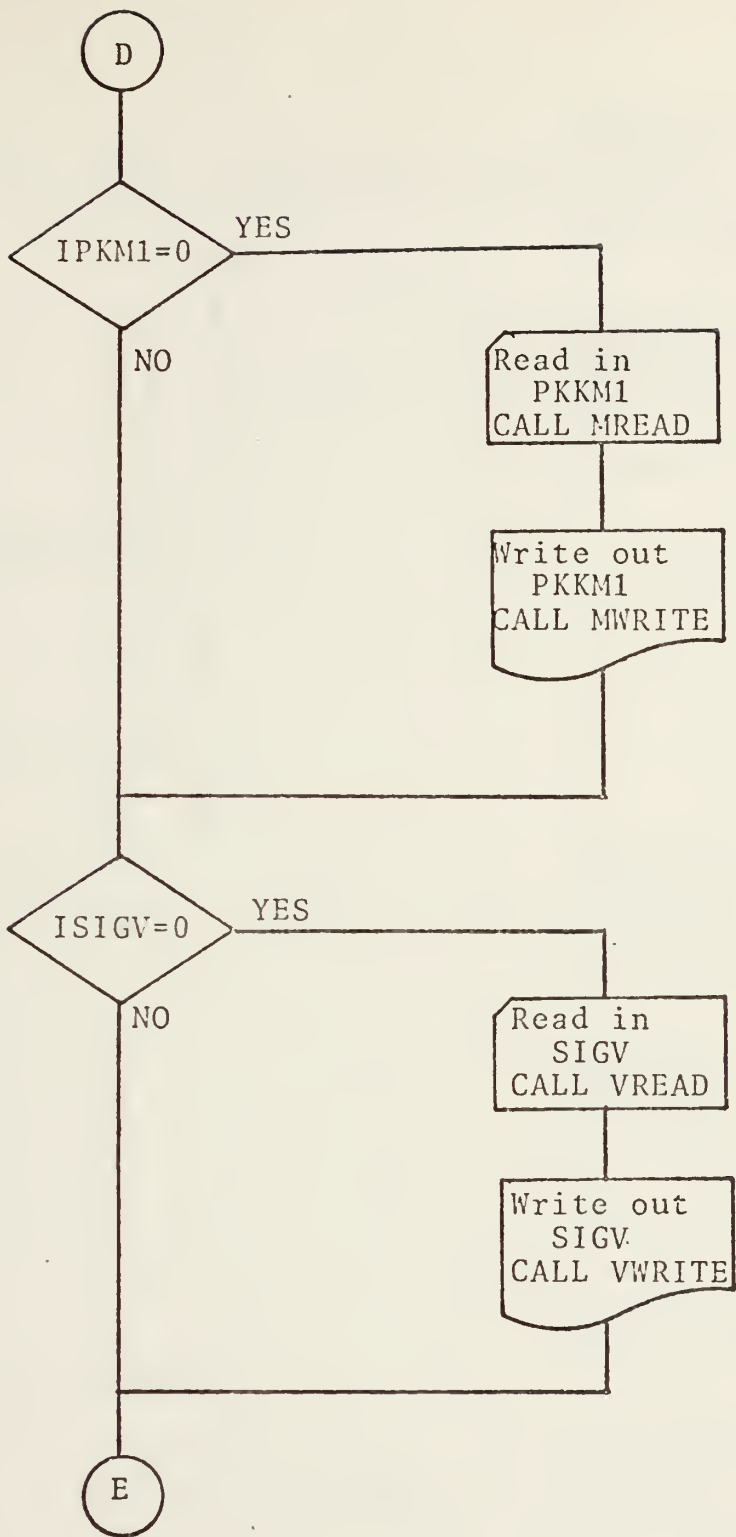






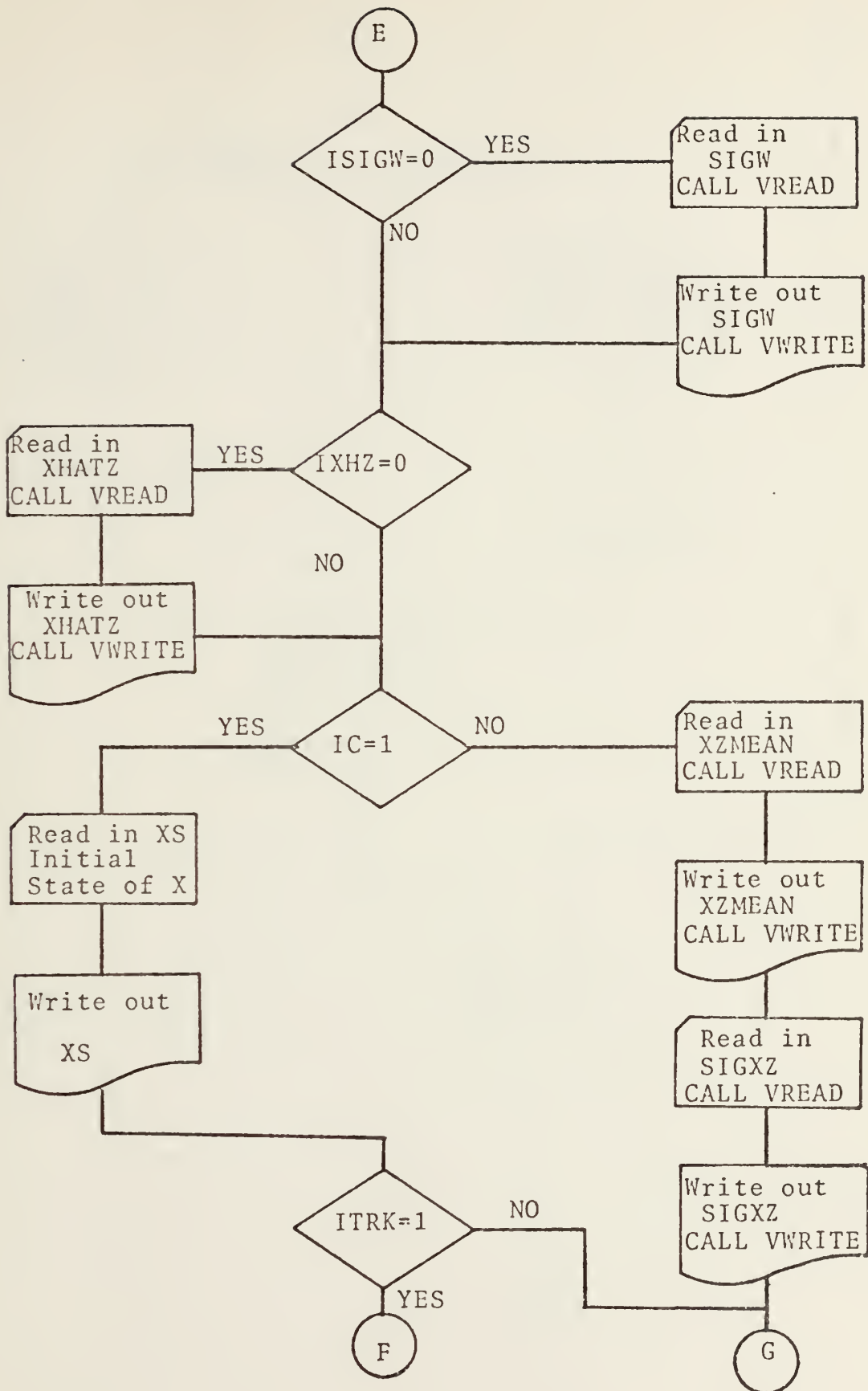




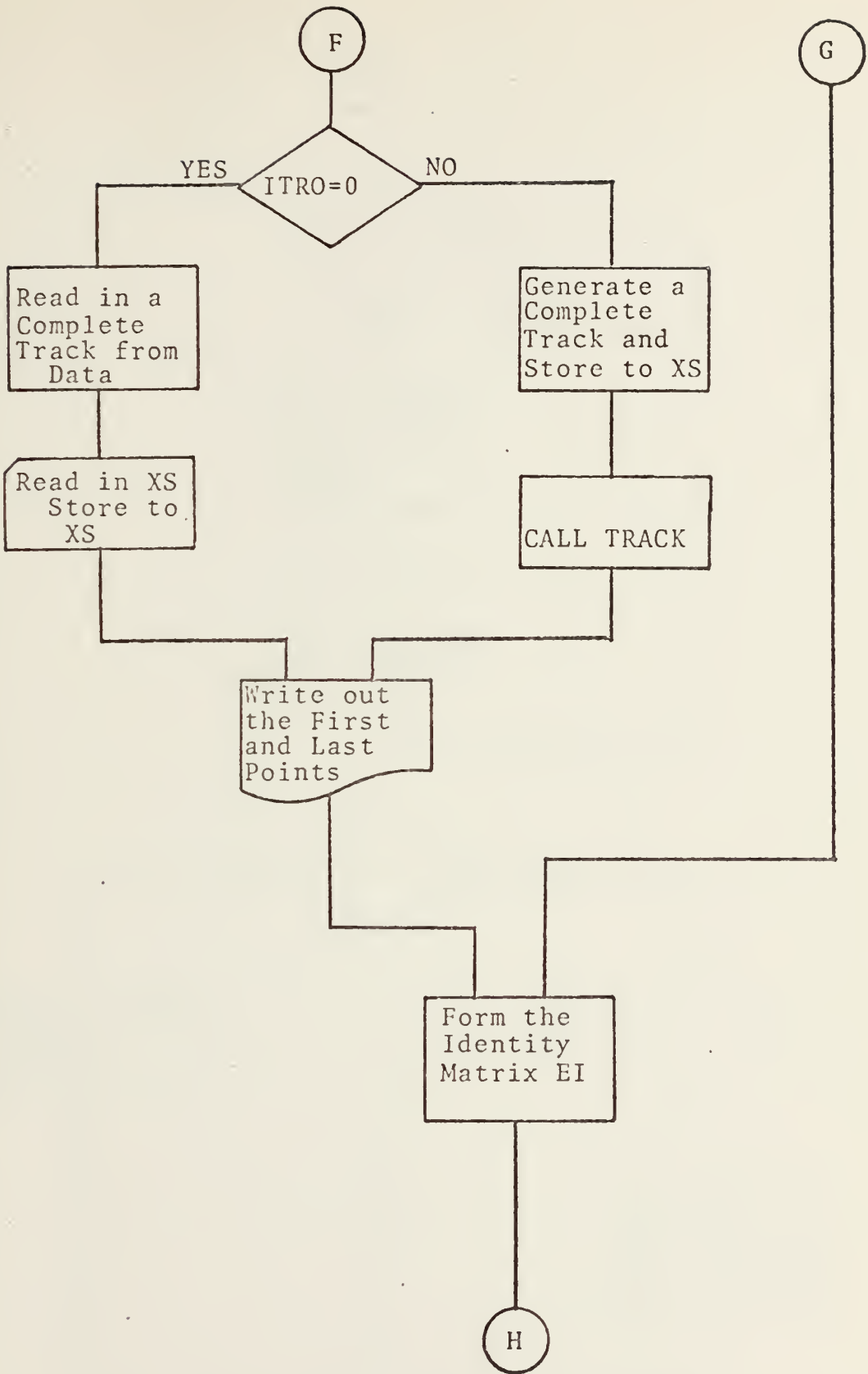




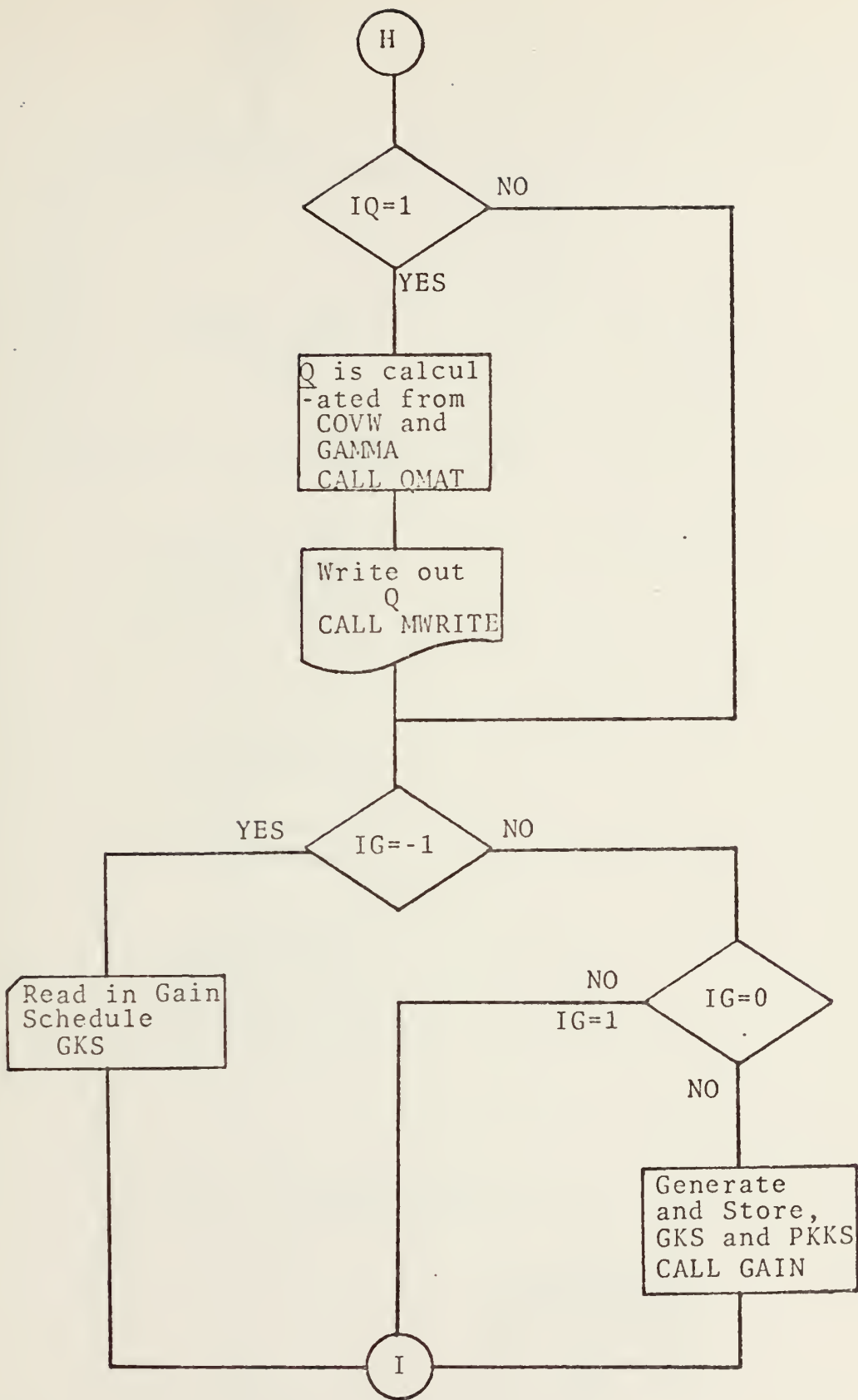




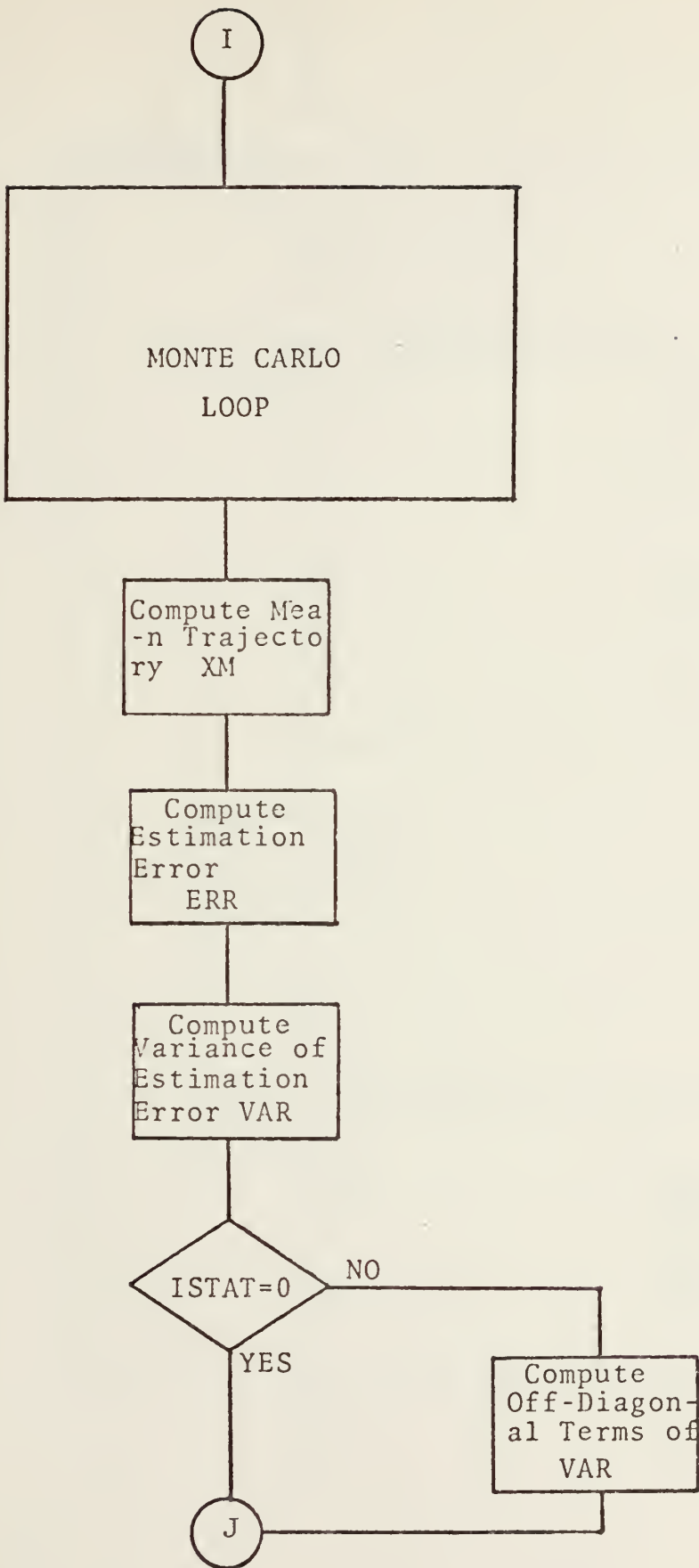






