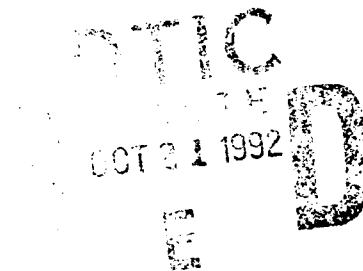




NAVAL POSTGRADUATE SCHOOL

Monterey, California



THESIS

NEURAL NETWORK BASED PROPULSION SYSTEM FAULT
DIAGNOSTICS FOR THE NPS AUV II

by

Juan A. Navarrete III

June, 1992

Thesis Advisor:

A.J. Healey

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**Neural Network Based Propulsion System Fault
Diagnostics for the NPS AUV II**

by

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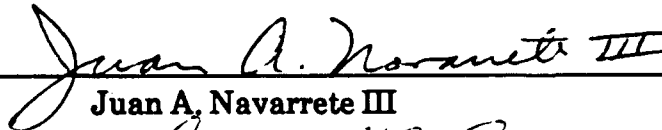
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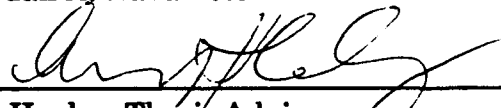
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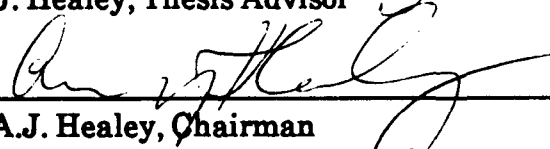


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ABSTRACT

The use of artificial neural networks to provide a method of detecting and isolating impending failures in an autonomous underwater vehicle propulsion system has been studied. Two types of fault diagnostic systems, each capable of detecting different types of faults, were designed. The first system addresses the fault identification process by looking at the raw data available from system sensors. The second design processes sensor data with a Kalman filter before it is input to a neural network. The Kalman filter was designed to identify system parameters that characterize its dynamic response. These parameters serve as input to the network. This system is capable of fault detection, isolation, and severity level determination.

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I. INTRODUCTION

Interest in the development of platforms capable of performing predetermined missions without the requirement of an onboard crew or a datalink has grow immensely in the last few years. The United States Navy in particular has a great interest in the development autonomous underwater vehicles (AUV's). Missions for such a vehicle include area search and survey, sensory package placement and sensory data gathering. Applications of such a vehicle are not limited to the military. An autonomous underwater vehicle would serve the ocean research and exploration community in many ways (Bellingham,1992).

The Naval Postgraduate School (NPS) has been involved in the research and development of this class of vehicle since 1987. Currently a second generation underwater vehicle denoted NPS AUV II serves as a controls testbed research vehicle for studies in intelligent control, mission planning, and data visualization (Healey and Good,1992). A point of further study had been the design of an onboard online automatic fault diagnostic system. This thesis addresses the development of one part of such a system for assessing the health of the vehicle's propulsion system. Artificial neural networks and Kalman parameter estimation filters form the basis of this

system, which is designed to recognize impending faults and signal the mission replanner to take corrective action.

Chapter II provides some background information concerning earlier work in the study of automatic fault diagnostic systems and also some insight into the reasoning behind choosing the artificial neural network approach.

Chapter III focuses on the development of the NPS AUV II propulsion model necessary for the generation of simulated sensor data, corresponding to simulated fault conditions, to be used in network training and evaluation.

Chapter IV presents the development of the Kalman parameter estimation filter and the results of tests associated with the propulsion model.

The design considerations for two fault diagnostic systems are contained in Chapter V. The first design uses system sensor data as the network's input. The second design takes the sensor data and processes it through a Kalman parameter estimation filter prior to network processing. It is concluded that for signals that are primarily static or slowly varying the first approach may be appropriate where for signals that are dynamic in nature, the second approach is to be preferred.

II. BACKGROUND

In this chapter we will introduce the subject of fault diagnostics based on assessment of system sensory outputs. We will first review some of the recent previous work in the subject of system fault diagnostics and will later give some background on the field of Artificial Neural Networks as it relates to this thesis.

A. FAULT DIAGNOSTICS

In the context of this work, a fault is viewed as deviation of a signal from a set of values that correspond to normal operations of a plant or process. We are not concerned with the monitoring of rotating machinery, bearings, and other mechanical equipment that often are monitored in terms of spectral analysis to detect wear. Here, systems that are under closed loop control, or more specifically, a maneuvering underwater vehicle underway, are the subject of study. Faults such as a bias shift in a sensor, fouling of the vehicle's speed sensor, increases in the friction loading on a propulsion shaft, motor overheating, propeller damage, control fin damage, sonar sensors loss of lock on target, and calibration factor shifts in gyros are examples of fault conditions that could lead to problems in mission reliability. Small signal deviations are not troublesome and can be tolerated. Other deviations may be indicative of some change

in the vehicle's operating condition. These changes may be slight and may not necessarily require a system shutdown to occur. It is these later conditions that are interesting because they admit a reconfiguration of the system control and continuation of the mission in some degraded way without total shutdown. In this way AUV reliability can be improved.

Work in the area of system fault detection has been undertaken by several investigators in the past including Himmelblau, (1978) and Pau, (1981). These works are primarily concerned with static signals and proposed the use of artificial intelligence with redundancy to detect failures in terms of signals that deviate from 'norms'. In this sense, signals that deviate from a preset band of values about a nominal 'normal level' will cause an alarm condition to be established. Levels beyond these preset limits can be used to indicate levels of severity of such alarms.

In principle, the detection of faults is first made by seeking changes in process measurements where signals are checked for excursions outside preset limits, or for trends, Trends are recognized as slow drifts of the measurement toward a limit. Limit exceedance could be gradual having different levels of severity from mere warnings to alarms to total plant shutdowns. Where the plants signals are primarily steady, limit and trending analysis have been sufficient to detect faults, and, through an appropriate set of rules, to set

respective alarm levels. It is in the area of dynamic signals that difficulty arises. These signals, by the nature of the system dynamics, vary with time over a considerable range. As an instance, consider the transient startup of an electromechanical machine. Signals such as voltage and current, speed and torque will normally vary with time outside static limits. Trends cannot be assessed. It follows that some form of dynamic signal analysis must be used to determine if the operation is normal or not.

Model based dynamic process response has been viewed as providing information that could be used to gain advanced warning of impending failures which could be recovered by reconfiguring the process controller. Such systems have been proposed and have been the subject of surveys by Willsky (1976), Isermann (1984), and Gertler (1986). These surveys indicated the state of the art to include diagnostic testing for aerospace, industrial plant as well as nuclear plant applications. Additionally, automotive sensor diagnostics have been described by de Benito (1990), where the issues of sensor failures and their isolation for active suspension systems was the objective. "Faults" such as sensor sticking, sensor disconnection, measurement bias, and increased sensor noise were stated as possibilities. Faults such as these are modeled as a change to the system parameters. It follows that a system dynamic model in the linear state space form has parameter matrix coefficients that depend on a particular

failure hypothesis. For each failure hypothesis, a model, M_i is constructed with an appropriate set of coefficients. A Kalman state filter for each model then provides an innovation (error between measurement and model prediction of that measurement subject to the particular model used), statistics of which are properties of the model. Using a statistical measure based on the innovations for each filter, failure hypothesis with maximum likelihood is selected at any particular time. Maximum likelihood methods are well established and have the advantage that a finite set of state filters are used (de Benito, 1990).

An alternative method using model based parameter identification with an expert system rule based decision process has been outlined in Isermann and Freyermuth, (1991). This concept was applied to the detection of DC armature motor winding failures and centrifugal pump performance losses including cavitational factors. Dietz (1989) and Aylward (1991), on the other hand, have studied the application of artificial neural networks directly to the sensor outputs; the latter, for the purpose of fault detection and classification during particular maneuvers of an F-15 airplane. The advantages of an artificial neural network based system were stated to be "...lower development cost, ...the ability to accommodate noisy input signals and real time processing." Lower cost arose because the experts needed to write rule based descriptions were not needed.

B. NEURAL NETWORKS

Artificial neural networks are a mathematical model aimed at representing the organizational structure present in a biological nervous system. Most would agree that when it comes to recognizing patterns and quickly attaining solutions to complex problems, biological systems perform much better than man made systems. The harnessing of the computational power of biological systems is one of the driving motivations behind the study of artificial neural networks.

Following Hebb's 1946 theory of learning, adaptive systems, adaptive control, adaptive signal processing and, more recently, artificial neural networks, have emerged. Neural networks have provided a method of establishing a link to connect an input with a desired output when a formula or set of rules does not exist. When a rule based technique is possible it is often easier and faster both in the development and implementation to utilize artificial neural networks. A neural network is not programmed or based on a set of rules, it is "taught". Simply by presenting a network with illustrative training examples it can be taught, using an adaptive algorithm for the adjustment of the synaptic weights, to discriminate patterns, complete a pattern, or perform some other task. Many papers have been written on neural networks and particularly their use for pattern recognition, but few have been related to the problems of fault diagnostics.

In particular, this thesis views system fault diagnostics as a pattern recognition problem either in terms of steady

state relations between sensor output signal values, or in terms of values of system dynamics parameters that have been identified by some preprocessing algorithm. (Least squares fits or use of Kalman filters are often suggested for this purpose). These preprocessed filtered data are then the input to a backpropagation network that is trained to recognize combinations of values that correspond to specified fault conditions. Not only can faults be detected, but isolation and level of severity may also be assessed.

The following chapters present the development and results of a neural network based fault diagnostic system for the propulsion system of the NPS AUV II.

III. PROPULSION SYSTEM

A. INTRODUCTION

The focus of this chapter is to develop an analytical model of the propulsion system of the NPS AUV II. Having a realistic model of the propulsion system allows for an investigation of the effects of key failures which can be simulated by the model. The fault diagnostic system may then be tested on data generated by the model as a preliminary to installation in a real vehicle.

B. OUTLINE OF THE PROPULSION SYSTEM

The propulsion system of the NPS AUV II consists of two 4 inch propellers each driven by a separate 24 volt electric motor as shown in Figure 3.1. The motors drive the two independent counter rotating propeller shafts. Additional propulsion system hardware consists of a shaft speed sensor on each propeller shaft (rpm), a motor controller which regulates the voltage supplied to each motor, a paddle wheel sensor to measure vehicle speed (ft/sec), and a speed controller. The controller accepts inputs from the paddle wheel speed sensor, the rudder and plane commands, and the commanded vehicle speed from the mission planner, to send the commanded rpm signal to the motor controllers.

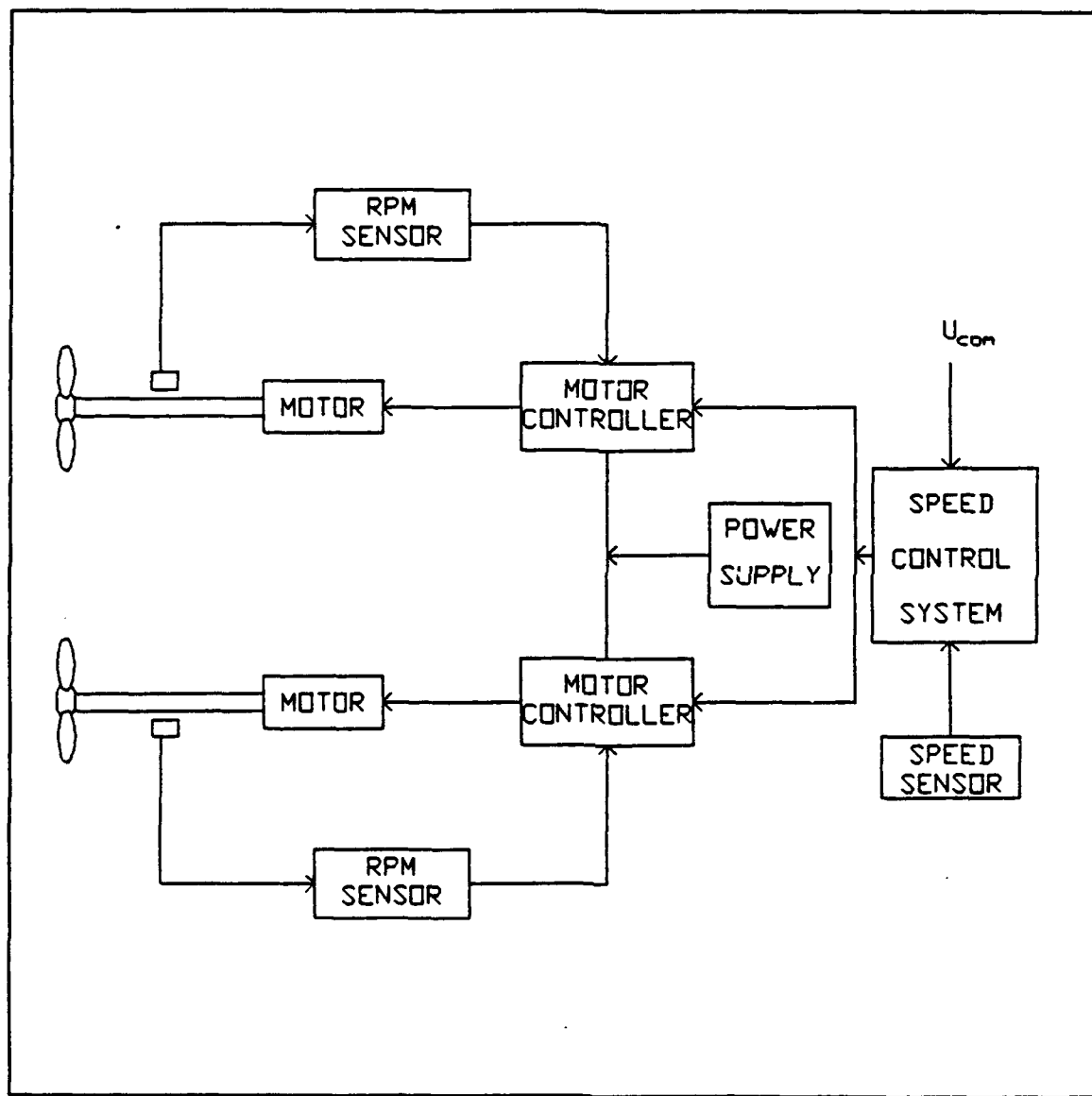


Figure 3.1 AUV propulsion system diagram

The speed of the propellers is controlled by the motor controllers operating on the error between the measured shaft rpm from the shaft speed sensor and the commanded shaft rpm received from the speed controller regulating the voltage supplied to the propulsion motors between 0 and 24 volts.

The propulsion system is governed by the Surge Equation of Motion. Using standard notation for vehicle maneuvering (Lewis, 1988) and simplifying the surge equation with the following assumptions, provides a basic starting point.

