To the Graduate Council:

I am submitting herewith a thesis written by Augusto V. Molina entitled "Evaluation of Infrastructure Systems Using Neural Networks." I have examined the final copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Civil Engineering.

Karen C. Chou

Karen C. Chou, Major Professor

We have read this thesis
and recommend its acceptance:

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Associate Vice Chancellor and
Dean of the Graduate School

Evaluation of Infrastructure Systems Using Neural Networks

A Thesis
Presented for the
Master of Science
Degree
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Augusto V. Molina
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Dedication

To my wife, Tess

who always manages to make me smile

in her own special way

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Abstract

The nation's infrastructure system is aging rapidly, but resources for the restoration of the infrastructure system are usually very limited. Therefore, decisions for allocating these resources must be made logically, consistently and effectively. Current evaluation methods rely heavily on the use of professional judgement and experience. This can lead to inconsistencies due to the varying opinions between engineers. Neural networks have the ability to make predictions based on a rational and consistent analysis of existing information. In this thesis, bridge rating and evaluation data were used to demonstrate the use of neural networks for infrastructure system evaluation. Data collected by the Tennessee Department of Transportation were used for developing a neural network that is capable of simulating bridge evaluation. Multi-layer feed forward networks were developed using the Levenberg-Marquardt training algorithm. All the neural networks considered consistency of at least one hidden layer of neurons. Hyperbolic tangent transfer functions were used in the first hidden layer and log-sigmoid transfer functions were used in the remaining hidden layers and output layer. The recommended neural network consisted of three hidden layers. This network contained three neurons in the first hidden layer, two neurons in the second hidden layer and one neuron in the third hidden layer. Neural network performance was compared with multi-variate linear regression analysis. The network performed well based on a target error of 10%. The results of this study indicate that the potential for using neural networks for evaluation of all types of infrastructure systems is very good.

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Chapter 1

Introduction

It is well known that our infrastructure systems are aging. The cost to restore them through repairs or replacements is enormous. In order to maintain a system's functional level, resources for restoration are allocated selectively based on issues such as safety, economic, and social impact. It is essential that these decisions be made logically, consistently and effectively.

Infrastructure system evaluation has been conducted using probability and statistics. However, these methods require the exact form and type of data as prescribed in the analysis procedures. When the exact form of information is not available, the analysis could be nullified or its function could be greatly compromised. Furthermore, one often faces the situation of making decisions with insufficient or poor quality data. Judgement and experience are needed to interpret the data in the decision making process. A neural network has the ability to make a reasonable response even when it is presented with incomplete or previously unseen input data. It has been shown that a neural network is an attractive tool in the decision making process in many areas including engineering (for example, Barai and Pandey, 1995; Chao and Skibniewski, 1994; Ellis et al., 1995; Faghri and Hua, 1995; Karaunanithi et al., 1994).

Engineers play an important role in determining allocation of resources for infrastructure system restorations. Field data, indicating current condition, are usually collected to help make these decisions. However, due to the nature of the data, ranging from precise to qualitative, the use of professional judgement and experience is inevitable during the decision making process. This has the risk of producing inconsistent conclusions among engineers for the same set of data. This may not cause a problem in cases where a system is in excellent or very poor condition. But in other cases, inconsistencies can result in delays in action and debates over resource allocation. Neural networks have the potential to enhance the decision making process. They can deliver a conclusion based on a rational and consistent analysis of a database that is larger than an individual engineer would have.

Neural networks differ from expert systems which simulate the function of a brain through a rule-based procedure. A neural network is analogous to a biological neural system both in structure and in function. It develops its analysis algorithm through examples that are fed to the network. The two main phases in the operation of neural networks are learning and recall. The learning (or training) phase tries to establish a relationship between the input and output variables through examples. The relationship is represented by weight connections which can be deterministic, probabilistic or fuzzy. In addition, the learning phase is not fixed. The neural network will continue to learn as more information is collected and fed to the network.

Based on the studies performed so far, neural networks have the potential to be a very useful tool for prioritizing the need for maintenance and allocation of resources through bridge ratings, repair technique performance predictions and other factors associated with infrastructure systems (for example, Fwa and Chan, 1993; Kaseko et al., 1994; Wu et al., 1992). Neural networks can be trained using examples from across a region, a state or the nation. Expert opinions can be collected and fed to the network during the learning phase and later they can continue to learn as more examples become available. It is anticipated that the conclusions drawn from neural networks will be more reliable than those from individuals since neural network approach is based on a database that is more comprehensive than an individual's.

The increasing number of PC-based programs has made the use of neural networks simple and affordable. Readily available PC-based software includes the *Neural Network Toolbox* (which runs with *MATLAB*) by The MathWorks, Inc., *NeuralWorks Predict* by NeuralWare, Inc. and *NeuFuz* by National Semiconductor. Almost all engineering firms, regardless of size, have the computing capability to use neural networks. For this study, the *Neural Network Toolbox*, Version 2.0b, was used (with *MATLAB for Windows*, Version 4.2c.1). It was run on an IBM PC with a 486DX2 processor and sixteen megabytes of extended memory.

The objective of this study is to show the potential advantages and benefits of using neural networks for evaluating infrastructure systems. This will be illustrated by focusing on bridges. Bridge rating and evaluation data, collected by the Tennessee Department of Transportation, have been obtained for neural network development. Several neural network models for bridge evaluation will be developed and compared to a traditional method of data analysis.

A brief discussion of the neural network concept and issues to be considered in neural network designs are presented in Chapter two. Chapter three presents the literature review of neural network applications in civil engineering and more specifically in structural engineering and system condition evaluation. The evaluation and rating of bridges is discussed in Chapter four. Rating methods used by the U.S. Department of Transportation are also described. Chapter five focuses on the design of several neural networks including training results, testing results and comparisons to multi-variate linear regression analysis. Finally, conclusions and suggestions for future studies are discussed in Chapter six.

Chapter 2

Neural Networks

Neural Network Concept

In its simplest form, a neural network can be classified as a function approximator. Given a set of input variables ($x_1,...,x_i$) and one or more output variables ($y_1,...,y_i$), a neural network finds the relationship or connection between the input and output. These connections are in the form of parameters called weights ($w_1,...,w_i$) and biases (b) (Masters, 1993). Equation 2.1 shows a linear relationship between one output variable and a set of input variables.

$$f(x_1,...,x_i) = x_1w_1 + x_2w_2 + ... + x_iw_i + b \tag{2.1}$$

Non-linear relationships between input and output are approximated by applying transfer functions to the value of Eq. 2.1. Two of the most common transfer functions employed in neural networks are the log-sigmoid function and the hyperbolic tangent function (see Eqs. 2.2 and 2.3).

$$f(x) = 1 \div (1 + e^{-x}) \tag{2.2}$$

$$f(x) = (e^x - e^{-x}) \div (e^x + e^{-x}) \tag{2.3}$$

A plot of each function is given in Figures 2.1 and 2.2. The plots show the limited output range and the useful input range of each function. The log-sigmoid function produces

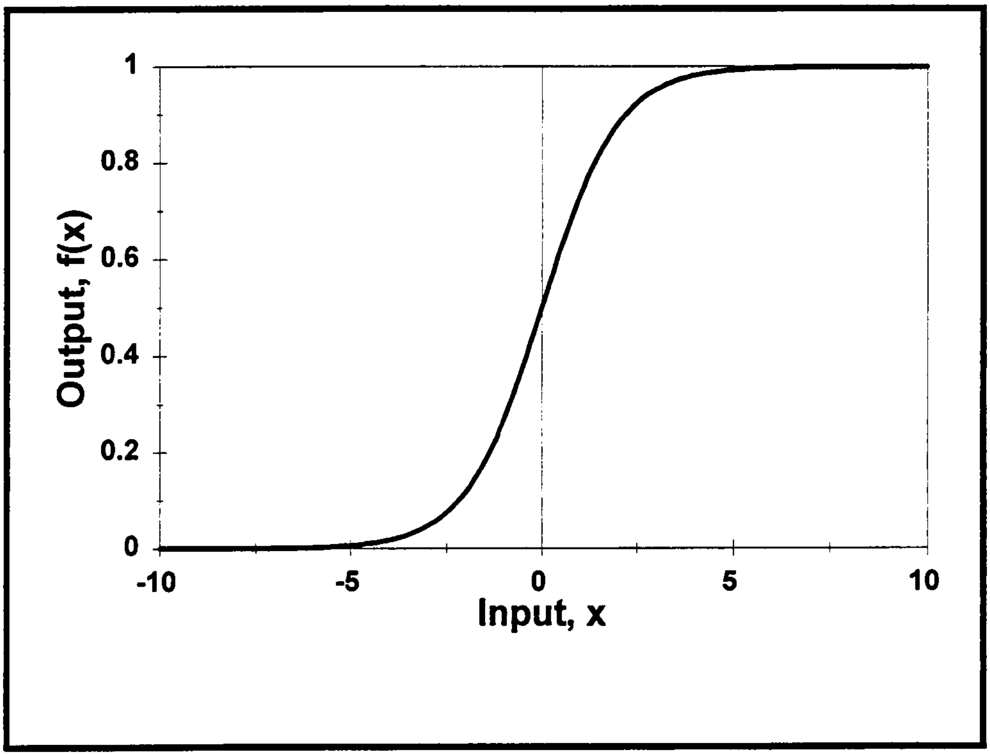

Figure 2.1. Log-Sigmoid Transfer Function

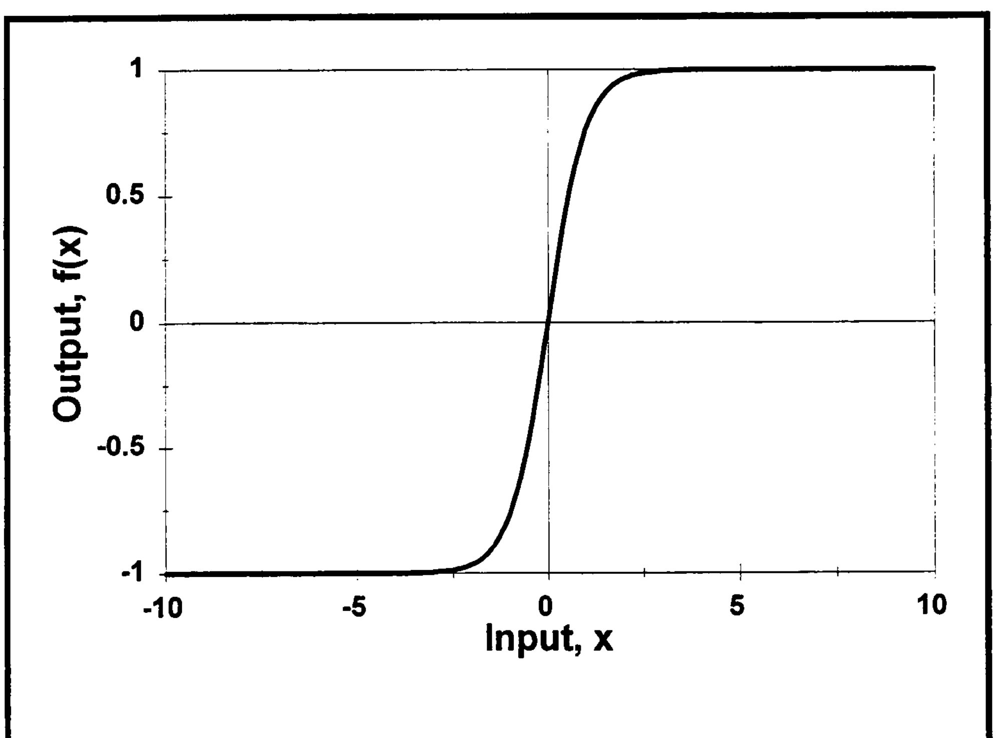

Figure 2.2. Hyperbolic Tangent Transfer Function

numbers between zero and positive one, while the hyperbolic tangent function produces numbers between negative one and positive one. Both functions produce a wide range of output values when input ranges from about negative two to positive two. Outside this range, the functions will only produces values close to their respective output limits.

Structure of a Neural Network

The basic building block of neural networks is the neuron; a neuron is where the processing of information takes place. Each neuron contains a set of weights and biases and an associated transfer function. The weights and biases are applied to the inputs, as indicated in Eq. 2.1, and further processing is performed by the transfer function. The output produced by a neuron can then be used as input by other neurons.

The arrangement of neurons within a neural network is commonly called the network architecture. One of the most popular architectures is the multi-layer feed forward network (Masters, 1993). The general structure of this model typically consists of one or more layers of intermediate neurons or hidden neurons and a final layer of output neurons. The network input is processed by hidden neurons whose resulting output can be accepted as input by subsequent hidden neuron layers or the final output layer. In some cases the network input is accepted directly by the output neurons without any intermediate processing.

