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THE DESIGN OF NEURAL NETWORKS FOR THE PERFORMANCE ESTIMATION OF SATELLITE TRANSPONDERS

by

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(ABSTRACT)

It has become increasingly important to improve upon the performance of satellite transponders, whose function is to receive and transmit signals automatically when triggered by an interrogator. The transponder of INTELSAT V whose performance parameters include: noise figure, group delay, gain, frequency translation, and power output is considered for investigation. The focus of this project is to design an Artificial Neural Network (ANN) as a new analytical model and computational technique to assess the intricate interactions between the transponder performance parameters and the environment in order to improve future satellite transponder performance and design.

The rationale for the use of ANN as a means of estimating the performance of a transponder lies in their parallel

computation, learning ability, optimization capability, distributed data presentation, and ability to handle various tasks that are difficult for traditional computer techniques. Computer analysis tools are used to generate an optimal ANN model that meets the design specifications.

Finally, several candidate ANN models are investigated and the proposed models are selected based upon the result that minimizes the mean square error. The analysis will address the design of ANN using hypothetical training and validation data which incorporates a comparative assessment of the ANN estimation accuracy relative to the number of training patterns, iterations, hidden units, and learning parameters. Consequently, the impact of dynamic threshold values to interpret the ANN's response relative to transponder performance specification by the postprocessor is discussed.

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1.0 INTRODUCTION

Satellite transponders are, by design, highly integrated electronic devices. Their primary function is to maintain reliable and efficient communication between the satellite and earth stations. SATCOM systems have undergone continuous change since their inception. This evolution is necessary to cope with increasing demand for better service quality and with the new operating requirements which result from advances in space craft navigation, communication, and computer technologies. Such changes have resulted in the expansion and upgrading of satellite control facilities, the introduction of new improved devices, the adoption of revised requirements, and new services.

In recent years, there has been increasing awareness of the high degree of interaction among the elements comprising the transponder and their implication on SATCOM operation. The interaction between transponder elements is one of the various factors that could cause a deterioration in the performance of SATCOM systems. In order to improve the reliability and performance of SATCOM systems, it is important that advanced analytical tools be utilized.

The existing methods currently used in the analysis of transponder performance models fail to guarantee the desired reliability because of the fact that the design life time is to long to permit the demonstration of high system reliability in a reasonable time. Besides, large test data base make it formidable the task of producing a reliable model because of the difficult in getting it into an appropriate form for modeling. With this fact recognized, Artificial Neural Network (ANN) methodology that is being proposed facilitates both transponder performance parameters analysis and detailed investigation of individual parts of the transponder based on hypothetical operational life data and field test result data.

The approach taken in this study is to base the future reliability assessment on hypothetical mission and test performance data which include: noise figure, power output, gain, frequency translation, and group delay measurements. To maximize the performance of satellite transponders, DIT (Degradation In Time interval) a single figure of merit that investigates all aspects of performance parameters into a single number is defined. DIT is defined as the average number of times the transponder's output power degrades by 1db within one hour time interval. The hypothetical data is divided into two main categories namely :

- overall SATCOM/transponder performance data
- a detailed transponder/component performance data.

The rationale for the use of ANNs lies in their ability to learn and to perform unstructured computation such as, statistical estimation. Their advantage over other statistical estimators is that a priori knowledge of the problem can be incorporated in the architecture of the network.

Finally, this report describes and explains the research done to develop performance assessment methodology and technique for SATCOM transponders. As such, the work is directed to the development of transponder performance estimation tools. While such tools do not yield transponder design directly, they support the transponder design process with critical assessment of trial or proposed design components and identification of any performance weaknesses. By identifying component's operation that manifest performance inadequacies, the performance estimation tools will provide information necessary for redesign or component re-selection.

2.0 PROJECTS OBJECTIVE, SCOPE, REQUIREMENTS & SPECIFICATION

2.1 PROJECT OBJECTIVE

The objective of this design is to develop an Artificial Neural Network (ANN) model for the performance and reliability estimation of SATCOM transponders and their constituent components given:

- hypothetical data gathered directly from the satellite once it is in orbit
- hypothetical data gathered during simulated testing

2.2 SCOPE

The scope of the project involves a methodology for the development of a transponder performance estimator and associated techniques to measure significant performance limiting behaviors. This requires:

- designing a fault tolerant ANN
- developing a preprocessor for automatic comprehensive data presentation
- analyzing and evaluating alternative performance measurement techniques
- developing a generally applicable postprocessor unit for ANN's output interpretation and transponder performance evaluation
- assessing and analyzing ANN's estimation usefulness based on hypothetical performance data.

2.3 REQUIREMENTS

The following requirements specify a course of action to achieve the objective stated above.

1) It is necessary to conduct analysis to answer the following questions:
   - what is a transponder?
   - what are the factors that limit transponder performance?
   - How can performance be estimated, and in what form and context is it appropriate to measure it?

2) It is necessary to determine and design a performance estimator model.

3) Finally, it is required that the model developed be implemented, tested and validated.

2.4 SPECIFICATIONS

It is necessary that the developed model meet the following specifications:

- The ANN developed must optimally generalize the input/output causal relation.
- Tolerable transponder performance in range operation of 0-5 DIT/24hrs.
- The ANN should at least estimate 30%-60% of the actual transponder performance degradations.

3.0 SATELLITE COMMUNICATION NETWORKS

To enhance the availability of satellite communication networks, satellite control facilities which reside at one of the earth stations continuously monitor the performance of the transponders (see figure 1). It is proposed that the ANN could be integrated with the control facility to monitor the transponders in real time and generate estimated values of the their performance parameters.

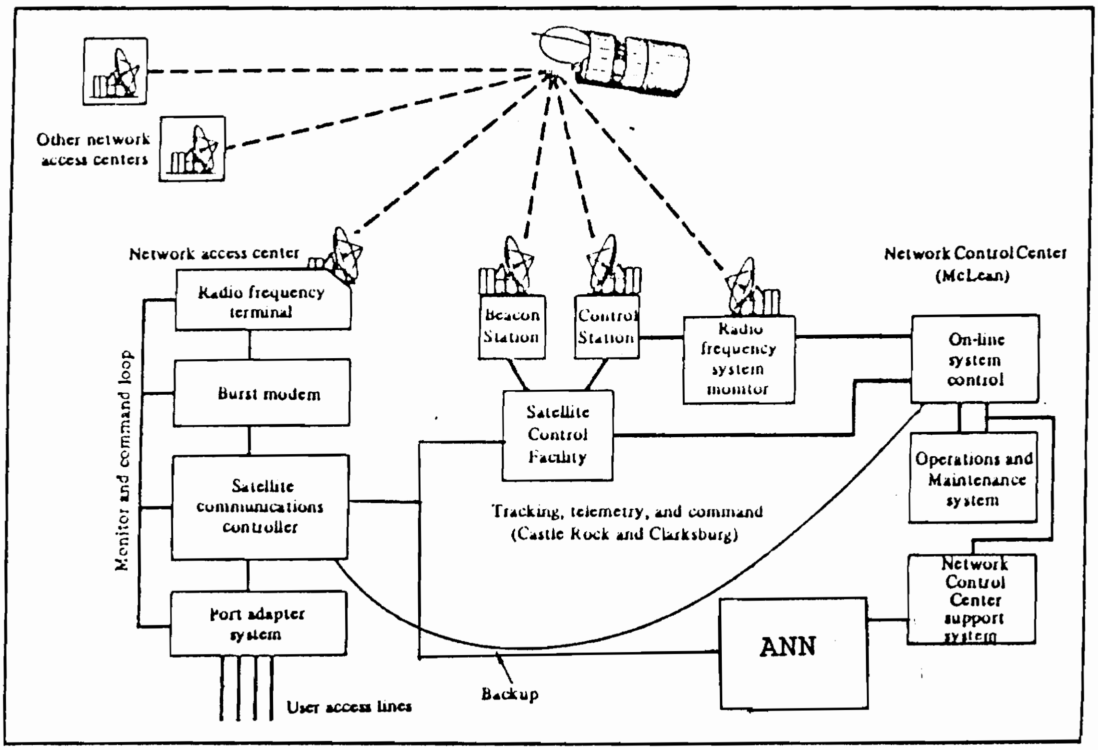


Figure 1. ANN integrated satellite control facility

Based upon the estimated values, the controller could then initiate a diagnostic command to check the health and diagnose problems of the transponders or reconfiguration command to switch in redundant components, i.e routing the traffic to avert any estimated failures. The diagnostic and reconfiguration commands are used to maximize the availability to the user, i.e the probability that a satellite is operating satisfactorily at any particular time. Thus, a combination of monitoring computers, ANN transponder performance estimator, and staff would keep the satellite communication system functioning well to the customers' satisfaction.

3.1 WHAT IS A TRANSPONDER?

A transponder (see figure 2) is a satellite communication subsystem composed of integrated electronic devices whose function is to amplify a received signal and change its carrier frequency with no essential change in the information content before it is retransmitted to the earth station [24]. In the interest of improving satellite availability it is therefore essential to optimize transponder design and monitor its performance as it is explained in the following sections.

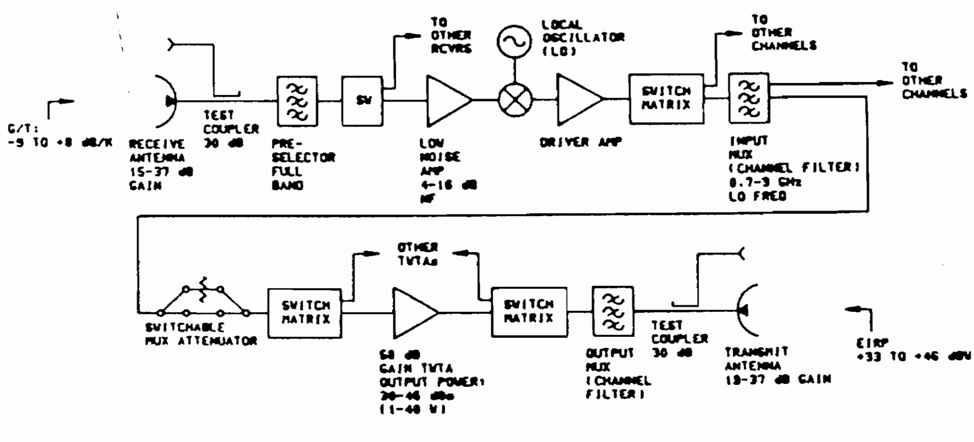


Figure 2 Typical satellite transponder

3.2 DESIGN CONSIDERATION

From the moment a mission is conceived and defined each transponder is designed taking into account the following criteria: minimum mass, minimized power consumption, and high reliability in addition to the particular function to be fulfilled.

Performance and reliability models are used in the design of transponders to ensure that customer specified objectives are meet. These models optimize some measure of transponder reliability; e.g, to minimize the probability of system shutdown due to limited redundancy or to minimize the probability of system failure. It is therefore crucial to identify good components and allocate redundant bearing in mind that the system's useful life time ought to be maximized.

3.3 PERFORMANCE CONSTRAINTS

The criterion for defining a components failure or degradation is when it either ceased to operate or performed below its prescribed specification. Satellite launches, testing chambers, and transponder electronic components have great impact in determining the performance of space craft [7]. As such, their inadequacies can induce limitation on the overall transponder performance. It is also worth noting that in many high reliable or fault tolerant subsystems such as transponders, component failures that do not cause a transponder failure can potentially degrade transponder performance by limiting, for instance power output on their utilization.

Apart from these mechanical inadequacies, other deleterious factors of transponder performance are: solar radiation, vacuum, thermal variation, meteorites and space debris. In order to support and meet customer specified performance objective therefore it is necessary to assess the performance of each part of the transponder as it operates in the context of the whole transponder system and operation condition.

4.0 PERFORMANCE EVALUATION

4.1 PRESENT TECHNIQUE

Preflight performance evaluation of a transponder is a rigorous process which involves exposing the transponder to predicted environments. Figure 3 depicts hardware block diagram of Integrated Satellite Test complex (ISTC) [19]. Each test performed evaluates important characteristics such as, noise figure, gain, output power etc. of some or all of the components relevant to the transponder. Tests are selected with care to produce maximum confidence in performance with minimum time. As such a maximum number of components are tested repeatedly to detect trends or changes in performance. This type of test is known as " Baseline Function ", and is repeated 11 times between different phases [19]. As a result, the existing performance evaluation technique is complicated and time consuming accentuating failures resulting from human carelessness which will degrade transponder performance and reliability.

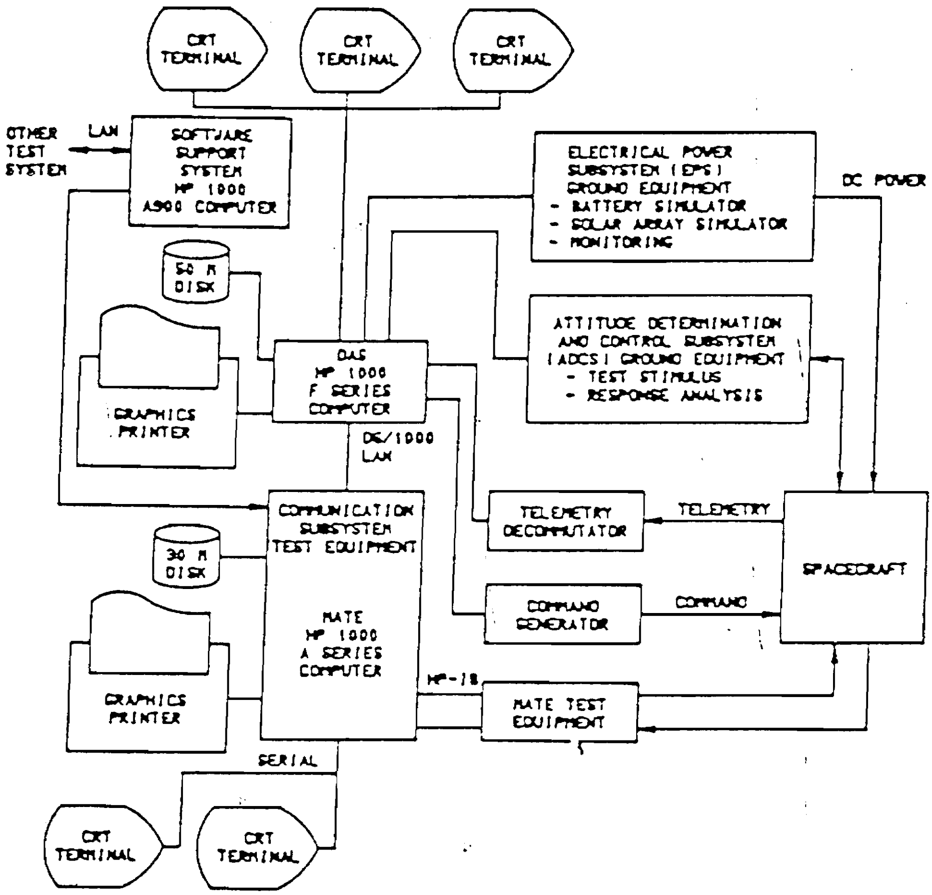


Figure 3 ISTC hardware block diagram

4.2 THE PROBLEM

Transponder random component failures represent one of the major sources of performance degradation. As a result it is necessary to estimate these random failures which result from environmental variation and/or wear out. The benefit of estimating random failures is to provides a leading time to take preventive action in order to avoid performance degradation or outages. However, the existing performance evaluation techniques and satellite control systems lack the flexibility to estimate and guarantee transponder's performance and reliability respectively.

4.3 THE SOLUTION

The goal is to improve the reliability and availability of transponders by estimating their performance based on the investigation of historical trends in the causes of random failures. The approach is to use the proposed methodology to model the behavior of the transponder from the given data. The expectation is that the defined methodology will be able to generalize or estimate transponder performance when it is presented with partial information.

4.4 PROPOSED NEW TECHNIQUE

The methodology being proposed complements both transponder performance analysis and detailed investigation of its constituent elements. Individual performance evaluation is treated at an appropriate level of detail which involves the analysis of the cross correlation of propagation delay, noise figure, frequency translation, gain and the corresponding DITs. Where DIT is defined as the average number of times when the transponder output power degrades by 1db. On the other hand, transponder performance analysis involves estimation of DITs based on the autocorrelation of DITs using sliding window techniques. The methodology therefore, requires development of a family of models which can be interchangeably used at different times and in different situations as appropriate, without requiring a single large and complex model.

In this sense, it is necessary to develop two primary ANN's with a set of criteria and requirements which their function include:

- estimation of time related transponder performance
- estimation of transponder/component performance.

The methodology is intended to enable performance estimation both of today's transponders and of transponders that evolve from today's system. Thus it is independent of transponders configuration, but solely dependent on transponders performance measurement data source. As such, ANN's transponder performance estimation technique in the context of the stipulated ideal environmental complexities in addition to the existing technique is believed to improve satellite communication networks in a reasonable cost.

5.0 ARTIFICIAL NEURAL NETWORK

5.1 WHY NEURAL NETS

The need to deal with increasingly complex systems and to improve quality and availability of services are challenging tasks facing performance analysts. it is believed that neural net models have greatest potential in areas where many processes are performed in parallel, high computation rates are required and the current best systems cannot solve [9]. Instead of performing programs of instructions sequentially as in a Von Neuman computer, neural net models explore many computing functions simultaneously using massively parallel nets composed of many computational elements connected by links with variable weights.

The potential benefit of neural nets extend beyond the high computation rates provided by massive parallelism. Neural nets typically provide a greater degree of robustness or fault tolerance than Von Neuman sequential computers because there are many processing nodes each with primary local connections. Damage to a few nodes or links thus need not impair overall performance significantly.