1. The vehicle is in straight line motion ψ, r and $v = 0$.

2. The vehicle is in level flight θ, ϕ, p, q and $w = 0$

The resulting simplified equation is as follows:

$$(m - X_u) \dot{u} = X_{res} u |u| + X_{prop} n |n| + u |u| (X_{\delta_s \delta_s} \delta_s^2 + X_{\delta_{rb} \delta_{rb}} \delta_{rb}^2 + X_{\delta_{rs} \delta_{rs}} \delta_{rs}^2)$$

The NPS AUV II is presently operated with the deflection of the bow rudder equal in magnitude but opposite in direction to the stern rudder and likewise for the dive planes. Therefore:

$$\delta_{rb} = - \delta_{rs}$$

and

$$\delta_b = - \delta_s$$

The rudder control surfaces are identical in size and shape to the dive plane control surfaces therefore:

$$X_{\delta_{rb}\delta_{rb}} = X_{\delta_{rs}\delta_{rs}} = X_{\delta_b\delta_b} = X_{\delta_s\delta_s}$$

Dividing through by the inertia term and using the above rudder and plane relations yields:

$$\dot{u} = \frac{X_{res}}{(m-X_u)} u|u| + \frac{X_{prop}}{(m-X_u)} n|n| + \frac{2 X_{\delta_s\delta_s}}{(m-X_u)} u|u|(\delta_s^2 + \delta_r^2)$$

A simplified nonlinear equation of motion used for the propulsion system follows:

$$\dot{u} = \alpha u|u| + \beta n|n| + \gamma u|u|\delta^2$$

This form of the equation is linear in parameters α , β and γ while the state of the system and the inputs are quadratic.

Where:

u is the state of the system (surge (ft/sec))

n is an input to the system (rpm)

$\delta^2 = (\delta_s^2 + \delta_r^2)$ is an input to the system (radians of plane or rudder deflection)

α is the longitudinal body drag coefficient

β is the longitudinal propulsion thrust coefficient

γ is the longitudinal rudder and plane drag coefficient

The values of α , β and γ were first determined analytically by Warner, (1991), based on geometric scaling of the SDV to the AUV II. The values were further refined using Kalman filters designed for parameter estimation by Bahrke, (1992). It was shown that no single unique set of α , β and γ

can characterize normal operation of an AUV although under normal maneuvering conditions they should be within a band. It is the deviation from that band that is suggested as a fault diagnostic feature.

C. PROPULSION MOTOR MODEL

In addition to a model for the surge motion of the vehicle, a model of the propulsion system and its controller was developed. This simulator had the purpose of generating a set of data that could be used to simulate system failures of various kinds prior to design of the detection system.

1. General

The equations of motion were derived by considering a simplified electromechanical system shown in Figure 3.2. The load torques applied to the motor included the inertias of the motor and propeller, the viscous friction of the motor/propeller shaft and the hydrodynamic loading of the propeller. In this model electrical properties are assumed to be linear.

2. Derivation of the Model Equations

The two basic laws required in this development to convert electrical power to mechanical and the reverse are the motor and generator laws (Coulomb, Faraday, and Lenz):

motor law	$T_M = K_T i$
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generator law	$e = K_b \omega_M$
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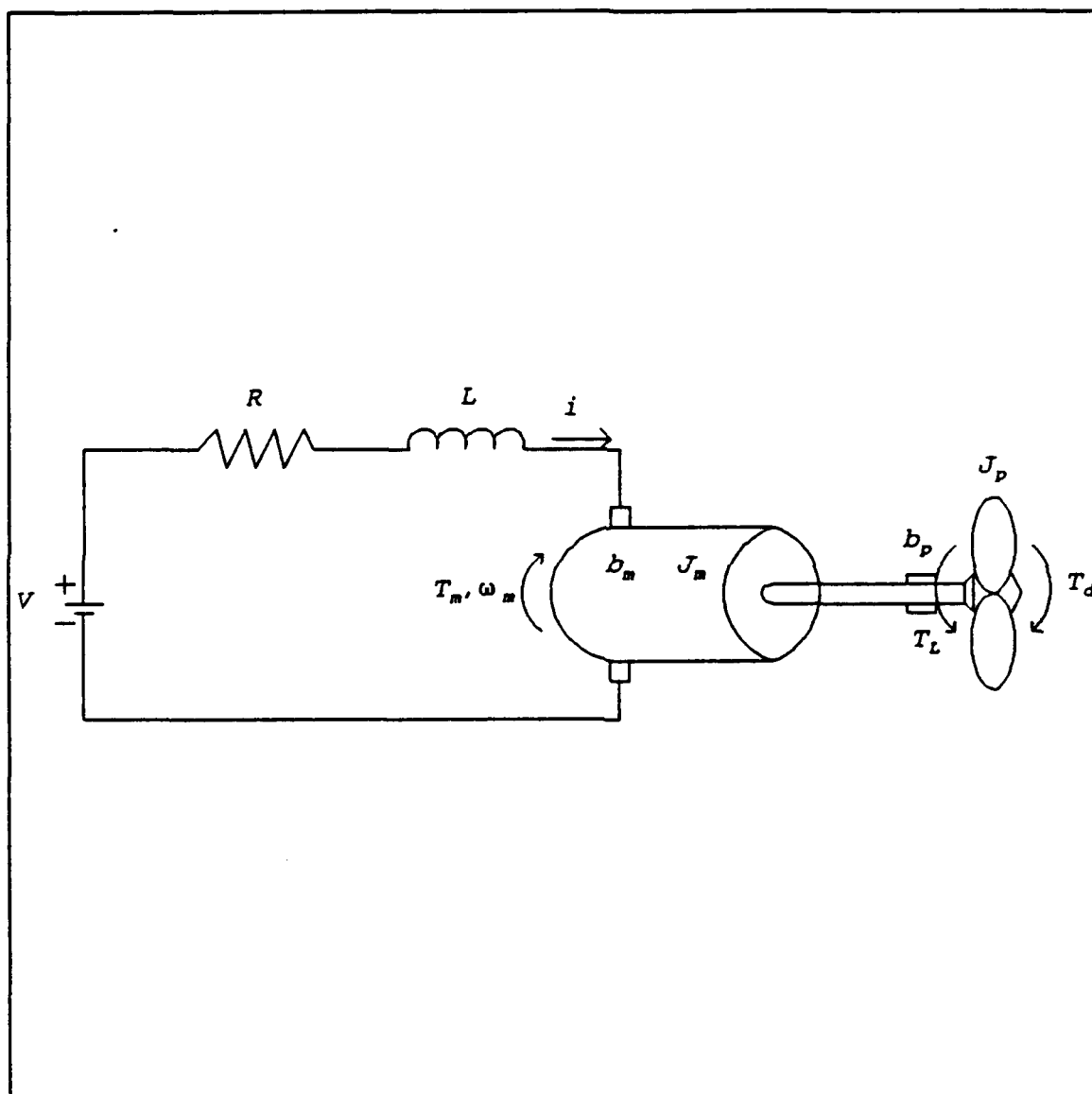


Figure 3.2 Simplified electromechanical system

Referring to Figure 3.2, the state equation for the electrical circuit is determined by using Kirchoff's voltage law around the loop. The equation is first order in the motor angular velocity ω .

$$L \frac{di}{dt} + Ri = V - K_b \omega_M$$

Since the electrical time constant is much smaller than the mechanical time constant a simplifying assumption is made and armature current is as follows:

$$i = \frac{(V - K_b \omega_M)}{R}$$

The motor and propeller equations are as follows:

$$\text{Motor} \quad J_M \dot{\omega}_M + b_M \omega_M + T_L = T_M$$

$$\text{Propeller} \quad T_L = J_P \dot{\omega}_P + b_P \omega_P + T_d$$

Now combining the motor and propeller equations, the result is:

$$T_M = (J_M + J_P) \dot{\omega}_M + (b_M + b_P) \omega_M + T_d$$

Combining this equation with the motor law and the equation for armature current:

$$K_T (V - K_b \omega) / R = J \dot{\omega} + b \omega + T_d$$

Here J is the polar moment of inertia of the entire rotating assembly and b is the total linear damping coefficient due to the motor bearings and the propeller shaft seal friction.

Solving for $\dot{\omega}$:

$$\dot{\omega} = 1/J \left[\frac{K_T}{R} (V - K_b \omega) - T_d - b\omega \right]$$

The propulsion drive motors are Pittman model 14202 D.C. servomotors. The manufacturer's data used in developing the propulsion model is shown in Appendix A. The armature inertia load of the motor was taken directly from this data. The polar mass moment of inertia of the propellers was calculated by dividing each blade into nine rectangular elements. The inertia from each was calculated and summed to get the total inertia of all four blades.

3. Propeller Hydrodynamic Model

The load torque due to the propeller (T_d) is a function of the water density, propeller rpm (n), vehicle surge velocity (u), propeller diameter (D) and the torque coefficient (K_q). The equation is as follows:

$$T_d = \rho |n| n D^5 K_q$$

The torque coefficient, under steady flow conditions is usually assumed to be a function of propeller rpm, propeller diameter, vehicle surge velocity and the wake fraction (w).

$$K_q = C_1 - C_2 \frac{u(1-w)}{nD}$$

C_1 and C_2 are constants which are usually obtained from

experimental data. Typical values for C_1 are 0.053 (Lewis, 1988) and 0.04 (Dand and Every, 1983). Values for C_2 range from 0.032 (Lewis, 1988) to 0.025 (Dand and Every, 1983). Average values were used in this case with a C_1 equal to 0.0465 and C_2 equal to 0.0285.

Normally the wake fraction is a function of the ratio of vehicle speed to wake velocity. In order to simplify the model the wake fraction was taken as a constant value of 0.1.

4. Putting the Model Together

The speed controller and the rpm controller used in the model are exactly as is used onboard the NPS AUV II. This "C" language code was translated to MATLAB and used together with the previously developed motor, propeller and vehicle dynamics. This provides a computer simulation of the longitudinal motion of the NPS AUV II through which data has been generated for use in the fault diagnostics systems .

IV. KALMAN FILTER FOR FAULT DIAGNOSING

A. INTRODUCTION

One method of detecting faults in a system is to detect changes of the system's parameters. In order to detect changes of a system's parameters we must first be able to identify them. Kalman filters have been successfully used in many applications (Gelb,1988) and in the identification of the NPS AUV II's parameters, Bahrke (1992).

B. PARAMETER IDENTIFICATION THROUGH KALMAN FILTERING

The discrete time Kalman filter equations from Gelb (1988) are stated below:

The Filter State Equations

$$\hat{x}(k+1|k) = \Phi \hat{x}(k|k) + \Gamma_1 u(k)$$

$$\hat{y}(k+1|k) = C \hat{x}(k+1|k)$$

$$\hat{x}(k+1|k+1) = \hat{x}(k+1|k) + G(k+1) [y(k+1) - \hat{y}(k+1|k)]$$

The Gain Equations

$$P(k+1|k) = \Phi P(k|k) \Phi^T + \Gamma_2 W \Gamma_2^T$$

$$G(k+1) = P(k+1|k) C^T [C P(k+1|k) C^T + V]^{-1}$$

$$P(k+1|k+1) = [I - G(k+1) C] P(k+1|k)$$

To implement these equations the following is required:

1. State space model (Φ , the dynamics matrix, Γ_1 input gain matrix)
2. Plant noise covariance (Γ_2)
3. Measurement noise covariance (V)
4. Initial state estimate ($\hat{x}(0)$)
5. Initial estimation error covariance ($P(0)$)
6. Weighing matrix (W)

1. State Filter

The form of these filter equations may be modified and have been arranged for state estimation first, followed by rearrangement for parameter estimation. The continuous time state space model is of the form:

$$\begin{aligned}\dot{x} &= Ax + B_1 u + B_2 w \\ y &= Cx + D_1 u + D_2 v\end{aligned}$$

where:

x is the state vector
 y is the measurement vector
 w is the system random noise
 v is the measurement random noise
 A is the system dynamics matrix
 $B_{1,2}$ is the system input matrix
 C is the system measurement matrix
 $D_{1,2}$ is the measurement input matrix

The continuous system is discretized to the following:

$$\begin{aligned}x(k+1) &= \Phi x(k) + \Gamma_1 u(k) + \Gamma_2 w(k) \\ y(k) &= Cx(k) + D_1 u(k) + D_2 v(k)\end{aligned}$$

where Γ_2 and V (the covariances of $w(k)$ and $v(k)$) are assumed white. Using this form of the state equation the Kalman filter is an optimal state estimator.

2. Parameter Filter

To use the filter for parameter identification, the form of the equations must be rearranged. It is assumed that from experimental data the inputs $u(k)$ are known and the states of the system $x(k)$ measured. We can rearrange the state space equation by first expanding the right hand side of the system equation, for example a two state system is as follows:

$$\begin{Bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{Bmatrix} = \begin{Bmatrix} a_{11}x_1 & a_{12}x_2 & b_1u \\ a_{21}x_1 & a_{22}x_2 & b_2u \end{Bmatrix} + \begin{bmatrix} w_1 \\ w_2 \end{bmatrix}$$

Each row of the expanded system is now in the form of a measurement equation for a Kalman Parameter Filter. By taking each row as an independent measurement equation, the row can be written with the parameter as the state as follows:

$$\dot{x}_1 = [x_1 \quad x_2 \quad u] \begin{Bmatrix} a_{11} \\ a_{12} \\ b_1 \end{Bmatrix} + w_1$$

The parameters of a_{11} , a_{12} and b_1 are treated as states of a normal Kalman State Filter where the inputs and the measured states are known and the filter is now an optimal parameter estimator. This is the basis of the measurement equation for the Kalman Parameter Filter where each row of the normal system is now a measurement equation for the filter.

The system equation for the parameters is created with the assumption that the parameters being identified are not time varying. This causes the parameter dynamics matrix to be a square matrix of zeros and the input matrix to the parameter dynamics to be the weighing matrix for the parameter noise Q estimated on each parameter as follows:

$$\dot{\theta} = A\theta + BQ$$

or

$$\dot{\theta} = BQ$$

θ is the vector of parameters being identified, Q is the parameter noise and B is the parameter noise input matrix which can be weighed to place more or less noise on any individual parameter. This is the system equation used for the Kalman Parameter filter.