The difference between neuron layers lies in the number of neurons and the associated transfer function. Neurons within the same layer commonly employ the same transfer function. Fig. 2.3 shows two output variables (y_1, y_2) approximated by processing four input variables (x_1,...,x_4) through a two-layer feed forward network. A multi-layer feed

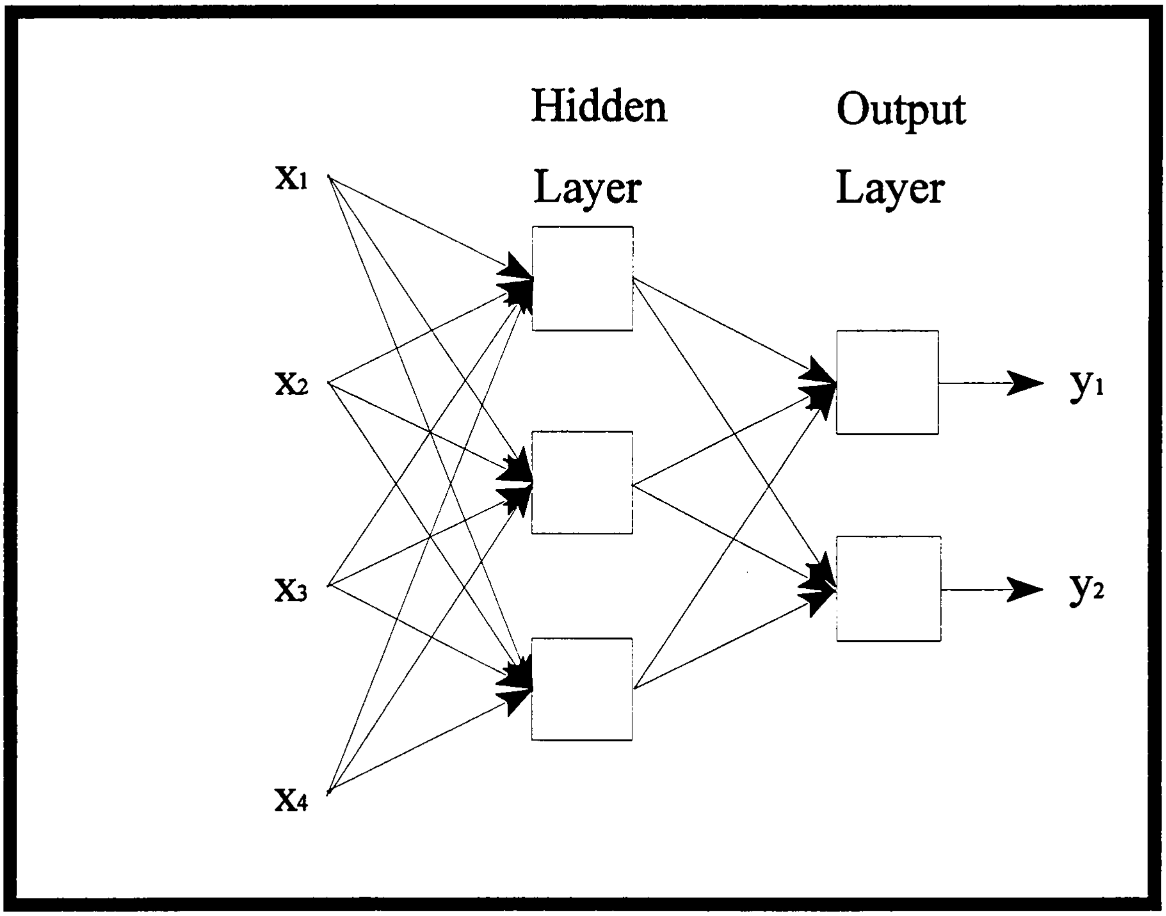

Figure 2.3. Two-Layer Feed Forward Network Structure

forward network consisting of a single hidden layer, with a non-linear transfer function, is considered a universal approximator (Cybenko, 1989; Funahashi, 1989; Haykin, 1994; Hornik et al., 1989). Therefore, this type of network is appropriate for performing function approximation, pattern association and pattern classification (Beale and Demuth, 1992). Consequently, the multi-layer feed forward network model was implemented in this study.

Neural Network Design

The process of designing a neural network consists of two phases: training and testing. During training the network determines or learns the weights and biases. After training is completed, testing is performed by processing new input through the network and comparing the predicted network output to the actual output. When a network is presented with new input, it will tend to produce output similar to output associated with similar input. This behavior is called generalization (Beale and Demuth, 1992). The design process is complete when the predicted output is judged acceptable.

Training is the principal phase of neural network design. Small initial weights and biases are chosen randomly and training data (containing actual input and output) are processed repeatedly through the network. Training is completed when the error between the predicted network output and the actual output is acceptable. For neural network design, the error is commonly measured in terms of sum-squared error (SSE). At the end of each training cycle, the SSE is calculated and the weights and biases are updated based on the size of the error. Several factors need to be considered before training can begin. They will affect how well the network will train and test and they also will have an impact on training time. These factors include:

- Selection of training data
- Number of hidden neurons and hidden layers
- Hidden layer and output layer transfer functions
- Scaling of input data
- Training rule for updating weights and biases

Selection of Training Data

Training data consist of actual input and output. Ideally, neural networks are trained using only a fraction of the total available data. A necessary property of the training data is that they must represent the total population. This is especially important when there are many discontinuities or subgroups within the total population (Masters, 1993). Training data should also include the maximum and minimum input and output values; a network will not generalize well when presented with values outside the training data range. Based on these criteria, selection of training data will greatly depend on the nature of the total population. As a result, there is no optimum training set size that should be used for all neural networks.

Number of Hidden Neurons and Hidden Layers

The number of neurons has a significant effect on a network's ability to train and generalize well. A network will almost always train successfully given enough neurons. Increasing the number of neurons provides more degrees of freedom for modeling a function. However, this can create a condition known as overfitting (Beale and Demuth, 1992). Overfitting occurs when a network learns the specific details of the training data instead of the general shape of the total population function. Overfitting of training data results in poor generalization of new data.

One way of minimizing overfitting (and in turn choosing the number of hidden neurons) is to use the minimum number of neurons required for successful training. Overfitting can also be identified and minimized using a technique called cross-validation. This technique is discussed later in this chapter.

Using one hidden layer is usually sufficient for designing an accurate network. But there are cases when additional hidden layers will benefit network performance; a function with discontinuities is an example (Masters, 1993). Increasing the number of hidden layers provides additional transfer functions. This can improve the information processing capability of a network.

Hidden Layer and Output Layer Transfer Functions

The use of non-linear transfer functions is essential since most neural networks are used to model non-linear data. These functions are usually more appropriate if placed in hidden layers, preceding the output layer. This enables a network to better process input data.

The choice of the output layer transfer function can be based on the output range. A linear function allows the output to take on any value. Functions such as the log-sigmoid or hyperbolic tangent functions may be more appropriate if the output is limited. These non-linear functions are especially useful if the output ranges from zero to positive one or negative one to positive one.

Scaling of Input Data

The use of non-linear transfer functions is very important. Unfortunately, the log-sigmoid and hyperbolic tangent functions have a limited useful input value range. Within a range of approximately negative two to positive two, the gradients (or slopes) of the functions are large (see Figs. 2.1 and 2.2). Outside of this range, the gradient is close to zero and the transfer functions will only produce values close to their respective output limits. During training, the size of weight and bias changes is related to the size of the gradient. Consequently, when a small gradient exists, training slows considerably. Large internal activations, which can be caused by input with large magnitudes, are mapped to small gradients in both the log-sigmoid and hyperbolic tangent functions, stopping training almost completely. This type of occurrence is known as premature saturation. Scaling the input within a specific range prevents premature saturation and results in faster training.

Two methods of scaling that are most frequently used are linear scaling and Z-score scaling. The linear method simply scales the input between +0.1 and +0.9. The Z-score method centers all the data around the mean and then scales the data to a unit variance. Z-score scaling assumes that the variables have an approximately normal distribution (Masters, 1993).

The scaling parameters that are calculated for the training input data (slope and intercept for linear scaling and mean and standard deviation for Z-score scaling) must also be applied to input processed by the network after training. These parameters have a direct affect on training since the weights and biases are determined based on scaled input versus actual input. Therefore, consistent correlation between different sets of input is maintained by using a consistent set of scaling parameters.

Training Rule for Updating Weights and Biases

For this study, all networks were trained using Levenberg-Marquardt optimization. This method typically converges to an answer more rapidly than other conventional methods such as back-propagation. It uses the reliable convergence of gradient descent, when far from the minimum error and the rapid convergence of the Gauss-Newton method, when close to the minimum error.

The gradient of a multi-variate function is the steepest direction that will result in the maximum increase of the function compared to all other directions. A step in the opposite direction will result in the maximum decrease of the function. For neural network training, the gradient of the error function is calculated and a step is taken in the opposite direction. This process is repeated as necessary. An important parameter in the gradient descent algorithm is the step size or learning rate. If a small learning rate is used, an excessive amount of time will be required for reaching the minimum error. If too large a learning rate is used, the minimum error maybe overstepped and the error may actually increase. For these reasons, gradient descent is reliable when far from the minimum and unreliable when close to the minimum (Masters, 1993).

Gradient descent makes use of the Jacobian vector, which consists of first order partial derivatives of the error function. The Gauss-Newton method uses an approximation of the Hessian matrix, which consists of second order partial derivatives (Haykin, 1994). Near the minimum error, the Jacobian gradient vector is zero and the Hessian matrix is positive definite. The Gauss-Newton method converges rapidly when close to the minimum error and performs poorly when far from the minimum.

The Levenberg-Marquardt rule for updating weights and biases is given by Eq. 2.4

$$\Delta w \text{ (or } \Delta b) = -(J^T J + \mu I)^{-1} J^T e \tag{2.4}$$

in which Δw is the weight change, Δb is the bias change, J is the Jacobian matrix of derivatives of each error to each weight (or bias), μ is a scalar, I is the identity matrix and e is an error vector. The variable μ determines whether Δw and Δb are calculated according to gradient descent or the Gauss-Newton method.

The variable μ is modified as the minimum error is approached. When far from the minimum, μ gets large and the $J^T J$ term becomes negligible. The calculation progresses according to $-\mu^{-1} J^T e$, which is gradient descent. When close to the minimum, μ is reduced and the calculation progresses according to $-(J^T J)^{-1} J^T e$, which is the Gauss-Newton method (Levenberg, 1944). The variable μ was first proposed by Goldfeld et al. (1966) for use in the Newton-Raphson method. The method for modifying μ was proposed by Marquardt (1963). It involves multiplying μ by ten until the error is reduced, incrementing Δw (or Δb). Then μ is divided by ten and the new Δw (or Δb) increment is checked to see if the error will reduce. If the error is not reduced, μ is multiplied by ten until the error reduces.

Cross-Validation Training

Overfitting is a common problem in neural network design. It can be caused by using an excessive number of hidden neurons or using training data that are not representative of the total population. With traditional design procedures, this problem is usually identified during the testing phase. Cross-validation provides a method for identifying overfitting during the training phase. It consists of simultaneous testing of a separate data set while training is performed on the training set; the separate data set is called the cross-validation set.

Overfitting occurs when the cross-validation error reaches a minimum and starts to increase. This point can be identified by the number of training cycles or the SSE. Subsequent training can then be stopped when the minimum error is reached (Haykin, 1994).

Training Time

Training time for neural networks is most affected by the network architecture and the number of samples in the training set. Complicated architectures and large training sets require more calculations and as a result training time increases. Minimizing training time furnishes another incentive for using a minimum number of hidden neurons and a minimum training set size.

Chapter 3

Literature Review: Neural Network Applications

Civil Engineering

The potential application of neural networks in civil engineering is unlimited. Over the past few years, applications in all civil engineering disciplines have increased dramatically. Transportation engineers have used neural networks for traffic pattern classification (Faghri and Hua, 1995; Lingras, 1995) and determination of truck attributes (such as velocity, axle spacings and axle loads) from strain-response readings taken from affected structures (Gagarin et al., 1994). Applications in construction include project management decision making (Moselhi et al., 1991), construction-site layout design (Yeh, 1995), estimation of construction productivity (Chao and Skibniewski, 1994) and preparation of competitive bids (Moselhi et al., 1993). In geotechnical engineering, neural networks were used in modeling soil properties (Goh, 1995), assessment of seismic liquefaction (Goh, 1994) and modeling of the stress-strain relationship of sands with varying grain size distribution and stress history (Ellis et al., 1995). Hydrologists have used neural networks for river flow prediction (Karunanithi et al., 1994) and stratified flow stability analysis (Grubert, 1995). The remainder of this chapter will focus on neural network applications in structural engineering and system condition evaluation.

Structural Engineering

Vanluchene and Sun (1990) presented an introduction to neural network technology and the potential applications in structural engineering. They included demonstrations involving three structural problems. The first problem demonstrated pattern recognition by determining the location of a concentrated load on a simply supported beam. Input data consisted of moments at interval points along the beam. A concentrated load at a specific interval produces a specific moment pattern. The second problem involved a simple concrete beam design. Input included the bending moment, the reinforcing steel strength, the concrete compressive strength, the reinforcing ratio and the width to depth ratio for the rectangular section. Output consisted of the required member depth. The final problem involved predicting the location and magnitude of maximum moment in a simply supported rectangular plate subjected to a concentrated load. Input included plate dimensions in both directions and x-y coordinates for the concentrated load. Output consisted of maximum moment and x-y location of the maximum moment for bending in both directions.

The study demonstrated that neural networks may be successfully applied to solve many civil engineering problems. The load location problem illustrates how a neural network can arrive at a solution that would be more difficult to find using other conventional programs. The concrete beam problem shows how typical design decisions can be made by a neural network. The simply supported plate example demonstrates a neural network's ability to model numerically complex problems.

Mukherjee and Deshpande (1995) focused on using neural networks for computerizing the initial design process. In this case the design of reinforced-concrete beams served as an example. A good initial design is important since it will reduce the number of subsequent analysis and design iterations and, in turn, reduce cost. Unfortunately, initial design is a subjective process that relies heavily on intuition and experience. Consequently, traditional procedures, such as rule-based expert systems, are not well suited for this type of application since they lack the learning capability of neural networks.

Span length, live load, dead load, steel strength and concrete strength were used as input variables. Output variables consisted of steel area, beam depth and width, cost per unit length and moment capacity. The study shows that the use of neural networks provides a very suitable approach for modeling the initial design process.

Accurate modeling of linear and non-linear dynamic systems, based on measured experimental data, has become more achievable with the development of more powerful computer technology. Chen et al. (1995b) studied the use of neural networks for structural dynamic model identification. A network was trained and tested using the responses recorded in a real apartment building during several earthquakes. Network input was comprised of three consecutive roof displacements and the ground floor acceleration. This data was measured with the use of acceleration sensors. Network output was the displacement on the roof at the next time step. The results show that the network was capable of representing the dynamic behavior (both linear and non-linear) of the building by using only the measured response data.

The potential of using neural networks for modeling dynamic behavior has also led to other structural engineering applications such as damage detection and structure control. Damage detection will be discussed in the next section. Chen et al. (1995a) also studied the potential of using neural networks for structure control. Using the same apartment building data, a second neural network was developed for controlling the building behavior. Input for this network consisted of the three consecutive roof displacements. Network output was the force needed to be applied to the building for control. The results show that the new network was quite capable of determining the required forces for successful structure control.

System Condition Evaluation

Several studies have focused on structural damage detection using neural networks. Szewczyk and Hajela (1994) used a neural network to relate static displacements (input) to reduction of Young's moduli of structural members (output). A reduction in Young's moduli indicates member damage. The structure types that were used included a six-bar truss, a portal frame and space truss. The neural network approach proved to be a promising alternative to other techniques.

Another method of damage detection considers changes in the dynamic properties of a structure. Wu et al. (1992) used a simple three-story frame modeled as a shear building with flexible columns and girders assumed to be infinitely rigid. Three degrees of freedom were represented by floor translations and the columns in each story represented one member. Changes in dynamic response were related to various damage states using one neural network.