Adaptation or learning is one of the major strengths of neural nets. The ability to adapt and continue learning is essential where training data is abundant and new environments are continuously encountered. Adaptation also provides a degree of robustness by compensating for minor variabilities in the characteristics of processing elements. Besides, neural net estimators are non-parametric and make weaker assumptions concerning the shapes of underlying distribution than traditional statistical estimators. They may thus prove to be more robust when distributions are generated by non-linear processes and are strongly non-Gaussian [1].

The preceding features therefore are the rationale for the use of neural nets as a means of estimating the performance of a SATCOM transponder.

6.2 DEVELOPING NEURAL NETS

It is a challenging task to build an efficient transponder performance estimating device which could estimate the transponder's performance even if the service quality requirements change overtime. However, the goal is to design a functioning neural network that provides the most accurate, consistent, and robust model possible.The design of neural network involves four major steps [5].

- Gathering and quality representation of training data.
- Selecting the optimum development environment.
- Testing and debugging the network.
- Implementing the neural network

The design methodology is depicted by the following flow chart.

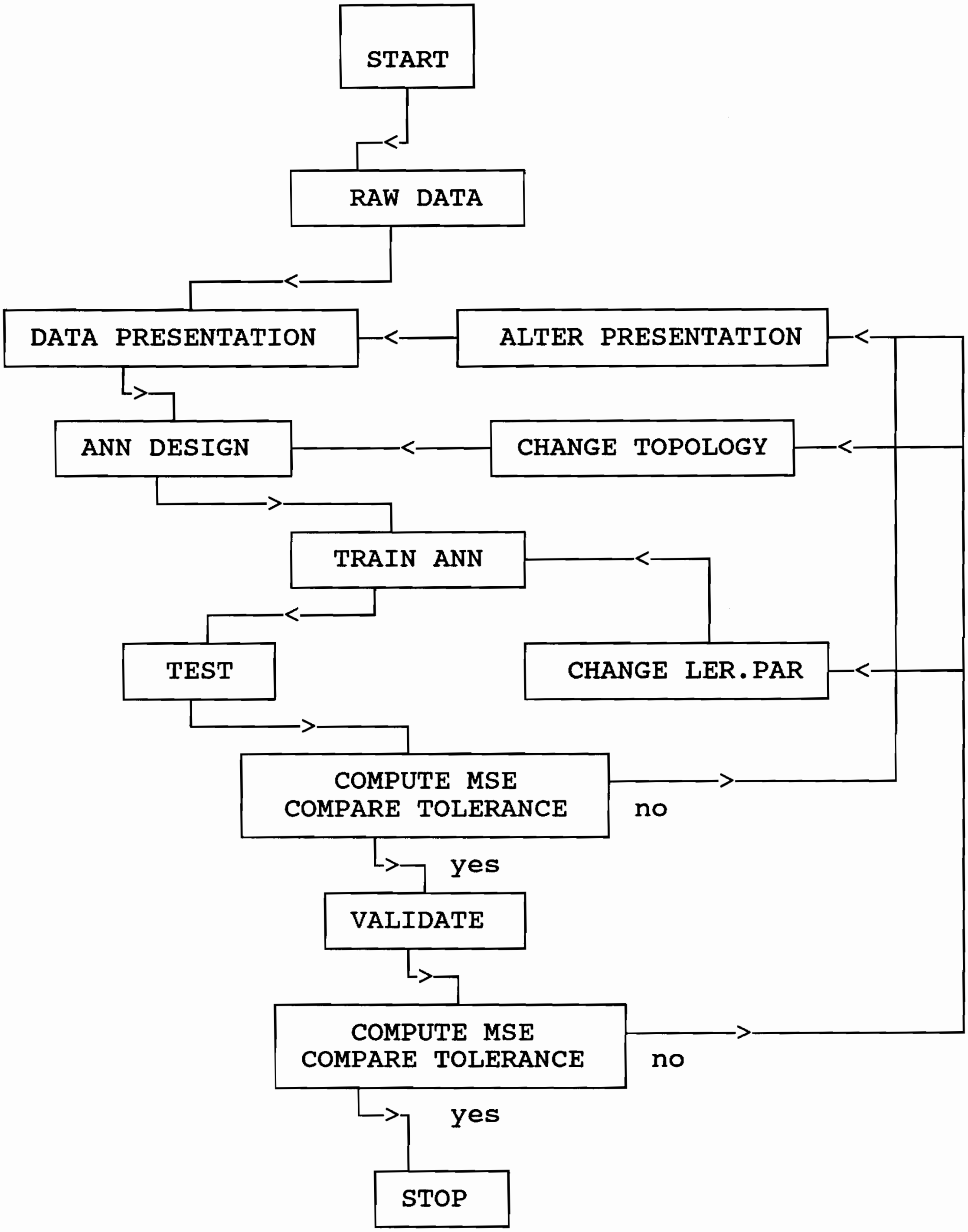


Figure 3 Flow chart of modeling

The first stage of the design methodology, involves the generation of an appropriate data representation which constitutes the basic information of interest of the problem to be solved. Collecting the training set and comprehensive data representation for the network is often tedious and time consuming. This is because of the fact that the more complete the training set is the easier it is for the network to pick and learn the input/output relationships. Therefore, training data representation is very crucial in the design of neural networks. The simulation results indicate that neural network's learning, generalization, and estimation improved significantly with various training data representations.

Selecting the optimum development environment is heuristic. The development environment involves: selection of appropriate neural network architecture, determination of optimum number of processing elements (PE) in the hidden layer, and adjustment of learning parameters. As a result a comparative assessment of different ANN topologies is made relative to the desired tolerance to determine the topology that minimizes the mean square error. After several iterations and variations in the number of hidden units, learning parameters, and subsequent elimination of expendable connection, an optimal topology is retained if the ANN topology satisfies the defined specification with the least mean square error.

Once the optimal neural paradigm is selected it is trained. Before training the ANN connections weight assignment is perturbed in order to avoid the ANN from converging to the local minima. The performance of the ANN is then computed empirically by presenting it a series of test cases to evaluate its response against the validation data. The ANN is tested with patterns it had seen before and patterns it had never seen before. If the testing results indicate significant errors in the ANN's response, it is essential to debug the training data, the ANN architecture, and learning parameters until the desired error tolerance criterion is achieved.

In addition, to optimize the ANN's estimation performance a postprocessor with dynamic threshold value adjuster is introduced to interpret the ANN's output to different levels of severity. These techniques will allow one to study and understand the behavior of the ANN and determine the relationship between the inputs/outputs.

Once the convergence criterion is met and the stability of the neural network is verified, the ANN transponder performance estimator is integrate with the existing systems to evaluate its performance. For instance, the ANN could be integrated with Microwave Automatic Test Equipment (MATE) to monitor the device under test in real time and evaluate its estimation's accuracy and consistence [19]. Doing so will assert the credibility of ANN's estimation capability in favor of the existing performance estimating tools.

6.3 SIMULATION PACKAGE

The PC based software package used extensively in the design of ANN transponder performance estimator is called Neural Works Professional II. The package was developed by Neural Ware, Inc. This package is used because it provides flexibility in adjusting the learning parameters, generating standard network types, and diagnostic tools. The package also provides neural probes and instruments for the incorporation of design specification as well as to monitor the dynamics of the network as it evolves during learning [13].

7.0 BASIC SYSTEM

The approach to modeling transponder performance estimator from the given data has yielded the concept and structure of an essentially three level hierarchy. This hierarchy and decomposition has been the result of the need to reduce computational requirement by the ANN and to compensate for the ANN's inherent generalization characteristics.

The basic system as it is depicted in figure 5, comprises preprocessor, artificial intelligence neural network (ANN), and a postprocessor with auxiliary threshold adjuster. Each module has a specific function to perform in order to enhance the overall performance of the system. In the following sections it is attempted to elaborate on each modules's function.

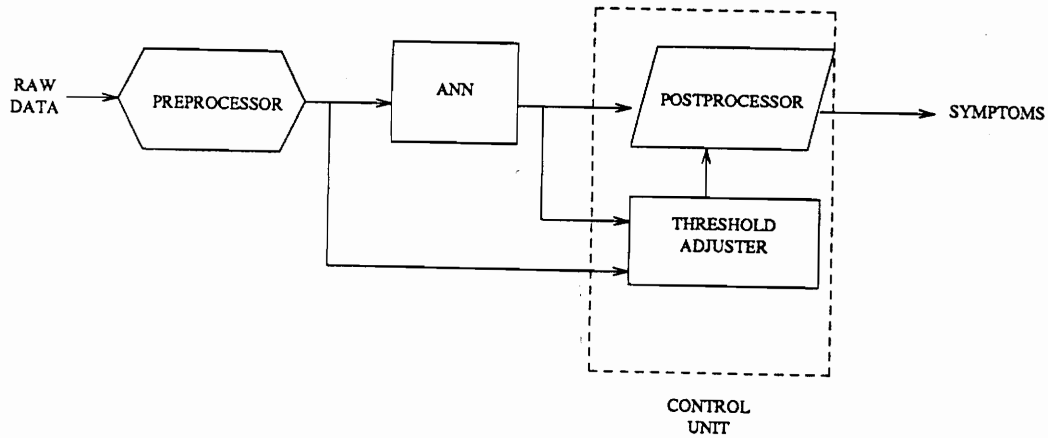


Figure 4 Block diagram of an ANN transponder performance estimator

7.1 SYSTEM INPUT

The data files contain hypothetically generated satellite transponder characteristics measurements. These characteristics include noise figure, gain, group delay, frequency translation, and DIT (Degradation in Time interval). DIT is defined as the average number of times the transponder's output power degrades by 1db in 1 hour time interval. The data for the design of ANN are delineated in two main files:

- A training file
- A testing file

(See Appendices A & B for both files).
These two files have the same format. However, the training file contains both input/output data where as the testing file contain the input data only. More precisely, the training file contains measurement of noise figure, gain, group delay and frequency translation as an input and the corresponding DITs as an output. Similarly, the testing file contains noise figure, gain, group delay, and frequency translation measurements.

The data is arranged such that a single input/output relation is represented by a single row. Each data column therefore, represents a single neuron either in the input or output layer of the ANN; e.g, one of the training files contains five columns which correspond to four input neurons and one output neuron. However, the test file contains four columns which are all inputs to the neurons in the input layer.

It is important to note that the hypothetical data are generated bearing in mind that the preceding parameters measurement vary for various test simulation. That is, each performance parameter has an associated thermal, gravitational, radiation etc. measurements.

Once the training and testing files are generated the Nworks simulation package provides the necessary features to design, train and test the ANN, as it will be emphasized in subsequent sections.

7.2 PREPROCESSOR

The function of a preprocessor is to transform the raw data into an intermediate representation which simplifies the problem for the neural network while making only small computation overhead. This includes supplementary processes:

- reducing randomness
- enhancing time information which does help estimation.

For example, the preprocessor furnishes unequally spaced overlapping samples from a series of transponder performance parameters to the ANN.

Nevertheless, the behavior of the transponder is modeled by the following functions:

$$F(N,P,F,G) = DIT$$

where N, P, F, and G represent noise figure, group delay, frequency translation, and gain measurements respectively. Whereas, DIT is the corresponding transponder degradation within a specified time interval; And

$$F(DIT1,DIT2,DIT3,DIT4) = ODIT4,ODIT3,ODIT2,ODIT1$$

where DIT1, DIT2, DIT3 and DIT4 are one, four, sixteen, and twenty four hours overlapping moving sums of transponder DIT counts history. Whereby, ODIT4, ODIT3, ODIT2 and ODIT1 are the corresponding expected DIT counts in the next respective windows. The intent of sliding windows of unequally spaced time intervals is to reduce randomness and incorporate time information of the DIT counts that the ANN would be trained with. The goal is to understand the relationship such us how the future performance of the transponder/component would have changed if the DIT counts in the defined windows go up or down. The preceding complex functional dependence is therefore modeled using neural networks.

7.3 NETWORK ARCHITECTURE

Two multi-layered feed-forward paradigms were designed to model the defined functions [15]. In feed-forward paradigm information flows amongst the processing elements (PEs) in one direction as opposed to the feed-back paradigm which allows information to flow amongst the PEs in either direction. Model1 has 4 PEs, 12 PEs, and 1 PE partially inter-connected in the input, hidden, and output layers respectively (see figure 6). On the other hand, model2 has three layers with four PEs fully inter-connected in each layers (see figure 7). Inter-connection is defined as a connection between PEs in different layers.

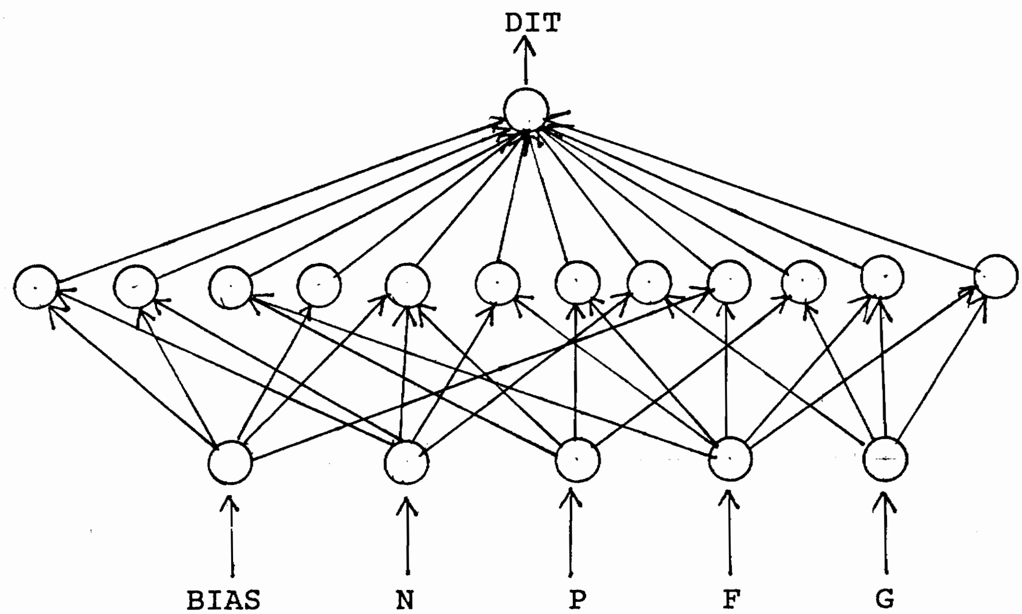


Figure 6 Model1 transponder performance estimator architecture

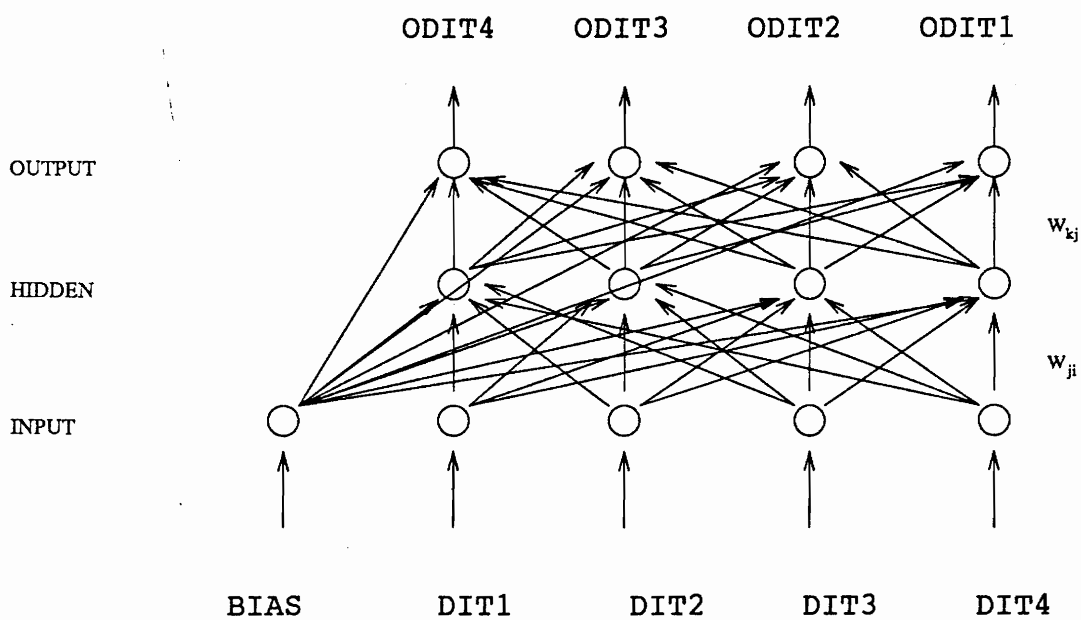


Figure 7 Model2 transponder performance estimator architecture

The back-propagation learning algorithm for layered, feed-forward network is selected because it represented a major advance in effective neural network learning. The metric that back-propagation learned was the one that minimized the mean square error (cost function). Back-propagation is a learning algorithm which is designed to solve the problem of choosing weight values for hidden units in a layered feed-forward network [1]. Hidden units are units in the intermediate layer which are neither input nor output units. They are introduced to give the network enhanced internal processing capabilities it could not have if only input and output units were present. However, the choice of the right number of processing elements in the hidden layer is a key factor to avoid output saturation. These phenomena were observed when the number of PEs in the hidden layer were varied beyond the optimal.

Since most of the input parameters are allowed to have values within a range, it is better to use a continuous neuron transfer function. The most pervasive sigmoid function that provides bounded, monotonic, non-decreasing and non-linear response is used [16]. The sigmoid function is used in the simulation in hope that the ANN models generalize the input/output relationship. The intriguing result was that the sigmoid transfer function for both hidden and output layer out performed the mostly recommended sigmoid linear transfer function in the hidden and the output layers respectively.

The basic paradigms considered here utilize supervised learning from examples. The algorithm tries to make adjustment to the set of synaptic weights so that the actual output is guided to a desired or target output, as opposed to unsupervised and reinforcement learning. For detail the reader is referred to [10]. The weight value of each connection for both models is listed in appendix d.