C. RESULTS OF PARAMETER IDENTIFICATION

Tests of the Kalman filter identification system proved very successful. The system was evaluated by simulating a change of the vehicle's alpha and beta parameters by using the AUV propulsion model. The model was run with normal parameters for the first ten seconds of the run. A change to either parameter was then imposed. The commanded speed of the model was then changed at ten seconds, twenty seconds, thirty seconds and forty seconds into the run. Two speed changes were sufficient to estimate the new parameter value to within two percent of the new value. Figure 4.1 shows the Kalman filter

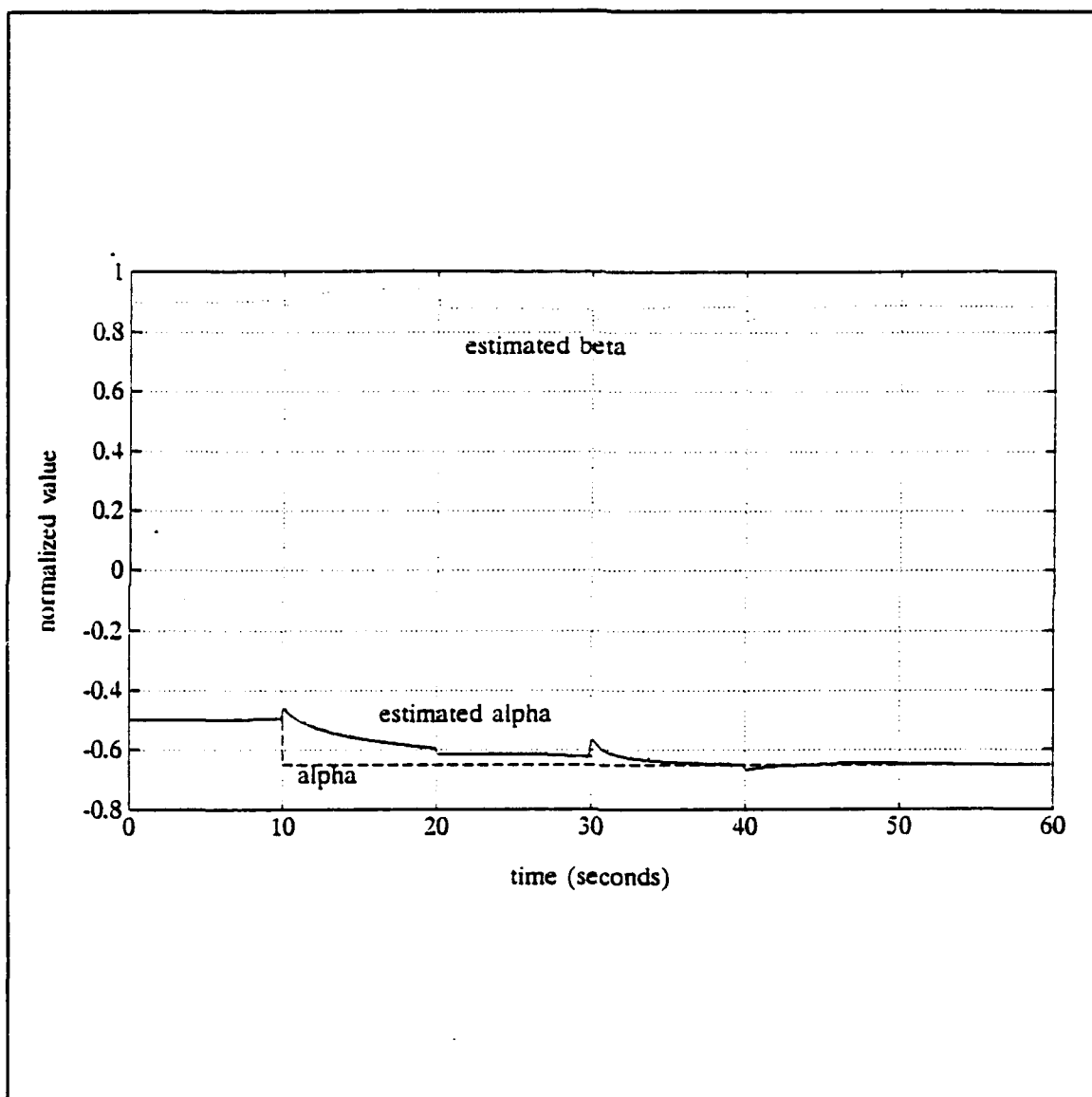


Figure 4.1 Kalman parameter filter response to 35% increase of the alpha parameter

results due to a 35 percent change in the alpha parameter. The alpha parameter was increased to -0.0333 . The Kalman filter identification provided a value of -0.0332, about a 0.3 percent error.

The beta parameter was also modified during a simulation. Figure 4.2 shows the results of this test. Beta was decreased by 35 percent to a value $2.1906\text{e-}07$. The Kalman filter identification provided a value of $2.1945\text{e-}07$, less than 0.2 percent error.

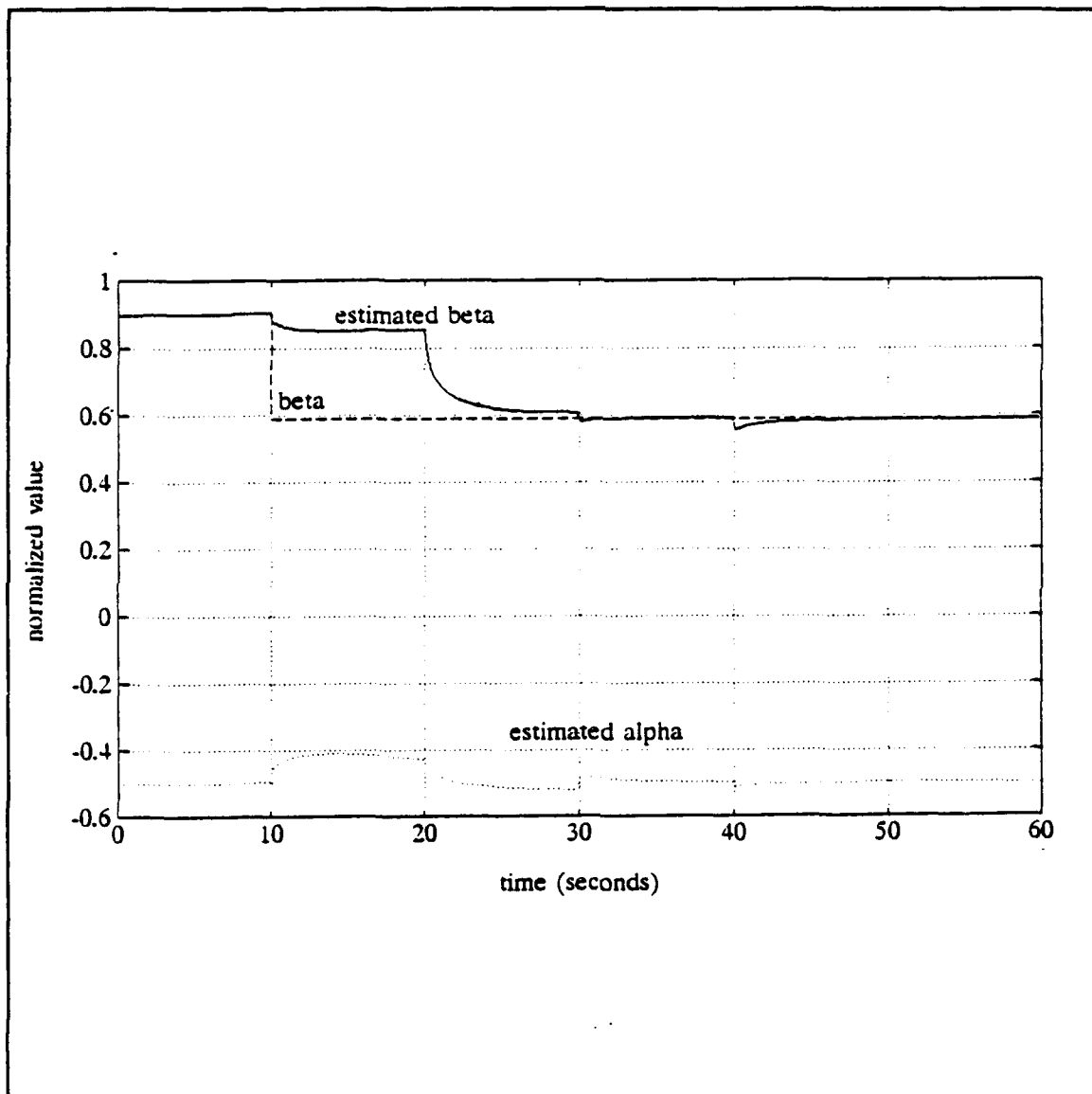


Figure 4.2 Kalman parameter filter response to 35% decrease of the beta parameter

V. NEURAL NETWORK DESIGN AND IMPLEMENTATION

A. INTRODUCTION

This thesis explores two methods of using neural networks to detect faults imposed on the AUV propulsion model previously discussed. Here we will address the design and training of each. The network used in each case is the feedforward single hidden layer type also referred to as a back-propagation network. Each network was designed and trained using NeuralWare Professional II software. The network was then encoded as a MATLAB routine and tested on data created by the auv propulsion simulator.

B. PARAMETER RANGES FOR NORMAL OPERATION

As in most diagnostic systems the problem of failure detection is concerned with the detection of changes in a system. In order to detect variations from the normal operating condition the no-fault operating conditions must be clearly defined. This thesis explores two options in implementing a fault diagnostic system. The first of which uses raw data (ie; motor voltages, current, rpm and speed of the vehicle) as monitored directly from the vehicle. The second option is the use of processed data (ie; Kalman filter parameter identification).

Normal operating parameters for the first alternative were developed by operating the AUV propulsion model over several

different speed ranges and speed changes. This resulted in a very large training set for the normal mode. The sensor output parameters available for monitoring include: propulsion motor voltage and current, propeller shaft rotation rate, vehicle speed sensor voltage.

In the second method the two parameters utilized are the vehicle drag coefficient (α) and the vehicle propulsive coefficient (β) as identified through the utilization of the Kalman filter parameter identification scheme on vehicle speed and propeller shaft speed data. The nominal values for these parameters were identified by Bahrke (1992) with the application of a Kalman Parameter identification system.

The range for normal operation was taken as up to twenty percent increase or decrease in α . Using a normalized α of 0.5 this yields a normal operating range of 0.4 to 0.6. The β parameter was normalized to a value of 0.9. The normal operating range being 0.65 to 1.0. The low end of the propulsive coefficient being approximately a 25 percent decrease. The fault map is shown in Figure 5.1 .

Several failure modes are indicated by this figure. The loss of one or more control surfaces would be indicated as a decreased drag condition. Increased drag would indicate some sort of entanglement, seaweed etc. Decreased propulsion would be due to propeller damage or a propeller loss.

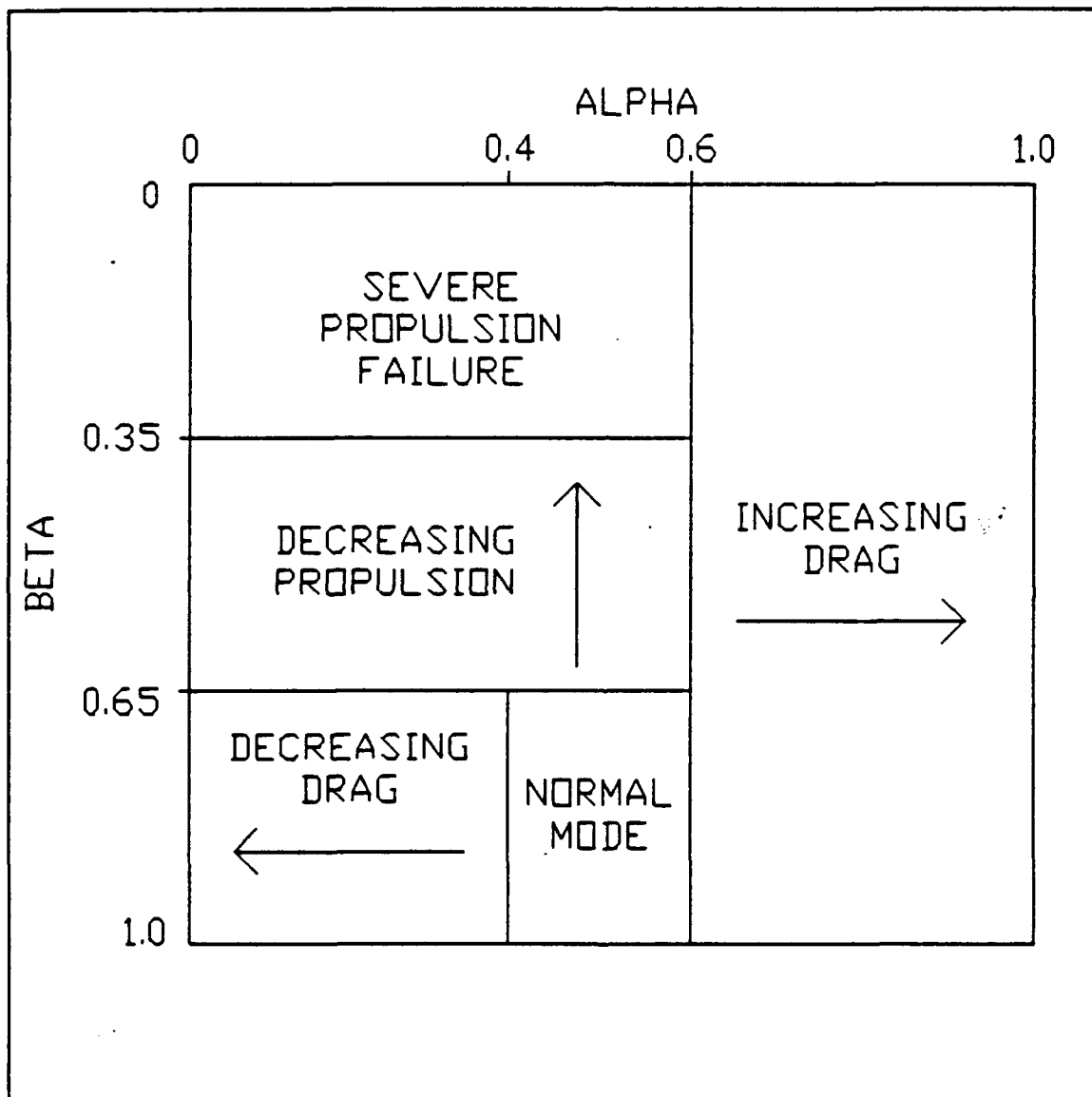


Figure 5.1 Fault mapping based on hydrodynamic parameters alpha and beta

C. UNPROCESSED DATA NETWORK

This network was designed to use data unmodified from the propulsion model. The four inputs to the network are: propulsion motor voltage and current, rpm sensor voltage and speed sensor voltage. The propulsion model was run several times to generate training data or training sets. Each set consisting of approximately 60 seconds of a simulated auv test run.

The NPS AUV II operates on a 10 hertz data rate. The propulsion model was designed to provide data at the same rate. Every tenth of a second of a simulated run data is stored into a file which is referred to as a training set. The auv program was also designed to pair an output vector with each time step of data. Numerous training sets were created simulating no fault operation. Each of these training sets was for the no fault condition but different transients were present for each. That is one set might start from rest and accelerate to 1.5 ft/sec, and another would decelerate or accelerate between different speeds. This was done to ensure the network would be presented with a training set which would encompass a large range of the normal operating mode. With each input vector a corresponding output vector is presented to the output side of the network in training as shown in Table 5.1.

**TABLE 5.1 AUV OPERATING MODES AND ASSOCIATED FAULT VECTORS
FOR RAW DATA NEURAL NETWORK**

OPERATING MODE	FAULT VECTOR
normal	$y1 = (1, 0, 0, 0)$
increased seal friction	$y2 = (0, 1, 0, 0)$
increased drag	$y3 = (0, 0, 1, 0)$
degraded propeller	$y4 = (0, 0, 0, 1)$

1. Network Design

The network designed for this case consisted of four input nodes to accept data from the four inputs created by the propulsion model. Four output nodes were used corresponding to the number of desired output fault vectors. The number of hidden layers was chosen as one for simplicity and because with only four input nodes and four output nodes a second hidden layer would not add to the network's discrimination capability. Figure 5.2 is a depiction of this network.