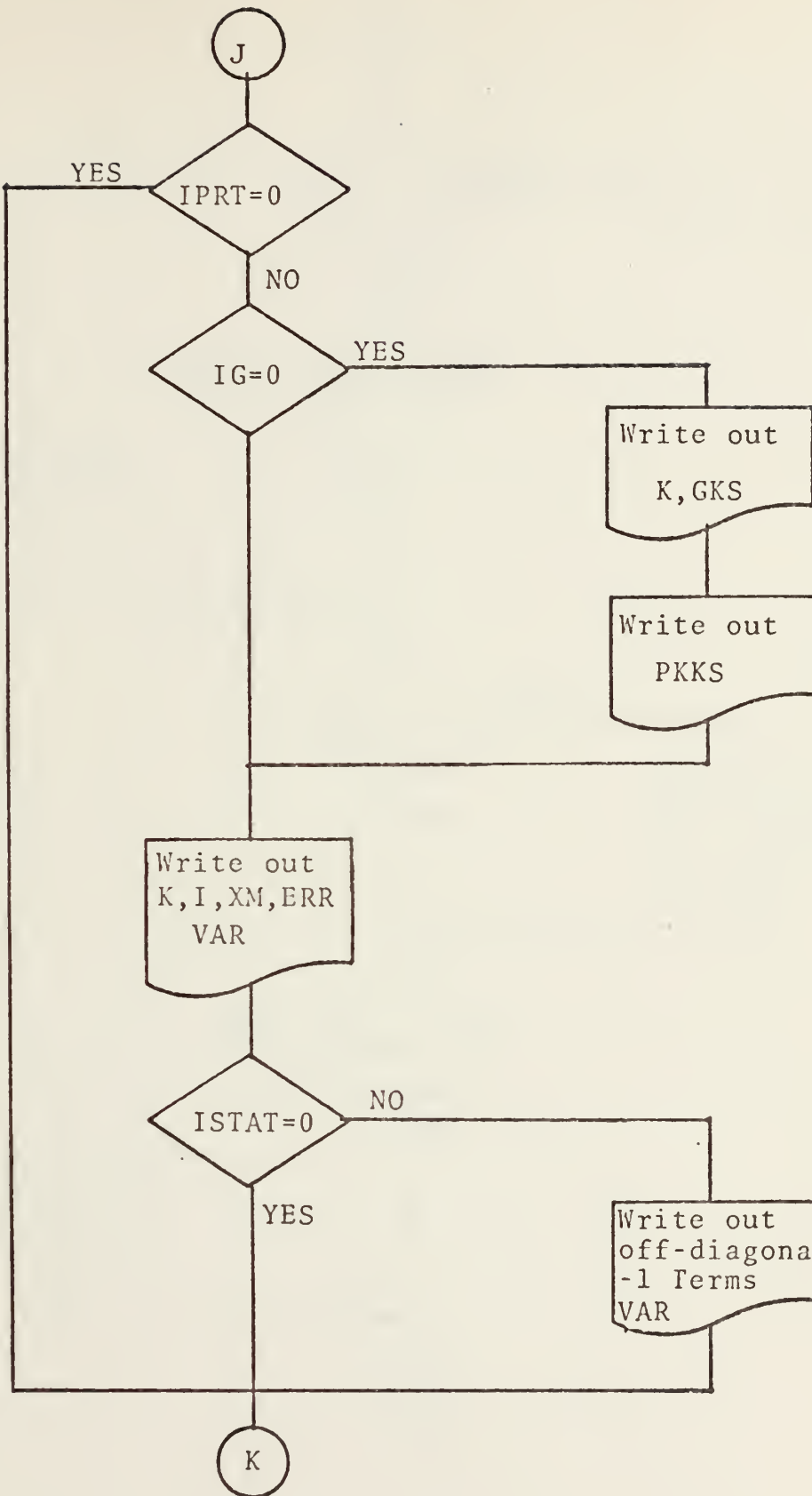




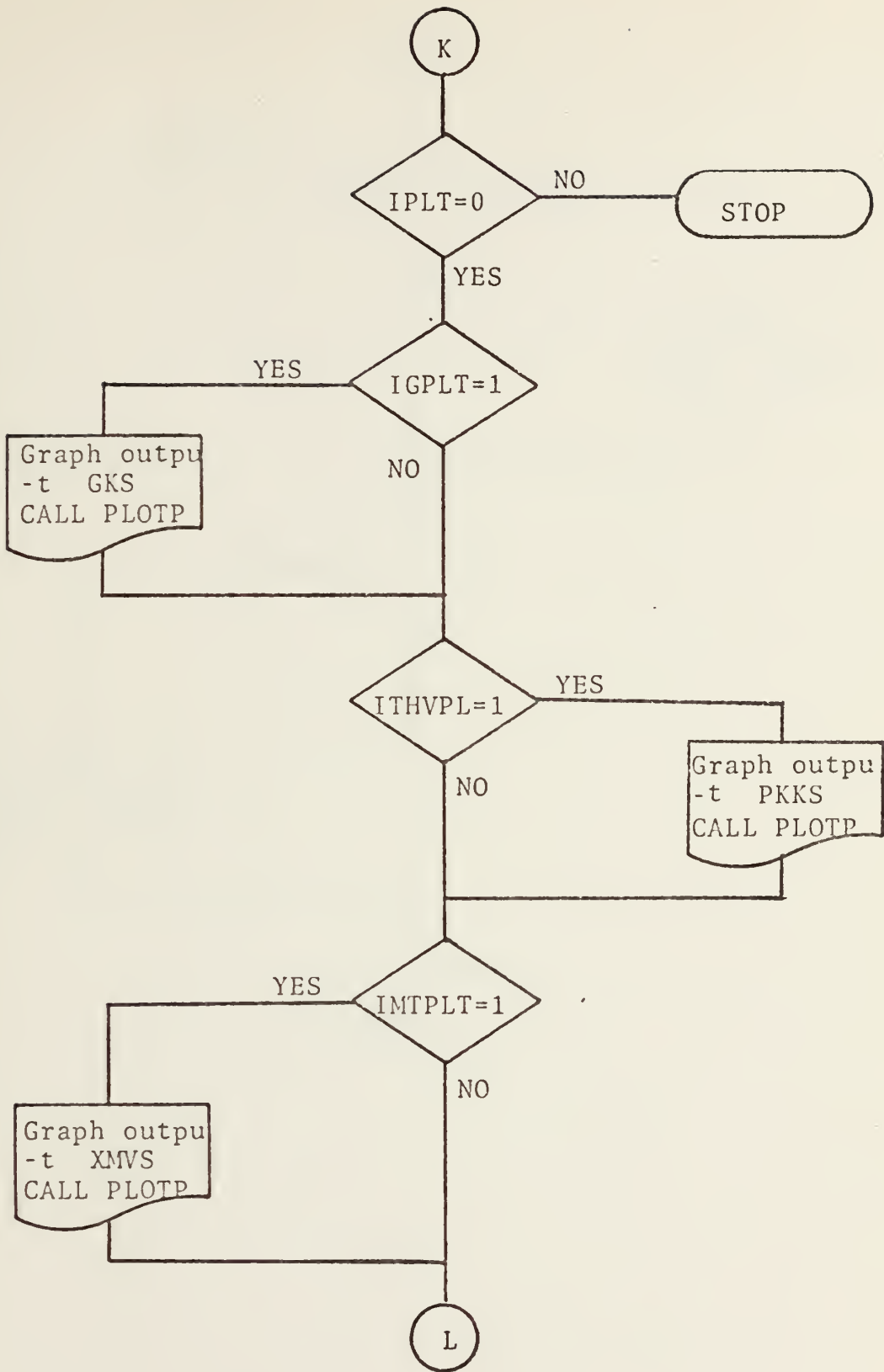




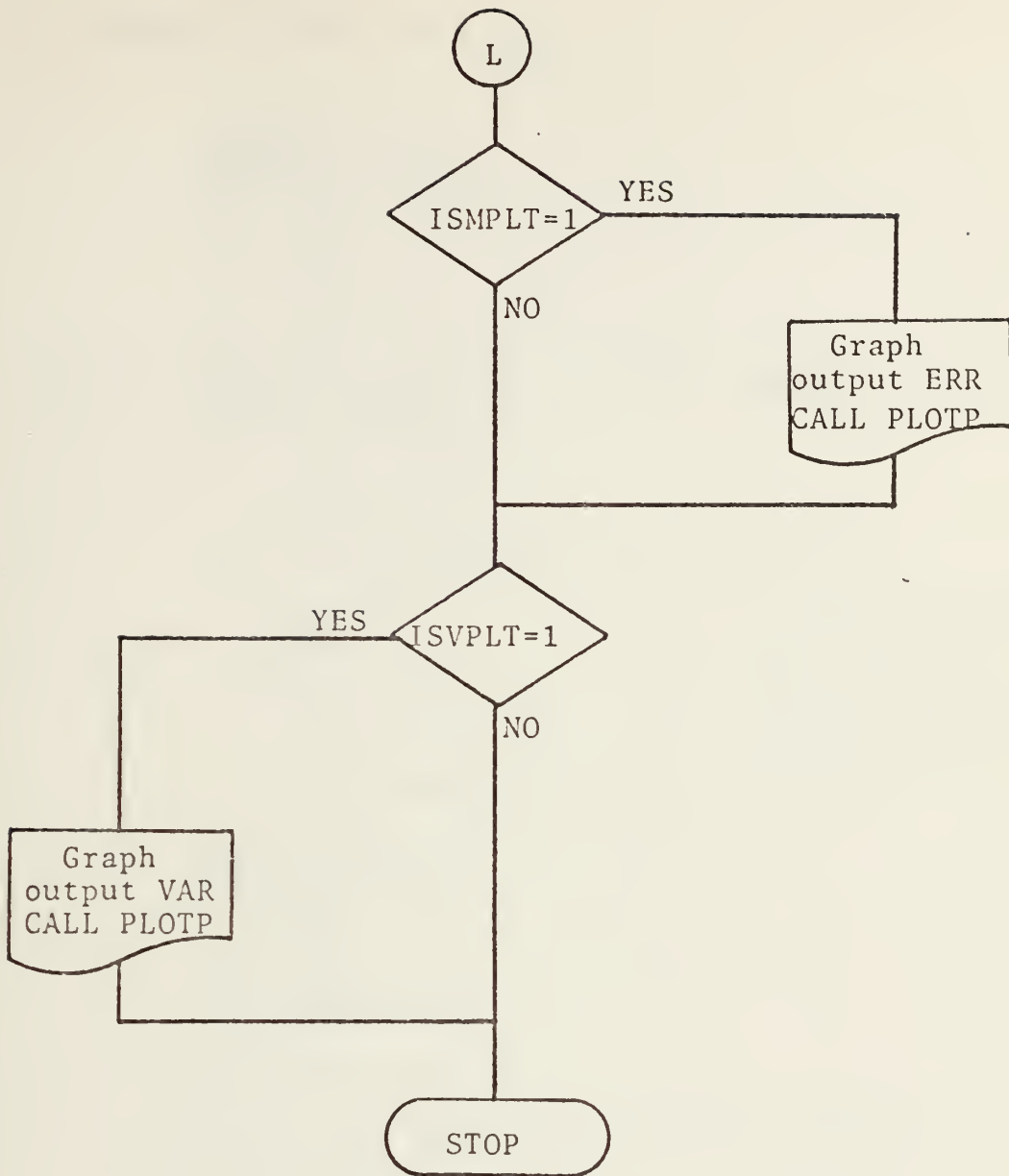






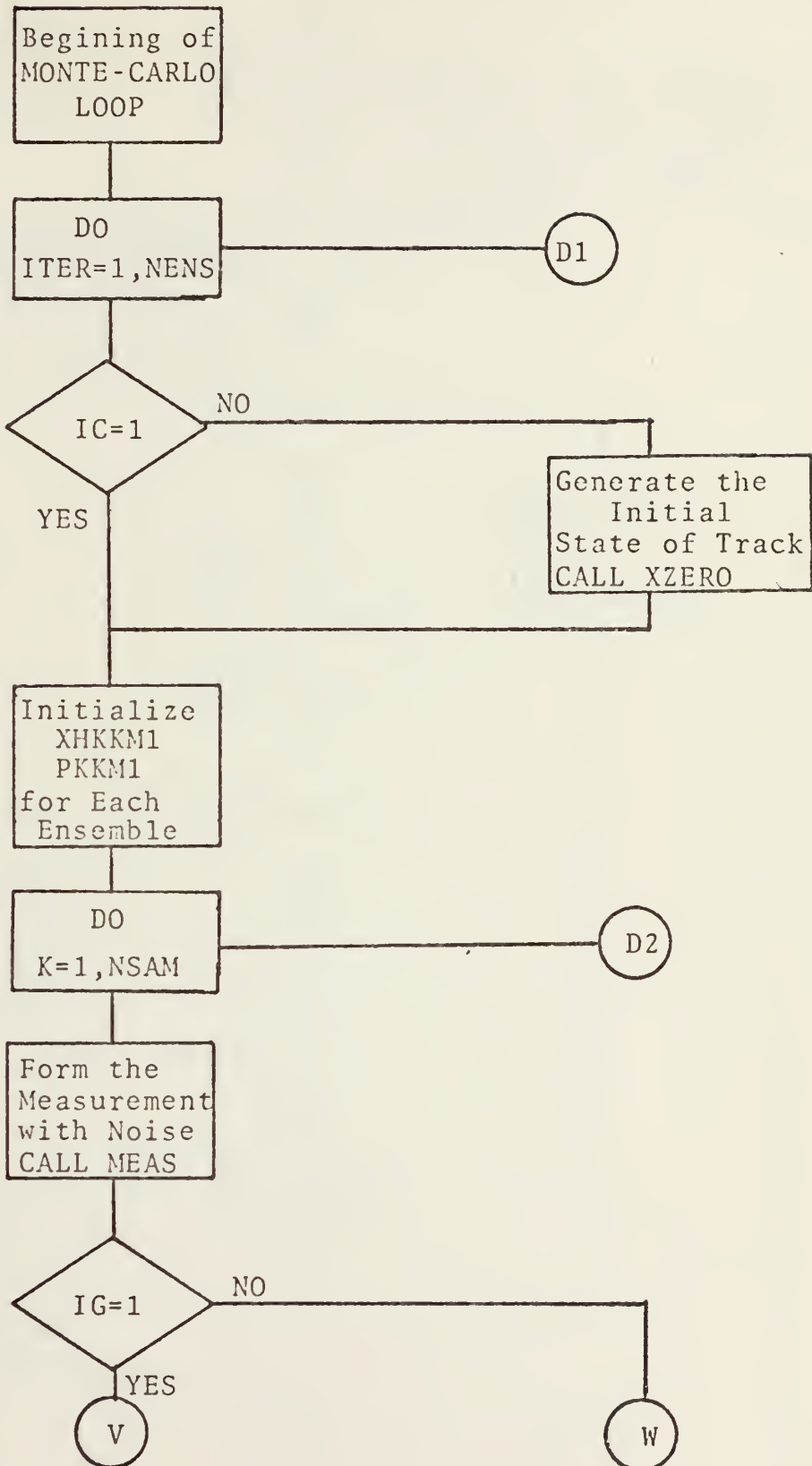