8.4 INFORMATION PROCESSING

The network maps inputs DIT1, DIT2, DIT3, and DIT4 into output ODIT1, ODIT2, ODIT3 and ODIT4 as depicted in figure 2. The input PEs send the signal across weighted connections to the hidden units. Any hidden unit j sees the sum of all the weighted inputs, X, and a bias term.

$$h_j = \sum_{i=0}^{i=4} w_{ji} x_{i.}$$

The bias term can be interpreted as coming from an input DIT0 that always has the value 1. The weights wji are weights to the jth hidden unit from the ith input unit. The hidden unit j outputs a signal,

$$H_j = F\left(\sum_{i=0}^{i=4} w_{ji} x_i\right)$$

where F() is a sigmoid function as mentioned earlier. In a similar fashion, the kth output unit sees the sum of the weighted hidden units,

$$o_k = \sum_{j=0}^{j=4} w_{kj} H_j$$

where wkj are the hidden to output weights. The output unit then produces a signal,

$$O_k = F\left(\sum_{j=0}^{j=4} w_{kj} h_j\right)$$

as a function of a sigmoid. If the expression Hj is substituted into the expression just given, the resulting output activation is given as a function of inputs and weights.

$$O_k = F\left(\sum_{j=0}^{j=4} w_{kj} F\left(\sum_{i=0}^{i=4} w_{ji} x_i\right)\right) = F(x, \beta).$$

Where B represents a vector of all the weights, and x represents a vector of all the input values, and F(x,B) represents a vector of all the network's output values.

It is therefore the role of back-propagation learning algorithm to perform the input output mapping by making weight connection, B, adjustment according to the error between the computed and desired output values. For detail the reader is referred to [15].

7.5 POSTPROCESSOR

Transponder component selection and transponder performance evaluation is not trivial. As such multiple aspects such as; noise figure, gain, group delay, frequency translation and DITs are considered inorder to determine the performance of the device under investigation. As it is mentioned in the preceding sections both network models include multiple transponder characteristics measurements. It is thus essential to include a postprocessor which incorporates an analytical technique to interpret the ANN's response.

One of the possible techniques adopted is to categorize transponder performance modes in a descending order. Four major transponder performance modes are proposed which are : failed, severely degraded, degraded, and good. Each mode is assigned empirically determined threshold range values such as 9.5, 7.5, 6.0, and 5.0 respectively for model1 which may be altered in real life application.

As it is depicted in figure 8, the control unit includes an auxiliary threshold adjuster, whose task is to adjust the threshold values by comparing the raw incoming data with the ANN's estimations. However, for network performance validation purpose an optimum fixed threshold based on maximum number of estimated hits and minimum number of false alarms is implemented to interpret the ANN's response. The design of an adaptive dynamic threshold adjuster is another topic for future research. Tables 1 through 4 list modell's performance as function of thresholds.

Table 1. modell performance for threshold = 9.5				
TS.SAP	#FALSE	#MISS	#HIT	ES.DIT%
157	0	146	11	7.1%
157	0	86	2	2.3%
194	0	191	3	1.6%
194	0	120	6	4.8%

Table 2. modell performance for threshold = 7.5				
TS.SAP	#FALSE	#MISS	#HIT	ES.DIT%
157	0	60	97	61.8%
157	42	0	88	100.0%
194	0	153	41	21.4%
194	0	82	38	19.5%

Table 3. model1 performance for threshold = 6.0				
TS.SAP	#FALSE	#MISS	#HIT	ES.DIT%
157	0	60	97	61.9%
157	57	0	88	100.0%
194	0	40	154	79.4%
194	46	51	69	57.6%

Table 4. model1 performance for threshold = 5.0				
TS.SAP	#FALSE	#MISS	#HIT	ES.DIT%
157	0	0	157	100.0%
157	69	0	88	100.0%
194	0	0	194	100.0%
194	74	0	120	100.0%

TS.SAP The number of testing samples

#FALSE The number of false alarms; i.e number of times the ANN's response exceeds the threshold value when the transponder performance measure is within the tolerable range.

#MISS The number of undetected alarms; i.e the number of times the ANN's response is less than the threshold when in fact the transponder's performance measure is beyond the tolerable range.

#HIT The number of detected alarms; i.e the number of times the ANN's response is greater than or equal to the threshold when the transponder's performance measure is beyond the tolerable range.

ES.DIT% Percent of time the ANN's estimated degraded transponder performance given a degraded transponder.

The evaluation of the performance of the transponder/component is based on cooperative assessment of its tolerable specification and the postprocessor threshold values that optimize correct estimations (hit) and minimize incorrect estimations (false alarms). Similarly model2's postprocessor utilizes 7.5, 1.6, 1.6,and 0.2 empirically determined threshold values for ODIT4, ODIT3, ODIT2 and ODIT1 respectively. Tables 5 through 8 depict model2's performance for output ODIT4 as a function of thresholds.

Table 5. Model2 performance for threshold = 9.5				
TS.SAP	#FALSE	#MISS	#HIT	ES.DIT%
157	0	146	11	7.0%
157	0	100	40	26.0%
194	0	191	3	1.6%
194	0	191	3	1.6%

Table 6. Model2 performance for threshold = 7.5				
TS.SAP	#FALSE	#MISS	#HIT	ES.DIT%
157	0	49	108	29.5%
157	0	100	53	34.6%
194	16	80	59	42.5%
194	0	82	38	31.6%

Table 7. Model2 performance for threshold = 6.0				
TS.SAP	#FALSE	#MISS	#HIT	ES.DIT%
157	0	60	97	61.8%
157	0	1	152	99.4%
194	46	56	69	52.9%
194	16	80	59	42.5%

Table 8. Model2 performance for threshold = 5.0				
TS.SAP	#FALSE	#MISS	#HIT	ES.DIT%
157	0	0	157	100.0%
157	0	1	88	99.0%
194	74	0	120	100.0%
194	16	80	59	42.0%

8.0 ANN MODEL1 PERFORMANCE ANALYSIS

8.1 THE IMPACT OF HIDDEN UNITS

Hidden units in the design of ANN topology play a particular role because they contribute to the error at the output layer. To optimize the performance of a neural net design, an adequate number of hidden units are chosen empirically. The advantage of hidden units is that they provide flexibility and control over noisy data. They also can be used to model higher order statistical structure of the set of input vectors and provide control over the amount of information retained by the estimation processes [12]. In contrast the disadvantages are increased complexity and hard or slow learning which involves searching a much larger weight space.

Yet, the size of the ANN is determined based on the number of input units, number of training samples, and number of output units. In order to reduce the complexity therefore it is necessary to balance these three factors. The simulation result indicates that the best estimation performance is obtained when only the complexity of the ANN is matched to the amount of number of hidden units. Thus, a comparative assessment of the ANN's estimation relative to the number of hidden units in the hidden layer is made to determine the optimum number of hidden units.

Table 9 delineates modell's percentile transponder DIT estimation performance as a function of hidden units. The ANN's transponder DIT estimation performance analysis for different candidate topologies is based upon the result that minimizes the cost function. The topologies considered had 2, 3, 4, 6, and 12 units in their hidden layer. Each topology is trained on 1000 samples with fixed learning parameters and algorithm.

Table 9. Modell transponder DIT estimation performance as function of hidden units				
Hidden	ES.DIT= DIT+/-5	ES.DIT= DIT+/-3	ES.DIT= DIT+/-1	ES.DIT= DIT+/-.5
2	80.0%	63.3%	8.3%	5.0%
3	80.0%	63.3%	8.3%	5.0%
4	80.0%	63.3%	20.3%	5.0%
8	80.0%	63.7%	30.0%	15.0%
12	80.0%	66.7%	26.7%	25.0%

ES.DIT Modell's estimated DIT.

DIT Expected actual transponder DIT.

It is illustrated in table 9 that the ANN's transponder DIT estimation performance improves drastically as the number of hidden units are increased. However, it is worth to mention that the ANN's performance improvement was usually negligible past 12 units in the hidden layer. It is therefore justified to retain the network with 12 units in the hidden layer based upon the relatively large percentile transponder DIT estimation of 25% of the training data DIT within +/-0.5.

Furthermore, figure 8 depicts the expected actual transponder's DIT counts with respect to gain. Whereas, figure 9 depicts the corresponding estimations of the transponder's DIT counts by the selected ANN topology versus gain. A comparative evaluation of these figures indicates the similarity of the expected and estimated modell's output. Thus, the similarity between the two curves is an indication of the correctness of the estimation.

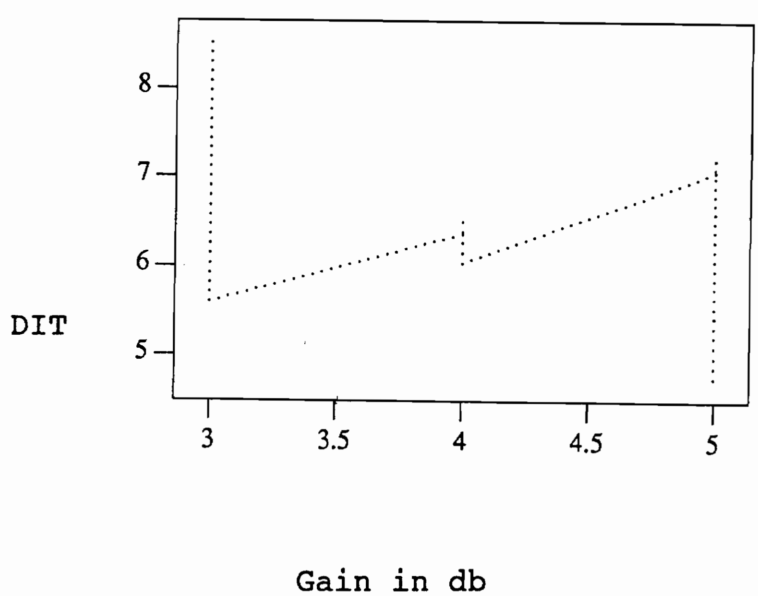


Figure 8 Transponder expected DIT w.r.t gain

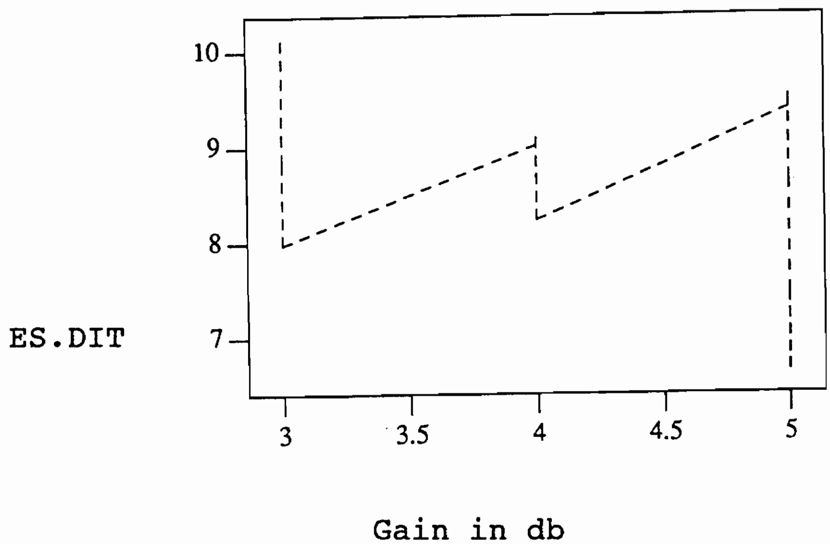


Figure 9 Modell DIT estimation w.r.t gain

8.2 THE IMPACT OF TRAINING & TESTING SETS

8.2.1 TRAINING PATTERNS

The first potential source of error lies with the specific input output training patterns used. Table 10 depicts ANN's performance for different training samples of the same set sizes. The result illustrates that different training samples lead to different estimation. For example, if the entire training set consisted of non-zero patterns, then the network would have a hard time extracting the onset for detecting extreme conditions. Similarly, if the training pattern consisted of a lot of zero patterns, the network would generalize to the zero function (output a zero regardless of the input). Although this specific scenario is highly unlikely, it points out that inappropriate training sample selection degrades the ANN's generalization and consequently estimation as it is depicted in table 10.

Table 10. ANN transponder DIT estimation performance as training patterns change

TR.PAT	ES.DIT= DIT+/-5	ES.DIT= DIT+/-3	ES.DIT= DIT+/-1	ES.DIT= DIT+/-.5
250	90.0%	75.0%	11.2%	3.8%
250	63.6%	35.0%	4.0%	2.2%
250	45.2%	23.0%	2.5%	0.0%
250	25.0%	14.0%	1.3%	0.8%

8.2.2 TESTING SET

Obviously, the choice of test patterns could also affect the performance measure that is obtained. The result of modell's transponder DIT estimation performance for various test sets is depicted in tables 11 and 12. A fairly good estimation figure is obtained as illustrated in table 11 if the test patterns are sampled from the same domain as the training patterns. However, a good estimation figure doesn't ensure that the ANN has learnt the function perfectly because the test set doesn't represent the population of all possible events.

Table 11. Modell transponder DIT estimation performance for trained test samples

TR.SAP	ES.DIT= DIT+/-5	ES.DIT= DIT+/-3	ES.DIT= DIT+/-1	ES.DIT= DIT+/-.5
150	95.2%	71.2%	7.6%	2.8%
200	68.0%	46.0%	4.0%	2.4%
250	53.6%	22.0%	4.4%	4.0%
300	84.8%	34.0%	0.8%	0.0%

TR.SAP   The number of training test samples.

Unfortunately, it is impossible to test the ANN on any significant fraction of all possible inputs to find out whether it is performing as expected. Yet, the doubt of the ANN's estimation could be overcome by averaging the ANN's performance measures over many training runs with different training and testing sets. The evaluation of the ANN transponder performance estimator is therefore dependent on the testing patterns selected; as it is illustrated in table 12. It is worth to note that the test data is only used to asses the estimation of the ANN and not to be trained with it.

Table 12. Modell transponder DIT estimation performance for test samples

TS.SAP	ES.DIT= DIT+/-5	ES.DIT= DIT+/-3	ES.DIT= DIT+/-1	ES.DIT= DIT+/-.5
100	78.0%	46.0%	10.0%	4.0%
100	71.0%	45.0%	17.0%	8.0%
100	60.0%	39.0%	5.0%	3.0%
100	96.4%	67.0%	0.0%	0.0%

TS.SAP The number of testing samples.

8.3 RESULTS AND PERFORMANCE ANALYSIS

8.3.1 RESULTS

It is necessary to provide a good estimation and prevent over-fitting the training data thereby the best performance is obtained when only the complexity of the network is matched to the amount of training data. Therefore, the analysis of the ANN behavior as a function of training data involves training the selected ANN topology with various training set sizes for a fixed number of iterations and learning parameters. The ANN was run for 200,000 iterations for training set1 through set5 which constitute 200, 400, 600, 800, and 1000 samples respectively. Table 13 shows model1's transponder DIT estimation performance on test patterns as a function of various training set sizes.

Table 13. Model1's transponder DIT estimation performance as function of training size

Samples	ES.DIT= DIT+/-5	ES.DIT= DIT+/-3	ES.DIT= DIT+/-1	ES.DIT= DIT+/-.5
200	65.0%	43.0%	13.3%	10.0%
400	66.7%	58.3%	31.7%	31.7%
600	86.7%	80.0%	43.3%	6.7%
800	80.0%	66.7%	20.0%	20.0%
1000	80.0%	63.3%	8.3%	5.0%

8.3.2 PERFORMANCE ANALYSIS

The ANN's performance analysis for different training set sizes is made relative to the specified error tolerance. The simulation process and the results indicate that the network learned the small training set size fairly well and quickly within the range of 10 to 20 minutes. However, for intermediate size of training samples the ANN hardly learned the input output relation. It is evident from table 13 that the ANN performs better in case of 400 training samples with 31.7% of the test data transponder DIT being estimated within +/-0.5 as opposed to the rival training sets.

Moreover, Figure 10 depicts model1's percentile transponders DIT estimation performance as a function of training samples for fixed learning parameters and iterations. Not surprisingly, the curve decreases as the training samples increase. Yet, two sharp humps are observed which could possibly be attributed to the resemblance of testing samples to the training samples. It is important to note that it doesn't necessarily mean that the ANN's performance decreases as the training samples increase, in contrast the ANN's performance will ultimately increase if the network is exposed to more input/output training samples with an appropriate choice of learning parameters and number of iterations. As a result, any estimation the ANN produces will be increasingly accurate and consistent with respect to the input space.

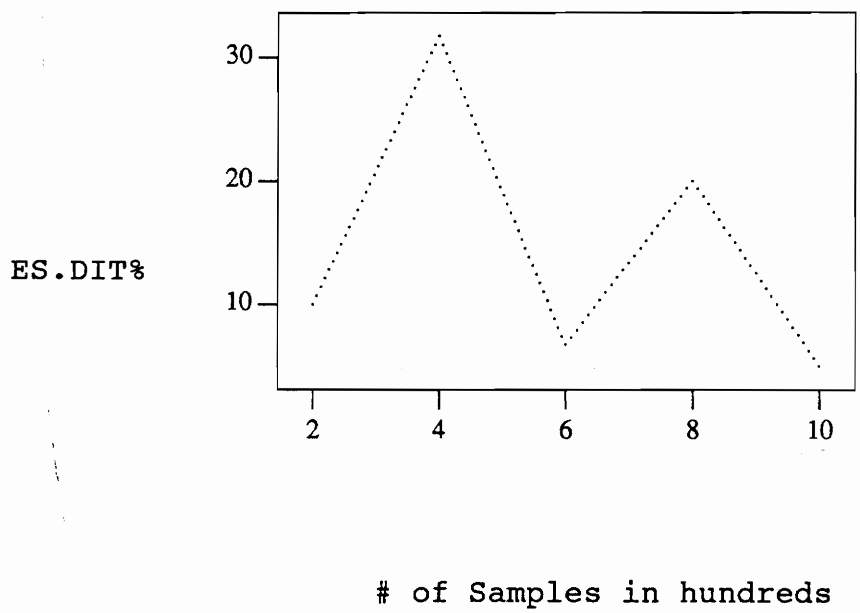


Figure 10 Modell's percentile transponder DIT estimation performance as function of training samples

A second explanation to this erratic humps could be, the outcome of the ANN generalization caused by the correlations within the training patterns or sufficient iterations required to achieve a steady state. That is, for small and large values of training samples, the ANN's estimation accuracy decreases due to over training and under training respectively. In contrast, for intermediate number of training samples the ANN's estimation accuracy increases because the ANN extracts the rule defining the input/output relation. These results, therefore indicate optimization of a feasible ANN architecture involves making an appropriate choice of training sets, iterations, and learning parameters.