The hidden layer was first designed with eight hidden nodes. After training and recall it was discovered that six hidden nodes would suffice. Reducing the number of hidden nodes to six significantly diminished the time required for training the network. The network was also tested with less than six hidden nodes. With less than six nodes in the hidden

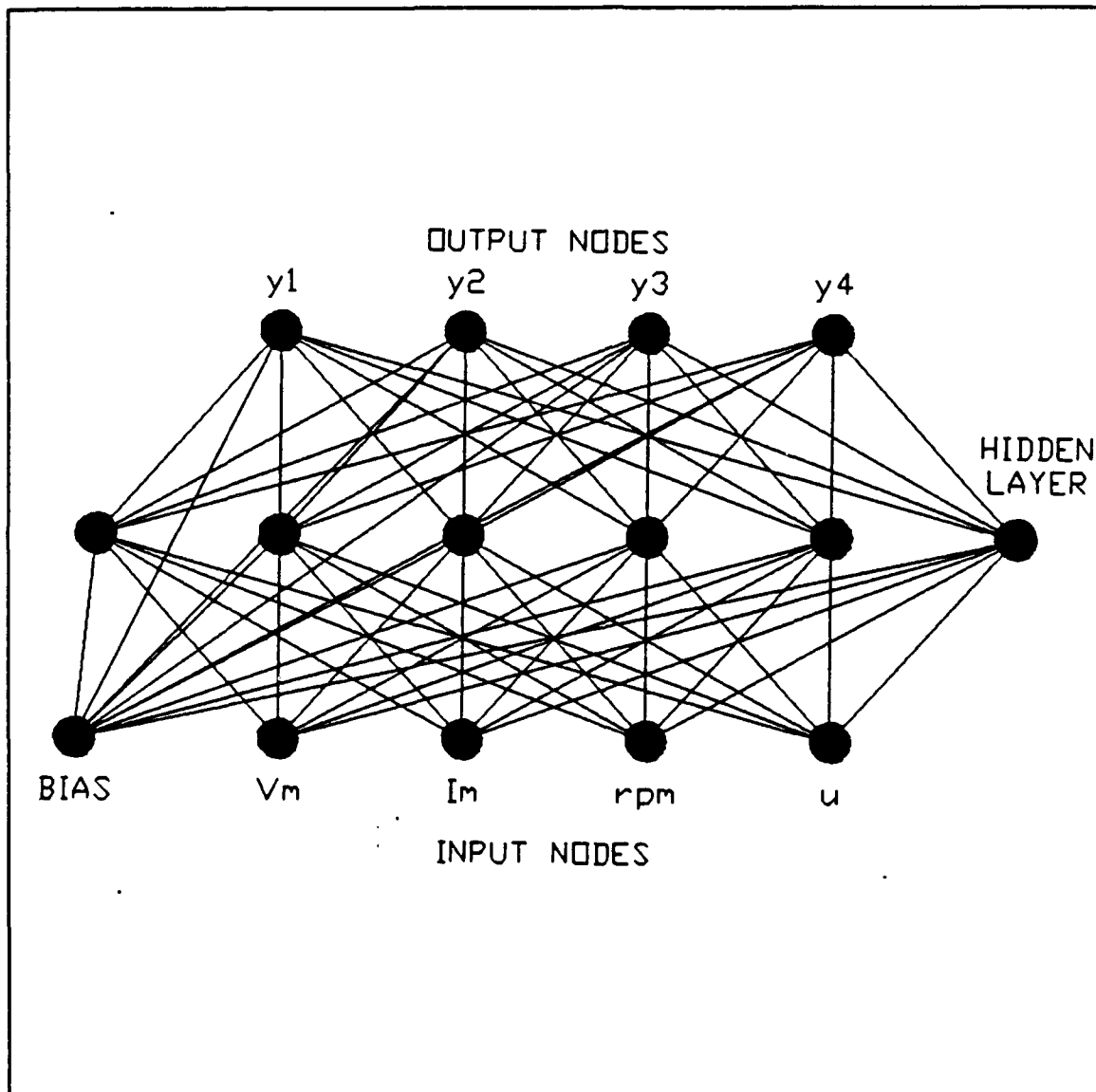


Figure 5.2 Unprocessed Data Network

layer the network was unable to distinguish the different fault conditions. Using the minimum required number of nodes in the network also reduces the number calculations required to process data.

2. Network Training

Each line of a training file is composed of an input vector and it's corresponding fault vector. These files were then combined into one file which contained the complete training set. The network was then trained using randomly selected entries from the single training file.

Training consists of applying an input vector to the input layer and the corresponding output fault vector to the output layer. The input vector is processed through the network and an output is computed. This output is compared with the output fault vector from the training set. The back-propagation learning rule is then used to redistribute the output error throughout the previous layers. This process continues until either the desired number of training presentations has been reached or the desired output error has been achieved. Normally training of the network continues until the rms output error is minimized. The network was trained using transient response data, following an acceleration to normal operating speed, produced via the AUV propulsion model. This data is shown in Figures 5.3 through 5.6. Each of these figures exhibits the transient data which was input to the network corresponding to each operating mode.