Computed acceleration time histories were used as the measured response of the frame. A Fast Fourier Transformation was performed on the acceleration response to convert it from time-domain to frequency-domain. The response ranged from zero to 20 Hz and was divided into intervals of 0.1 Hz. This resulted in network input consisting of two hundred data points. Network output was the magnitude of damage for each member. Member damage was defined as a reduction in member stiffness. The results indicate that neural networks are capable of identifying damaged members and damage extent from patterns in the structure's frequency response.

Elkordy et al. (1994) focused on a more intricate study by using three neural networks to detect damage in a five-story, three-dimensional steel frame model. The model was subjected to a series of shake-table tests and damage states were simulated by reducing the bracing areas in the first and second floors. Displacement mode shapes and strain mode shapes were recorded for each damage state. Relative changes in mode shapes due to damage states were used as network input.

The first neural network was trained to detect damage and location (first or second floor). The second and third networks were trained to estimate damage level (percent reduction in bracing areas). Strain modes shapes were used as input for the first and second networks and displacement mode shapes were used for the third network. The results show that the neural networks were able to identify different damage states with a high degree of accuracy.

The two previously discussed studies focused on structural damage detection using a frequency-based approach. Barai and Pandey (1995) proposed a time-domain approach by using the displacement response of a typical bridge structure subjected to a moving load. A twenty-one-member truss was modeled and responses were generated using a standard finite-element program. Three different neural network architectures were used with input represented by the vertical displacements at the nodes along the bottom truss chord. The displacements were recorded at intervals of 0.04 seconds. Network output was represented by the cross-sectional areas of the twenty-one members. Damaged members were identified by reduced cross-sectional area.

The first neural network was trained with the displacement response from only one point while the second network used the response from only two points. The last network considered all points (a total of five). All the networks were able to identify the damaged members for a particular damage pattern. They also generated reasonable values for member cross-sectional areas.

Other engineering systems are evaluated based on visual inspection and rating of specific attributes. Highway condition is one such example. Fwa and Chan (1993) investigated the feasibility of using neural networks for the priority assessment of highway pavement maintenance needs. They considered the modeling of three different assessment methodologies. A pavement priority rating (ranging from zero to one) was calculated from attributes such as skid resistance, crack width and crack length.

The first methodology considered a linear combination of rating attributes while the second considered a non-linear combination. The final methodology used subjective priority ratings provided by a pavement engineer. The study demonstrated that neural networks are quite capable of modeling a variety of highway maintenance assessment schemes.

Kaseko et al. (1994) focused specifically on using neural networks to detect and classify cracks in video images of asphalt-concrete pavement surfaces. A multi-layer feed forward network and a two-stage piecewise linear network were compared to two traditional classifiers (Bayes classifier and a k-nearest-neighbor classifier). Classification falls under five categories which indicate crack existence and orientation. They include no cracking, transverse, longitudinal, diagonal and combination cracking. Actual classification was determined by human visual inspection of two observers.

Input consisted of processed video images and the output was crack classification. The results show that the neural network classifiers performed slightly better than the two traditional classifiers. The advantages of using neural networks for this type of application include high computation rate, self-organization and a greater degree of fault tolerance.

Chapter 4

Evaluation and Rating of Bridges

General

The evaluation of bridges in the United States is generally performed by state government agencies such as departments of transportation. As a result, the methods for determining overall bridge ratings vary between agencies. Typically, bridges are evaluated based on the condition of key components such as girders, bracing, bearing devices, deck, expansion joint devices, and so forth. In many instances these components are rated on a numerical scale such as a range from zero to nine (zero indicating the worst condition and nine indicating the best condition).

After data are collected and key components are rated, a bridge is given an overall rating which can indicate level of structural adequacy, need for repair or final life expectancy. These ratings can then be used to prioritize the allocation of funds for rehabilitation or re-building. Overall ratings can be calculated based on a structured mathematical formulation of the component ratings. But in many situations, overall ratings are formulated based on engineering judgement and experience. This can lead to inconsistent rating methodologies due to the varying opinions between engineers.

For bridges in which all the key components are either in excellent condition or very poor condition, an overall rating is quite obvious and is easily determined. For these situations, ratings are fairly consistent among engineers. But a large percentage of bridges usually contain only a few components that are in poor condition while the remaining components are in fair to excellent condition. It is for this population of bridges that overall ratings depend highly on judgement and experience. Opinions may vary significantly as to which key component is considered most critical. Neural networks have the capability of producing consistent ratings for all bridges regardless of the specific condition of key components.

U.S. Department of Transportation Bridge Evaluation

The U.S. Department of Transportation (DOT) provides a bridge evaluation guide for use by the States. The data collected via this guide is used for Federal reporting requirements. They include reports for the Highway Bridge Replacement and Rehabilitation Program and the National Bridge Inspection Program. This guide also provides a means of standardizing bridge evaluation across the entire country (U.S. DOT / Federal Highway Administration, 1979).

Structure Inventory and Appraisal

A total of ninety inventory items are recorded for each bridge. These items are grouped under the categories of Identification, Classification, Structure Data, Condition, Appraisal and Proposed Improvements. Of the ninety items, only nineteen are actually used to determine the overall condition of a bridge. Table 4.1 lists the nineteen items under their corresponding categories.

Overall condition is measured in terms of a percentage called the Sufficiency Rating (SR). An entirely acceptable bridge has an SR of 100% and 0% represents an entirely deficient bridge. The SR is composed of four variables each of which represents a rating category (see Eq. 4.1).

$$SR = S_1 + S_2 + S_3 - S_4 \quad (0\% \leq SR \leq 100\%) \tag{4.1}$$

Where:

- S_1 represents Structural Adequacy and Safety and ranges from 0% to 55%
- S_2 represents Serviceability and Functional Obsoleteness and ranges from 0% to 30%
- S_3 represents Essential Public Use and ranges from 0% to 15%
- S_4 represents Special Reductions and ranges from 0% to 13%

The variables are calculated based on a structured mathematical formulation of the nineteen inventory items. Table 4.2 lists the items that are used by each variable. The procedure for calculating SR is found in Appendix A.

Subjective Inventory Items

Eleven of the nineteen inventory items are rated subjectively. The remaining eight items consist of precise data such as structure dimensions and material type. Table 4.1 identifies the subjective items. Ten of the items fall under the categories of Condition and Appraisal and the remaining item (Traffic Safety Features) falls under Structure Data.

Except for Inventory Rating (Item 66), the Condition and Appraisal items are rated based on a numerical scale of zero to nine (zero indicates the worst condition and nine

Table 4.1. Bridge Rating Inventory Items

Item Number	Item Title	Evaluation Method	SR Correlation Coefficient
Category: Identification			
12	Designated Defense Highway No.	Precise	0.3460
19	Detour Length	Precise	-0.1950
Category: Structure Data			
28	Lanes On Structure	Precise	0.1387
29	Average Daily Traffic	Precise	0.2259
32	Approach Roadway Width	Precise	0.1143
36	Traffic Safety Features	Subjective	0.5156
43	Structure Type	Precise	0.1204
51	Bridge Roadway Width	Precise	0.3754
53	Vertical Clearance Over Deck	Precise	0.0806
Category: Condition			
58	Deck	Subjective	0.4653
59	Superstructure	Subjective	0.6676
60	Substructure	Subjective	0.5652
62	Culvert & Retaining Walls	Subjective	-0.2061
66	Inventory Rating	Subjective	0.8275
Category: Appraisal			
67	Structure Condition	Subjective	0.7209
68	Deck Geometry	Subjective	0.5074
69	Underclearance - Vertical & Lateral	Subjective	-0.2793
71	Waterway Adequacy	Subjective	0.4626
72	Approach Roadway Allignment	Subjective	0.4085

Table 4.2. Bridge Rating Variable and Inventory Item Cross-Reference

Variable	Item Number Used												
S1	59	60	62	66									
S2	12	28	29	32	43	51	53	58	67	68	69	71	72
S3	12	19	29										
S4	19	36	43										

indicates the best condition). The Inventory Rating is an appraisal of the current safe load capacity of the structure. A three-digit code is used for this item. The first digit ranges from one to nine and represents load type (i.e., HS, railroad, pedestrian, etc.). The second and third digits represent the gross loading in tons.

The remaining subjective item, Traffic Safety Features, is recorded as a four-digit code. This item evaluates the condition of four safety features: (1) bridge railings, (2) transitions, (3) approach guardrail and (4) approach rail ends. Each safety feature is given a rating of zero or one (zero indicates not acceptable and one indicates acceptable).

Tennessee Department of Transportation Bridge Rating Data

Bridge rating data used in this study were collected by the Tennessee Department of Transportation. A total of 447 samples were obtained between November, 1979 and September, 1983 with ratings ranging from 2% to 99.8%. The rating mean and sample standard deviation are 67.99% and 21.68%, respectively. Fig. 4.1 shows the Sufficiency Ratings in ascending order. The entire sample set is tabulated in Appendix B.

Correlation coefficients were calculated to determine the influence each inventory item has on the SR (see Table 4.1). The correlation coefficient is a measure of the degree of linear relationship between two variables. It can range between zero and ±1. A correlation coefficient equal to positive one or negative one indicates a perfect linear relationship (Ang and Tang, 1975). For this case, the coefficients with the largest magnitude are related to items which are subjective. This suggests subjective ratings have an important impact on bridge evaluation.

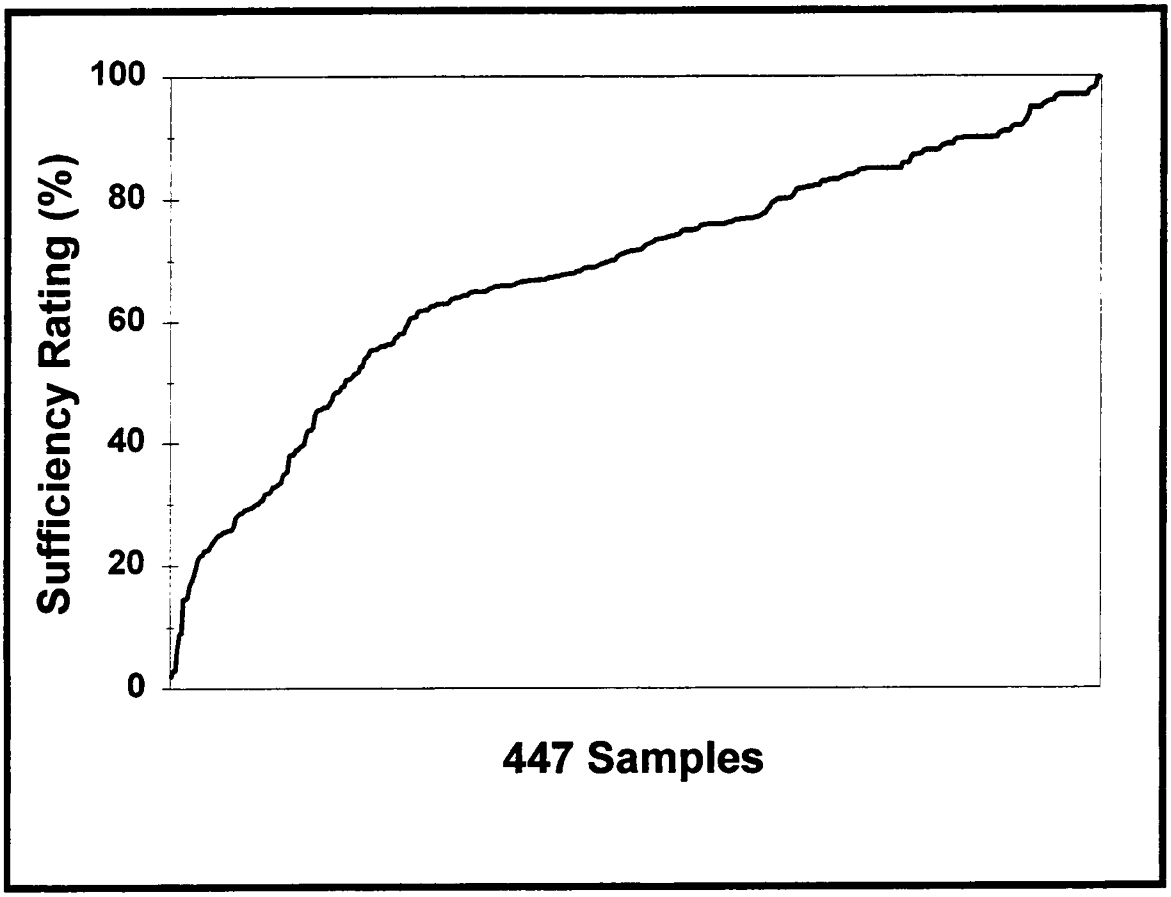

Figure 4.1. Tennessee DOT Bridge Ratings

Chapter 5

Neural Network Prediction of Bridge Rating Data

Training Parameters

Input Data Conversion

Some of the bridge rating inventory items are recorded with text (such as "Defense Highway" for Item 12 and "NA" for Condition and Appraisal items) and some are composed of several sub-items (Items 36, 43, 53 and 66). For the purpose of training with *MATLAB*, these items were converted to a consistent numbering system. The following list indicates the conversions:

- Item 12: Defense highway bridges are identified by the number one.
- Item 36: The overall condition of highway safety features are determined based on the number of features that are unacceptable (an unacceptable rating equals zero). Therefore, the safety feature ratings were added to form one number (ranging from zero to four).
- Item 43: Structure type is recorded as a three-digit code. The first digit represents the type of design and material but, it is not used in the calculation of the SR. The second and third digits represent the type of design and/or construction. There are

nineteen possible types, with each one identified by a specific number ranging from one to nineteen. All other types were identified by the number twenty.

- Item 53: Vertical clearance is recorded as a four-digit code indicating feet and inches. The first two digits represent the number of feet and the last two digits represent the number of inches. For neural network training, the vertical clearance was converted to a single number measured to the nearest hundredth of a foot.
- Item 66: Inventory rating is recorded as a three-digit code. The first digit represents load type and the second and third digits represent gross loading (in tons). A review of the data indicates that all the bridges are of load type number two. Therefore, only the gross loading was considered for training.
- Items 58, 59, 60, 62, 67, 68, 69, 71 and 72: These items are grouped under the categories of Condition and Appraisal and are rated on a scale of zero to nine. Items that do not apply are identified by "NA." For training, "NA" was replaced by the number ten.