8.4 THE IMPACT OF ITERATIONS

It is questionable whether the learning procedure which the heuristically selected topology implements learns the input output relation in a reasonable number of training iterations. It is interesting to ask how the ANN's performance is affected as a function of iteration for fixed learning parameters and training size of 800 samples. After the ANN is trained for 200,000, 400,000, 600,000, 800,000, and 1,000,000 iterations it is subsequently tested and its statistical performance is delineated in table 14. The statistics indicate the level of estimation the ANN performs thereby justifying the use of varying iteration to improve its transponder DIT estimation performance. It is evident from table 14 that the ANN's performance is optimum in the case of 800,000 iterations with 31.7% of the test data being estimated within +/-.5 of the expected transponder DIT performance measurements.

Table 14. Modell's transponder DIT estimation performance as function of iterations				
Iterations	ES.DIT= DIT+/-5	ES.DIT= DIT+/-3	ES.DIT= DIT=+/-1	ES.DIT= DIT+/-.5
200,000	66.7%	45.0%	13.3%	20.0%
400,000	65.0%	43.0%	31.0%	6.7%
600,000	78.3%	61.7%	5.0%	5.0%
800,000	66.7%	50.3%	31.7%	31.7%
1000,000	86.7%	61.7%	5.0%	3.3%

Figure 11 illustrates, modell's percentile transponder DIT estimation performance for several iterations. It is clear from figure 11 that the ANN's estimation performance is optimum for 800,000 iterations and drastically rolls off as the iterations are increased. This effect is usually attributed to the fact that the ANN starts to memorize the individual training patterns after some cycles through the training set rather than using some rule to categorize them. These results therefore justifies the possibility of memorizing or overtraining leading to performance degradation.

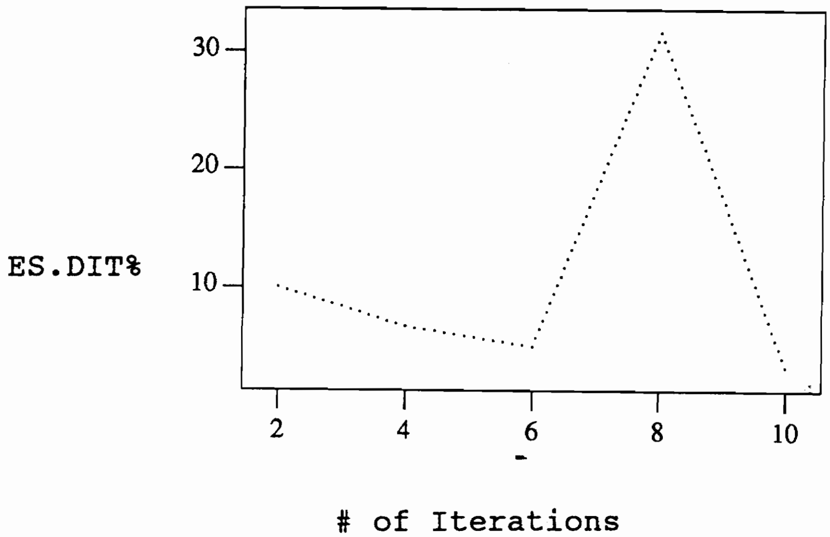


Figure 11 modell's percentile transponder DIT estimation performance as function of iterations.

8.5 THE IMPACT OF LEARNING PARAMETERS

The learning procedure adopted involves a set of weights which yield an arbitrary mapping from input to output. The procedure utilized is the gradient descent algorithm, which is bound by the problem of local minima [2]. Moreover, there arises a question of how long it might take a system to learn, adjusting the learning parameters in order to determine the halting criterion.

8.5.1 LEARNING RATE ALPHA & BETA

Since the sigmoid function can not actually reach its extreme values of 1 or 0, the error of the network will never be exactly zero, although it could get arbitrarily close. The training is thus halted when the network learns the training patterns to within 0.15 of the desired outputs; since it is impractical to train the ANN indefinitely. However, one of the problems of a gradient descent algorithm is setting an appropriate learning coefficient (alpha) to improve the convergence or learning rate. As a result, alpha is set to 0.9, 0.8, 0.7, 0.6, and 0.5 for fixed iterations and training size to determine its impact on the learning rate.

Table 15. Model1's transponder DIT estimation performance as function of learning coefficients

Alpha	ES.DIT= DIT+/-5	ES.DIT= DIT+/-3	ES.DIT= DIT+/-1	ES.DIT= DIT+/-.5
0.5	78.3%	61.7%	5.0%	5.0%
0.6	80.0%	63.3%	20.0%	5.0%
0.7	86.7%	63.3%	5.0%	5.0%
0.8	80.0%	61.7%	5.0%	5.0%
0.9	86.0%	61.7%	5.0%	3.3%

Table 15 delineates modell's transponder DIT estimation performance for several learning coefficients. It is possible to infer from table 15 that the rate of convergence is improved by setting alpha to 0.6 at the expense of a very slow learning rate. It is also evident from figure 12 that the ANN's percentile transponder DIT estimation performance versus alpha is average over the intermediate values between 0 and 1. To further optimize the ANN's performance and to solve the preceding dichotomy a momentum term (beta) is introduced.

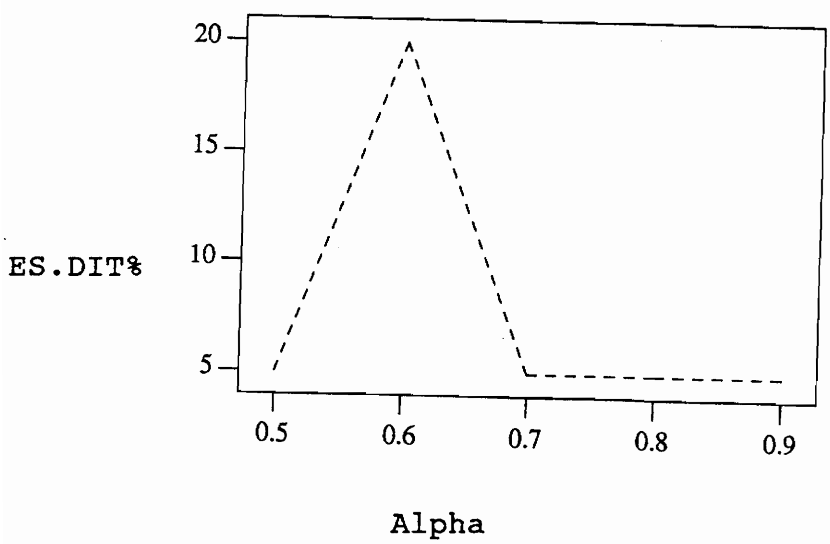
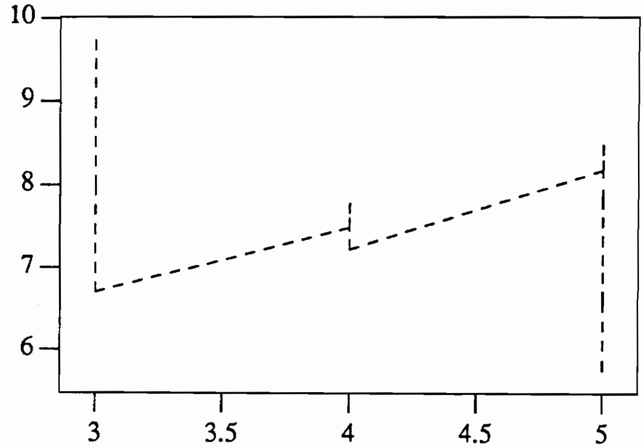


Figure 12 Modell percentile transponder DIT estimation as function of learning coefficient

To analyze the impact of beta two strategies are planned. The primary strategy was to train the ANN setting beta to 0.5, 0.4, 0.3, 0.2, and 0.1 while maintaining other parameters fixed. The simulation results indicated that the ANN's performance improvement as a result of this setting was not impressive; i.e the total error for the testing sets was very large. Nevertheless, the secondary plan was to vary both alpha and beta. Figure 13 shows model1's improved transponder DIT estimation performance relative to figure 9 as a result of the combined effect.

The ANN's performance improvement is due to the fact that the momentum term modifies the rate of weight update inorder to minimize the mean square error. The process of weight update is based on portion of the previous delta weight which is feed through to the current delta weight. This interdependence of the previous and current delta weights act as low pass filter on the delta weight term since general trends are reinforced whereas oscillatory behaviors cancel themselves out (see appendix c) [13].

ES.DIT



Gain in db

Figure 13 Modell's transponder DIT estimation for learning coefficients.

8.5.2 AUXILIARY COUNTER

The third parameter that has an impact on convergence and estimation of the ANN is an auxiliary counter which is referred to as an epoch [5]. In order to analyze the impact of an auxiliary counter on the performance of the ANN's transponder performance estimator, the strategy used is to vary the epoch while maintaining optimal: learning rates, topology, iteration, and training samples. The epoch is randomly set to 25, 75, 1000, and 1100. Table 16 delineates the modell's transponder DIT estimation performance for several epoch settings. The results indicate that the ANN's performance is optimum for an epoch value of 25.

Table 16. Modell's transponder DIT estimation performance as function of auxiliary counters

Aux.Cou	ES.DIT= DIT+/-5	ES.DIT= DIT+/-3	ES.DIT= DIT+/-1	ES.DIT= DIT+/-.5
25	66.7%	58.0%	31.7%	31.7%
35	80.0%	63.3%	8.3%	5.0%
75	65.0%	56.7%	31.7%	26.7%
1000	66.7%	58.3%	36.7%	16.7%
1100	66.7%	45.0%	21.7%	11.7%

Aux.Cou   Value of Auxiliary Counter.

Figure 14 shows improved modell's transponder DIT estimation performance versus gain for auxiliary counter equal to 25 relative to figure 13. The figure illustrates an intriguing effect of the epoch. This result is attributed to cumulative back-propagation learning rule used [5]. The simulation results justifies that this rule over performed the standard rule which is defined earlier. This improved performance is attributed to the fact that individual weight updates only reduce the error function for a particular pattern pair but increase other patterns error function. Whereas, the global update will always work towards reducing the overall error function. Thus, varying the epoch, the number of input/output pairs presented during accumulation, lead to faster convergence and improved performance.

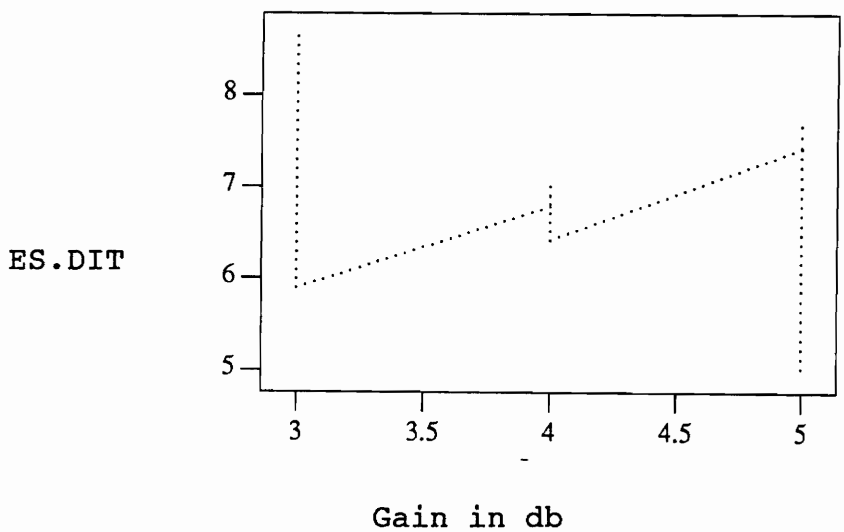
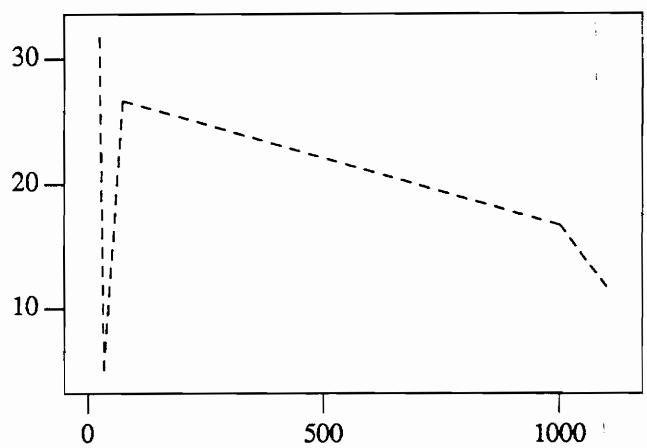


Figure 14 Modell's transponder DIT estimation performance for auxiliary=25

Figure 15 depicts modell's percentile transponder DIT estimation performance as a result of the described strategy indicating that intermediate epoch values yield improved performance as opposed to large epoch values . As it is illustrated in table 16 and depicted in figure 15 the ANN's performance degrades drastically when the epoch is relatively large. This is attributed to the fact that cumulative back-propagation requires many more calculation to be done to achieve a single update and the benefit of using an overall error function is lost when the epoch is large.

ES.DIT%



Values of Auxiliary counter

Figure 15 Modell's percentile transponder DIT estimation performance as function of auxiliary counters

Surprisingly at the time of the simulation, it was not known whether the various learning parameters could have an impact on the ANN's estimation. The learning parameters were normally varied to affect the convergence rate of the network. However, on testing the network, it was found for the most part the parameters affected the ANN's estimation. A notable exception was when the momentum was set to several values its impact on ANN's transponder DIT estimation performance was negligible. But, varying the epoch and the alpha improved the ANN's transponder DIT estimation performance greatly with the exception that the influence of the epoch was distinguishably pronounced.

9.0 ANN MODEL2 PERFORMANCE ANALYSIS

Identical procedure as model1 with minor modification is used to determine the number of hidden units, the learning parameters, the number of iterations and the number of training samples. The distinction between the two models is the complexity of the function that they are intended to extrapolate from the data.

9.1 TRAINING THE ANN

The ANN is trained with one thousand randomly selected input output samples generated by the preprocessor. The training time varied from two to eight hours depending on the type of the computer the software it is installed and the size of the training files. A comparative assessment of the ANN's estimation relative to the training file size is made to determine the appropriate size.It is found that for small number of training samples the ANN learned the training set fairly quickly within 1 to 2 hours. However for intermediate value of training samples, the ANN required relatively large number of runs and time which range from 12 to 24 hours. Table

17 delineates model2's percentile transponder ODIT4 estimation performance for various patterns within the training file. Since the mean square error never approaches zero, the training of the ANN is terminated when the it learned 75% of the training patterns to within +/-5 of the desired output.

After the network learned the training patterns, it is tested by presenting only the input fields and is left alone to estimate the output fields. It is important to note that in testing mode, unlike the training mode the learning rule does not adjust the connection strength of the ANN to compensate for the errors incurred.

Table 17. Model2's transponder ODIT4 estimation performance on training data

TR.DATA	ES.ODIT4= ODIT4+-5	ES.ODIT4= ODIT4+-3	ES.ODIT4= ODIT4+-1	ES.ODIT4= ODIT4+-.5
200	48.0%	37.9%	8.2%	1.8%
200	65.0%	60.6%	5.9%	1.5%
200	89.5%	70.3%	4.5%	2.4%
200	86.7%	75.3%	6.5%	3.0%
200	93.3%	90.0%	11.8%	5.6%

TR.DATA The number of trained test samples.

9.2 TEST RESULTS AND PERFORMANCE ANALYSIS

9.2.1 TEST RESULTS

Testing the trained ANN on testing files the following results are obtained. Table 18 delineates model2's percentile transponder ODIT4 estimation performance for various ranges within the testing sets.

Table 18. Model2's percentile transponder ODIT4 estimation performance on test data

TS.DATA	ES.ODIT4= ODIT4+-5	ES.ODIT4= ODIT4+-3	ES.ODIT4= ODIT4+-1	ES.ODIT4= ODIT4+-.5
200	55.7%	45.8%	8.0%	4.0%
200	60.0%	50.0%	7.0%	3.0%
200	65.0%	58.4%	9.0%	5.0%
200	73.0%	62.5%	11.0%	8.0%
200	96.0%	86.5%	4.0%	1.2%

9.2.2 PERFORMANCE ANALYSIS

The ANN's results are analyzed and compared to the validation file to determine their goodness relative to the transponder tolerable performance specification. The results indicate that most of the learnt input vectors are correctly estimated. To quantify it the ANN estimated 67% and 77% of the training ODIT4 data within +/-3 and +/-5 of the expected transponder ODIT4 performance measurements respectively. Inorder to assess the ANN's transponder performance parameters estimation the ANN is presented with test data that has never seen before. As it is illustrate in table 18, the ANN estimated on the average 61% and 70% of the testing ODIT4 data within (+-3) and (+-5) of the expected transponder ODIT4 performance measurements respectively. It is evident from tables 17 and 18 that model2 meets the objective specifications.