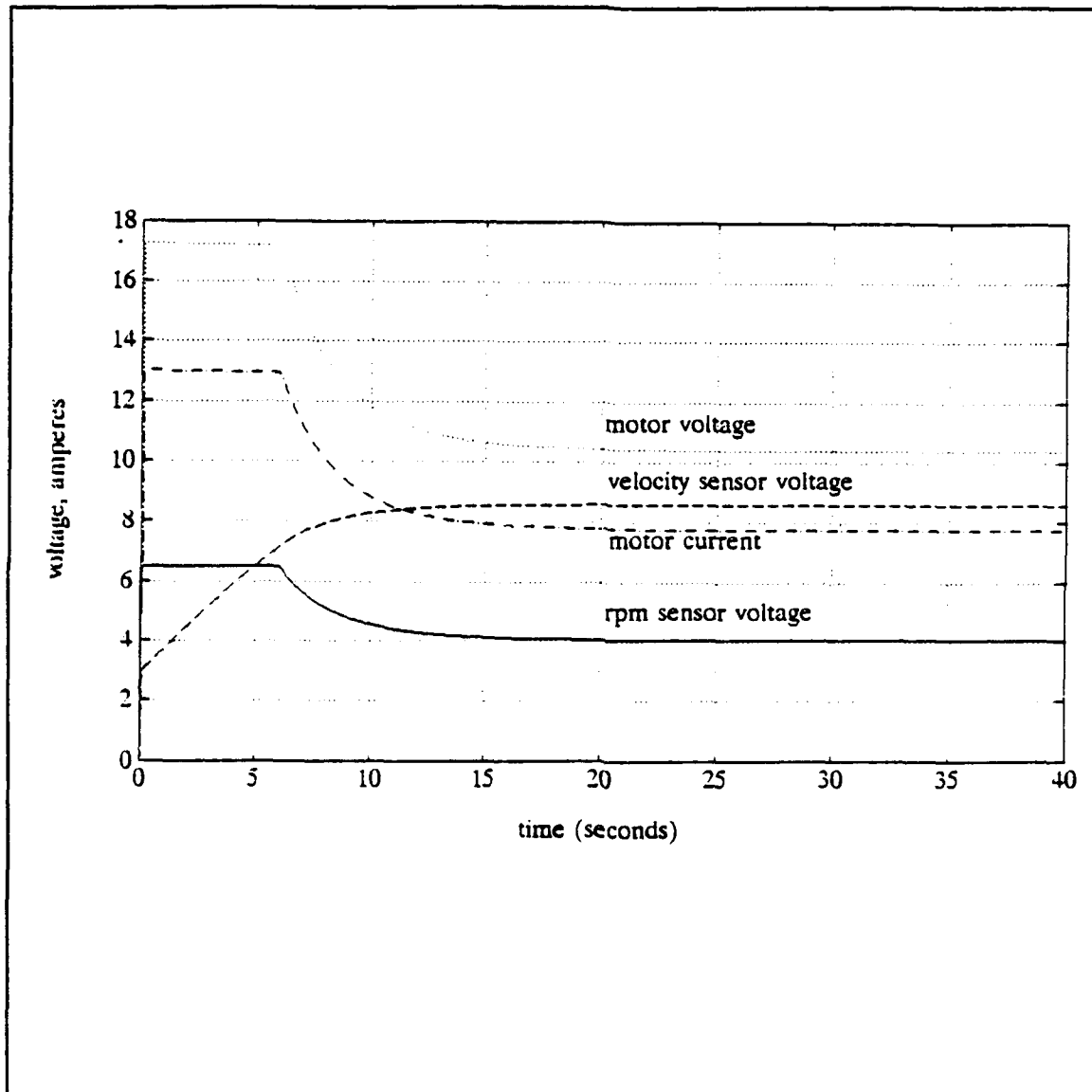


Figure 5.3 AUV propulsion model normal mode transient data

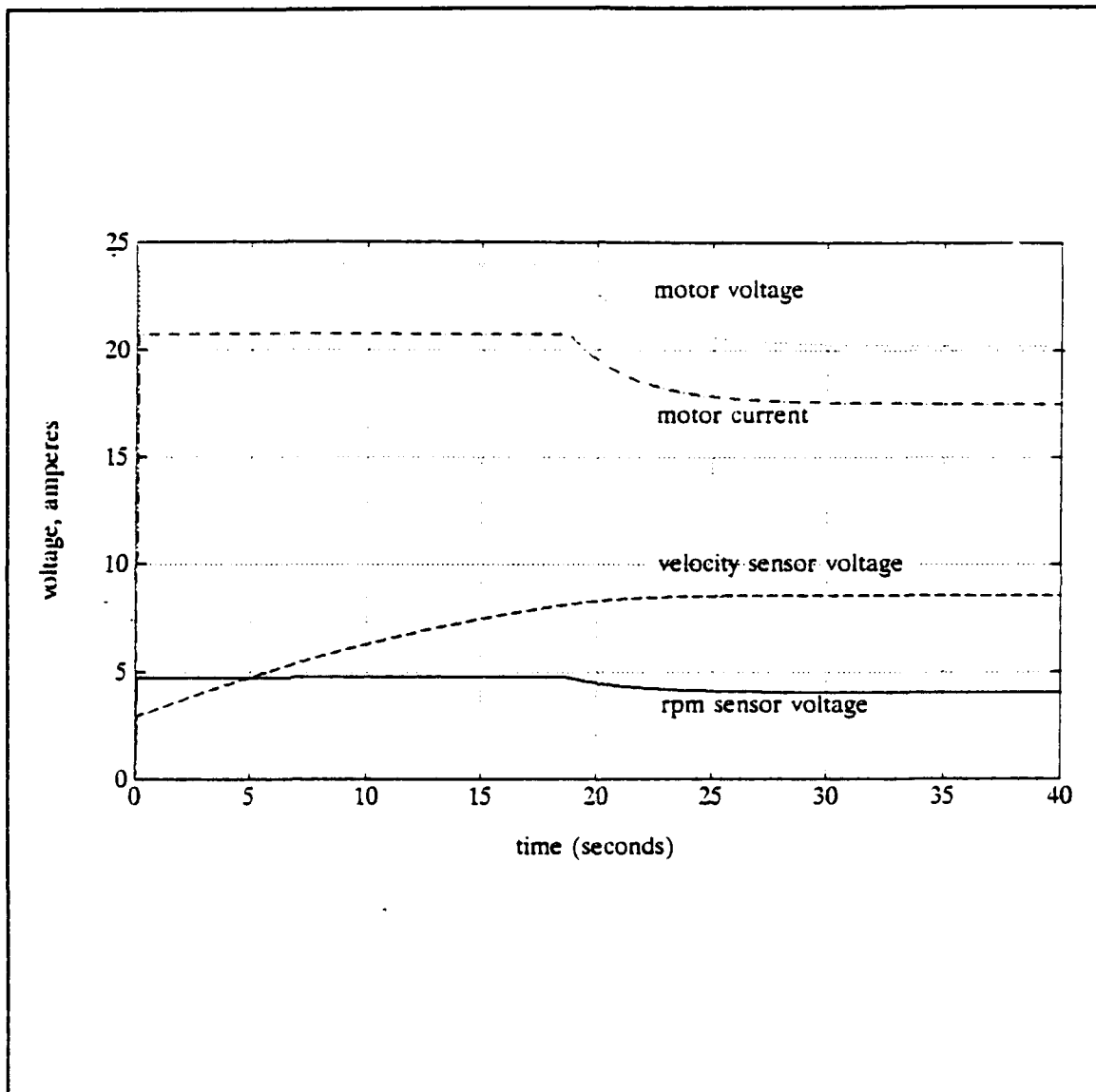


Figure 5.4 AUV propulsion model increased seal friction transient data

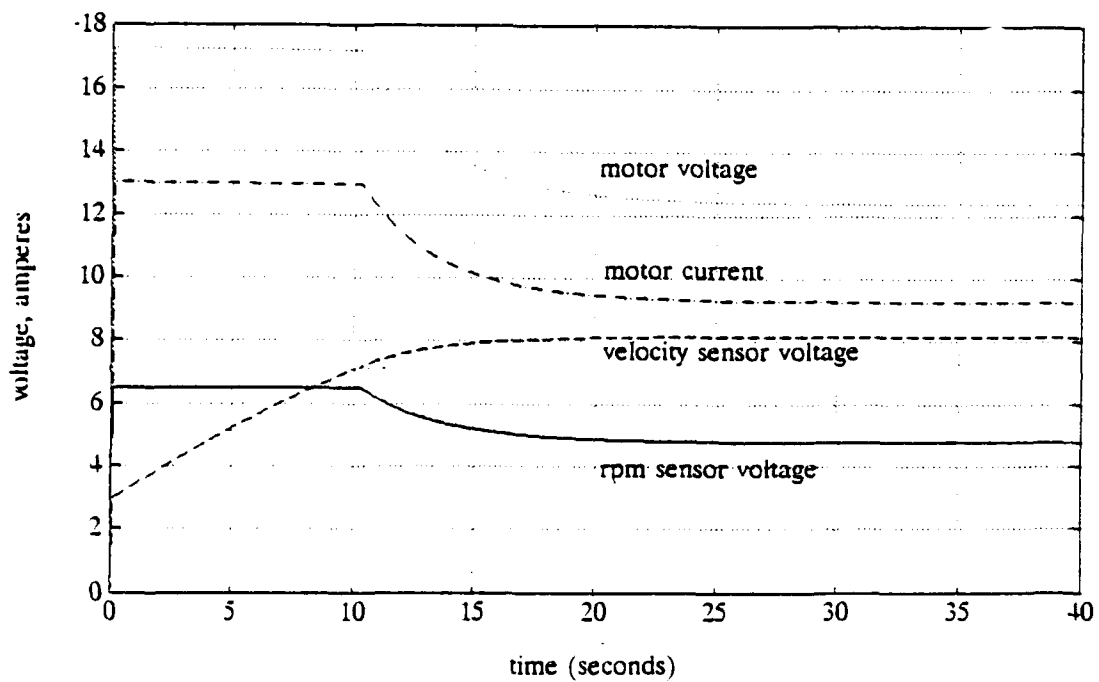


Figure 5.5 AUV propulsion model degraded propeller transient data

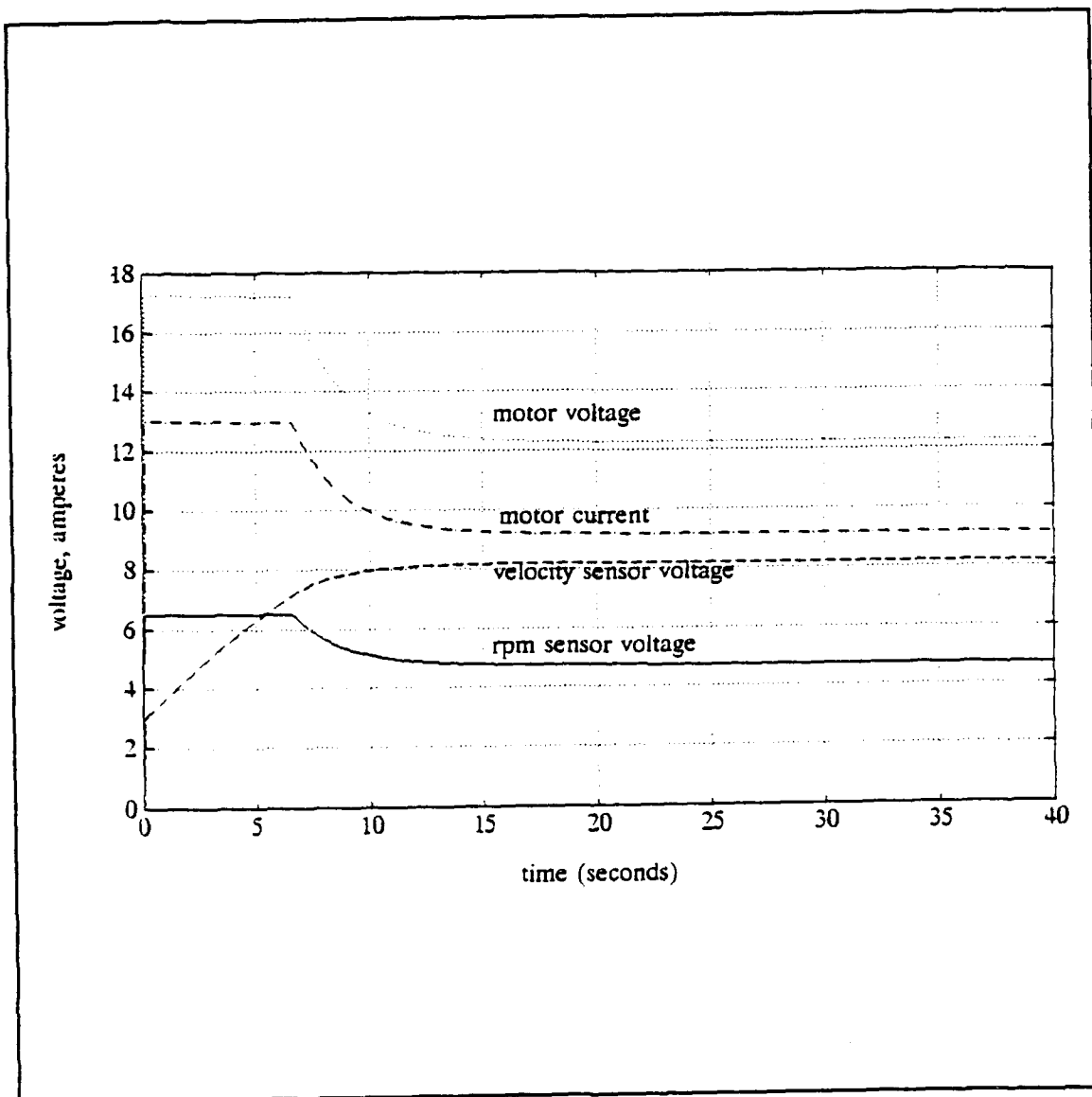


Figure 5.6 AUV propulsion model increased drag transient data

The compilation of the data contained in these figures formed the training set of this network.

The effects of training are illustrated by Figures 5.7 through 5.10. Each figure shows the recall of the training set and the effects of training through a set number of iterations. In each of these figures, the first 400 data points represent the recall of the network on the normal operating condition. The next 400 data points (400-800) are the recall of the increased seal friction fault. These two operating conditions are well distinguished even with only 24,000 data presentations to the network in training.

The last two fault conditions are not as easily distinguished. The increased drag condition occurs in data from 800-1200, and the propeller is degraded from 1200-1600. In all four figures operation in the increased drag mode is first recognized as a degraded propeller fault. Only after 100 data points is the true operating mode determined.

Another point illustrated by these four figures is that training to 90,000 or even only 60,000 iterations as compared to 150,000 yields a better overall response even though the rms output error is not minimized until 150,000 iterations.

In this first set of tests we were interested in fault detection and fault isolation. Level of fault severity, the next step in fault diagnosis, would be very difficult to treat