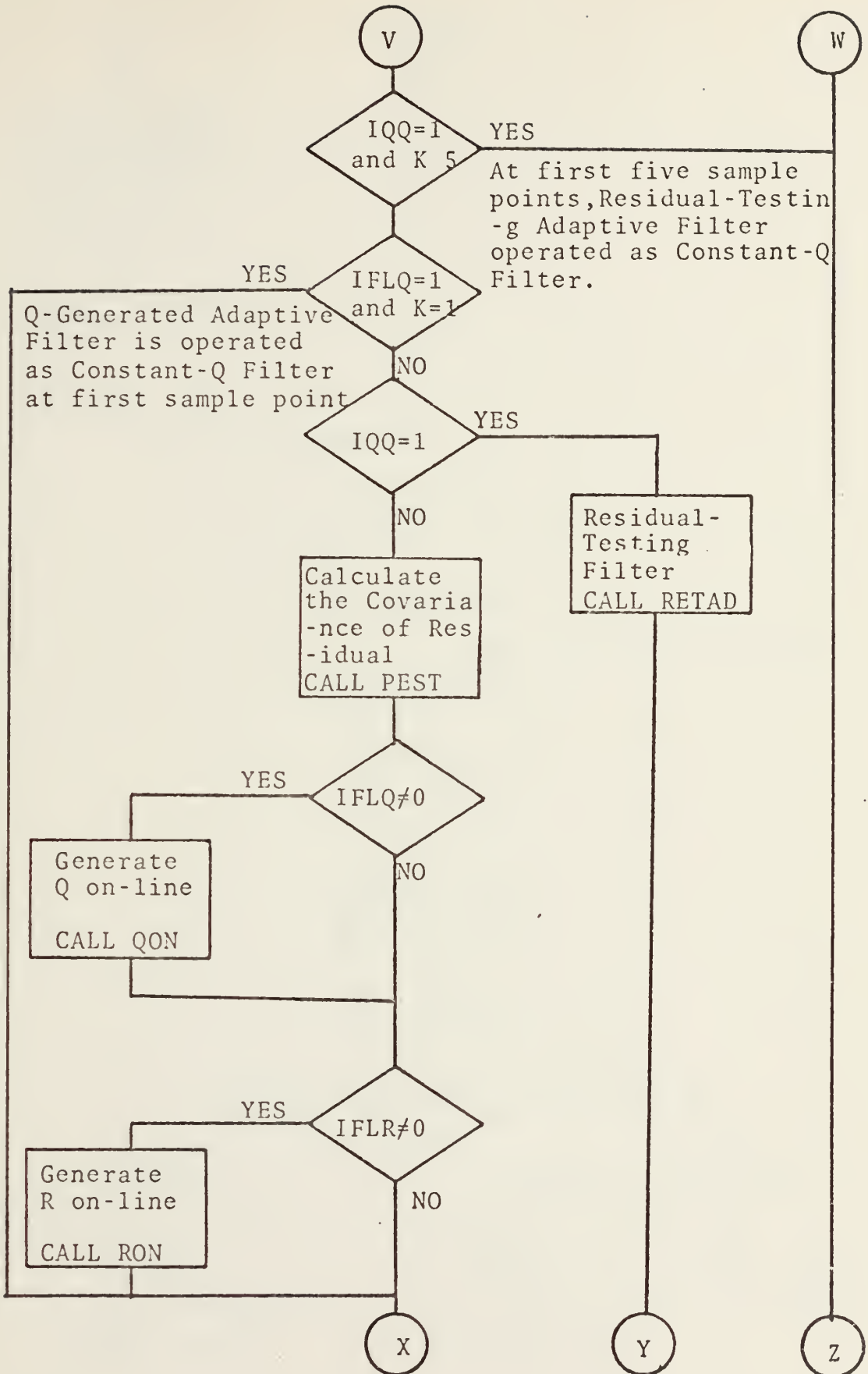


2. Flowchart of Monte Carlo Loop

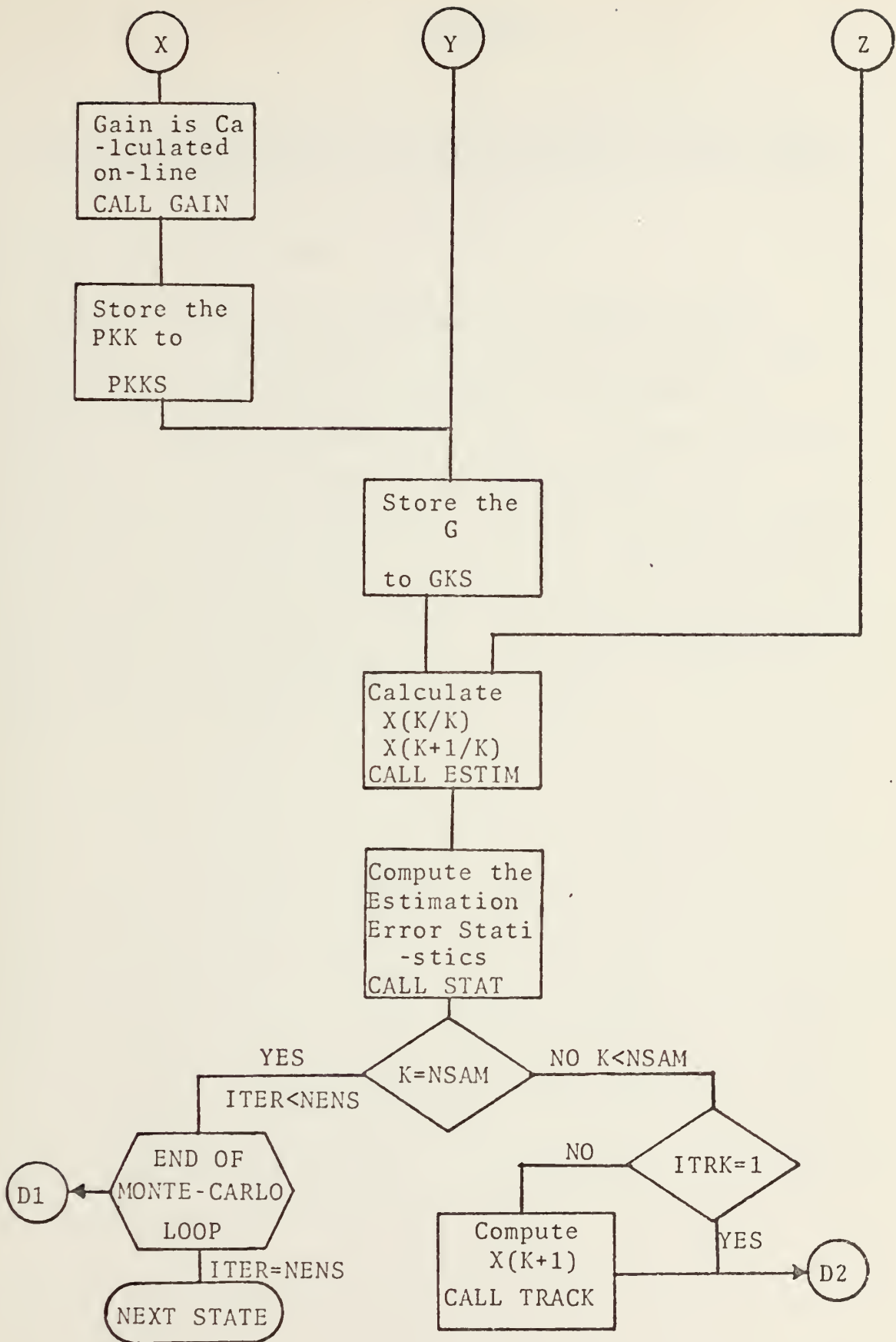














## APPENDIX B

### COMPUTER PROGRAM FOR Q-GENERATED ADAPTIVE FILTER (QON)

#### B.1 Program description

Subroutine QON is programmed to accomplish the generation of the Q-matrix . In addition to this , the program that calculates the predicted covariance of estimation error is included in "QON" . To have the gain calculation on-line under the adaptive scheme , the one-state predicted covariance of estimation error must be calculated before the gain calculation . Subroutine GAIN has the capability of calculating the one-state predicted covariance of estimation error , but this calculation is done after the gain calculation . To avoid complexity , the same program was added to subroutine QON .