Apart from these statistical figures, the ANN generalized quantitatively by picking up the more complex relationship between the windows. More precisely, the ANN reflected the input's interdependence by out putting variable activation levels depending on the correlation between the window values. This justifies the networks sensitivity to the input patterns and the need of a comprehensible data presentation.

9.3 LEARNING AND ANN RESPONSE

The ANN model2's function is to estimate the performance of a given transponder circuit from the four window values. In difficult cases the ANN's estimation may get confused. Difficult cases include situations where the ANN fails to derive the input/output mapping function, such as; strange input patterns and one to many or vice versa input/output mapping. As a result the ANN's output vectors could be looked at as learned, spurious, or correct inference [10].

It is evident from table 17 and table 18 that model2's transponder ODIT4 estimation performance for several test sets reflects the preceding classifications. This is probably due to some mistakes made by the ANN during learning and could be caused by the correlation within the training patterns. For instance, let us consider a situation where multiple input patterns map into a single output pattern. That is a subset of the training set comprises input/output patterns that satisfy the many to one relationships. This many to one mapping generates a lot of noise which confuses the ANN's intuition. However, the ANN is forced to discover the best mapping possible and generalizes to the mean of all possible outputs which is always desired.

As a result of this generalization it is found that model2's estimation for test samples that resemble to the training patterns to be more accurate with 75.3% (table 17) of the training ODIT4 data being estimated within +/-3 of the expected transponder ODIT4 performance measurements. This is an indication that the learning procedure is properly capturing the mapping between the presented data and consequently the ANN's response is referred to as learned.

In contrast, a subset of the training file also comprises of single input patterns mapping into multiple output patterns. It is not always true that the ANN will be able to converge as in the previous case. The consequence of model2's divergent behavior is clearly illustrated in table 17 with 37.9% of the training ODIT4 data being estimated within +/-3 of the expected transponder ODIT4 performance measurements. This is an indication of the spurious model2's response justifying the need to impose constraints to minimize patterns leading to divergent behavior. As a result, model2's improved estimation is illustrated in table 17 with 90% of the training ODIT4 data being estimated within +/-3 of the expected transponder ODIT4 performance measurements. The overall model2's transponder performance parameters estimation is therefore satisfactory to meet the desired specifications.

9.4 RECALL CAPABILITY

Model2's recall capability is greatly affected by the amount of differences among the elements of the given windows. That is the bigger the difference among the elements of the given windows the most likely the ANN will estimate or recall the corresponding event correctly. For instance, it would be quite difficult for model2 to tell apart 7 from 8. This could be attributed to the fact that the connectivity weights of 7 and 8 are more or less about the same. As a result, when the model2 sees this numbers in the input it maps them into identical output values. This recall mechanism is referred to as the nearest-neighbor recall. On the other hand, the ANN accepts an input pattern and interpolates in a non-linear fashion form the entire set of stored inputs to produce the corresponding output. Referring to table 18 and table 17 it is possible to infer that model2's transponder ODIT4 estimation performance on the test set to mirror the performance on the trained set which is the result of an interpolative recall.

However, substantial price is paid due to the inaccuracy emitting from the inherent characteristics of generalization and estimation of model2. Thus, to improve model2's performance a postprocessor, as mentioned earlier to interpret the its response to different degree order of severity, is introduced. Table 19 depict model2's transponder performance estimation for various threshold values.

Table 19. model2's transponder performance estimation as function of thresholds

THRES.	FALSE%	MISS%	HIT%
9.5	0.0%	88.4%	9.1%
7.5	2.1%	55.3%	34.6%
6.0	12.1%	35.3%	64.2%
5.0	18.3%	14.7 %	85.3%

THRES. Postprocessor's threshold values.

It is evident, from the table that both correct estimation (hit) and incorrect estimation (false) rates are inversely proportional to the threshold value. However, a threshold value which maximizes the detection of degrading transponder circuits and minimizes the rate of false estimations is selected.

10.0 ANN IMPLEMENTATION

10.1 ANN AND TRANSPONDER AVAILABILITY

One of the major proposed applications of ANN is to improve satellite communication systems availability and reliability based on SATCOM transponder estimated performance. A comparative evaluation of figures 16, 17, and 18 indicates that the transponder's degraded performance in figure 16 is detected prior to its occurrence by the spikes both in figure 17 and 18. That is, degraded ODIT1 transponder performance measurement is detected when model2's transponder ODIT3 and ODIT4 estimations exceed 1.6 and 7.5 empirically selected postprocessor thresholds respectively.

One factor favoring the selection of 7.5 as an optimum threshold for model2's postprocessor is the percentile comparison of the correct estimations versus incorrect estimations tradeoffs are small than they are for the rival thresholds. Thought the postprocessor with 5.0 as a threshold performs better in case of hit (85.3%table 19), false alarm percentile is relatively high (18.3%table 19). Justification for the selection of 7.5 as a threshold for the postprocessor therefore, lies in its relative low false alarms (1.2%) and relatively high hits (34.6%).

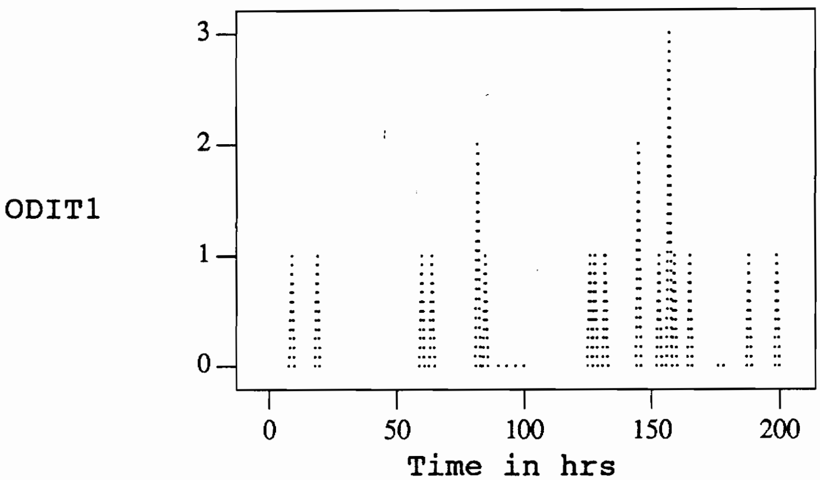


Figure 16 Expected transponder ODIT1 performance measurements for test samples as function of time

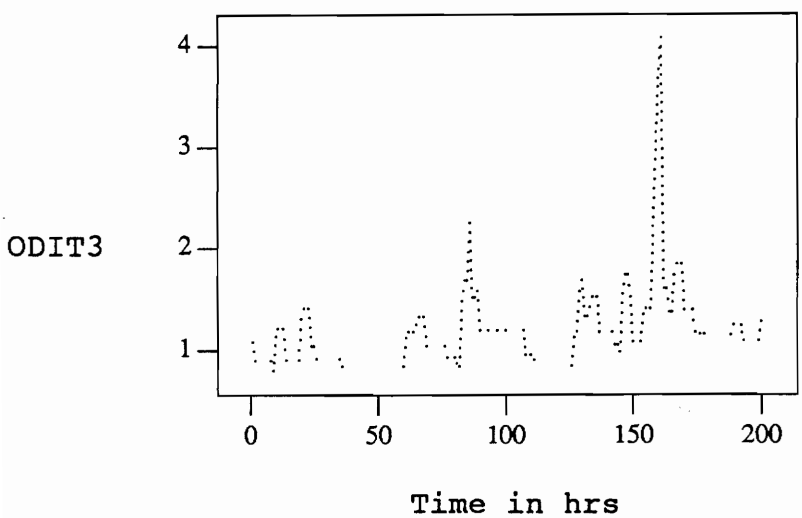


Figure 17 Model2's transponder ODIT3 performance measurement estimation as function of time

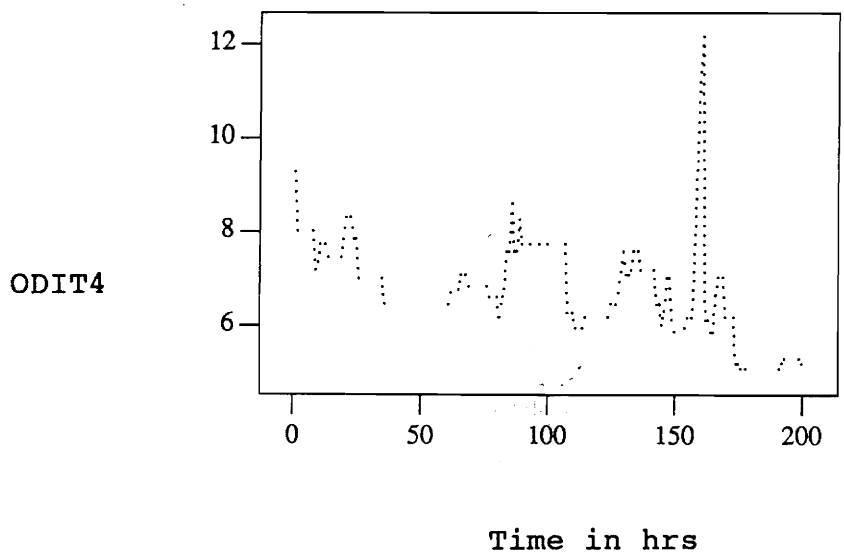


Figure 18 Model2's transponder ODIT4 performance measurement estimation as function of time

As it is mentioned in the previous section, each model2's transponder performance estimation response posses time information and is assigned a rank to be utilized to evaluate transponder performance. This time information is used to compute the average MLT to degraded transponder performance. The average MLT derived from model2's estimated responses are 15 hours and 4 hours for ODIT4 and ODIT3 respectively. These figures in conjunction with the postprocessor results serve two major purposes; i.e to improve the reliability and the availability of SATCOM transponders.

Primarily, the knowledge of MLT is useful to allocate and determine the number of redundant depending on the number of estimated degraded transponder performance keeping in mind that the use of the component will end at some specified time. Secondly, the knowledge of MLT enables ground station controllers to set an alternative path through the transponder by telecommand following the ANN's estimation of the primary path or activate a stand by component. The operation of both the standby and an active component simultaneously parallel will then guarantee the availability of the system around the time the failure is expected. As a result, the ANN's transponder performance estimation will optimize transponder reliability and availability which in turn will optimize satellite communication systems service quality as it is mentioned in the objective.

10.1 ANN AND TRANSPONDER RELIABILITY

As it is stated in the preceding section fault tolerant systems degrade gracefully even if there are component failures. Appropriate components choice using ANN estimation will then eliminate the degradation due to components failures. Table 20 delineates, modell's correct transponder/components performance estimation that exceeded different levels of thresholds. It is therefore possible to select components that show tolerable performance degradation. For instance, 7.5 is chosen as modell's transponder/component rejection criterion. The factors in selecting 7.5 as a threshold include: the tradeoffs between the coast of eliminating good transponder/component versus the coast of bad components in orbit and the importance of the transponder failure to mission success.

Table 20. modell Tra./Comp. performance estimation as function of thresholds

THRES.	FALSE%	MISS%	HIT%
9.5	0.0%	94.9%	9.1%
7.5	2.9%	55.6%	44.4%
6.0	12.1%	35.4%	64.2%
5.0	18.3%	14.4%	85.3%

However, the rate of incorrect estimation introduces a draw back in the fidelity of ANN's transponder/component performance estimation. The draw back could be minimized by using stringent threshold values. That is, the rate of incorrect estimation decreases as the performance requirements increase thereby pronouncing the certainty of the transponder performance estimation.

It is illustrated in the preceding tables, that the percentage of hits, misses, and false estimation varies significantly for various testing data sets. But on the average 30%-60% of the actual failed transponder/components performance were correctly estimated given failed transponders. The result achieved therefore meets the desired ANN design specification.

Finally, the benefit of improved screening is invaluable because the added screening using ANN eliminates transponder/components which would have failed during prelaunch test or in orbit. Thus ANN's estimation will be useful to system designers and controllers in judging transponder/component degradation in order to improve its reliability and availability.

11.0 SUMMARY AND CONCLUSION

The over all transponder design philosophy is generally conservative in that the number of entirely new developments is kept low to a minimum. To the design engineer this conservatism can be frustrating, since it retards the acceptance of technical improvements, the very life blood of technology. However, the proposed methodology using ANN for performance estimation and component selection will hopefully break the technophobia in the SATCOM arena.

What neural networks technology would bring to the transponder circuit performance estimation problem would be two new components that open up the range of possibilities for solution:

- The potential for massively parallel computational hardware
- The potential for improved programmability by using learning algorithms.

Powerful learning algorithms are one of the main strengths of the neural network approach in solving the performance analysis problem mentioned in the first section, because the basic processing elements, referred to as short term memory, of the ANN are relatively simple. It is found that a particular ANN can represent a desired function if an appropriate data based on input output examples exists. The result is showing that ANN learning could be used to calculate the connection weights so that the ANN could approximate the function. Ultimately, ANN learning could be used for addressing the SATCOM transponder service performance analysis need for adaptation to new services requirement and new technologies.

In summary, this design proposes two models of ANN architecture as candidates for statistical estimation of the performance of SATCOM transponder and its constituent components. One of the models contains 12 PEs, a bias, 3 layers, and 128 connections. Each layer contains 4 PEs. Whereas, the second model contains 17 PEs, a bias, 3 layers, and 55 connections. Whereby, each the input, hidden, and output layers contain 4, 12, and 1 PE(s) respectively. The

ANNs were trained on hypothetical data generated based on the characteristics of INTELSAT V transponder and hypothetical assumption based on experience acquired from relevant work which relates to the issue discussed in this paper. The specification and requirements are based on considerations of both neural net characteristics and the problem's complexity. Based on the specification set forth for the ANN transponder performance estimators, five ANN topologies for each model were modeled and two models with 4 and 12 PEs in the hidden layer were selected based on minimum mean square error, minimum mean false alarms, maximum mean alarms, and minimum undetected alarms.

Finally, upon testing, the ANN accurately estimated 30% - 40% of the actual one day critical degradations with roughly 2% - 5% false alarms. Estimating critical degradations with a flexible model such as ANN will increase customer satisfaction by improving service quality and availability of the transponder by taking preventive actions. Therefore, the possibility of artificial common sense for estimation combined with traditional computation for precision, becomes attractive. Perhaps now it is practical to develop a different class of artificial systems, ANN, to aid designers and performance analysts with mechanical common sense to solve the growing and complex transponder performance analysis and design problems.

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APPENDIX A. Model1 Training File

N	P	F	G	DIT
0	0	0	4	11
0	0	0	4	11
0	0	0	4	11
0	0	0	3	11
0	0	0	3	11
0	0	0	3	11
1	1	1	4	10
0	1	1	4	10
0	1	1	4	10
1	2	2	5	9
0	1	2	5	10
0	1	2	5	10
0	1	2	5	10
0	0	2	5	10
2	2	4	7	8
0	2	4	7	8
0	2	4	7	8
0	2	4	7	8
0	0	4	7	8
1	1	5	8	7
0	1	5	8	7
1	2	6	8	6
0	2	5	8	6
0	1	5	6	6
1	2	6	7	5
0	1	5	7	5
0	1	5	7	5
0	1	5	7	5
0	0	5	7	5
0	0	5	7	5
0	0	3	7	5
0	0	3	7	6
0	0	3	7	6
1	1	4	8	5
0	1	4	8	5
0	1	3	8	5
0	1	3	8	5
0	0	2	8	5
0	0	2	8	5
0	0	2	8	5
0	0	1	8	5
0	0	1	8	5
0	0	1	8	5
0	0	1	8	5
0	0	1	8	5
0	0	1	8	5

0	0	1	8	5
0	0	1	8	5
0	0	1	8	5
0	0	0	8	5
0	0	0	8	5
0	0	0	8	5
0	0	0	8	5
0	0	0	8	5
0	0	0	8	5
1	1	1	9	4
0	1	1	9	4
1	2	2	10	3
0	2	2	10	3
0	1	2	10	3
0	1	2	10	3
0	0	2	10	3
0	0	2	10	3
0	0	2	10	3
0	0	2	10	3
0	0	2	10	3
0	0	2	10	3
0	0	2	10	3
0	0	2	10	3
0	0	2	10	3
0	0	2	10	3
0	0	1	10	3
0	0	1	10	3
0	0	0	10	3
0	0	0	10	3
0	0	0	10	3
0	0	0	10	3
0	0	0	10	3
0	0	0	10	3
0	0	0	10	3
0	0	0	10	3
0	0	0	10	3
0	0	0	10	3
0	0	0	10	3
0	0	0	10	3
0	0	0	10	3
0	0	0	10	5
0	0	0	10	5
0	0	0	10	5
0	0	0	10	5
0	0	0	10	5
0	0	0	10	5
0	0	0	10	5
1	1	1	11	4
0	1	1	11	4
0	1	1	11	4

APPENDIX B. Modell Test File

F	P	G	N
0	0	2	3
0	0	1	3
0	0	1	3
0	0	1	3
0	0	1	3
0	0	1	3
0	0	1	3
0	0	1	3
0	0	0	3
1	1	1	4
0	1	1	4
0	1	1	4
0	1	1	4
0	0	1	4
0	0	1	4
0	0	1	4
0	0	1	4
0	0	1	4
0	0	1	4
1	1	2	5
0	1	2	5
0	1	2	5
0	1	2	5
0	0	2	5
0	0	2	5
0	0	1	5
0	0	1	5
0	0	1	5
0	0	1	5
0	0	1	5
0	0	1	5
0	0	1	5
0	0	1	5
0	0	1	5
0	0	1	5
0	0	0	5
0	0	0	5
0	0	0	5
0	0	0	5
0	0	0	5
0	0	0	5
0	0	0	5
0	0	0	5
0	0	0	5
0	0	0	5
0	0	0	5

0	0	0	5
0	0	0	5
0	0	0	5
0	0	0	5
0	0	0	5
0	0	0	5
0	0	0	5
0	0	0	5
0	0	0	5
0	0	0	5
0	0	0	5
0	0	0	5
0	0	0	5
0	0	0	5
1	1	1	6
0	1	1	6
0	1	1	6
0	1	1	6
1	1	2	7
0	1	2	7
0	1	2	7
0	1	2	7
0	0	2	7
0	0	2	7
0	0	2	7
0	0	2	7
0	0	2	7
0	0	2	7
0	0	2	7
0	0	2	7
0	0	1	6
0	0	1	6
0	0	1	6
0	0	1	6
0	0	0	6
0	0	0	5
2	2	2	7
0	2	2	7
0	2	2	7
1	3	3	8
0	1	3	8
0	1	3	8
0	1	3	7
0	0	3	7
0	0	3	7
0	0	3	7
0	0	3	7
0	0	3	7
0	0	3	7

APPENDIX C Back-Propagation Learning Algorithm

This appendix summarizes the back-propagation learning algorithm.