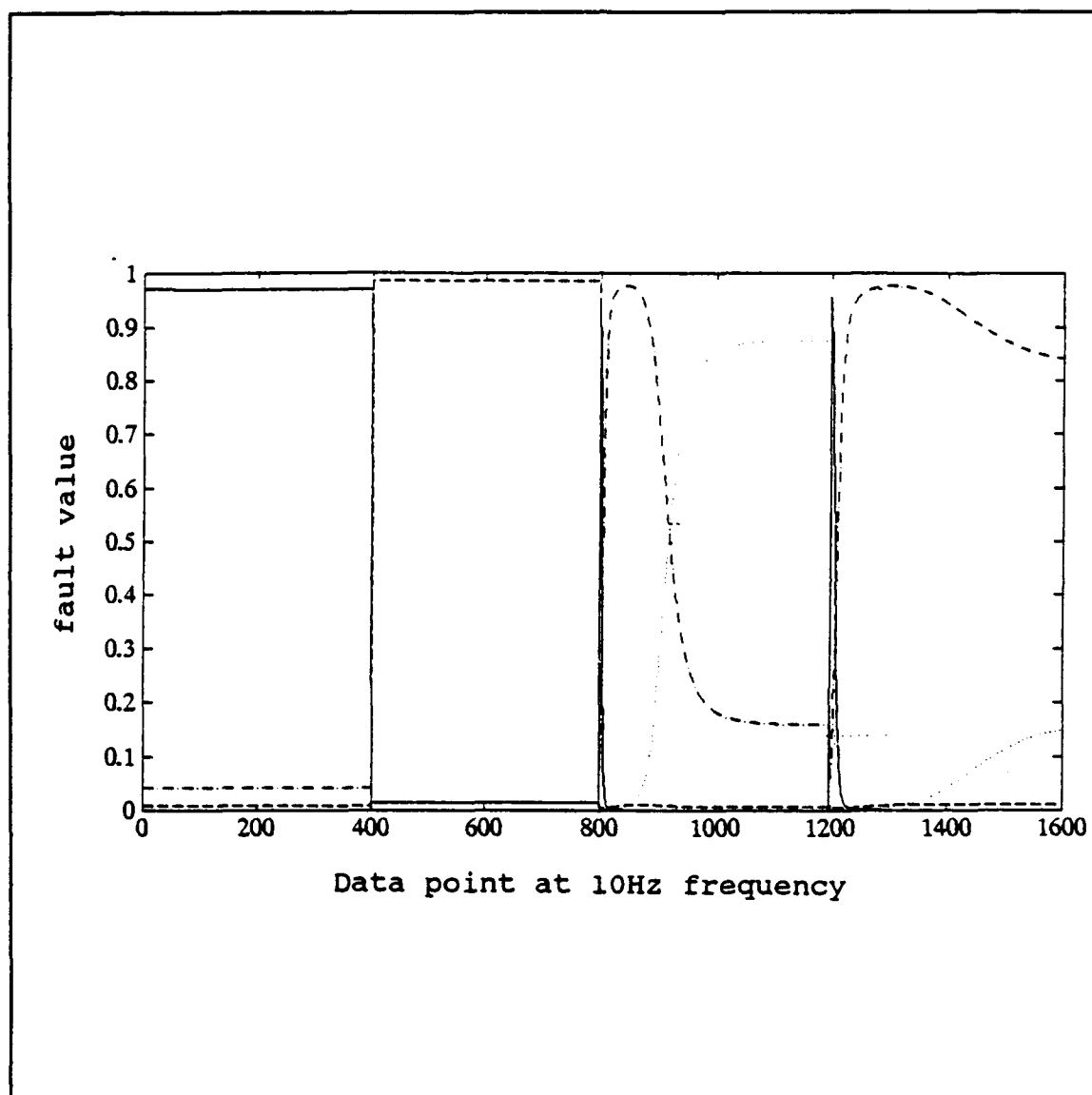


Figure 5.7 Network recall of training set after 24000 iterations

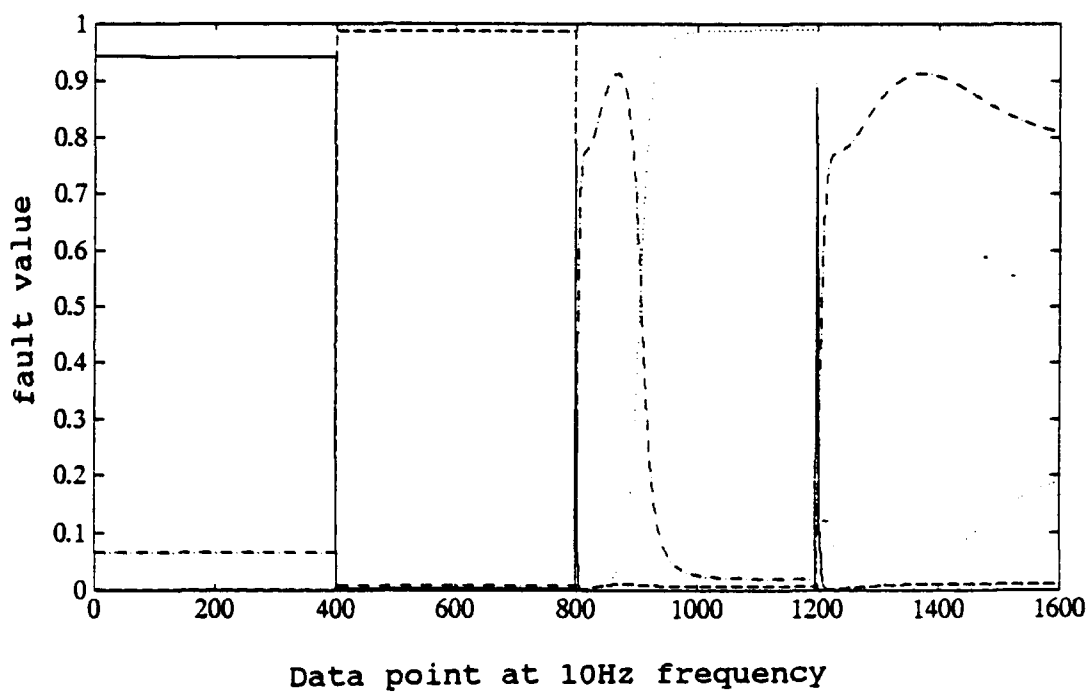


Figure 5.8 Network recall of training set after 60000 iterations

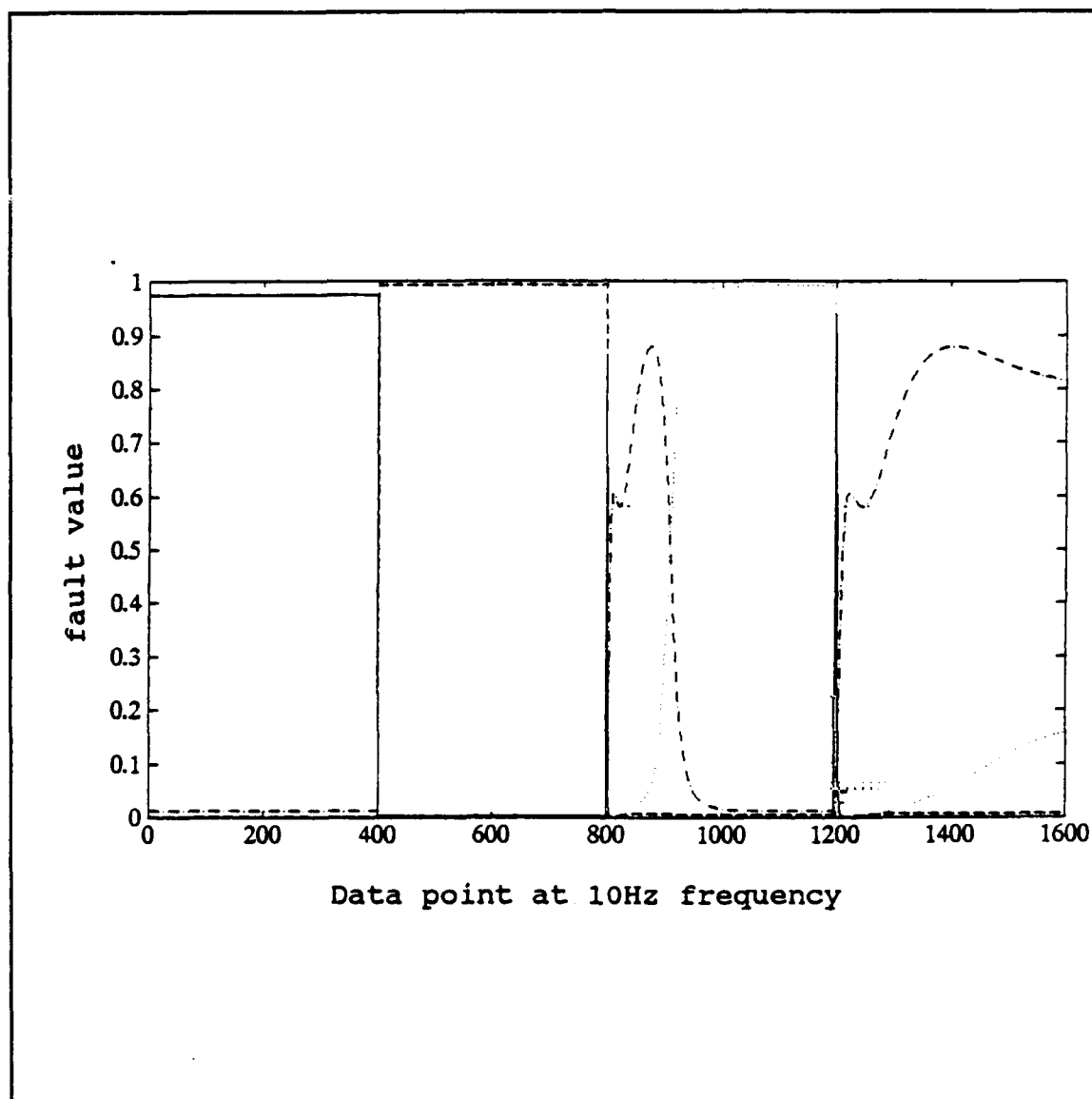


Figure 5.9 Network recall of training set after 90000 iterations

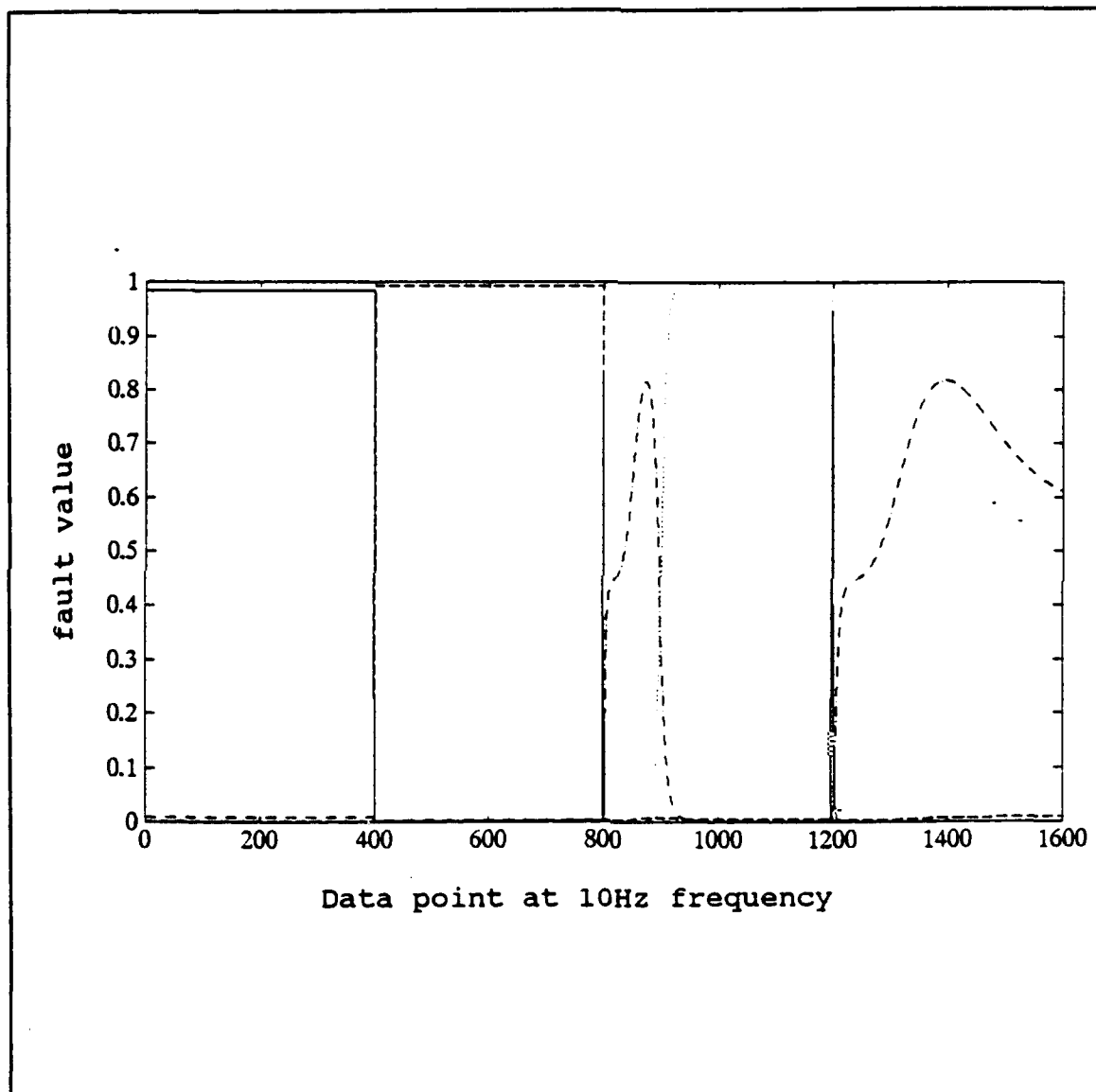


Figure 5.10 Network recall of training set after 150000 iterations

with a fault diagnosing system as described above. A training set would be required for each different fault at each level of severity. The training time would increase greatly and the ability of the network to distinguish between different fault types at low levels of severity would undoubtedly decrease with decreasing severity levels.

D. KALMAN FILTER PROCESSED FAULT DIAGNOSTIC SYSTEM

This system first uses a Kalman filter parameter identification step to simplify the network operations. Data from the auv propulsion model is processed by the Kalman filter to identify alpha (drag coefficient) and beta (propulsion coefficient). The inputs to the Kalman filter generated by the propulsion model are vehicle speed, acceleration, left shaft rpm, right shaft rpm, rudder deflection and plane deflection.

1. Network Design

The network was designed for fault detection, isolation and determination of level of severity based upon the mapping of alpha and beta. Figure 5.1 shown earlier gave the failure modes and the fault mapping selected based on normalized values of alpha and beta.

The network itself was composed of an input layer with two input nodes and an output layer with a node for each fault condition as shown in Figure 5.11. The hidden layer as first designed contained only four nodes. Attempts at training this

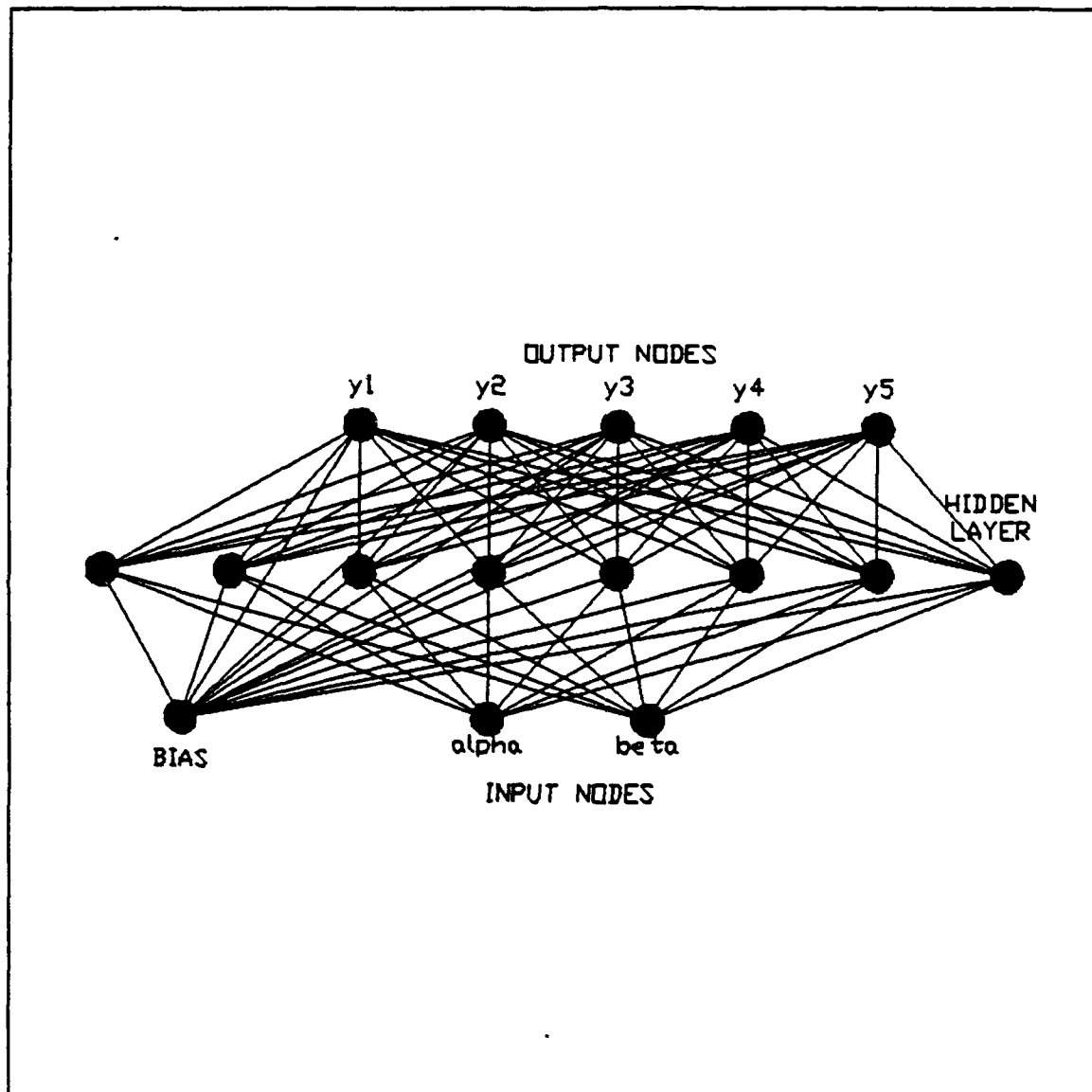


Figure 5.11 Kalman parameter filter processed data network

network were unsuccessful. Four nodes in the hidden layer were insufficient in allowing the network to provide reliable output of the level of fault severity. The network was capable of fault detection and identification however. The identification of the level of fault severity was achieved by the addition of four more nodes to the hidden layer.

2. Network Training

Training of this network was rudimentary in comparison to that of the raw data network. A single training file which contained the mapping of Figure 5.1 was all that was required. The operating modes and corresponding fault vectors are shown in Table 5.2.

**TABLE 5.2 AUV OPERATING MODES AND ASSOCIATED FAULT VECTORS
FOR KALMAN FILTER PROCESSED DATA NEURAL NETWORK**

OPERATING MODE	FAULT VECTOR
normal	y1
increased drag	y2
decreased drag	y3
decreased propulsion	y4
severe propulsion failure	y5

The network was trained on the mapping of Figure 5.1. Figure 5.12 displays the decision surface of the network capable of fault severity determination. This decision surface was generated by performing a network recall of the training file containing the fault severity mapping. The mapping height is then given as the weighted sum of the elements of the network output vector. The network was trained to a minimum rms output error prior to recall.

In order to test the fault diagnostic system (Kalman parameter filter and neural network) faults were imposed in the propulsion model and the resulting data was processed by the Kalman filter. Faults were simulated in the model by changing the values of the alpha and beta parameters during a simulated run. Each run started with the vehicle operating under normal conditions at a speed of 0.5 feet per second(fps). After ten seconds a step increase in speed, to 1.0 fps, was commanded. Ten seconds later the commanded speed was reduced to 0.5 fps. This cycle of commanded speed changes was then repeated. Figure 5.13 illustrates the normal transient response of the AUV propulsion model to this commanded speed profile. This series of speed changes provided the stimulus for the Kalman parameter estimation filter.

During a normal run the parameter values in the propulsion model were set at the normal operating values for the entire run. To simulate a fault as it might occur during actual operation, the alpha and beta parameters are set to

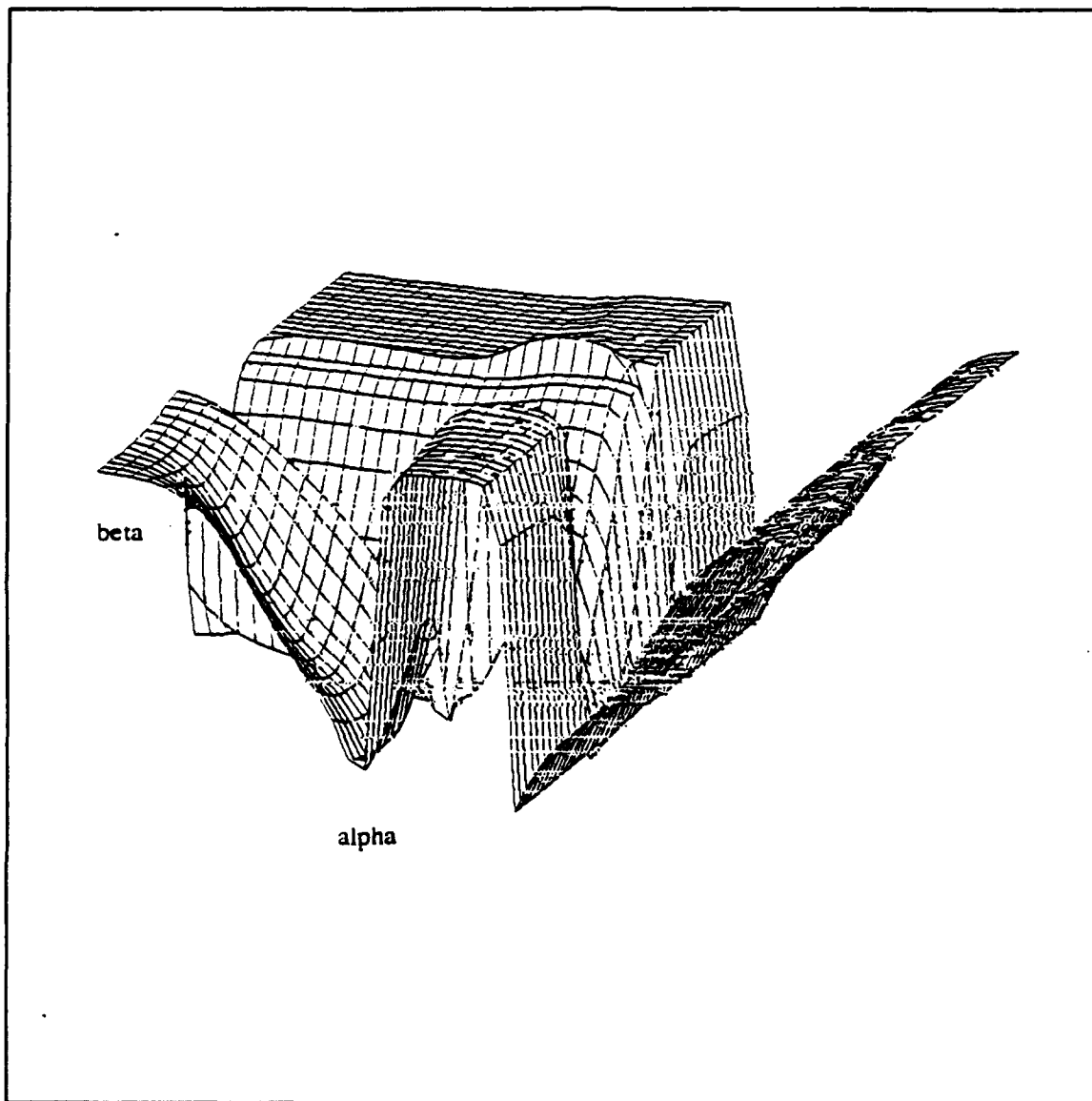


Figure 5.12 Fault Severity Decision Surface

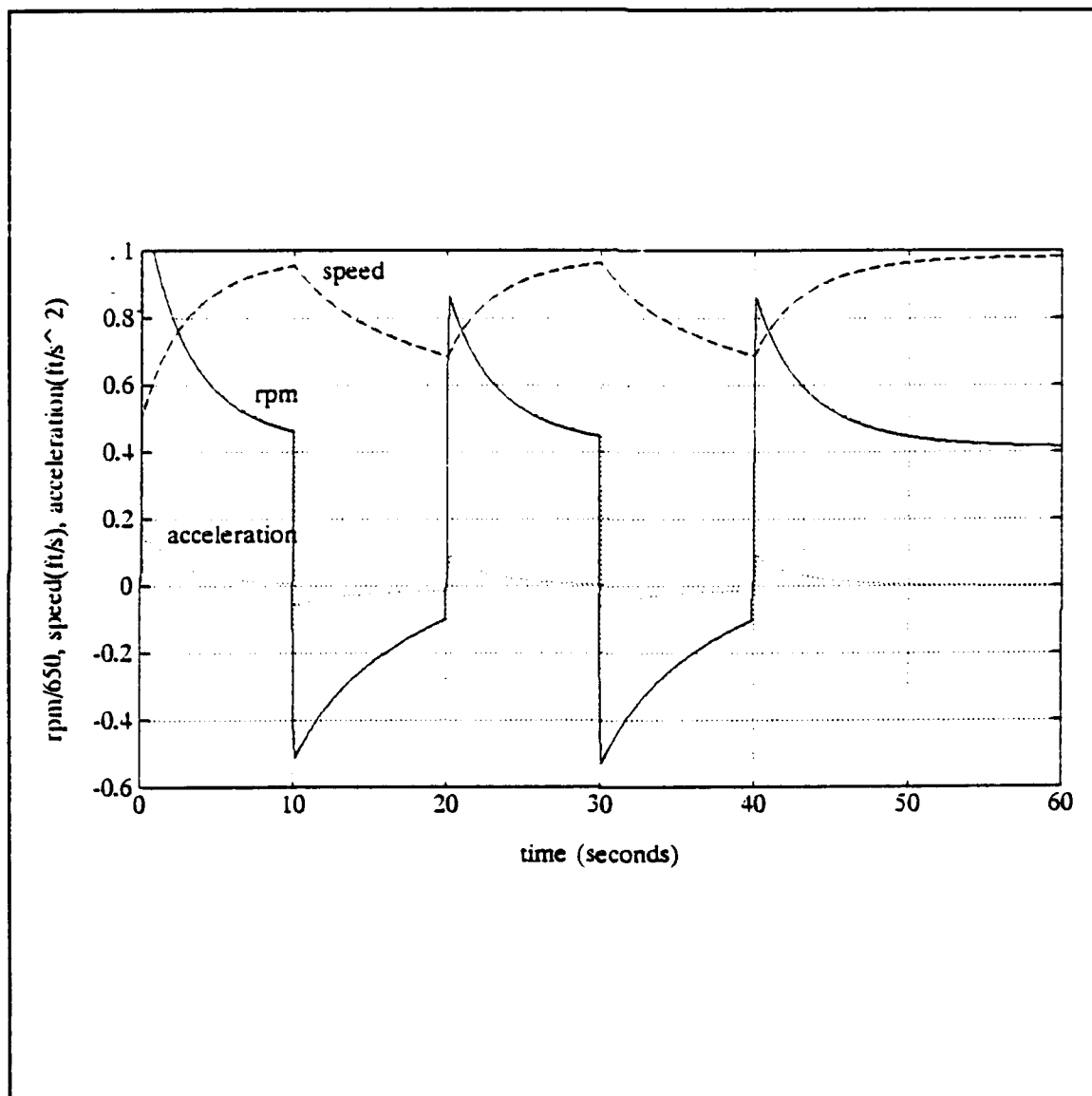


Figure 5.13 AUV propulsion model response to commanded velocity profile

their respective nominal values for the first ten seconds of the run. The value of one of the parameters is then changed. Increasing the alpha value to indicate increased drag and decreasing the beta value to indicate a loss of propulsion.