<u>Output Data Conversion</u>

The sufficiency rating is calculated in terms of percentage, with the minimum and maximum equal to 0% and 100%, respectively. The log-sigmoid transfer function has a limited output range between zero and positive one. To take advantage of this range, log-sigmoid functions were used in the output layer and the SR values were converted to decimal equivalents. This guarantees that a neural network will predict the SR within the minimum and maximum values.

Scaling of Input Data

Scaling is necessary to prevent premature saturation (see Ch. 2). All the inventory items are recorded as positive numbers with values greater than or equal to zero. Therefore, all inputs were scaled between +0.1 and +0.9.

Transfer Functions

The use of non-linear transfer functions is essential for successful neural network design. For this study, all networks were designed as multi-layer with at least one hidden layer. Hyperbolic tangent functions were used in the first hidden layer. This function produces a wide range of output values between zero and positive one (approximately) since the inputs are scaled between +0.1 and +0.9. Log-sigmoid functions were used in the remaining hidden layers and the output layer to ensure output values between zero and positive one.

MATLAB Training Commands

Levenberg-Marquardt training is implemented in *MATLAB* by using the "trainlm" function.

Example: [w,b,te,tr] = trainlm(w_i,b_i,'F',x,y,tp)

In which:

- w = Final weight
- b = Final bias
- te = Number of training epochs (cycles)
- tr = Training record (SSE for each epoch)
- w_i = Initial weight

- b_i = Initial bias
- 'F' = Transfer function (string)
- x = Training input data
- y = Training output data
- tp = Training parameters

The term tp is a single row matrix consisting of eight variables. They include:

- tp(1) = Display frequency of training progress, default = every 25 epochs
- tp(2) = Maximum number of training epochs, default = 1000
- tp(3) = Sum-squared error (SSE) goal, default = 0.02
- tp(4) = Minimum gradient, default = 0.0001
- tp(5) = Initial value for μ, default = 0.001
- tp(6) = Multiplier for increasing μ, default = 10
- tp(7) = Multiplier for decreasing μ, default = 0.1
- tp(8) = Maximum value for μ, default = 1×10^{10}

For all training cases, the default parameters were used with the exception of tp(2) and tp(3). The number of training epochs was limited to 250 and the SSE goal was calculated for each training case.

Small initial weight and bias vectors were generated using the *MATLAB* "rands(nr,nc)" function. This function generates a matrix of uniformly distributed random numbers with values between negative one and positive one (nr = number of rows and nc = number of columns). The values generated by the "rands" function were multiplied by a factor of 0.5 to decrease their magnitude. Decreasing the magnitude of the initial weights and biases reduces the magnitude of the input values that are processed through the transfer functions. This further reduces the probability of premature saturation.

Evaluation of Neural Network Accuracy

The accuracy of neural network predictions were evaluated by comparing to multi-variate linear regression analysis. This procedure was selected because it is readily available in many spreadsheet programs. In this case *Quattro Pro for Windows* (Version 5.0) was used. Other data analysis methods are also available in a variety of PC-based statistical programs. But most engineering consulting firms and government agencies only use the latest spreadsheet package.

Neural Network Design #1

Two hundred samples were selected for training. The training set included twenty-five samples that contained the minimum and maximum input and output values. The remaining 175 samples were selected randomly using the "rand" function in *MATLAB*. This function selects random numbers based on a uniform distribution. Another set of two hundred samples were selected randomly for use as a cross-validation set. The cross-validation samples were selected from the same 447 samples as the training data. The sum-squared error goal was calculated based on 5% error per output ($SSE = \sum (y_i * 0.05)^2$). For the first training set, the SSE goal equaled 0.2557 (see Table 5.1 for summary of training parameters).

Three different feed forward networks were developed for training. The first contained one hidden layer, the second contained two hidden layers and the third contained

Table 5.1. Neural Network Design Training Parameters

Design No.	No. of Training Samples*	No. of Cross-Validation Samples	Sample Selection Method	Average Error Goal Per Sample (%)	Sum-Squared Error Goal	No. of Input Variables
1	200	200	Random	5	0.2557	19
2	300	300	Random	5	0.3822	19
3	200	200	Random	10	1.0227	19
4	200	200	Random	10	1.0227	6
5	200	200	Random	10	1.0227	10
6	239	239	Random	10	1.1840	19

*Training samples include minimum and maximum input and output values (25 samples) three hidden layers. Each network was trained with the minimum number of neurons required to reach the SSE goal. A small number of neurons were initially used for training and the amount was gradually increased until training was successful. Training for specific network architectures was considered unsuccessful after three trials. Since the initial weights and biases are chosen randomly, training results will vary from one trial to the next. Therefore, more than one trial is necessary to consider training unsuccessful (Masters, 1993).

The first network contained four neurons in the hidden layer (notation = 4N) and reached the error goal after thirty-six epochs. The second network contained three neurons in the first hidden layer and two neurons in the second hidden layer (notation = 3N-2N) and reached the error goal after twenty-four epochs. The third network contained three neurons in the first hidden layer, two neurons in the second hidden layer and one neuron in the third hidden layer (notation = 3N-2N-1N). This network reached the error goal after eighty-three epochs. Figs. 5.1 - 5.3 show plots of SSE versus epochs for each network.

In every case, the cross-validation error increased before training was completed, suggesting overfitting of the training data. The plots show training and cross-validation error deviating at an SSE equal to approximately 1.0. This is equivalent to 10% error per output. Since the minimum number of neurons was used for successful training, overfitting could have occurred due to insufficient training data. Therefore, the training set size for the second network design was increased to three hundred samples.

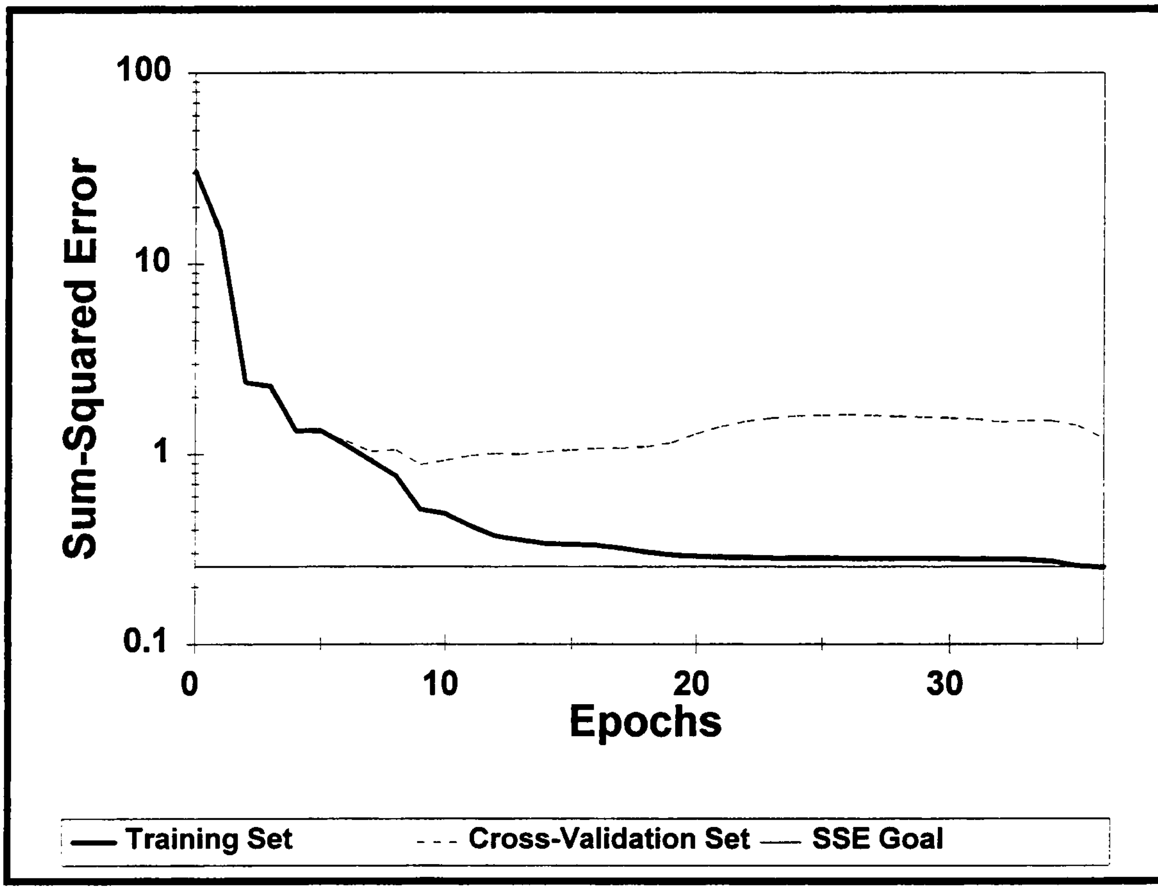

Figure 5.1. Design #1 Training Progress for 4N Network

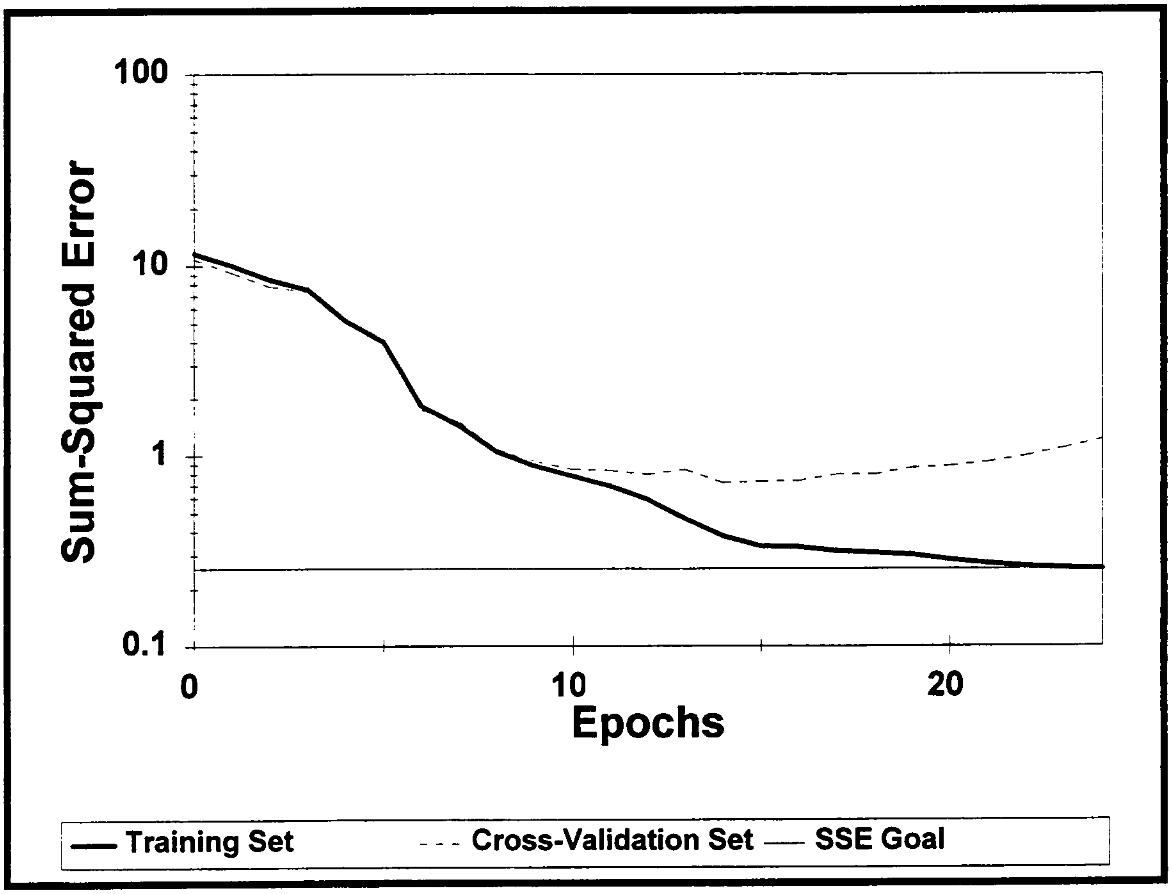

Figure 5.2. Design #1 Training Progress for 3N-2N Network

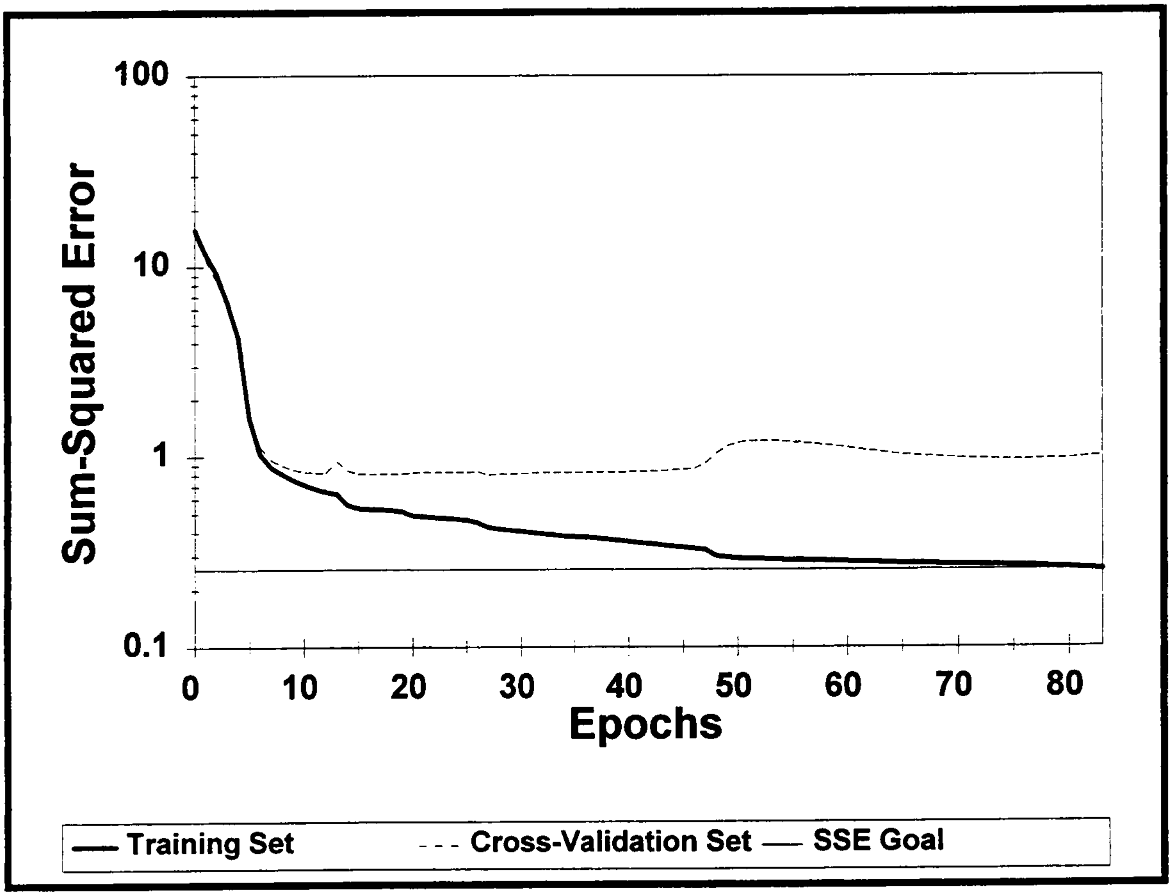

Figure 5.3. Design #1 Training Progress for 3N-2N-1N Network

Neural Network Design #2

For the second design, three hundred samples were selected for training. The training set included the twenty-five samples that contained the minimum and maximum input and output values. The remaining 275 samples were selected randomly using the "rand" function in *MATLAB*. The SSE goal increased to 0.3822. Another set of three hundred samples were selected randomly for use as a cross-validation set. The cross-validation samples were selected from the same 447 samples as the training data (see Table 5.1). The same network architectures used in the first design were used on the second training set. Only the 4N network was trained successfully, reaching the error goal after thirty-two epochs (see Figs. 5.4 - 5.6).