Xj[s] current output state of Jth neuron in layer [s].
Wji[s] weight on connection joining Ith neuron in layer[s-1] to Jth neuron in layer [s].
Ij[s] weighted summation of inputs to Jth neuron in layer [s].

$$\begin{aligned} Xj[s] &= F\{sumi\ (Wji*Xi)\} \\ &= F(Ij[s]) \end{aligned}$$

where F is the sigmoid function

$$F(z) = 1/(1+e\hat{}-z)$$

Let the global error function be E which is differentiable function of all the connection weights in the network.

$$E = 0.5\{sumk\ (Dk-Ok)\hat{}2\}$$

where Dk desired output
Ok network's output

The local error of each processing element is therefore the partial derivative of the global error function w.r.t. Ij[s]. i.e

$$ej[s] = Xj[s]*(1.0-Xj[s])*\{sumj\ (ek[s=1]*Wkj[s=1])\}.$$

To minimize the global error it requires to determine the delta weight using the gradient descent rule. The delta weight is a product of the learning coefficient, alpha, and the partial derivative of E w.r.t Wji[s]. i.e

$$DeltaWji[s] = -alpha*ej[s]*Xi[s-1]$$

Finally the back-propagation updates all weight in the network by adding the delta weight to the corresponding previous weights.
To improve the learning rate delta weight is modified so that a portion of the previous delta weight is feed through the current delta eight.

$$DeltaWji[s] = alpha*ej[s]*Xi[s-1] + beta*Wji[s-1].$$

APPENDIX D ANN Final Connection Weight Vectors

Title: MODEL1 ANN TRANSPONDER /COMPONENT PERFORMANCE ESTIMATOR
Display Mode: Network Type:
Hetero-Associative
Display Style: default
Control Strategy: backprop L/R Schedule:
backprop
800001 Learn 0 Recall 0
Layer
25 Aux 1 0 Aux 2 0 Aux
3
L/R Schedule: backprop
Recall Step 1 0 0
0 0
Input Clamp 0.0000 0.0000 0.0000
0.0000 0.0000
Firing Density 100.0000 0.0000 0.0000
0.0000 0.0000
Temperature 0.0000 0.0000 0.0000
0.0000 0.0000
Gain 1.0000 0.0000 0.0000
0.0000 0.0000
Modifier 1.0000 0.0000 0.0000
0.0000 0.0000
Learn Step 200000 200000 200000
100000 100000
Coefficient 1 0.9000 0.8000 0.7000
0.6000 0.5000
Coefficient 2 0.6000 0.5000 0.4000
0.3000 0.2000
Coefficient 3 0.0000 0.0000 0.0000
0.0000 0.0000
Temperature 0.0000 0.0000 0.0000
0.0000 0.0000
IO Parameters
Learn Data: File Rand. (trmod1) Binary
Recall Data: File Seq. (tsmod1)
Result File: Input, Desired Output, Output
UserIO Program: userio
I/P Ranges: 0.0000, 1.0000
O/P Ranges: 0.0000, 1.0000
I/P Start Col: 1 O/P Start Col:
5
MinMax Table: trmod1 # entries:
5
Col: 1 2 3 4
5
Min: 0.0000 0.0000 0.0000 0.0000

```
0.0000
Max:              3             6            11            22
22
Layer: 1
        PEs: 1                                             Sum: Sum
    Spacing: 5        F' offset: 0.00                  Transfer:
Linear
      Shape: Square                                      Output:
Direct
      Scale: 1.00      Low Limit: 0.00              Error Func:
standard
     Offset: 0.00    High Limit: 9999.00                  Learn:
--None--
   Init Low: -0.100   Init High: 0.100          L/R Schedule:
(Network)
   Winner 1: None                                    Winner 2:
None
   PE: Bias
       1.000 Error Factor
       0.000 Sum                1.000 Transfer             1.000
Output
           0 Weights       -152.994 Error                  0.000
Current Error
Layer: In
        PEs: 4                                             Sum: Sum
    Spacing: 5        F' offset: 0.00                  Transfer:
Linear
      Shape: Square                                      Output:
Direct
      Scale: 1.00      Low Limit: -9999.00          Error Func:
standard
     Offset: 0.00    High Limit: 9999.00                  Learn:
--None--
   Init Low: -0.100   Init High: 0.100          L/R Schedule:
(Network)
   Winner 1: None                                    Winner 2:
None
   PE: N
       1.000 Error Factor
       0.000 Sum                0.000 Transfer             0.000
Output
           0 Weights          0.004 Error                  0.000
Current Error
           Input PE  Input Value Weight Type Delta Weight
   PE: P
       1.000 Error Factor
       0.000 Sum                0.000 Transfer             0.000
Output
           0 Weights         -0.010 Error                  0.000
```

```
Current Error
             Input PE  Input Value Weight Type Delta Weight
   PE: F
       1.000 Error Factor
       0.000 Sum                0.000 Transfer          0.000
Output
             0 Weights         -0.062 Error             0.000
Current Error
             Input PE  Input Value Weight Type Delta Weight
   PE: G
       1.000 Error Factor
       0.136 Sum                0.136 Transfer          0.136
Output
             0 Weights          0.074 Error             0.000
Current Error
             Input PE  Input Value Weight Type Delta Weight
Layer: Hidden 1
        PEs: 12                                      Sum: Sum
    Spacing: 5       F' offset: 0.00               Transfer:
Sigmoid
      Shape: Square                                  Output:
Direct
      Scale: 1.00     Low Limit: -9999.00       Error Func:
standard
     Offset: 0.00    High Limit: 9999.00             Learn:
Norm-Cum-Delta
   Init Low: -0.100   Init High: 0.100       L/R Schedule:
(Network)
   Winner 1: None                                Winner 2:
None
   PE: 6
       1.000 Error Factor
      -1.521 Sum                0.179 Transfer          0.179
Output
             4 Weights         -0.005 Error            -0.035
Current Error
             Input PE  Input Value Weight Type Delta Weight
                 Bias   +1.0000   -1.7136 V-a   -0.0005
                    N   +0.0000   -0.7987 V-a   +0.0000
                    P   +0.0000   -0.8423 V-a   +0.0000
                    G   +0.1364   +1.4093 V-a   -0.0001
   PE: 7
       1.000 Error Factor
      -1.326 Sum                0.210 Transfer          0.210
Output
             4 Weights         -0.006 Error            -0.033
Current Error
             Input PE  Input Value Weight Type Delta Weight
                 Bias   +1.0000   -1.5028 V-a   -0.0006
```

```
                    P    +0.0000    -0.7301 V-a    +0.0000
                    F    +0.0000    -0.8322 V-a    +0.0000
                    G    +0.1364    +1.2938 V-a    -0.0001
   PE: 8
       1.000 Error Factor
      -1.123 Sum               0.245 Transfer              0.245
Output
           5 Weights          -0.005 Error                -0.027
Current Error
           Input PE  Input Value Weight Type Delta Weight
               Bias  +1.0000    -1.1073 V-a    -0.0005
                  N  +0.0000    +0.0355 V-a    +0.0000
                  P  +0.0000    -0.6265 V-a    +0.0000
                  F  +0.0000    -1.6455 V-a    +0.0000
                  G  +0.1364    -0.1155 V-a    -0.0001
   PE: 9
       1.000 Error Factor
      -1.324 Sum               0.210 Transfer              0.210
Output
           4 Weights          -0.002 Error                -0.010
Current Error
           Input PE  Input Value Weight Type Delta Weight
               Bias  +1.0000    -1.3297 V-a    -0.0002
                  P  +0.0000    -0.3443 V-a    +0.0000
                  F  +0.0000    -0.5624 V-a    +0.0000
                  G  +0.1364    +0.0391 V-a    -0.0000
   PE: 10
       1.000 Error Factor
      -1.351 Sum               0.206 Transfer              0.206
Output
           5 Weights          -0.002 Error                -0.010
Current Error
           Input PE  Input Value Weight Type Delta Weight
               Bias  +1.0000    -1.3043 V-a    -0.0002
                  N  +0.0000    +0.0397 V-a    +0.0000
                  P  +0.0000    -0.2798 V-a    +0.0000
                  F  +0.0000    -0.8608 V-a    +0.0000
                  G  +0.1364    -0.3454 V-a    -0.0000
   PE: 11
       1.000 Error Factor
      -1.279 Sum               0.218 Transfer              0.218
Output
           4 Weights          -0.002 Error                -0.014
Current Error
           Input PE  Input Value Weight Type Delta Weight
               Bias  +1.0000    -1.3077 V-a    -0.0002
                  P  +0.0000    -0.5387 V-a    +0.0000
                  F  +0.0000    -0.5317 V-a    +0.0000
                  G  +0.1364    +0.2102 V-a    -0.0000
```

```
   PE: 12
       1.000 Error Factor
      -1.229 Sum                   0.226 Transfer              0.226
Output
           4 Weights             -0.003 Error                  -0.017
Current Error
           Input PE  Input Value Weight Type Delta Weight
               Bias   +1.0000    -1.2288 V-a    -0.0003
                  N   +0.0000    -0.1764 V-a    +0.0000
                  P   +0.0000    -0.4628 V-a    +0.0000
                  F   +0.0000    -1.0022 V-a    +0.0000
   PE: 13
       1.000 Error Factor
      -1.285 Sum                   0.217 Transfer              0.217
Output
           5 Weights             -0.003 Error                  -0.016
Current Error
           Input PE  Input Value Weight Type Delta Weight
               Bias   +1.0000    -1.2674 V-a    -0.0003
                  N   +0.0000    -0.0238 V-a    +0.0000
                  P   +0.0000    -0.3901 V-a    +0.0000
                  F   +0.0000    -1.1110 V-a    +0.0000
                  G   +0.1364    -0.1318 V-a    -0.0000
   PE: 14
       1.000 Error Factor
      -1.475 Sum                   0.186 Transfer              0.186
Output
           4 Weights             -0.004 Error                  -0.029
Current Error
           Input PE  Input Value Weight Type Delta Weight
               Bias   +1.0000    -1.6537 V-a    -0.0004
                  P   +0.0000    -0.7066 V-a    +0.0000
                  F   +0.0000    -0.3329 V-a    +0.0000
                  G   +0.1364    +1.3107 V-a    -0.0001
   PE: 15
       1.000 Error Factor
      -1.338 Sum                   0.208 Transfer              0.208
Output
           5 Weights             -0.001 Error                  -0.009
Current Error
           Input PE  Input Value Weight Type Delta Weight
               Bias   +1.0000    -1.3040 V-a    -0.0001
                  N   +0.0000    +0.0313 V-a    +0.0000
                  P   +0.0000    -0.2215 V-a    +0.0000
                  F   +0.0000    -0.7801 V-a    +0.0000
                  G   +0.1364    -0.2472 V-a    -0.0000
   PE: 16
       1.000 Error Factor
      -1.311 Sum                   0.212 Transfer              0.212
```

```
Output
            3 Weights         -0.001 Error                 -0.008
Current Error
            Input PE  Input Value Weight Type Delta Weight
                Bias   +1.0000    -1.3209 V-a   -0.0001
                   F   +0.0000    -0.5174 V-a   +0.0000
                   G   +0.1364    +0.0711 V-a   -0.0000
   PE: 17
       1.000 Error Factor
       1.310 Sum               0.787 Transfer          0.787
Output
            4 Weights          0.017 Error                  0.104
Current Error
            Input PE  Input Value Weight Type Delta Weight
                Bias   +1.0000    +0.5788 V-a   +0.0017
                   P   +0.0000    -1.6992 V-a   +0.0000
                   F   +0.0000    -5.0218 V-a   +0.0000
                   G   +0.1364    +5.3607 V-a   +0.0002
Layer: Out
        PEs: 1                                       Sum: Sum
    Spacing: 5          F' offset: 0.00             Transfer:
Sigmoid
      Shape: Square                                   Output:
Direct
      Scale: 1.00       Low Limit: -9999.00       Error Func:
standard
     Offset: 0.00     High Limit: 9999.00             Learn:
Norm-Cum-Delta
   Init Low: -0.100    Init High: 0.100        L/R Schedule:
(Network)
   Winner 1: None                                  Winner 2:
None
   PE: DIT
       1.000 Error Factor
      -0.836 Sum               0.302 Transfer          0.302
Output
           13 Weights         -0.025 Error                 -0.120
Current Error
            Input PE  Input Value Weight Type Delta Weight
                Bias   +1.0000    +0.6792 V-a   -0.0025
                   6   +0.1792    +1.3745 V-a   -0.0005
                   7   +0.2098    +1.3148 V-a   -0.0005
                   8   +0.2454    +1.0675 V-a   -0.0006
                   9   +0.2101    +0.4031 V-a   -0.0005
                  10   +0.2056    +0.3817 V-a   -0.0005
                  11   +0.2177    +0.5314 V-a   -0.0006
                  12   +0.2264    +0.6862 V-a   -0.0006
                  13   +0.2166    +0.6460 V-a   -0.0006
                  14   +0.1862    +1.1515 V-a   -0.0005
```