Figure 5.14 shows the Kalman filter response to a normal run and Figure 5.15 shows the Kalman filter response to a 35 percent increase in alpha after ten seconds into the run. The beta parameter appears to change and then returns to normal as the Kalman filter determines that alpha is the only parameter which was altered. This illustrates the motivation for positioning a twenty percent plus or minus window for the normal mode of alpha and a similar window for the normal mode of beta.

In an operational design, the variability of alpha and beta that would be considered 'normal' variability must be tied to the parameters of the filter, the particular characteristics of the test signal used, and the normal variability in the vehicle operating conditions. It is recommended that as a result of this effort that the test signal and filter design parameters be determined and fixed prior to the design of the failure mapping. Operational test data will therefore be needed to finalize the specification of the failure map by understanding the natural variability expected of the parameter set.

The network's response to the 35 percent increase in alpha is shown in Figure 5.16. For the first ten seconds the

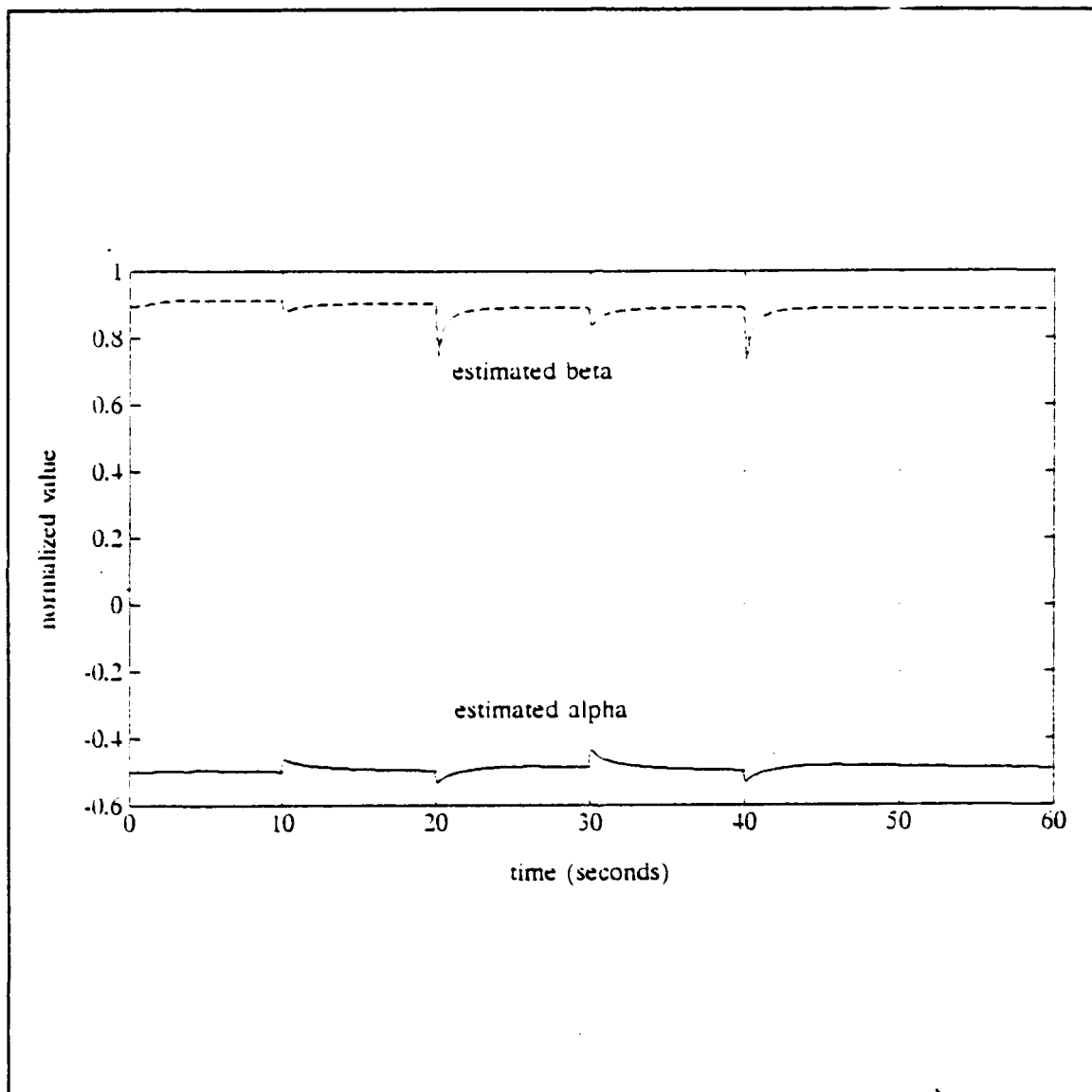


Figure 5.14 Kalman parameter filter response to normal operation

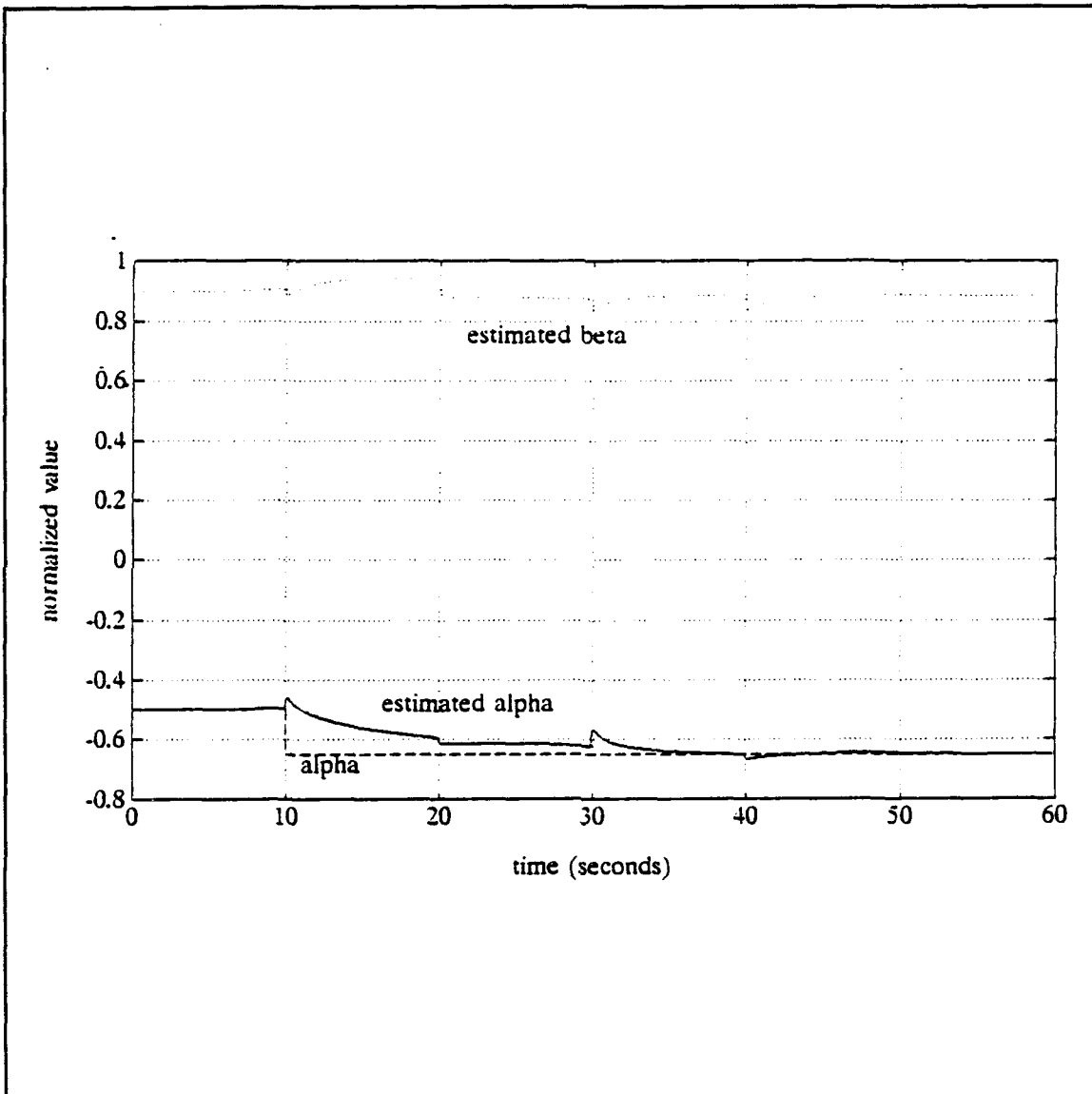


Figure 5.15 Kalman parameter filter response to increased drag operating condition

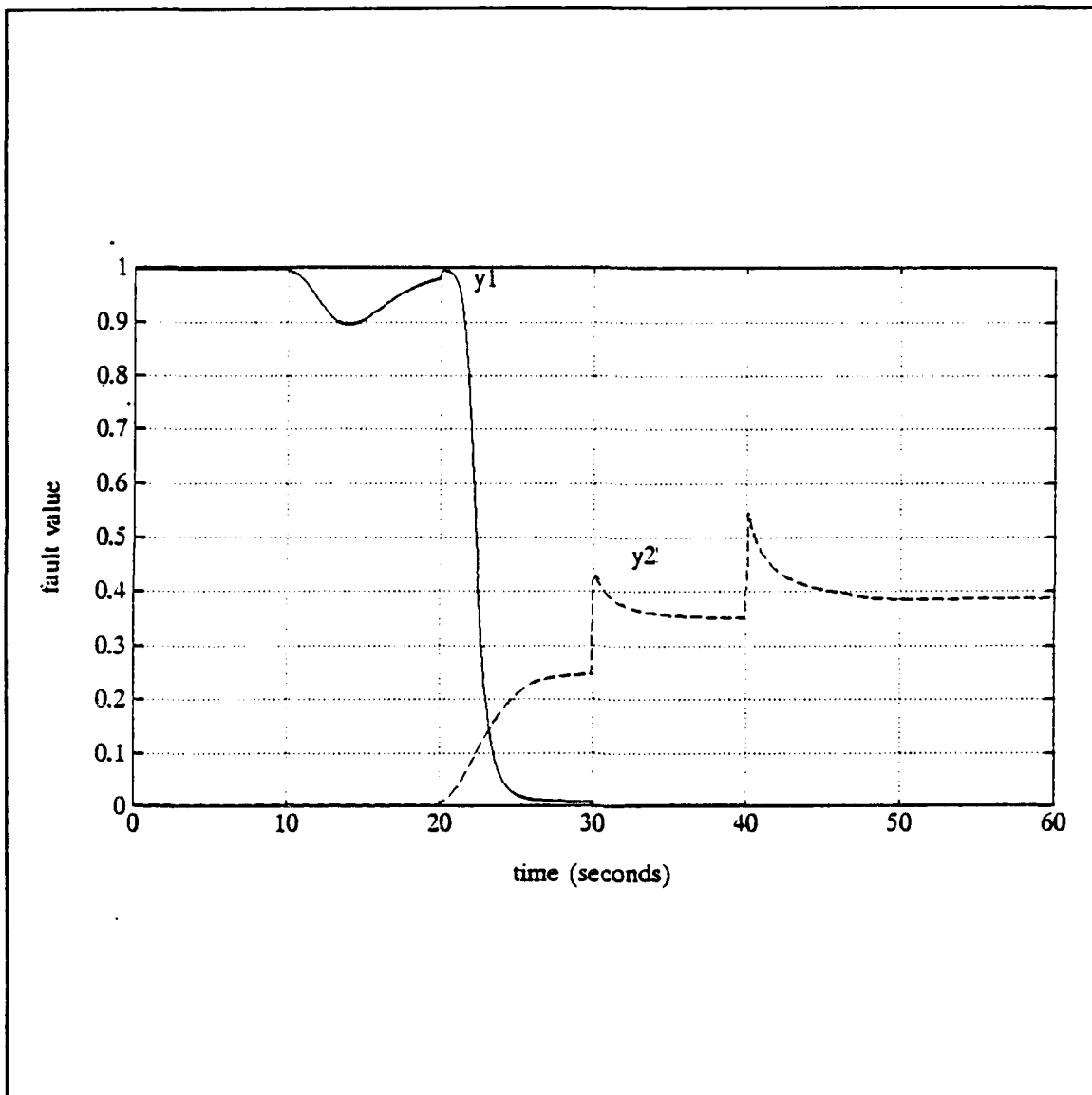


Figure 5.16 Neural network response to increased drag operating condition

network recognizes the normal mode. Between ten and twenty seconds the transition is made in identifying the fault as an increase in drag. Figure 5.17 further illustrates the transition from the normal mode to one of increased drag. At the beginning of the run, the system is in the normal mode at the normalized values of $\beta=0.5$ and $\alpha=0.9$. After the fault is initiated the operating condition traverses to the increased drag mode.

The fault diagnostic system was also tested under a propeller loss condition. This was simulated by setting the β value of one propeller to zero. The transient response from the vehicle's sensors is shown in Figure 5.18. The Kalman parameter identification result is shown in Figure 5.19. The loss of one propeller resulted in β dropping by fifty percent as one would expect. The network's response is shown in Figure 5.20. The fault mapping was designed to yield a high fault value for such a decrease in β .