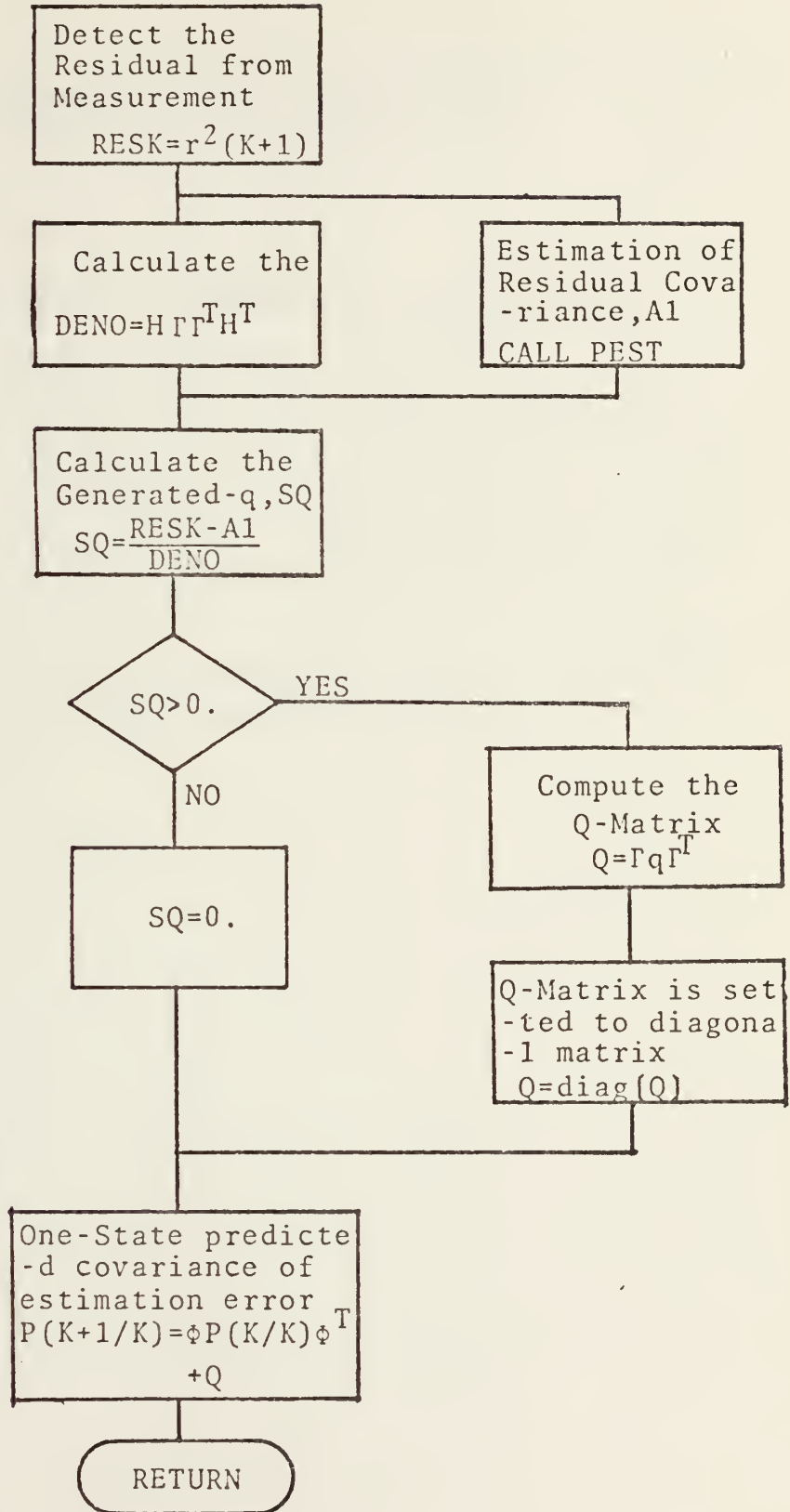
MC SP 0440  
 MC SP 0450  
 MC SP 0460  
 MC SP 0470  
 MC SP 0480  
 MC SP 0490  
 MC SP 0500  
 MC SP 0510  
 MC SP 0520  
 MC SP 0530  
 MC SP 0540  
 MC SP 0550  
 MC SP 0560  
 MC SP 0570  
 MC SP 0580  
 MC SP 0590  
 MC SP 0600  
 MC SP 0610  
 MC SP 0620  
 MC SP 0630  
 MC SP 0640  
 MC SP 0650

```

C      10 CALL TRANS(GAMMA,N,IN,TEMP2)
C      CALL PROD(GAMMA,TEMP1,N,IN,IN,TEMP1)
C      CALL PROD(TEMP1,TEMP2,N,IN,N,Q)
C      SET THE Q-MATRIX TO DIAGONAL
C      DC 15 I=1,N
C      DO 15 J=1,N
C      IF (I.NE.J) Q(I,J)=0.0
C      15 CCNTINUE
C      CCMPUTE THE PKKMI FOR GAIN CALCULATION
C      NOTE HERE   PKKMI(I,J) = P(K/K-1)  WHERE
C      P(K/K-1)= PHI*P(K-1/K-1)*PHIT + Q
C      CALL TRANS(PHI,N,N,TEMP2)
C      CALL PROD(PKK,TEMP2,N,N,N,TEMP)
C      CALL PROD(PHI,TEMP,N,N,N,TEMP1)
C      CALL ADD(TEMP1,Q,N,N,PKKMI)
C      RETURN
C      END
  
```



B.3 Flowchart for Q-Generated Adaptive Filter Program  
 SUBROUTINE QON





## APPENDIX C

### RESIDUAL-TESTING ADAPTIVE FILTER (RETAD)

#### C.1 Program description

Subroutine RETAD is programmed to accomplish the Residual-testing adaptive estimator technique . This program can be separated into three parts : compute the residual from the noisy measurement , apply the Switch-on adaptive scheme , and classify the residual and assign the gains . The difference between Filter A and Filter B is only in classifying the residuals and assigning the gains .

This subroutine "retad" is called by the flag IQQ=1 , when the other flags , IFLQ and IG are equal to 1 .









MCSP0440  
 MCSP0450  
 MCSP0460  
 MCSP0470  
 MCSP0480  
 MCSP0490  
 MCSP0500  
 MCSP0510  
 MCSP0520  
 MCSP0530  
 MCSP0540  
 MCSP0550  
 MCSP0560  
 MCSP0570  
 MCSP0580  
 MCSP0590  
 MCSP0600  
 MCSP0610  
 MCSP0620  
 MCSP0630  
 MCSP0640  
 MCSP0650  
 MCSP0660  
 MCSP0670  
 MCSP0680  
 MCSP0690  
 MCSP0700  
 MCSP0710  
 MCSP0720  
 MCSP0730  
 MCSP0740  
 MCSP0750  
 MCSP0760  
 MCSP0770  
 MCSP0780  
 MCSP0790  
 MCSP0800  
 MCSP0810  
 MCSP0820  
 MCSP0830  
 MCSP0840

```

C      STEADY STATE GAINS FOR Q=64
      G(1,1)=0.928215
      G(2,1)=0.700369
      G(3,1)=0.129066
      GO TO 100
9     IF(RESK.GT.3.25) GO TO 10
C
C      STEADY STATE GAINS FOR Q=144
      G(1,1)=0.961589
      G(2,1)=0.758942
      G(3,1)=0.146380
      GO TO 100
10    IF(RESK.GT.6.41) GO TO 20
C
C      STEADY STATE GAINS FOR Q=400
      G(1,1)=0.984379
      G(2,1)=0.800035
      G(3,1)=0.158887
      GO TO 100
20    IF(RESK.GT.12.75) GO TO 30
C
C      STEADY STATE GAINS FOR Q=625
      G(1,1)=0.989719
      G(2,1)=0.809785
      G(3,1)=0.161896
      GO TO 100
30    IF(RESK.GT.19.08) GO TO 40
C
C      STEADY STATE GAINS FOR Q=1600
      G(1,1)=0.995854
      G(2,1)=0.821043
      G(3,1)=0.165389
      GO TO 100
C
C      STEADY STATE GAINS FOR Q=10000
      G(1,1)=0.999325
      G(2,1)=0.827438
      G(3,1)=0.167382
C      100 RETURN
      END
  