15	+0.2079	+0.3566 V-a	-0.0005
16	+0.2123	+0.2962 V-a	-0.0005
17	+0.7875	-4.0958 V-a	-0.0020

```
Title: MODEL2 ANN TRANSPONDER/COMPONENT PERFORMANCE ESTIMATOR
       Display Mode: Network                              Type:
Hetero-Associative
      Display Style: default
   Control Strategy: backprop                     L/R Schedule:
backprop
     5003001 Learn                  0 Recall                 0
Layer
          35 Aux 1                0 Aux 2                0 Aux
3
L/R Schedule: backprop
   Recall Step                1          0          0
 0         0
     Input Clamp           0.0000     0.0000     0.0000
0.0000     0.0000
     Firing Density      100.0000     0.0000     0.0000
0.0000     0.0000
     Temperature           0.0000     0.0000     0.0000
0.0000     0.0000
     Gain                  1.0000     0.0000     0.0000
0.0000     0.0000
     Modifier              1.0000     0.0000     0.0000
0.0000     0.0000
   Learn Step             1000000    1000000    1000000
1000000    1000000
     Coefficient 1         0.9000     0.8000     0.7000
0.6000     0.5000
     Coefficient 2         0.6000     0.5000     0.3000
0.2500     0.1000
     Coefficient 3         0.0000     0.0000     0.0000
0.0000     0.0000
     Temperature           0.0000     0.0000     0.0000
0.0000     0.0000
IO Parameters
        Learn Data: File Rand. (trmod2) Binary
       Recall Data: File Seq. (fsnwts1)
       Result File: Input, Desired Output, Output
    UserIO Program: userio
        I/P Ranges:     0.0000,     1.0000
        O/P Ranges:     0.0000,     1.0000
     I/P Start Col:          1           O/P Start Col:
      5
      MinMax Table: trmod2                      # entries:
      8
```

```
Col:           1            2            3            4
5           6
Min:      0.0000       0.0000       0.0000       0.0000
0.0000      0.0000
Max:          22           11            6            3
3           6
Col:           7            8
Min:      0.0000       0.0000
Max:          11           22
Layer: 1
        PEs: 1                                        Sum: Sum
    Spacing: 5        F' offset: 0.00               Transfer:
Linear
      Shape: Square                                   Output:
Direct
      Scale: 1.00      Low Limit: 0.00           Error Func:
standard
     Offset: 0.00     High Limit: 9999.00             Learn:
--None--
   Init Low: -0.100    Init High: 0.100        L/R Schedule:
(Network)
   Winner 1: None                                  Winner 2:
None
   PE: Bias
       1.000 Error Factor
       0.000 Sum               1.000 Transfer          1.000
Output
           0 Weights      -2920.927 Error              0.000
Current Error
Layer: In
        PEs: 4                                        Sum: Sum
    Spacing: 5        F' offset: 0.00               Transfer:
Linear
      Shape: Square                                   Output:
Direct
      Scale: 1.00      Low Limit: -9999.00       Error Func:
standard
     Offset: 0.00     High Limit: 9999.00             Learn:
--None--
   Init Low: -0.100    Init High: 0.100        L/R Schedule:
(Network)
   Winner 1: None                                  Winner 2:
None
   PE: DIT4
       1.000 Error Factor
       0.227 Sum               0.227 Transfer          0.227
Output
           0 Weights         -0.079 Error              0.000
Current Error
```

```
           Input PE  Input Value Weight Type Delta Weight
   PE: DIT3
       1.000 Error Factor
       0.000 Sum               0.000 Transfer          0.000
Output
           0 Weights           0.096 Error             0.000
Current Error
           Input PE  Input Value Weight Type Delta Weight
   PE: DIT2
       1.000 Error Factor
       0.000 Sum               0.000 Transfer          0.000
Output
           0 Weights           0.040 Error             0.000
Current Error
           Input PE  Input Value Weight Type Delta Weight
   PE: DIT1
       1.000 Error Factor
       0.000 Sum               0.000 Transfer          0.000
Output
           0 Weights          -0.010 Error             0.000
Current Error
           Input PE  Input Value Weight Type Delta Weight
Layer: Hidden 1
        PEs: 4                                      Sum: Sum
    Spacing: 5        F' offset: 0.00             Transfer:
Sigmoid
      Shape: Square                                 Output:
Direct
      Scale: 1.00      Low Limit: -9999.00       Error Func:
standard
     Offset: 0.00     High Limit: 9999.00            Learn:
Norm-Cum-Delta
   Init Low: -0.100    Init High: 0.100        L/R Schedule:
backprop
   Winner 1: None                                 Winner 2:
None
L/R Schedule: backprop
   Recall Step                 1          0          0
 0          0
     Input Clamp            0.0000     0.0000     0.0000
0.0000     0.0000
     Firing Density       100.0000     0.0000     0.0000
0.0000     0.0000
     Temperature            0.0000     0.0000     0.0000
0.0000     0.0000
     Gain                   1.0000     0.0000     0.0000
0.0000     0.0000
     Modifier               1.0000     0.0000     0.0000
0.0000     0.0000
```

```
   Learn Step                    1000000      1000000      1000000
1000000    1000000
     Coefficient 1               0.9000       0.8000       0.7000
0.6000     0.5000
     Coefficient 2               0.6000       0.5000       0.3000
0.2500     0.1000
     Coefficient 3               0.0000       0.0000       0.0000
0.0000     0.0000
     Temperature                 0.0000       0.0000       0.0000
0.0000     0.0000
   PE: 6
       1.000 Error Factor
      -1.619 Sum                    0.165 Transfer              0.165
Output
           5 Weights               -0.002 Error                -0.013
Current Error
           Input PE  Input Value Weight Type Delta Weight
               Bias   +1.0000   -1.1865 V-a   +0.0014
               DIT4   +0.2270   -1.9025 V-a   +0.0004
               DIT3   +0.0000   +0.0163 V-a   +0.0003
               DIT2   +0.0000   -1.6075 V-a   +0.0003
               DIT1   +0.0000   +0.0087 V-a   +0.0002
   PE: 7
       1.000 Error Factor
      -1.188 Sum                    0.234 Transfer              0.234
Output
           5 Weights                0.001 Error                 0.007
Current Error
           Input PE  Input Value Weight Type Delta Weight
               Bias   +1.0000   -0.6553 V-a   +0.0020
               DIT4   +0.2270   -2.3437 V-a   +0.0006
               DIT3   +0.0000   +0.3114 V-a   +0.0003
               DIT2   +0.0000   -1.9495 V-a   +0.0004
               DIT1   +0.0000   +0.0844 V-a   +0.0003
   PE: 8
       1.000 Error Factor
       2.754 Sum                    0.940 Transfer              0.940
Output
           5 Weights               -0.015 Error                -0.272
Current Error
           Input PE  Input Value Weight Type Delta Weight
               Bias   +1.0000   +1.5199 V-a   +0.0099
               DIT4   +0.2270   +5.4313 V-a   +0.0036
               DIT3   +0.0000   -6.2347 V-a   +0.0047
               DIT2   +0.0000   -2.4225 V-a   +0.0028
               DIT1   +0.0000   +0.6400 V-a   +0.0019
   PE: 9
       1.000 Error Factor
      -1.777 Sum                    0.145 Transfer              0.145
```

```
Output
           5 Weights        -0.002 Error             -0.016
Current Error
           Input PE  Input Value Weight Type Delta Weight
               Bias  +1.0000   -1.3625 V-a   +0.0011
               DIT4  +0.2270   -1.8221 V-a   +0.0004
               DIT3  +0.0000   -0.3172 V-a   +0.0003
               DIT2  +0.0000   -1.4475 V-a   +0.0003
               DIT1  +0.0000   -0.0844 V-a   +0.0002
Layer: Out
        PEs: 4                                       Sum: Sum
    Spacing: 5        F' offset: 0.00              Transfer:
Sigmoid
      Shape: Square                                  Output:
Direct
      Scale: 1.00      Low Limit: -9999.00       Error Func:
standard
     Offset: 0.00     High Limit: 9999.00            Learn:
Norm-Cum-Delta
   Init Low: -0.100   Init High: 0.100        L/R Schedule:
backprop
   Winner 1: None                                Winner 2:
None
L/R Schedule: backprop
   Recall Step               1          0          0
 0          0
     Input Clamp          0.0000     0.0000     0.0000
0.0000     0.0000
     Firing Density     100.0000     0.0000     0.0000
0.0000     0.0000
     Temperature          0.0000     0.0000     0.0000
0.0000     0.0000
     Gain                 1.0000     0.0000     0.0000
0.0000     0.0000
     Modifier             1.0000     0.0000     0.0000
0.0000     0.0000
   Learn Step            1000000    1000000    1000000
1000000    1000000
     Coefficient 1        0.9000     0.8000     0.7000
0.6000     0.5000
     Coefficient 2        0.6000     0.5000     0.3000
0.2500     0.1000
     Coefficient 3        0.0000     0.0000     0.0000
0.0000     0.0000
     Temperature          0.0000     0.0000     0.0000
0.0000     0.0000
   PE: ODIT1
       1.000 Error Factor
      -4.028 Sum            0.017 Transfer            0.017
```

```
Output
           5 Weights          0.000 Error                -0.017
Current Error
           Input PE  Input Value Weight Type Delta Weight
               Bias   +1.0000    -1.1476 V-a   -0.0002
                  6   +0.1654    -1.8044 V-a   +0.0000
                  7   +0.2336    -1.9479 V-a   +0.0000
                  8   +0.9402    -1.9952 V-a   +0.0002
                  9   +0.1447    -1.7381 V-a   +0.0000
   PE: ODIT2
       1.000 Error Factor
      -3.391 Sum                  0.033 Transfer             0.033
Output
           5 Weights         -0.001 Error                -0.033
Current Error
           Input PE  Input Value Weight Type Delta Weight
               Bias   +1.0000    +0.0400 V-a   -0.0031
                  6   +0.1654    -1.9197 V-a   -0.0003
                  7   +0.2336    -2.2471 V-a   -0.0004
                  8   +0.9402    -2.4149 V-a   -0.0025
                  9   +0.1447    -2.1952 V-a   -0.0002
   PE: ODIT3
       1.000 Error Factor
      -2.440 Sum                  0.080 Transfer             0.080
Output
           5 Weights          0.034 Error                 0.465
Current Error
           Input PE  Input Value Weight Type Delta Weight
               Bias   +1.0000    +0.5728 V-a   -0.0084
                  6   +0.1654    -1.5429 V-a   -0.0007
                  7   +0.2336    -1.8399 V-a   -0.0011
                  8   +0.9402    -2.2784 V-a   -0.0050
                  9   +0.1447    -1.2867 V-a   -0.0006
   PE: ODIT4
       1.000 Error Factor
      -1.039 Sum                  0.261 Transfer             0.261
Output
           5 Weights         0.072 Error               0.375
Current Error

          Input PE  Input Value Weight Type Delta Weight
               Bias   +1.0000    +1.1638 V-a   -0.0039
                  6   +0.1654    +0.5217 V-a   -0.0001
                  7   +0.2336    +0.9328 V-a   -0.0002
                  8   +0.9402    -2.7203 V-a   +0.0003
                  9   +0.1447    +0.3507 V-a   -0.0000
```

APPENDIX E ANN Transponder DIT Estimation Results

ANN'S TRANSPONDER PERFORMANCE ESTIMATION FOR HID = 12

N	P	F	G	DIT	ES.DIT
0.00	0.00	2.00	3.00	7.00	8.64
0.00	0.00	1.00	3.00	7.00	7.09
0.00	0.00	1.00	3.00	7.00	7.09
0.00	0.00	1.00	3.00	7.00	7.09
0.00	0.00	1.00	3.00	7.00	7.09
0.00	0.00	1.00	3.00	7.00	7.09
0.00	0.00	1.00	3.00	7.00	7.09
0.00	0.00	1.00	3.00	7.00	7.09
0.00	0.00	0.00	3.00	7.00	5.89
1.00	1.00	1.00	4.00	6.00	6.79
0.00	1.00	1.00	4.00	6.00	7.01
0.00	1.00	1.00	4.00	6.00	7.01
0.00	1.00	1.00	4.00	6.00	7.01
0.00	0.00	1.00	4.00	6.00	6.42
0.00	0.00	1.00	4.00	6.00	6.42
0.00	0.00	1.00	4.00	6.00	6.42
0.00	0.00	1.00	4.00	6.00	6.42
0.00	0.00	1.00	4.00	6.00	6.42
0.00	0.00	1.00	4.00	6.00	6.42
1.00	1.00	2.00	5.00	5.00	7.43
0.00	1.00	2.00	5.00	5.00	7.67
0.00	1.00	2.00	5.00	6.00	7.67
0.00	1.00	2.00	5.00	6.00	7.67
0.00	0.00	2.00	5.00	7.00	7.00
0.00	0.00	2.00	5.00	7.00	7.00
0.00	0.00	1.00	5.00	7.00	5.86
0.00	0.00	1.00	5.00	7.00	5.86
0.00	0.00	1.00	5.00	8.00	5.86
0.00	0.00	1.00	5.00	8.00	5.86
0.00	0.00	1.00	5.00	8.00	5.86
0.00	0.00	1.00	5.00	8.00	5.86
0.00	0.00	1.00	5.00	8.00	5.86
0.00	0.00	1.00	5.00	8.00	5.86
0.00	0.00	1.00	5.00	8.00	5.86
0.00	0.00	1.00	5.00	8.00	5.86
0.00	0.00	0.00	5.00	8.00	5.02
0.00	0.00	0.00	5.00	8.00	5.02
0.00	0.00	0.00	5.00	8.00	5.02
0.00	0.00	0.00	5.00	8.00	5.02
0.00	0.00	0.00	5.00	8.00	5.02
0.00	0.00	0.00	5.00	10.00	5.02
0.00	0.00	0.00	5.00	10.00	5.02
0.00	0.00	0.00	5.00	10.00	5.02
0.00	0.00	0.00	5.00	10.00	5.02

0.00	0.00	0.00	5.00	10.00	5.02
0.00	0.00	0.00	5.00	10.00	5.02
0.00	0.00	0.00	5.00	10.00	5.02
0.00	0.00	0.00	5.00	10.00	5.02
0.00	0.00	0.00	5.00	11.00	5.02
0.00	0.00	0.00	5.00	11.00	5.02
0.00	0.00	0.00	5.00	11.00	5.02
0.00	0.00	0.00	5.00	11.00	5.02
0.00	0.00	0.00	5.00	14.00	5.02
0.00	0.00	0.00	5.00	14.00	5.02
0.00	0.00	0.00	5.00	15.00	5.02
0.00	0.00	0.00	5.00	15.00	5.02
0.00	0.00	0.00	5.00	15.00	5.02
0.00	0.00	0.00	5.00	15.00	5.02
0.00	0.00	0.00	5.00	15.00	5.02
0.00	0.00	0.00	5.00	15.00	5.02

ES.DIT=DIT+-5	ES.DIT=DIT+-3	ES.DIT=DIT+-1	ES.DIT=DIT+-0.5
48/60 80%	40/60 66.6%	16/60 26.6%	15/60 25%

ANN'S TRANSPONDER PERFORMANCE ESTIMATION FOR ITER = 800000

N	P	F	G	DIT	ES.DIT
0.00	0.00	2.00	3.00	7.00	8.51
0.00	0.00	1.00	3.00	7.00	6.79
0.00	0.00	1.00	3.00	7.00	6.79
0.00	0.00	1.00	3.00	7.00	6.79
0.00	0.00	1.00	3.00	7.00	6.79
0.00	0.00	1.00	3.00	7.00	6.79
0.00	0.00	1.00	3.00	7.00	6.79
0.00	0.00	1.00	3.00	7.00	6.79
0.00	0.00	0.00	3.00	7.00	5.60
1.00	1.00	1.00	4.00	6.00	6.36
0.00	1.00	1.00	4.00	6.00	6.50
0.00	1.00	1.00	4.00	6.00	6.50
0.00	1.00	1.00	4.00	6.00	6.50
0.00	0.00	1.00	4.00	6.00	6.04
0.00	0.00	1.00	4.00	6.00	6.04
0.00	0.00	1.00	4.00	6.00	6.04
0.00	0.00	1.00	4.00	6.00	6.04
0.00	0.00	1.00	4.00	6.00	6.04
0.00	0.00	1.00	4.00	6.00	6.04
1.00	1.00	2.00	5.00	5.00	7.06
0.00	1.00	2.00	5.00	5.00	7.20
0.00	1.00	2.00	5.00	6.00	7.20
0.00	1.00	2.00	5.00	6.00	7.20
0.00	0.00	2.00	5.00	7.00	6.60
0.00	0.00	2.00	5.00	7.00	6.60

0.00	0.00	1.00	5.00	7.00	5.44
0.00	0.00	1.00	5.00	7.00	5.44
0.00	0.00	1.00	5.00	8.00	5.44
0.00	0.00	1.00	5.00	8.00	5.44
0.00	0.00	1.00	5.00	8.00	5.44
0.00	0.00	1.00	5.00	8.00	5.44
0.00	0.00	1.00	5.00	8.00	5.44
0.00	0.00	1.00	5.00	8.00	5.44
0.00	0.00	1.00	5.00	8.00	5.44
0.00	0.00	1.00	5.00	8.00	5.44
0.00	0.00	0.00	5.00	8.00	4.76
0.00	0.00	0.00	5.00	8.00	4.76
0.00	0.00	0.00	5.00	8.00	4.76
0.00	0.00	0.00	5.00	8.00	4.76
0.00	0.00	0.00	5.00	8.00	4.76
0.00	0.00	0.00	5.00	10.00	4.76
0.00	0.00	0.00	5.00	10.00	4.76
0.00	0.00	0.00	5.00	10.00	4.76
0.00	0.00	0.00	5.00	10.00	4.76
0.00	0.00	0.00	5.00	10.00	4.76
0.00	0.00	0.00	5.00	10.00	4.76
0.00	0.00	0.00	5.00	10.00	4.76
0.00	0.00	0.00	5.00	10.00	4.76
0.00	0.00	0.00	5.00	11.00	4.76
0.00	0.00	0.00	5.00	11.00	4.76
0.00	0.00	0.00	5.00	11.00	4.76
0.00	0.00	0.00	5.00	11.00	4.76
0.00	0.00	0.00	5.00	14.00	4.76
0.00	0.00	0.00	5.00	14.00	4.76
0.00	0.00	0.00	5.00	15.00	4.76
0.00	0.00	0.00	5.00	15.00	4.76
0.00	0.00	0.00	5.00	15.00	4.76
0.00	0.00	0.00	5.00	15.00	4.76
0.00	0.00	0.00	5.00	15.00	4.76
0.00	0.00	0.00	5.00	15.00	4.76

ES.DIT=DIT+-5		ES.DIT=DIT+-3		ES.DIT=DIT+-1		ES.DIT=DIT+-0.5	
40/60	66.7%	35/60	58.3%	19/60	31.7%	19/60	31.7%

ANN'S TRANSPONDER PERFORMANCE ESTIMATION FOR ALPHA = 0.6

N	P	F	G	DIT	ES.DIT
0.00	0.00	2.00	3.00	7.00	9.74
0.00	0.00	1.00	3.00	7.00	7.99
0.00	0.00	1.00	3.00	7.00	7.99
0.00	0.00	1.00	3.00	7.00	7.99
0.00	0.00	1.00	3.00	7.00	7.99
0.00	0.00	1.00	3.00	7.00	7.99

0.00	0.00	1.00	3.00	7.00	7.99
0.00	0.00	1.00	3.00	7.00	7.99
0.00	0.00	0.00	3.00	7.00	6.70
1.00	1.00	1.00	4.00	6.00	7.48
0.00	1.00	1.00	4.00	6.00	7.77
0.00	1.00	1.00	4.00	6.00	7.77
0.00	1.00	1.00	4.00	6.00	7.77
0.00	0.00	1.00	4.00	6.00	7.22
0.00	0.00	1.00	4.00	6.00	7.22
0.00	0.00	1.00	4.00	6.00	7.22
0.00	0.00	1.00	4.00	6.00	7.22
0.00	0.00	1.00	4.00	6.00	7.22
0.00	0.00	1.00	4.00	6.00	7.22
1.00	1.00	2.00	5.00	5.00	8.18
0.00	1.00	2.00	5.00	5.00	8.48
0.00	1.00	2.00	5.00	6.00	8.48
0.00	1.00	2.00	5.00	6.00	8.48
0.00	0.00	2.00	5.00	7.00	7.83
0.00	0.00	2.00	5.00	7.00	7.83
0.00	0.00	1.00	5.00	7.00	6.59
0.00	0.00	1.00	5.00	7.00	6.59
0.00	0.00	1.00	5.00	8.00	6.59
0.00	0.00	1.00	5.00	8.00	6.59
0.00	0.00	1.00	5.00	8.00	6.59
0.00	0.00	1.00	5.00	8.00	6.59
0.00	0.00	1.00	5.00	8.00	6.59
0.00	0.00	1.00	5.00	8.00	6.59
0.00	0.00	1.00	5.00	8.00	6.59
0.00	0.00	1.00	5.00	8.00	6.59
0.00	0.00	0.00	5.00	8.00	5.76
0.00	0.00	0.00	5.00	8.00	5.76
0.00	0.00	0.00	5.00	8.00	5.76
0.00	0.00	0.00	5.00	8.00	5.76
0.00	0.00	0.00	5.00	8.00	5.76
0.00	0.00	0.00	5.00	10.00	5.76
0.00	0.00	0.00	5.00	10.00	5.76
0.00	0.00	0.00	5.00	10.00	5.76
0.00	0.00	0.00	5.00	10.00	5.76
0.00	0.00	0.00	5.00	10.00	5.76
0.00	0.00	0.00	5.00	10.00	5.76
0.00	0.00	0.00	5.00	10.00	5.76
0.00	0.00	0.00	5.00	10.00	5.76
0.00	0.00	0.00	5.00	11.00	5.76
0.00	0.00	0.00	5.00	11.00	5.76
0.00	0.00	0.00	5.00	11.00	5.76
0.00	0.00	0.00	5.00	11.00	5.76
0.00	0.00	0.00	5.00	14.00	5.76
0.00	0.00	0.00	5.00	14.00	5.76
0.00	0.00	0.00	5.00	15.00	5.76