The training results for the second design were consistent with those for the first. Overfitting of the training data occurred. The training and cross-validation error deviated after reaching an SSE of approximately 10% error per output. These results suggest that the best predictions that could be made by the neural networks were within 10% of the actual data. Therefore, the remaining networks were designed based on an SSE equal to 10% error per output using the two hundred sample training set.

Neural Network Design #3

The third design used the training and cross-validation sets selected from the first design. Based on 10% error per output, the sum-squared error equaled 1.0227 (see Table 5.1). The same architectures were applied and trained successfully in each case (see Figs. 5.7 - 5.9). In addition, three more networks were developed, each with only one neuron per

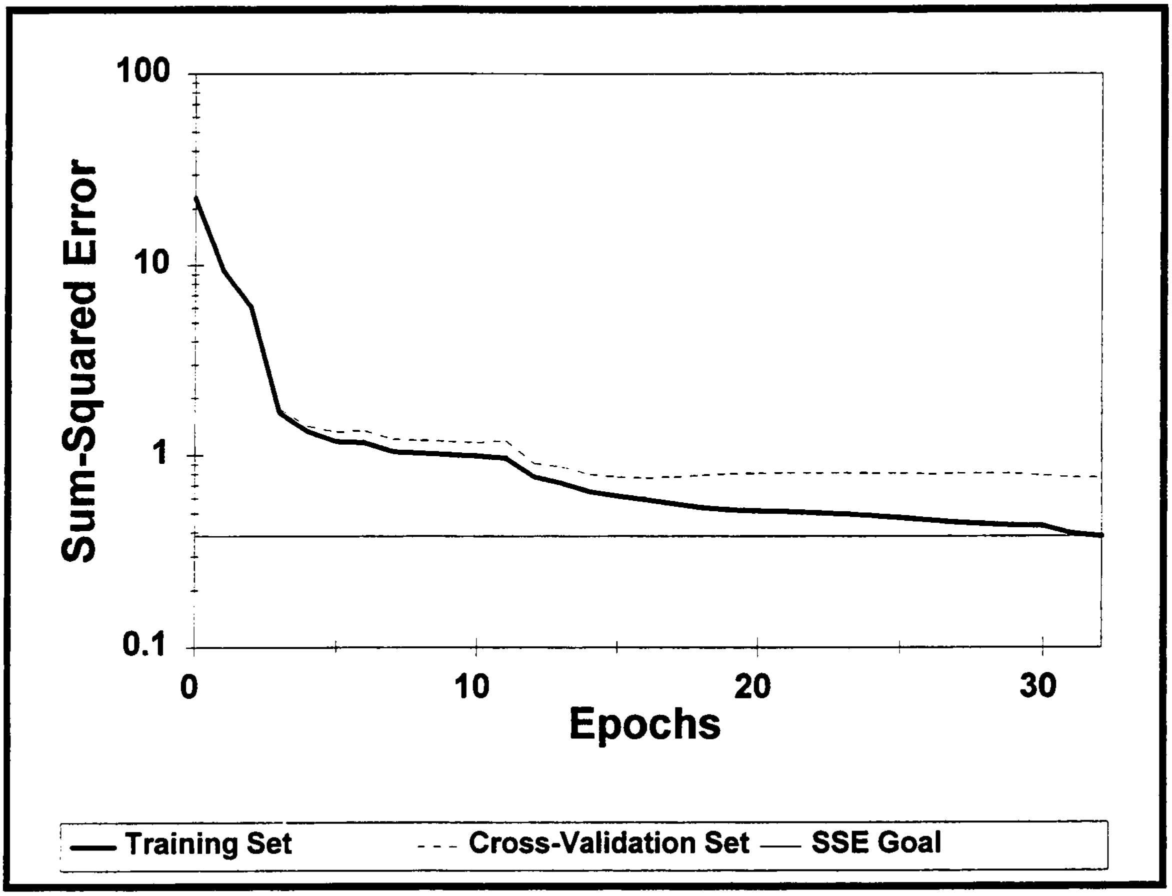

Figure 5.4. Design #2 Training Progress for 4N Network

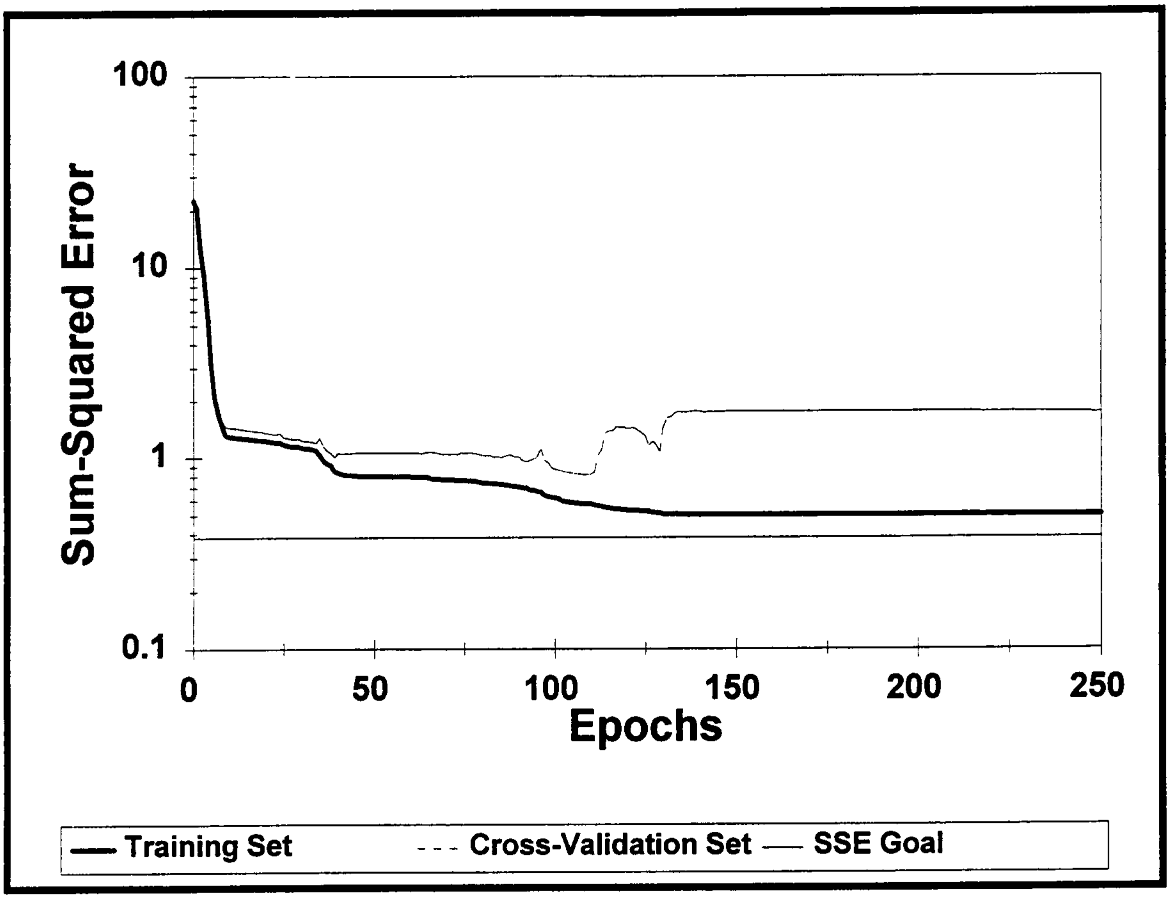

Figure 5.5. Design #2 Training Progress for 3N-2N Network

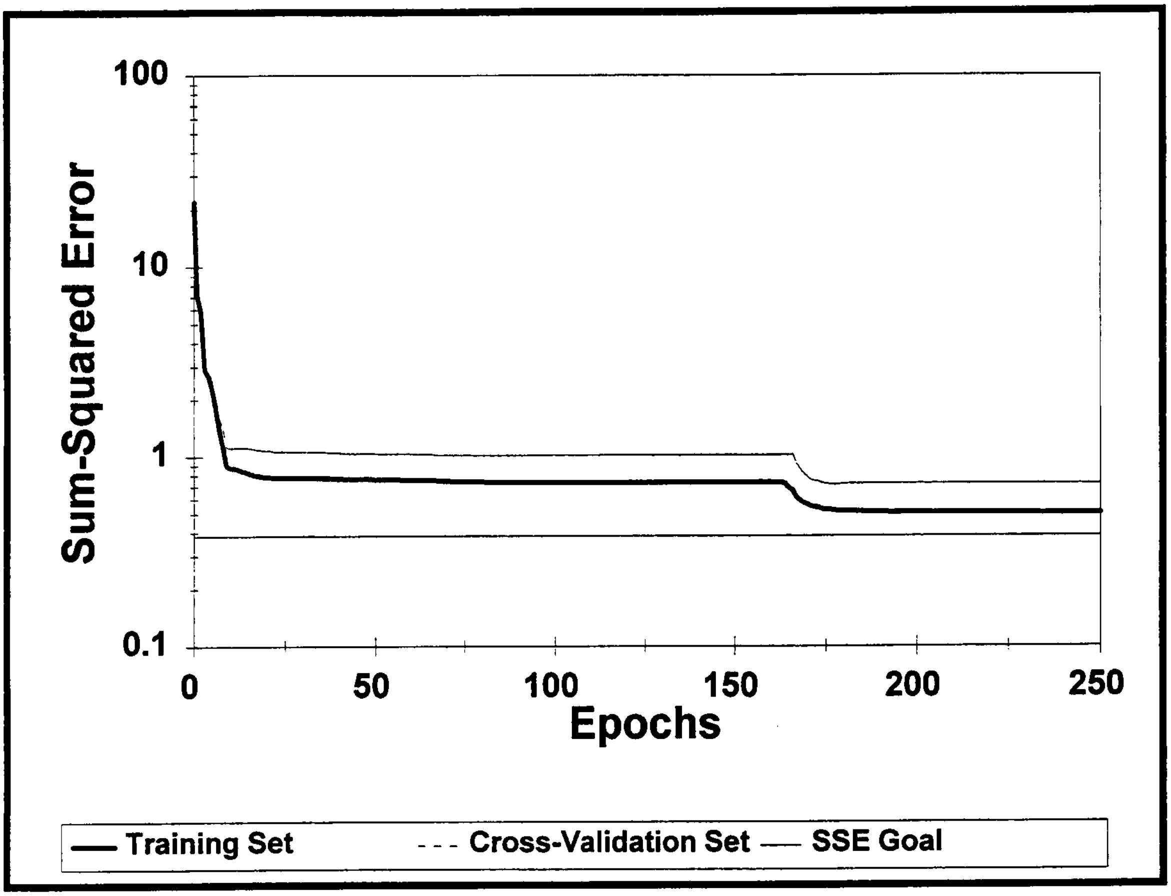

Figure 5.6. Design #2 Training Progress for 3N-2N-1N Network

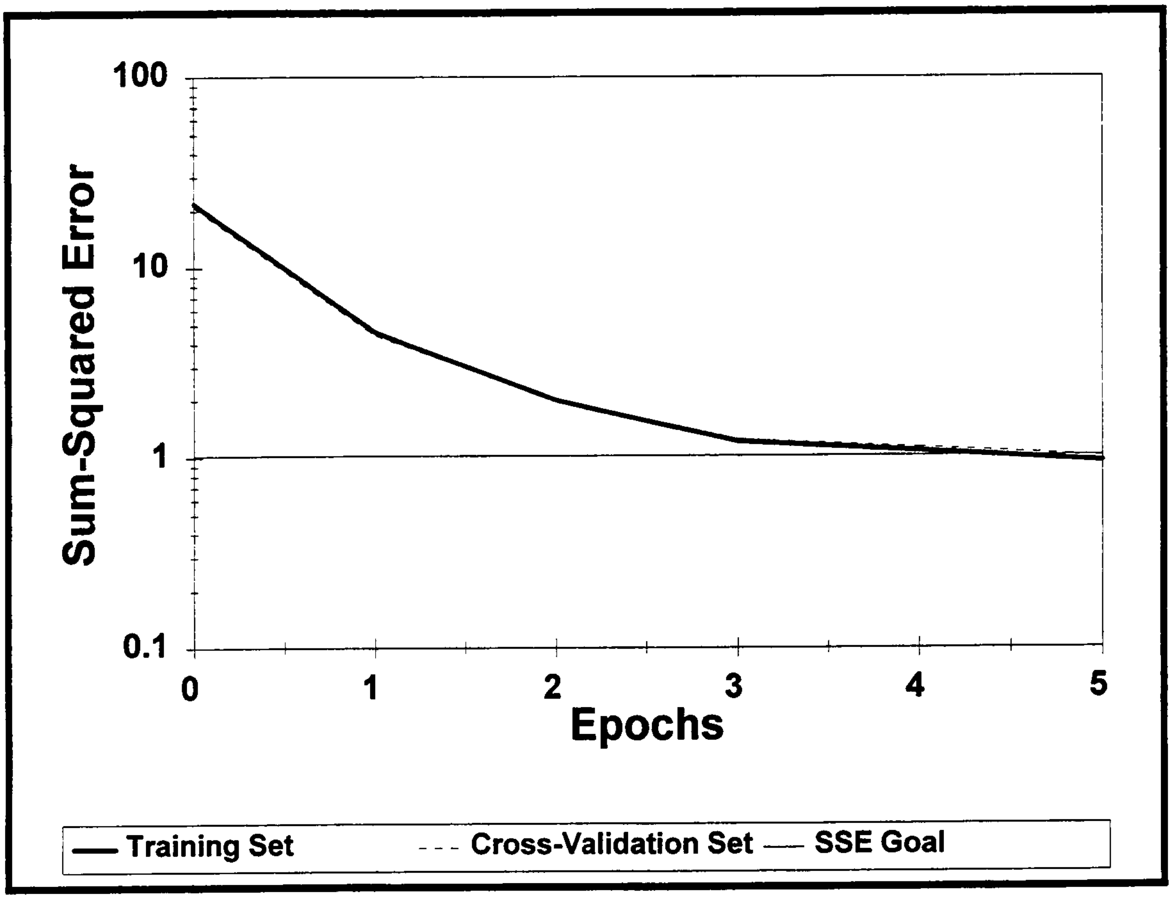

Figure 5.7. Design #3 Training Progress for 4N Network

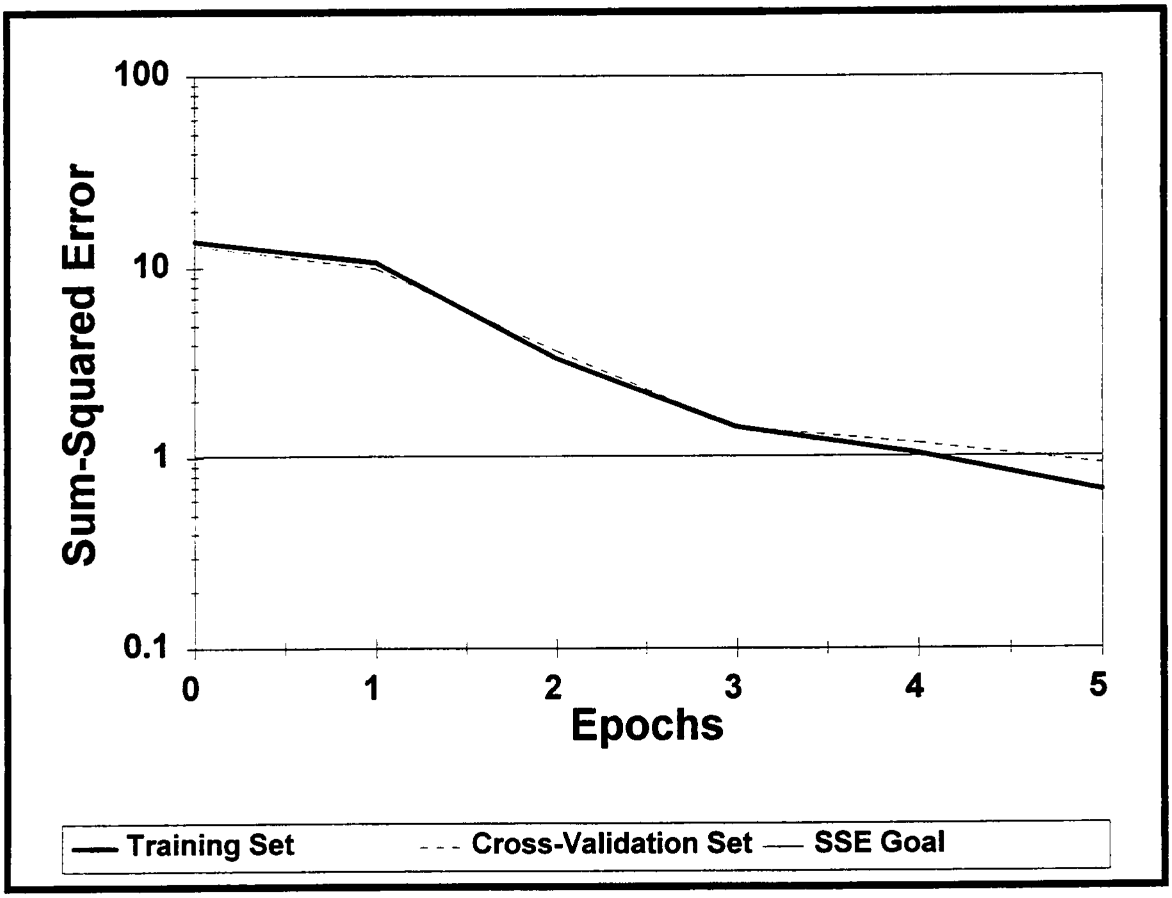

Figure 5.8. Design #3 Training Progress for 3N-2N Network

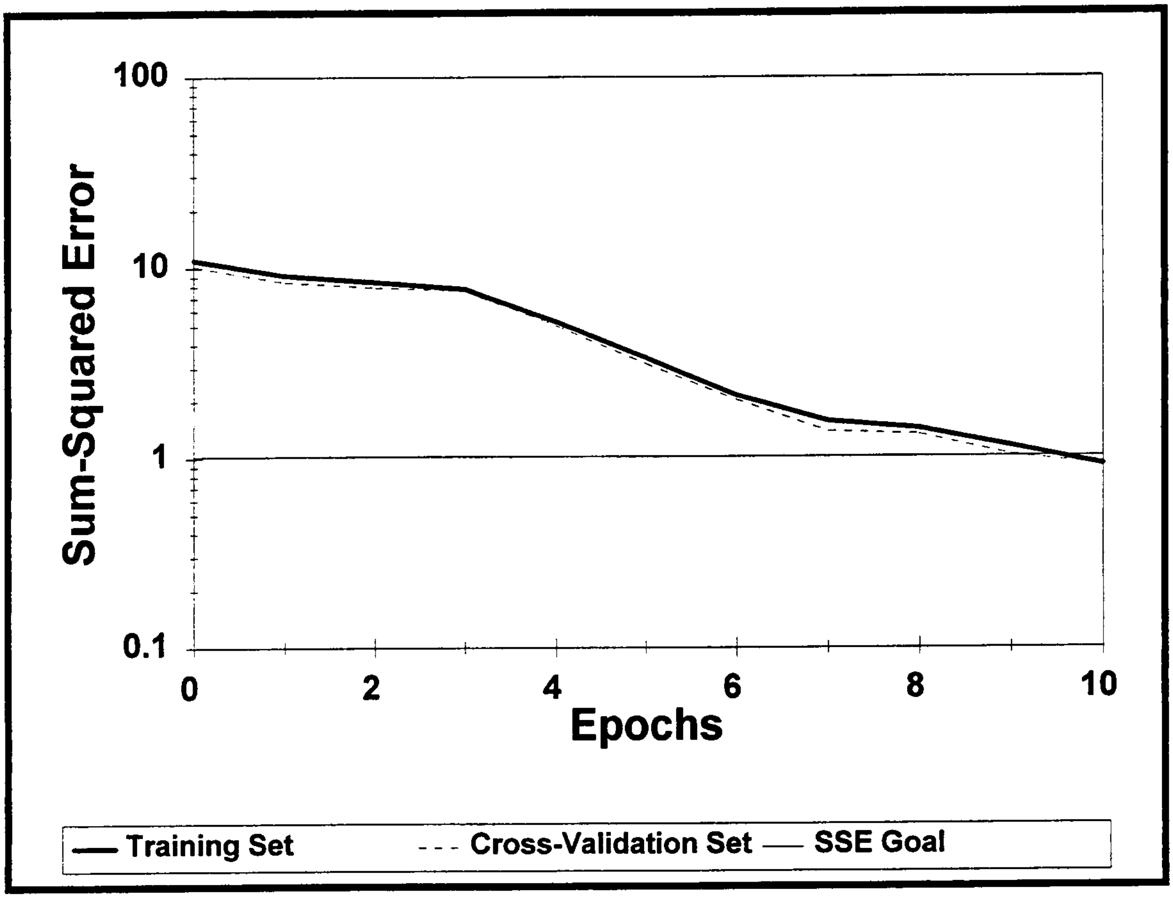

Figure 5.9. Design #3 Training Progress for 3N-2N-1N Network

hidden layer (1N, 1N-1N, & 1N-1N-1N). The new networks also trained successfully (see Figs. 5.10 - 5.12).

The results show no overfitting of training data. In every case, the cross-validation error decreased consistently as training progressed. This further suggests that an average of 10% error per output is the optimum prediction that could be made by the neural networks.

The six networks were tested against the remaining data that were not used for training (247 samples). Figs. 5.13 - 5.18 show plots of the actual SR and predicted SR. Table 5.2 summarizes the maximum error and error distribution for each network. A comparison between the networks shows that the single neuron networks produced the worst results. Each had maximum errors greater than 100% and the error distribution was larger than the multi neuron networks.

A multi-variate linear regression analysis was performed on the same neural network training data and tested against the remaining data. Fig. 5.19 shows a plot of the actual SR and predicted SR and Table 5.2 lists the maximum error and error distribution. The overall results indicate that neural network predictions were more accurate than regression, with the 3N-2N-1N network producing the best results.

Neural Network Design #4

The fourth design used the training and cross-validation sets selected from the first design. But in this case, the number of input variables was reduced to six (see Table 5.1). These variables were selected based on the magnitude of their SR correlation coefficient. All variables with a correlation coefficient greater than 0.5 were selected. They include