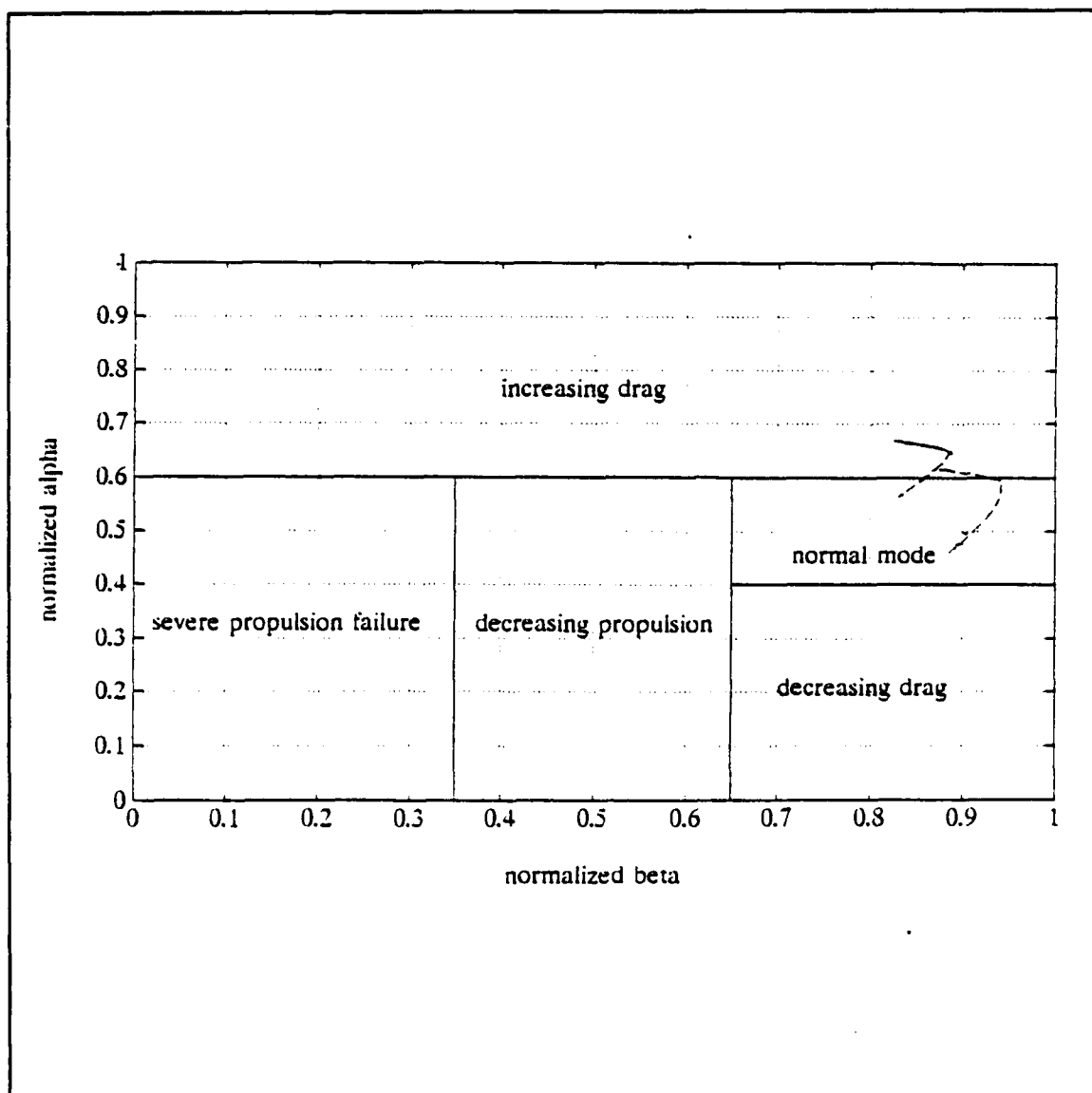


Figure 5.17 Change in parameters alpha and beta due to increased drag shown over fault map

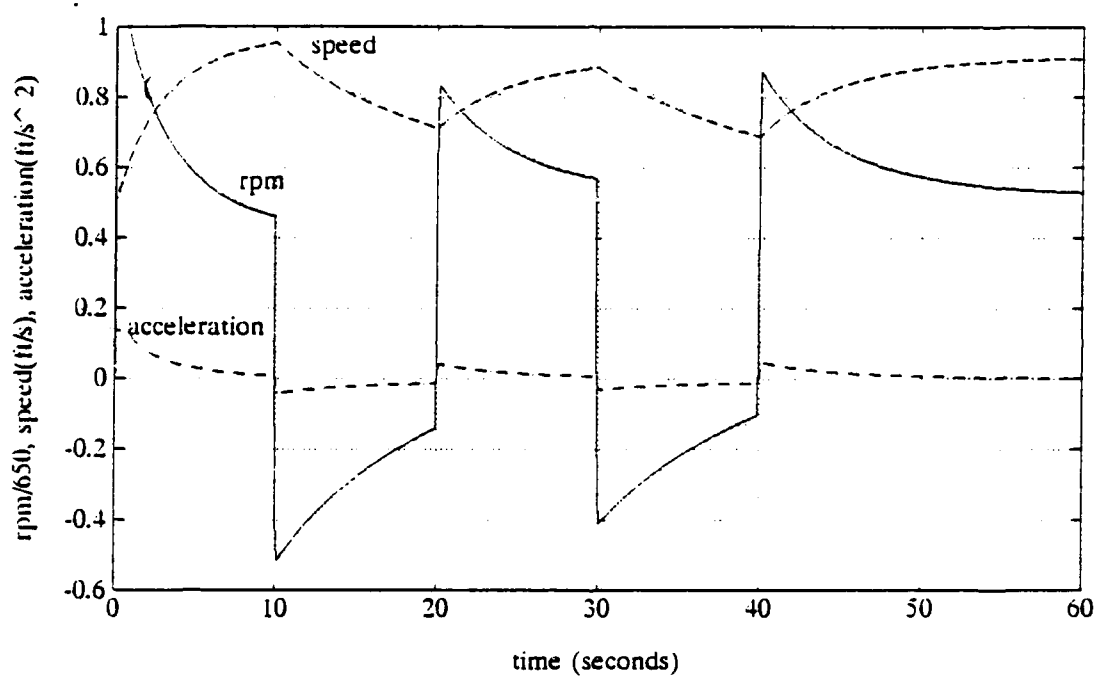


Figure 5.18 Auv propulsion model propeller loss transient response

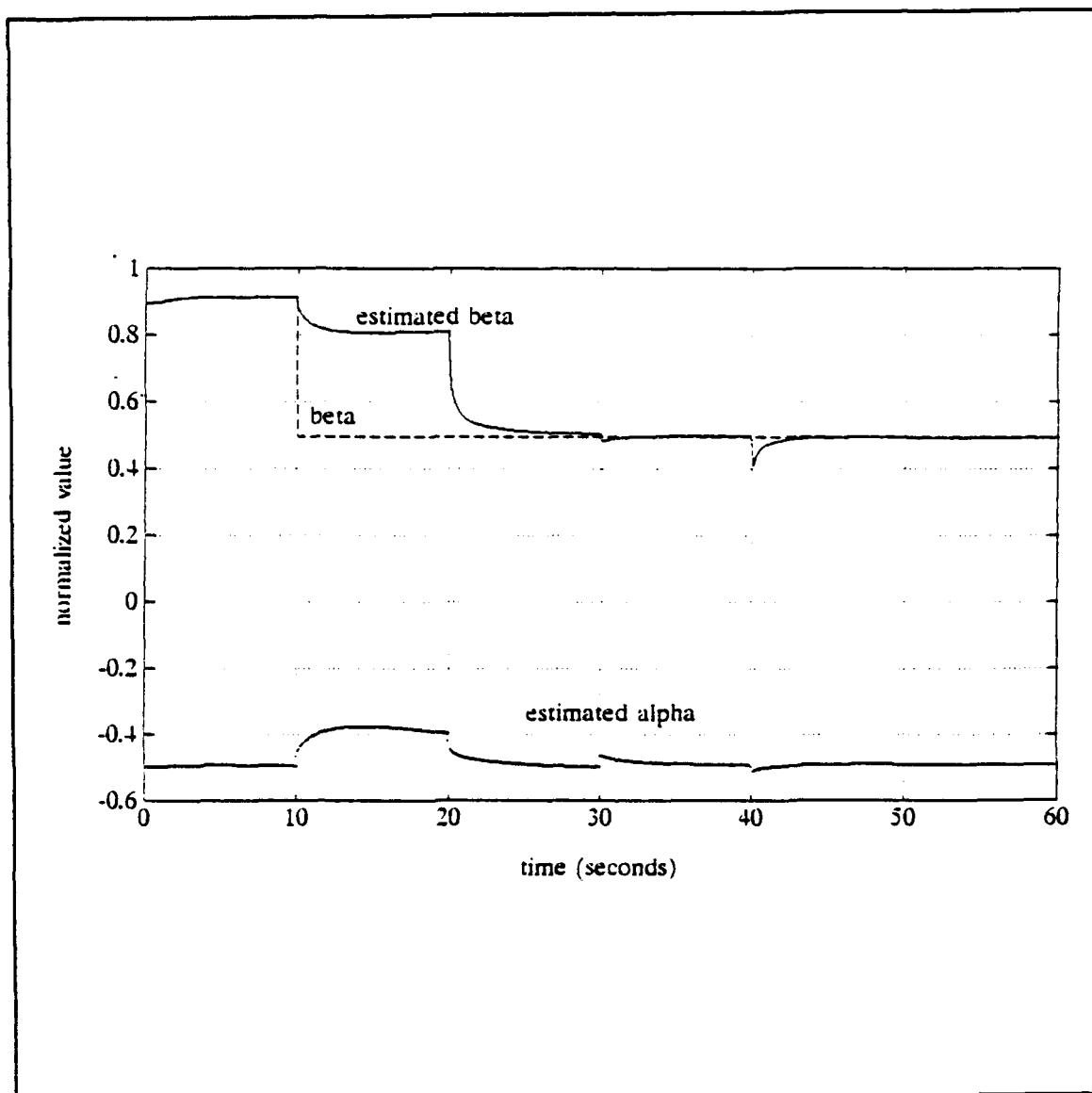


Figure 5.19 Kalman parameter filter response to propeller loss

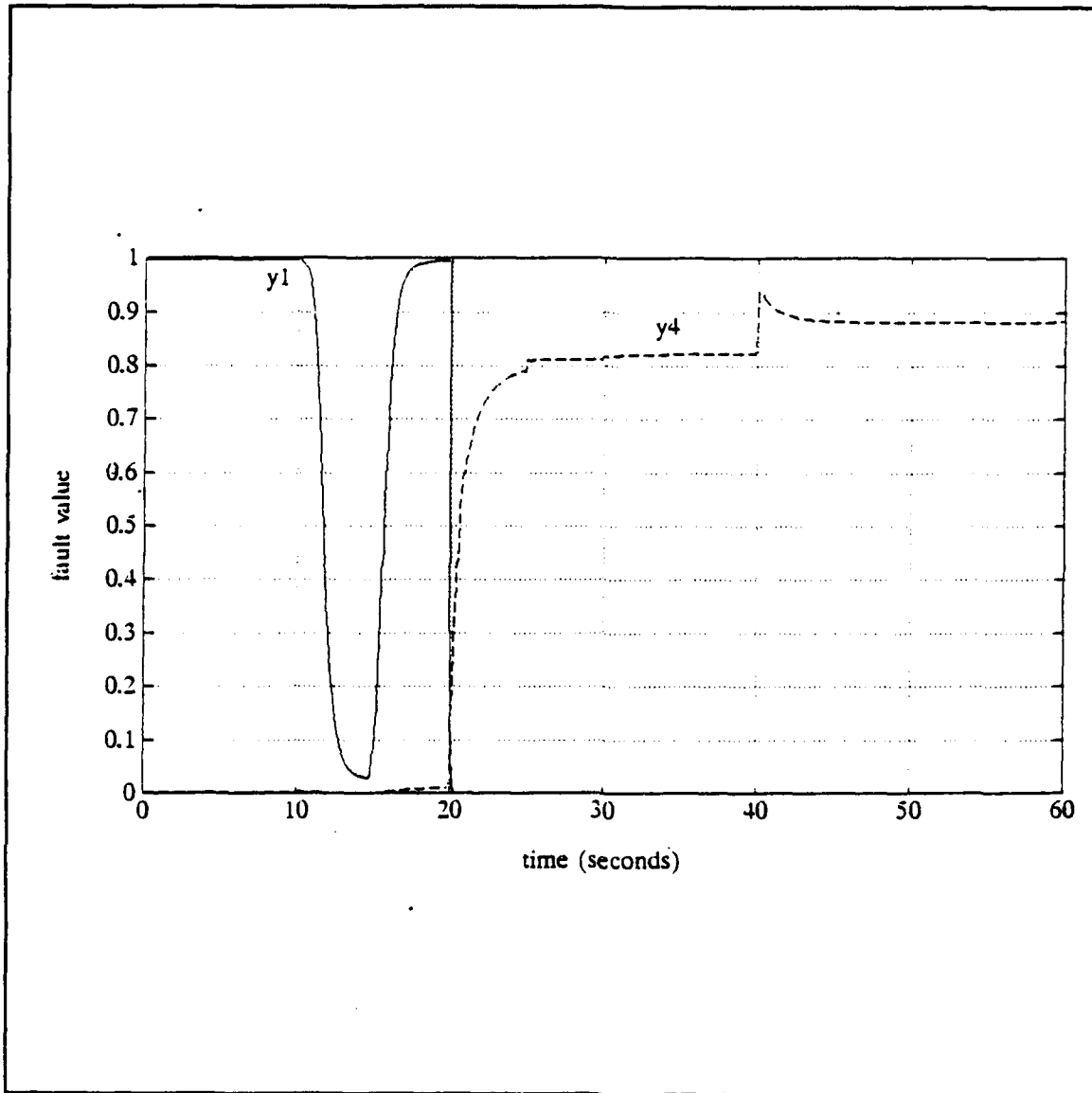


Figure 5.20 Neural network response to propeller loss

VI. CONCLUSION AND RECOMMENDATIONS

A. CONCLUSION

In the NPS AUV II we have determined two types of faults which we would like to identify. Those associated with the propulsion motor system and those related to the vehicle's longitudinal response.

It has been shown that the identification of faults associated with systems having a very fast response such as the AUV propulsion motor system can be accomplished with a network that uses steady state values of sensor output signals as it's input. A fault can be detected from a change in the steady state relation between the input values. Specifically the presence of increased friction in the propulsion motor drive system is easily detected by a network using steady state values of motor voltage, motor current, motor rpm and vehicle speed as inputs.

In order to identify faults related to the vehicle's longitudinal motion performance it has been shown that the implementation of a Kalman parameter identification filter is quite useful. Changes in the vehicle's surge motion parameters were easily identified by the Kalman parameter filter. Faults were then characterized by an artificial neural network trained on a mapping of the system's parameter values. The level of fault severity was also determined by the same

network. The use of the Kalman parameter identification filter to preprocess data available from system sensors greatly reduced complexity and training of the neural network.

B. RECOMMENDATIONS

It is recommended that further study in developing a single fault diagnostic system capable of detecting internal system faults and dynamic response faults be conducted. The capability of identifying both types of faults might be accomplished by the combination of the two methods described in this thesis. A system with both networks operating in parallel, one identifying each fault type, would certainly be capable.

Another approach would be to integrate the two networks in such a way that a single network would accept input from system sensors and from a Kalman parameter identification filter.

**APPENDIX A
PROPULSION MOTOR CHARACTERISTICS**

PITTMAN MOTOR SERIES	14202
ELECTRICAL TIME CONSTANT milliseconds	1.47
MECHANICAL TIME CONSTANT milliseconds	8.5
FRICTION TORQUE ounce-inches	1.79
ARMATURE INERTIA ounce-inches-seconds ²	2.3×10^{-3}
MOTOR WEIGHT ounces	26.0
MOTOR CONSTANT ounce-inches/watt ^{0.5}	5.81
VOLTAGE volts	24.0
TORQUE CONSTANT ounce-inches/amp	8.67
TERMINAL RESISTANCE ohms	1.01
BACK EMF volt-seconds/radian	0.061
NO LOAD CURRENT amps	0.210
STALL CURRENT amps	23.8

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