0.00	0.00	0.00	5.00	15.00	5.76
0.00	0.00	0.00	5.00	15.00	5.76
0.00	0.00	0.00	5.00	15.00	5.76
0.00	0.00	0.00	5.00	15.00	5.76
0.00	0.00	0.00	5.00	15.00	5.76

ES.DIT=DIT+-5	ES.DIT=DIT+-3	ES.DIT=DIT+-1	E.DIT=DIT+-0.5
48/60 80%	38/60 63.3%	12/60 20%	3/ 60 5%

ANN'S TRANSPONDER PERFORMANCE ESTIMATION FOR BETA = 0.5,0.4,0.3,0.2,0.1

N	P	F	G	DIT	ES.DIT
0.00	0.00	1.00	3.00	7.00	7.81
0.00	0.00	1.00	3.00	7.00	7.81
0.00	0.00	1.00	3.00	7.00	7.81
0.00	0.00	1.00	3.00	7.00	7.81
0.00	0.00	1.00	3.00	7.00	7.81
0.00	0.00	1.00	3.00	7.00	7.81
0.00	0.00	1.00	3.00	7.00	7.81
0.00	0.00	0.00	3.00	7.00	6.80
1.00	1.00	1.00	4.00	6.00	7.89
0.00	1.00	1.00	4.00	6.00	7.97
0.00	1.00	1.00	4.00	6.00	7.97
0.00	1.00	1.00	4.00	6.00	7.97
0.00	0.00	1.00	4.00	6.00	7.26
0.00	0.00	1.00	4.00	6.00	7.26
0.00	0.00	1.00	4.00	6.00	7.26
0.00	0.00	1.00	4.00	6.00	7.26
0.00	0.00	1.00	4.00	6.00	7.26
0.00	0.00	1.00	4.00	6.00	7.26
1.00	1.00	2.00	5.00	5.00	8.42
0.00	1.00	2.00	5.00	5.00	8.51
0.00	1.00	2.00	5.00	6.00	8.51
0.00	1.00	2.00	5.00	6.00	8.51
0.00	0.00	2.00	5.00	7.00	7.76
0.00	0.00	2.00	5.00	7.00	7.76
0.00	0.00	1.00	5.00	7.00	6.76
0.00	0.00	1.00	5.00	7.00	6.76
0.00	0.00	1.00	5.00	8.00	6.76
0.00	0.00	1.00	5.00	8.00	6.76
0.00	0.00	1.00	5.00	8.00	6.76
0.00	0.00	1.00	5.00	8.00	6.76
0.00	0.00	1.00	5.00	8.00	6.76
0.00	0.00	1.00	5.00	8.00	6.76
0.00	0.00	1.00	5.00	8.00	6.76
0.00	0.00	1.00	5.00	8.00	6.76
0.00	0.00	0.00	5.00	8.00	5.92

0.00	0.00	0.00	5.00	8.00	5.92
0.00	0.00	0.00	5.00	8.00	5.92
0.00	0.00	0.00	5.00	8.00	5.92
0.00	0.00	0.00	5.00	8.00	5.92
0.00	0.00	0.00	5.00	10.00	5.92
0.00	0.00	0.00	5.00	10.00	5.92
0.00	0.00	0.00	5.00	10.00	5.92
0.00	0.00	0.00	5.00	10.00	5.92
0.00	0.00	0.00	5.00	10.00	5.92
0.00	0.00	0.00	5.00	10.00	5.92
0.00	0.00	0.00	5.00	10.00	5.92
0.00	0.00	0.00	5.00	10.00	5.92
0.00	0.00	0.00	5.00	11.00	5.92
0.00	0.00	0.00	5.00	11.00	5.92
0.00	0.00	0.00	5.00	11.00	5.92
0.00	0.00	0.00	5.00	11.00	5.92
0.00	0.00	0.00	5.00	14.00	5.92
0.00	0.00	0.00	5.00	14.00	5.92
0.00	0.00	0.00	5.00	15.00	5.92
0.00	0.00	0.00	5.00	15.00	5.92
0.00	0.00	0.00	5.00	15.00	5.92
0.00	0.00	0.00	5.00	15.00	5.92
0.00	0.00	0.00	5.00	15.00	5.92
0.00	0.00	0.00	5.00	15.00	5.92
1.00	1.00	1.00	6.00	15.00	6.83

ES.DIT=DIT+-5	ES.DIT=DIT+-3	ES.DIT=DIT+-1	ES.DIT=DIT+-0.5
47/60 78.3%	37/60 61.7%	12/60 20%	3/60 5%

ANN'S TRANSPONDER PERFORMANCE ESTIMATION FOR AUX = 25

N	P	F	G	DIT	ES.DIT
0.00	0.00	2.00	3.00	7.00	8.52
0.00	0.00	1.00	3.00	7.00	6.83
0.00	0.00	1.00	3.00	7.00	6.83
0.00	0.00	1.00	3.00	7.00	6.83
0.00	0.00	1.00	3.00	7.00	6.83
0.00	0.00	1.00	3.00	7.00	6.83
0.00	0.00	1.00	3.00	7.00	6.83
0.00	0.00	1.00	3.00	7.00	6.83
0.00	0.00	0.00	3.00	7.00	5.70
1.00	1.00	1.00	4.00	6.00	6.40
0.00	1.00	1.00	4.00	6.00	6.50
0.00	1.00	1.00	4.00	6.00	6.50
0.00	1.00	1.00	4.00	6.00	6.50
0.00	0.00	1.00	4.00	6.00	6.07
0.00	0.00	1.00	4.00	6.00	6.07
0.00	0.00	1.00	4.00	6.00	6.07

0.00	0.00	1.00	4.00	6.00	6.07
0.00	0.00	1.00	4.00	6.00	6.07
0.00	0.00	1.00	4.00	6.00	6.07
1.00	1.00	2.00	5.00	5.00	7.10
0.00	1.00	2.00	5.00	5.00	7.20
0.00	1.00	2.00	5.00	6.00	7.20
0.00	1.00	2.00	5.00	6.00	7.20
0.00	0.00	2.00	5.00	7.00	6.60
0.00	0.00	2.00	5.00	7.00	6.60
0.00	0.00	1.00	5.00	7.00	5.45
0.00	0.00	1.00	5.00	7.00	5.45
0.00	0.00	1.00	5.00	8.00	5.45
0.00	0.00	1.00	5.00	8.00	5.45
0.00	0.00	1.00	5.00	8.00	5.45
0.00	0.00	1.00	5.00	8.00	5.45
0.00	0.00	1.00	5.00	8.00	5.45
0.00	0.00	1.00	5.00	8.00	5.45
0.00	0.00	1.00	5.00	8.00	5.45
0.00	0.00	1.00	5.00	8.00	5.45
0.00	0.00	0.00	5.00	8.00	4.83
0.00	0.00	0.00	5.00	8.00	4.83
0.00	0.00	0.00	5.00	8.00	4.83
0.00	0.00	0.00	5.00	8.00	4.83
0.00	0.00	0.00	5.00	8.00	4.83
0.00	0.00	0.00	5.00	10.00	4.83
0.00	0.00	0.00	5.00	10.00	4.83
0.00	0.00	0.00	5.00	10.00	4.83
0.00	0.00	0.00	5.00	10.00	4.83
0.00	0.00	0.00	5.00	10.00	4.83
0.00	0.00	0.00	5.00	10.00	4.83
0.00	0.00	0.00	5.00	10.00	4.83
0.00	0.00	0.00	5.00	10.00	4.83
0.00	0.00	0.00	5.00	11.00	4.83
0.00	0.00	0.00	5.00	11.00	4.83
0.00	0.00	0.00	5.00	11.00	4.83
0.00	0.00	0.00	5.00	11.00	4.83
0.00	0.00	0.00	5.00	14.00	4.83
0.00	0.00	0.00	5.00	14.00	4.83
0.00	0.00	0.00	5.00	15.00	4.83
0.00	0.00	0.00	5.00	15.00	4.83
0.00	0.00	0.00	5.00	15.00	4.83
0.00	0.00	0.00	5.00	15.00	4.83
0.00	0.00	0.00	5.00	15.00	4.83
0.00	0.00	0.00	5.00	15.00	4.83

ES.DIT=DIT+-5	ES.DIT=DIT+-3	ES.DIT=DIT+-1	ES.DIT=DIT+-0.5
40/60 66.7%	35/60 58.3%	19/60 31.7%	19/60 31.7%

APPENDIX F ANN Validation Results

```
! Date: Thu Jan 24 10:27:10 1991
! Result File: test.nnr   Input File: test.nna
! Network: ANN MODEL1 TRANSPONDER/COMPONENT PERFORMANCE
  ESTIMATOR
 0.000000 0.000000 2.000000 5.000000 7.844067
 0.000000 0.000000 2.000000 5.000000 7.844067
 0.000000 0.000000 1.000000 5.000000 6.553322
 0.000000 0.000000 1.000000 5.000000 6.553322
 0.000000 0.000000 1.000000 5.000000 6.553322
 0.000000 0.000000 1.000000 5.000000 6.553322
 0.000000 0.000000 1.000000 5.000000 6.553322
 0.000000 0.000000 1.000000 5.000000 6.553322
 0.000000 0.000000 1.000000 5.000000 6.553322
 0.000000 0.000000 1.000000 5.000000 6.553322
 0.000000 0.000000 1.000000 5.000000 6.553322
 0.000000 0.000000 1.000000 5.000000 6.553322
 0.000000 0.000000 0.000000 5.000000 5.730761
 0.000000 0.000000 0.000000 5.000000 5.730761
 0.000000 0.000000 0.000000 5.000000 5.730761
 0.000000 0.000000 0.000000 5.000000 5.730761
 0.000000 0.000000 0.000000 5.000000 5.730761
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 0.000000 0.000000 0.000000 5.000000 5.730761
 0.000000 0.000000 0.000000 5.000000 5.730761
 0.000000 0.000000 0.000000 5.000000 5.730761
 0.000000 0.000000 0.000000 5.000000 5.730761
 1.000000 1.000000 1.000000 6.000000 6.094922
 0.000000 1.000000 1.000000 6.000000 6.270413
 0.000000 1.000000 1.000000 6.000000 6.270413
 0.000000 1.000000 1.000000 6.000000 6.270413
 1.000000 1.000000 2.000000 7.000000 6.564447
 0.000000 1.000000 2.000000 7.000000 6.765225
```

0.000000	1.000000	2.000000	7.000000	6.765225
0.000000	1.000000	2.000000	7.000000	6.765225
0.000000	0.000000	2.000000	7.000000	6.379199
0.000000	0.000000	2.000000	7.000000	6.379199
0.000000	0.000000	2.000000	7.000000	6.379199
0.000000	0.000000	2.000000	7.000000	6.379199
0.000000	0.000000	2.000000	7.000000	6.379199
0.000000	0.000000	2.000000	7.000000	6.379199
0.000000	0.000000	2.000000	7.000000	6.379199
0.000000	0.000000	2.000000	7.000000	6.379199
0.000000	0.000000	1.000000	6.000000	5.999375
0.000000	0.000000	1.000000	6.000000	5.999375
0.000000	0.000000	1.000000	6.000000	5.999375
0.000000	0.000000	1.000000	6.000000	5.999375
0.000000	0.000000	0.000000	6.000000	5.389122
0.000000	0.000000	0.000000	5.000000	5.730761
2.000000	2.000000	2.000000	7.000000	7.049856
0.000000	2.000000	2.000000	7.000000	7.324726
0.000000	2.000000	2.000000	7.000000	7.324726
1.000000	3.000000	3.000000	8.000000	8.733727
0.000000	1.000000	3.000000	8.000000	7.390013
0.000000	1.000000	3.000000	8.000000	7.390013
0.000000	1.000000	3.000000	7.000000	8.304701
0.000000	0.000000	3.000000	7.000000	7.657302
0.000000	0.000000	3.000000	7.000000	7.657302
0.000000	0.000000	1.000000	7.000000	5.571971
0.000000	0.000000	1.000000	7.000000	5.571971
0.000000	0.000000	1.000000	7.000000	5.571971
0.000000	0.000000	0.000000	7.000000	5.145529
0.000000	0.000000	0.000000	7.000000	5.145529
0.000000	0.000000	0.000000	7.000000	5.145529
0.000000	0.000000	0.000000	7.000000	5.145529
0.000000	0.000000	0.000000	6.000000	5.389122
0.000000	0.000000	0.000000	6.000000	5.389122
0.000000	0.000000	0.000000	6.000000	5.389122
1.000000	1.000000	1.000000	6.000000	6.094922
0.000000	1.000000	1.000000	6.000000	6.270413
1.000000	2.000000	2.000000	7.000000	7.156773
0.000000	0.000000	3.000000	8.000000	6.883368
0.000000	0.000000	3.000000	8.000000	6.883368
0.000000	0.000000	3.000000	8.000000	6.883368
0.000000	0.000000	3.000000	8.000000	6.883368
0.000000	0.000000	2.000000	8.000000	5.854261
0.000000	0.000000	2.000000	8.000000	5.854261
0.000000	0.000000	1.000000	8.000000	5.255471
3.000000	3.000000	6.000000	14.000000	7.849429
0.000000	3.000000	6.000000	14.000000	8.514798
1.000000	4.000000	7.000000	15.000000	10.192085
0.000000	4.000000	7.000000	15.000000	10.473755

APPENDIX G ANN Root Mean Square error values

```
!Instrument:               test2 instrument
!Variable:                 Current-Error
!Transformation Mode:      Component
!Transformation Type:      Root Mean Square
!learn_count recall_count        value_1        value_2   ...
     1000001            0       0.310355       0.000000
     1000001            0       0.230924       0.000000
     1000001            0       0.230924       0.000000
     1000001            0       0.230924       0.000000
     1000001            0       0.230924       0.000000
     1000001            0       0.230924       0.000000
     1000001            0       0.230924       0.000000
     1000001            0       0.230924       0.000000
     1000001            0       0.171448       0.000000
     1000001            0       0.211499       0.000000
     1000001            0       0.218247       0.000000
     1000001            0       0.218247       0.000000
     1000001            0       0.218247       0.000000
     1000001            0       0.192992       0.000000
     1000001            0       0.192992       0.000000
     1000001            0       0.192992       0.000000
     1000001            0       0.192992       0.000000
     1000001            0       0.192992       0.000000
     1000001            0       0.192992       0.000000
     1000001            0       0.242717       0.000000
     1000001            0       0.250615       0.000000
     1000001            0       0.250615       0.000000
     1000001            0       0.250615       0.000000
     1000001            0       0.220185       0.000000
     1000001            0       0.220185       0.000000
     1000001            0       0.161515       0.000000
     1000001            0       0.161515       0.000000
     1000001            0       0.161515       0.000000
     1000001            0       0.161515       0.000000
     1000001            0       0.161515       0.000000
     1000001            0       0.161515       0.000000
     1000001            0       0.161515       0.000000
     1000001            0       0.161515       0.000000
     1000001            0       0.161515       0.000000
     1000001            0       0.161515       0.000000
     1000001            0       0.124125       0.000000
     1000001            0       0.124125       0.000000
     1000001            0       0.124125       0.000000
     1000001            0       0.124125       0.000000
     1000001            0       0.124125       0.000000
     1000001            0       0.124125       0.000000
     1000001            0       0.124125       0.000000
```

1000001	0	0.124125	0.000000
1000001	0	0.124125	0.000000
1000001	0	0.124125	0.000000
1000001	0	0.124125	0.000000
1000001	0	0.124125	0.000000
1000001	0	0.124125	0.000000
1000001	0	0.124125	0.000000
1000001	0	0.124125	0.000000
1000001	0	0.124125	0.000000
1000001	0	0.124125	0.000000
1000001	0	0.124125	0.000000
1000001	0	0.124125	0.000000
1000001	0	0.124125	0.000000
1000001	0	0.124125	0.000000
1000001	0	0.124125	0.000000
1000001	0	0.124125	0.000000
1000001	0	0.124125	0.000000
1000001	0	0.124125	0.000000
1000001	0	0.140678	0.000000
1000001	0	0.148655	0.000000
1000001	0	0.148655	0.000000
1000001	0	0.148655	0.000000
1000001	0	0.162020	0.000000
1000001	0	0.171147	0.000000
1000001	0	0.171147	0.000000
1000001	0	0.171147	0.000000
1000001	0	0.153600	0.000000
1000001	0	0.153600	0.000000
1000001	0	0.153600	0.000000
1000001	0	0.153600	0.000000
1000001	0	0.153600	0.000000
1000001	0	0.153600	0.000000
1000001	0	0.153600	0.000000
1000001	0	0.153600	0.000000
1000001	0	0.136335	0.000000
1000001	0	0.136335	0.000000
1000001	0	0.136335	0.000000
1000001	0	0.136335	0.000000
1000001	0	0.108596	0.000000
1000001	0	0.124125	0.000000
1000001	0	0.184084	0.000000
1000001	0	0.196578	0.000000
1000001	0	0.196578	0.000000
1000001	0	0.260624	0.000000
1000001	0	0.199546	0.000000
1000001	0	0.199546	0.000000
1000001	0	0.241123	0.000000
1000001	0	0.211696	0.000000
1000001	0	0.211696	0.000000