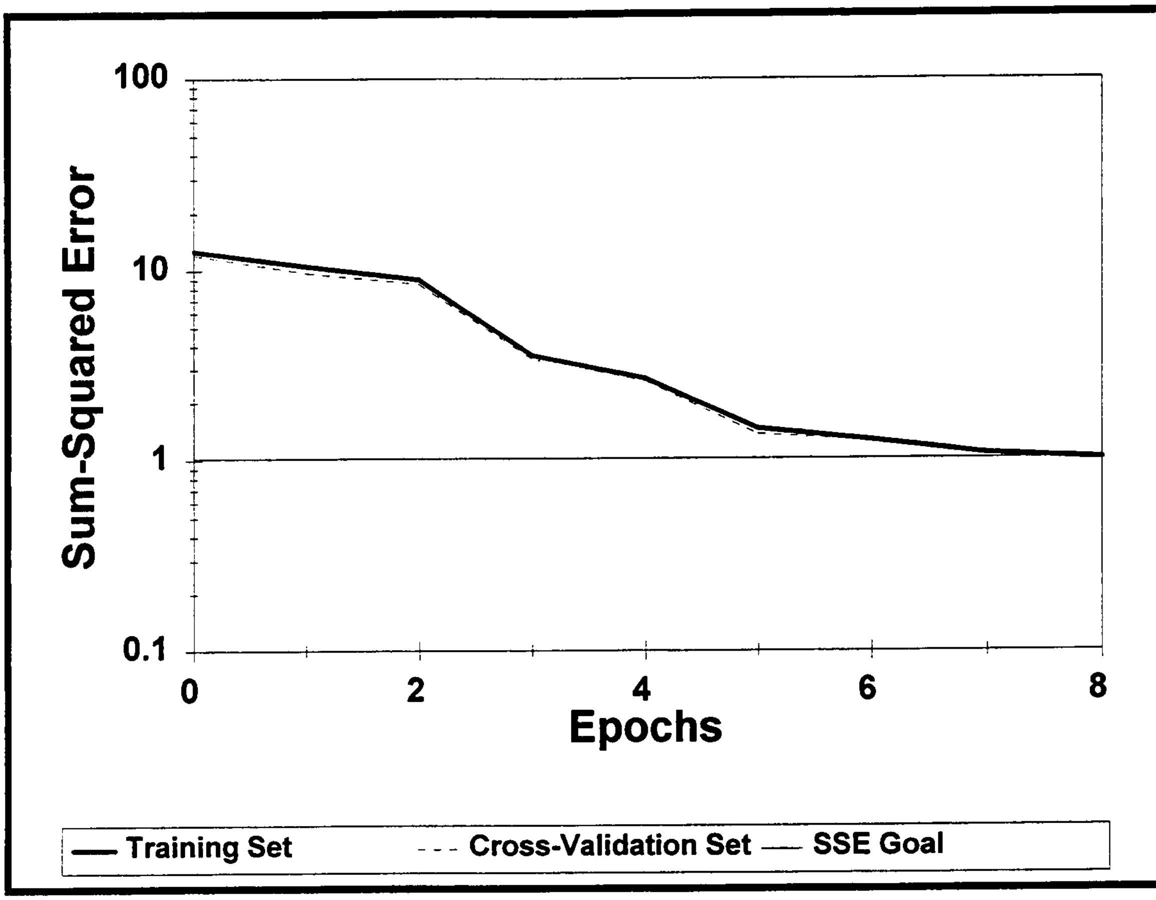

Figure 5.10. Design #3 Training Progress for 1N Network

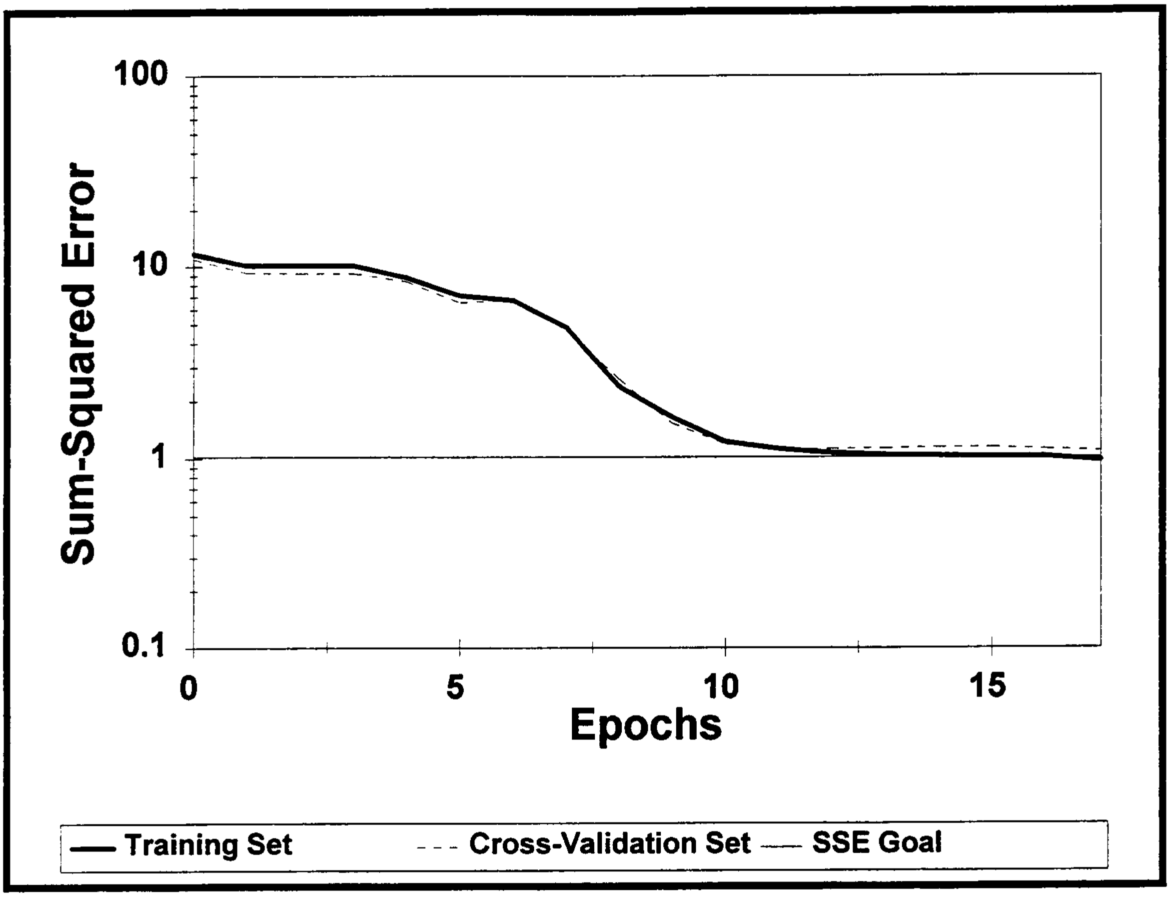

Figure 5.11. Design #3 Training Progress for 1N-1N Network

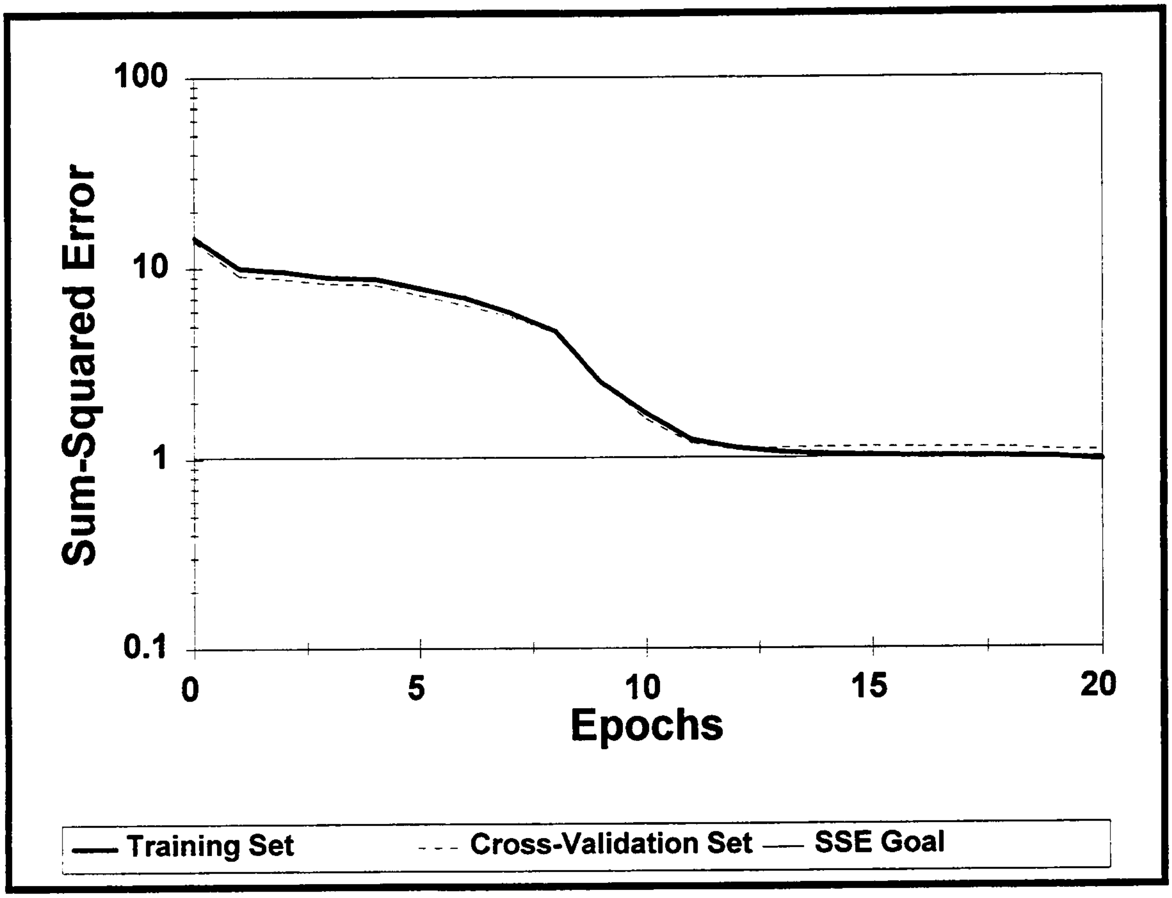

Figure 5.12. Design #3 Training Progress for 1N-1N-1N Network

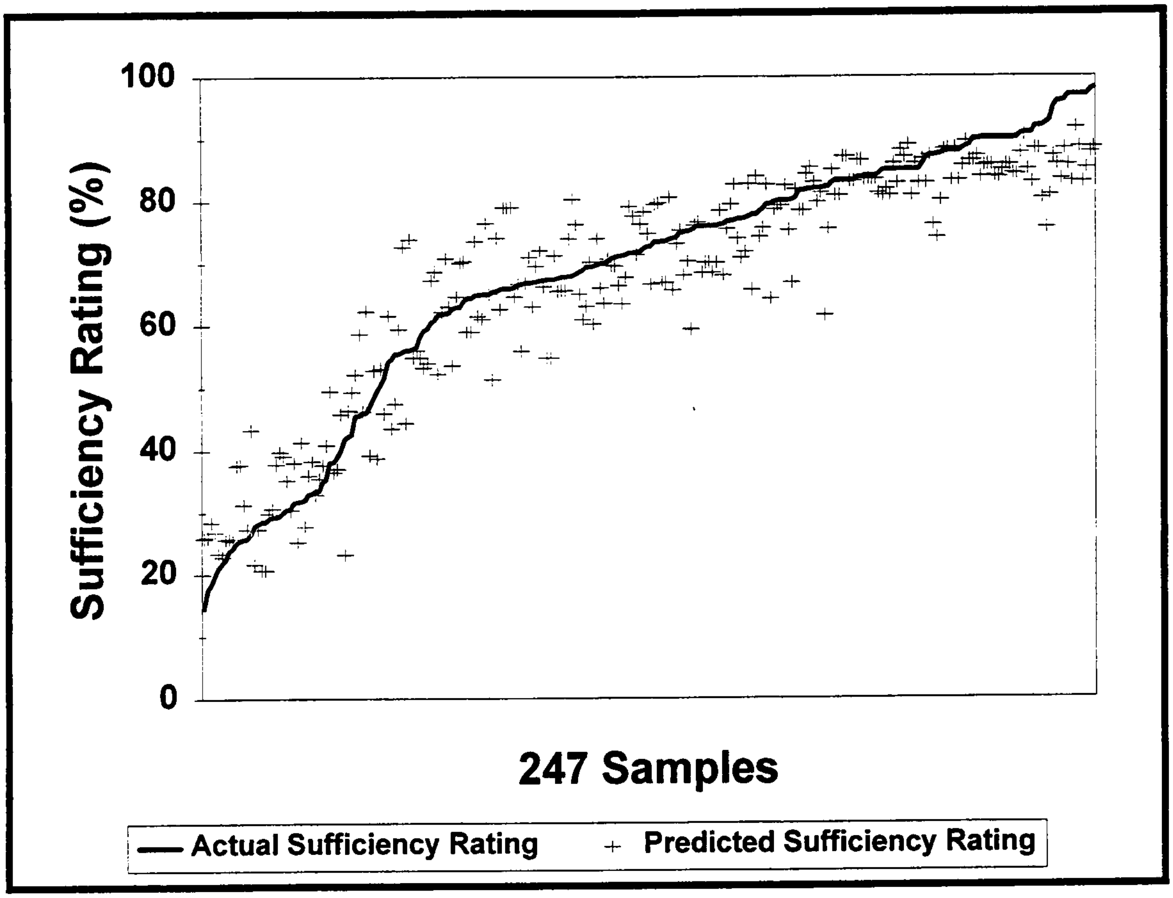

Figure 5.13. Design #3 Testing Results for 4N Network

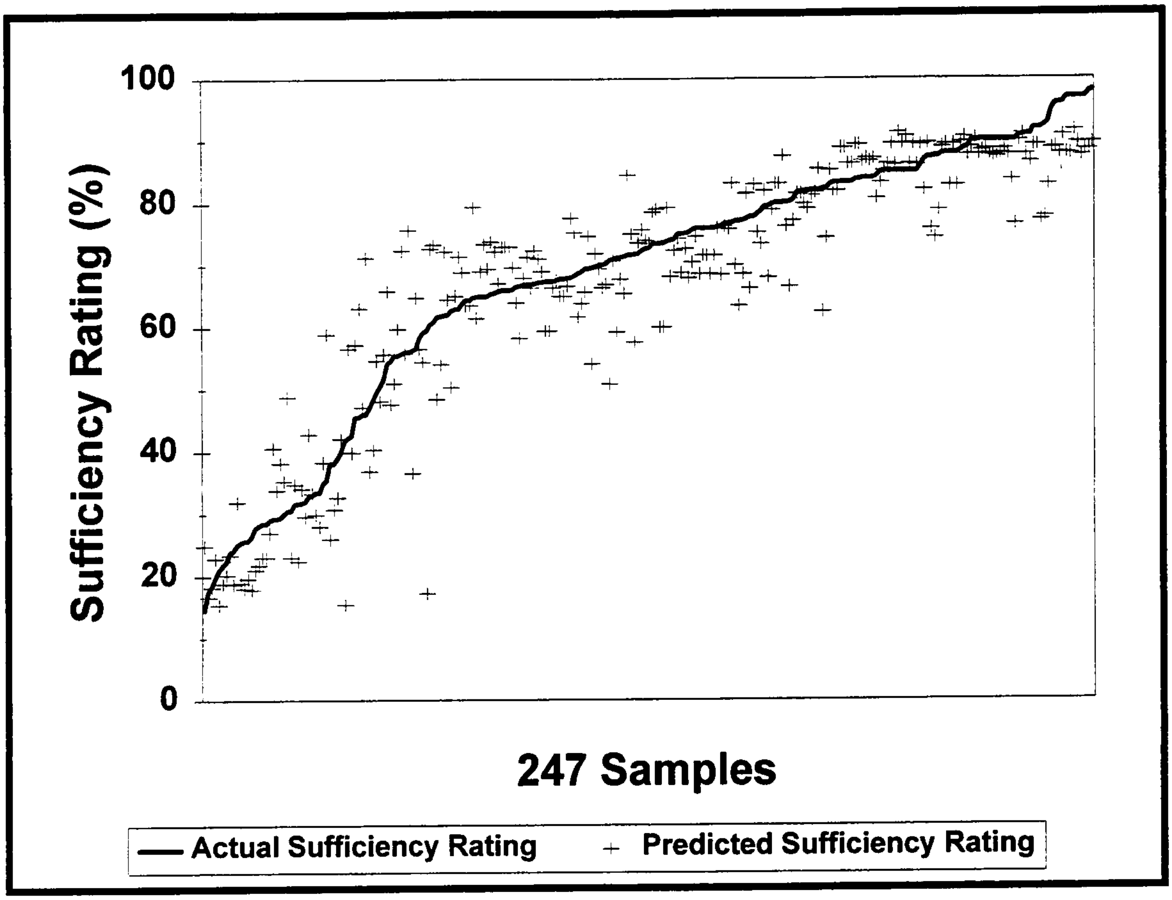

Figure 5.14. Design #3 Testing Results for 3N-2N Network

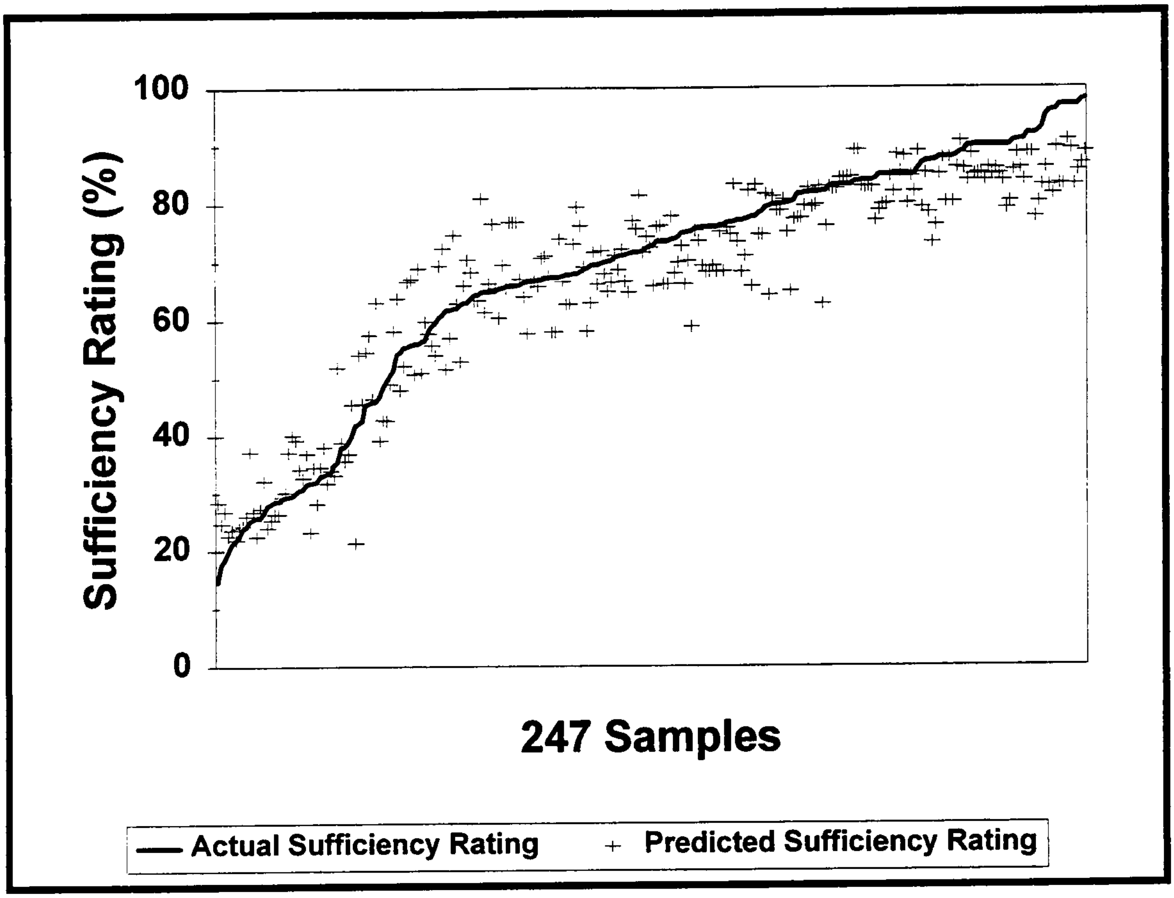

Figure 5.15. Design #3 Testing Results for 3N-2N-1N Network

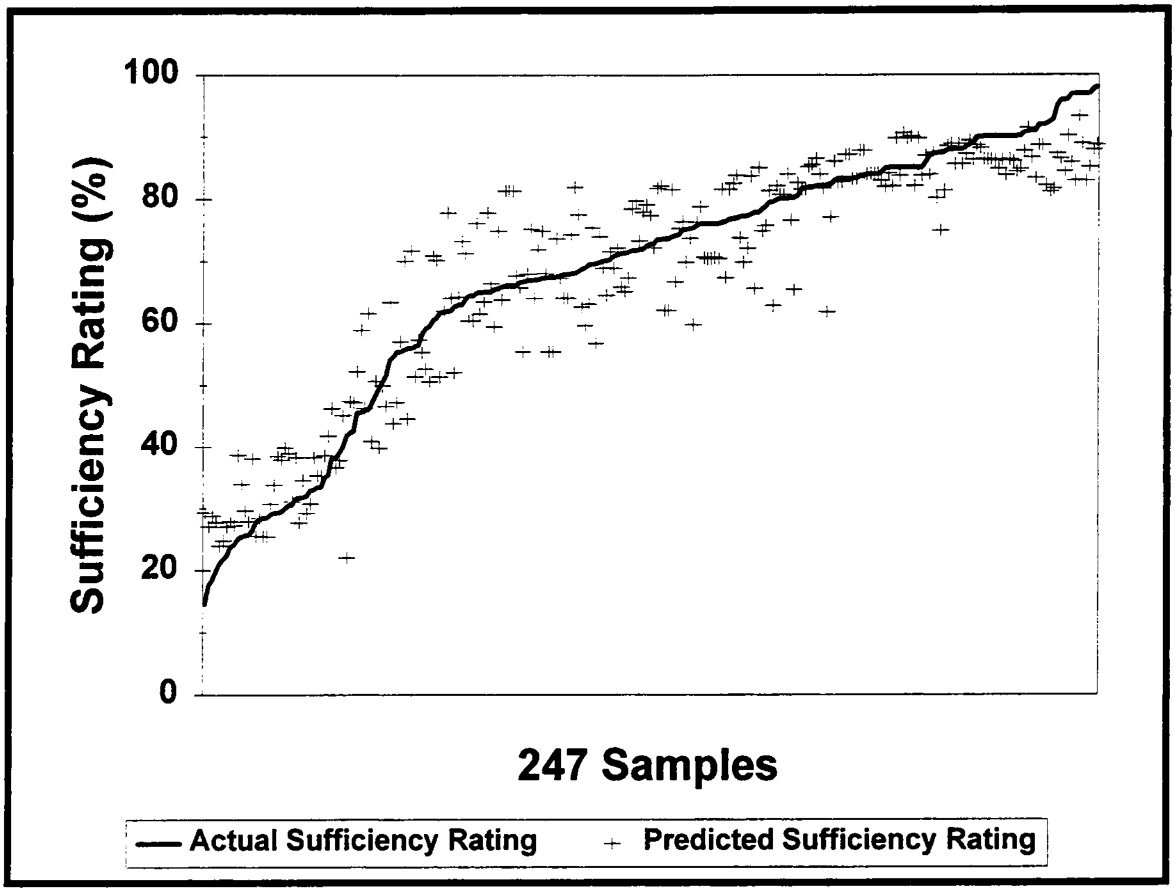

Figure 5.16. Design #3 Testing Results for 1N Network

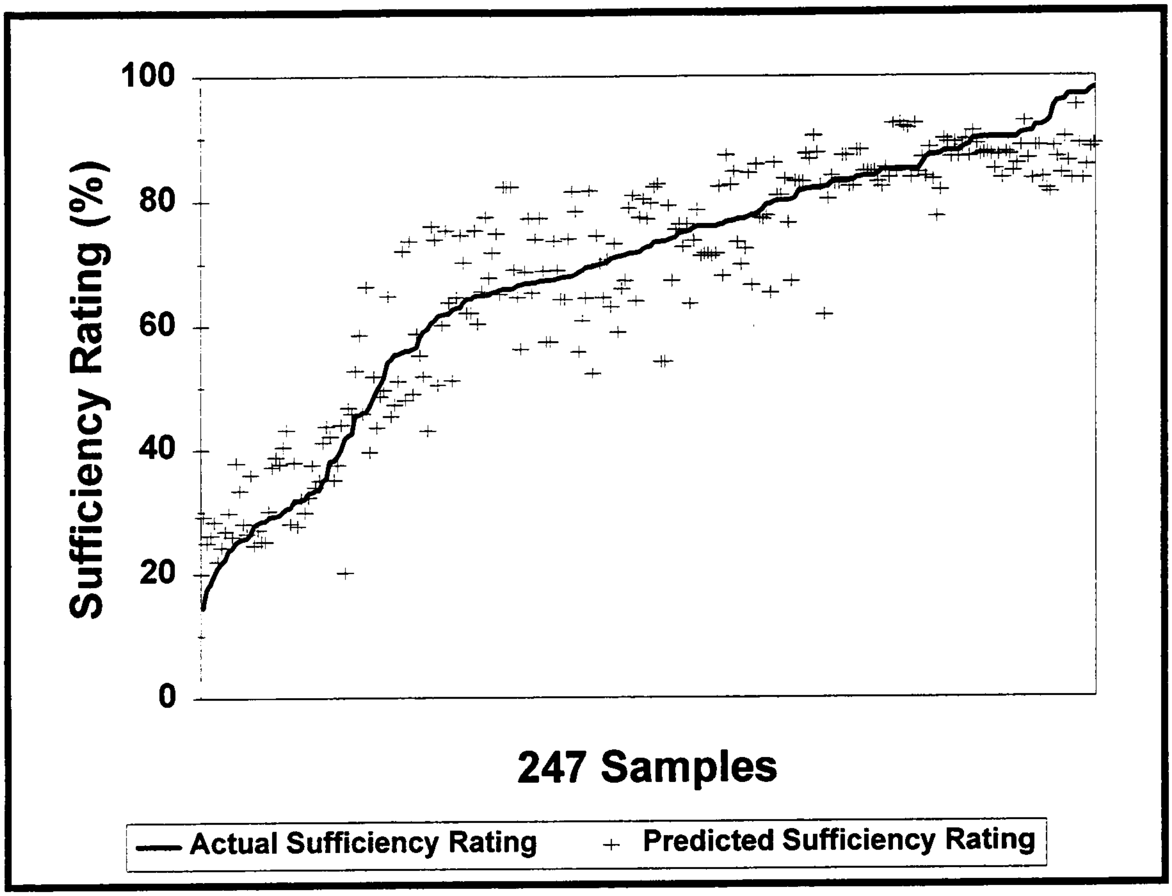

Figure 5.17. Design #3 Testing Results for 1N-1N Network

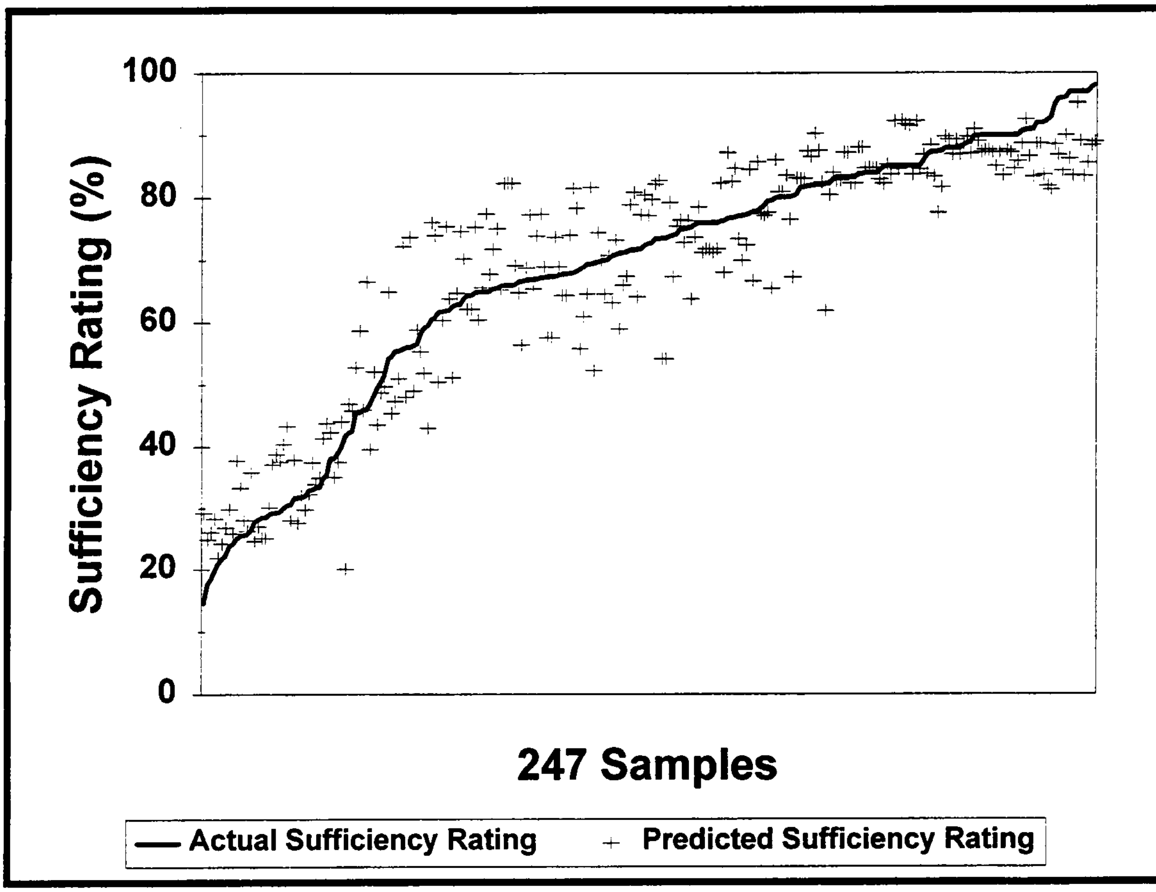

Figure 5.18. Design #3 Testing Results for 1N-1N-1N Network

Table 5.2. Neural Network and Multi-Variate Regression Testing Summary

Network Architecture	Max % Error	Percent of Test Samples with Error less than or equal to:									
		10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Design #3		**Testing Sample Size = 247**				**Number of Input Variables = 19**					
1N	102.09	64.37	88.66	95.55	97.17	98.38	99.60	99.60	99.60	99.60	99.60
1N - 1N	101.10	62.35	87.45	94.74	96.76	98.79	99.60	99.60	99.60	99.60	99.60
1N - 1N - 1N	101.01	62.35	87.85	94.74	96.76	98.79	99.60	99.60	99.60	99.60	99.60