```



C.2-2 RESIDUAL-TESTING ADAPTIVE FILTER PROGRAM FOR FILTER-2

```

C      SUBROUTINE RETAD
C      REAL*8 GAMMA,COVW,R,PHI,H,TEMP,TEMP1,TEMP2,PKKMI,G,PKK,Q,EI
C      CCNMCN EI(4,4),Q(4,4),G(4,4),PKK(4,4),GAMMA(4,4),COVW(4,4),
C      TEMP(4,4),TEMP1(4,4),TEMP2(4,4),H(4,4),PKKMI(4,4),R(4,4),PHI(4,4),
C      VAR(4,4,60),GKS(4,4,60),PKKS(4,4,60),XM(4,60),ERP(4,50),
C      GAMMAS(4,4),PHIS(4,4),XS(4,60),HS(4,4),GK(4,4),SIGW(4),X(4),
C      SIGXZ(4),XZMEAN(4),XHKK(4),XHKKMI(4),VIMP(4),Z(4),V(4),SIGV(4),
C      XHATZ(4),
C      N,NSAM,IQ,M,ITER,ITRK,IN,ISTAT,K,ITRO,IXZ,IV,IW,IEST,ND
C      DETECT THE RESIDUAL
C      RESK=ABS(Z(1)-XHKKMI(1))
C      SWITCH ON ADAPTIVE SCHEME IS DOING HERE
C      SWITCH LEVEL FOR THE SWITCH-ON ADAPTIVE SCHEME SETTED AS 7.0
C      IF(RESK.GT.7.00) GO TO 31
C      IF(LL.EC.0) GO TO 35
C      ZERO-Q STEADY STATE GAIN
C      G(1,1)=0.112731
C      G(2,1)=0.0050795
C      G(3,1)=2.46745E-10
C      GO TO 100
C      35 LL=1
C      GO TO 32
C      31 LL=0
C      IN FOLLOWING PART, RESIDUAL IS TESTED.
C      32 IF(RESK.GT.1.00) GO TO 8
C      ZERO-Q STEADY-STATE GAINS
C      G(1,1)=0.112731
C      G(2,1)=0.0050795
C      G(3,1)=2.46745E-10
C      GC TO 100
C      8 IF (RESK.GT.1.67) GO TO 9

```

- MCSP0010
- MCSP0020
- MCSP0030
- MCSP0040
- MCSP0050
- MCSP0060
- MCSP0070
- MCSP0080
- MCSP0090
- MCSP0100
- MCSP0110
- MCSP0120
- MCSP0130
- MCSP0140
- MCSP0150
- MCSP0160
- MCSP0170
- MCSP0180
- MCSP0190
- MCSP0200
- MCSP0210
- MCSP0220
- MCSP0230
- MCSP0240
- MCSP0250
- MCSP0260
- MCSP0270
- MCSP0280
- MCSP0290
- MCSP0300
- MCSP0310
- MCSP0320
- MCSP0330
- MCSP0340
- MCSP0350
- MCSP0360
- MCSP0370
- MCSP0380
- MCSP0390
- MCSP0400
- MCSP0410
- MCSP0420
- MCSP0430



```

C      STEADY STATE GAINS FOR Q=64
C      G(1,1)=0.928215
C      G(2,1)=0.700369
C      G(3,1)=0.129066
C      GO TO 100
C      9 IF (RESK.GT.3.25) GO TO 10
C
C      STEADY STATE GAINS FOR Q=625
C      G(1,1)=0.989719
C      G(2,1)=0.809785
C      G(3,1)=0.161896
C      GO TO 100
C      10 IF(RESK.GT.0.415) GO TO 20
C
C      STEADY STATE GAINS FOR Q=1600
C      G(1,1)=0.995854
C      G(2,1)=0.821043
C      G(3,1)=0.165389
C      GO TO 100
C      20 IF(RESK.GT.12.750) GO TO 30
C
C      STEADY STATE GAINS FOR Q=2500
C      G(1,1)=0.997326
C      G(2,1)=0.823754
C      G(3,1)=0.166233
C      GO TO 100
C      30 IF (RESK.GT.19.0800) GO TO 40
C
C      STEADY STATE GAINS FOR Q=10000
C      G(1,1)=0.999325
C      G(2,1)=0.827438
C      G(3,1)=0.167382
C      GO TO 100
C      40 STEADY STATE GAINS FOR Q=100000
C      G(1,1)=0.999932
C      G(2,1)=0.828560
C      G(3,1)=0.167732
C      100 RETURN
C      END

```

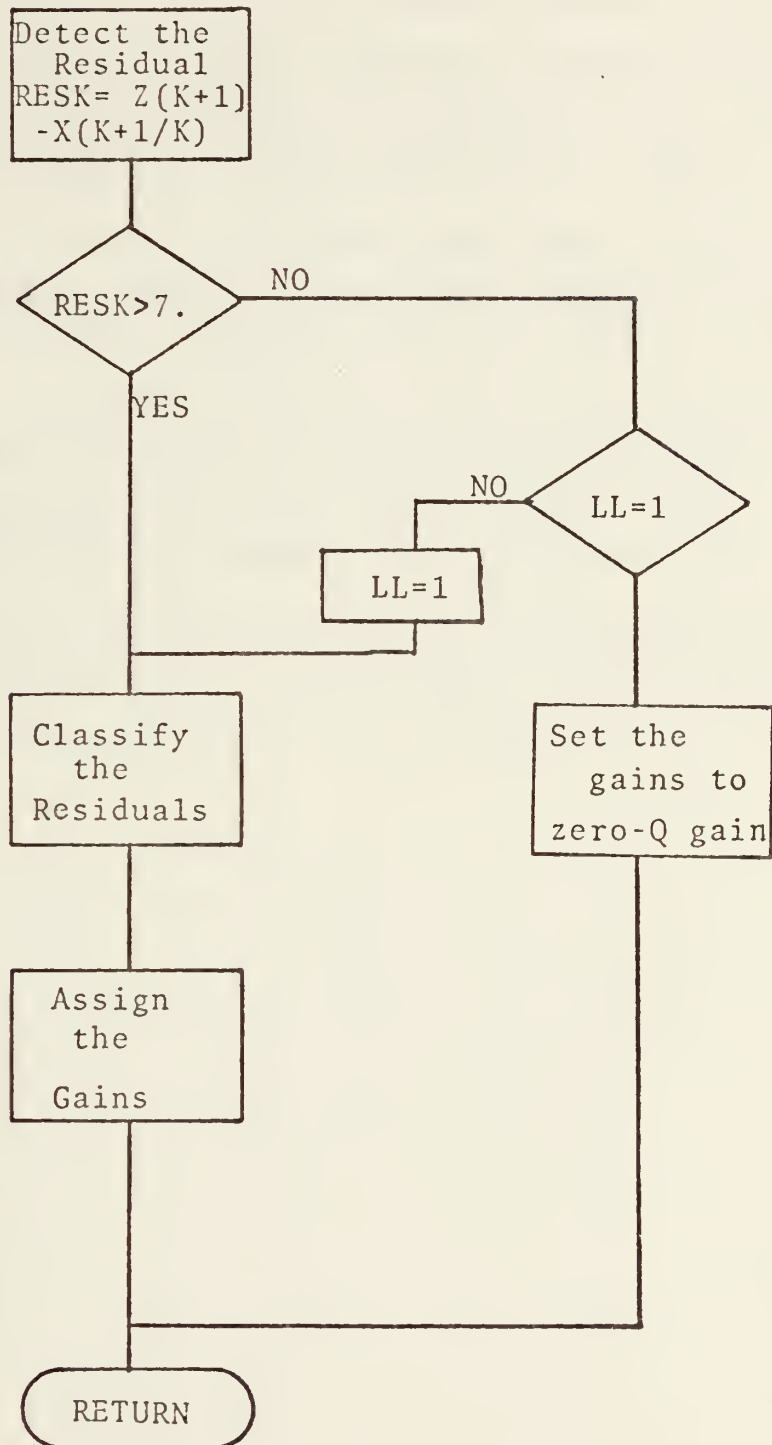
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MCSP0450
MCSP0460
MCSP0470
MCSP0480
MCSP0490
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MCSP0800
MCSP0810
MCSP0820
MCSP0830
MCSP0840

```



C.3 Flowchart for Residual-Testing Adaptive Filter Program ,SUBROUTINE RETAD







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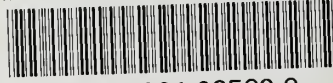
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