4N	78.08	67.21	88.26	94.74	97.17	98.79	99.19	99.60	* **100.00**	100.00	100.00
3N - 2N	71.58	65.99	85.43	94.74	97.57	97.57	98.38	99.19	**100.00**	100.00	100.00
3N - 2N - 1N	95.15	68.42	91.50	96.36	97.57	**99.60**	99.60	99.60	99.60	99.60	**100.00**
M.V. Regr.	109.35	60.73	86.23	94.74	96.36	97.98	98.79	99.19	99.60	99.60	99.60
Design #4		**Testing Sample Size = 247**				**Number of Input Variables = 6**					
4N	**58.03**	60.32	85.43	92.31	96.76	99.19	**100.00**	100.00	100.00	100.00	100.00
3 - 2	61.75	59.51	82.19	91.90	95.55	97.98	99.60	**100.00**	100.00	100.00	100.00
3N - 2N - 1N	64.05	63.97	82.59	93.52	96.76	98.79	99.60	**100.00**	100.00	100.00	100.00
M.V. Regr.	106.63	51.01	80.97	91.09	95.95	98.38	98.38	98.79	99.60	99.60	99.60
Design #5		**Testing Sample Size = 247**				**Number of Input Variables = 10**					
4N	69.11	54.25	81.78	91.50	98.38	98.79	99.60	**100.00**	100.00	100.00	100.00
3N - 2N	59.30	55.47	77.33	89.88	94.74	98.38	**100.00**	100.00	100.00	100.00	100.00
3N - 2N - 1N	64.80	56.68	81.38	91.90	95.55	98.38	98.79	**100.00**	100.00	100.00	100.00
M.V. Regr.	104.48	50.20	79.76	91.09	95.55	97.98	98.38	99.19	99.60	99.60	99.60
Design #6		**Testing Sample Size = 208**				**Number of Input Variables = 19**					
3N - 2N - 1N	86.28	**77.88**	**94.71**	**98.08**	**98.56**	99.52	99.52	99.52	99.52	**100.00**	100.00
M.V. Regr.	103.96	66.35	89.42	97.60	**98.56**	99.04	99.52	99.52	99.52	99.52	99.52

*Values in bold represent best category performance

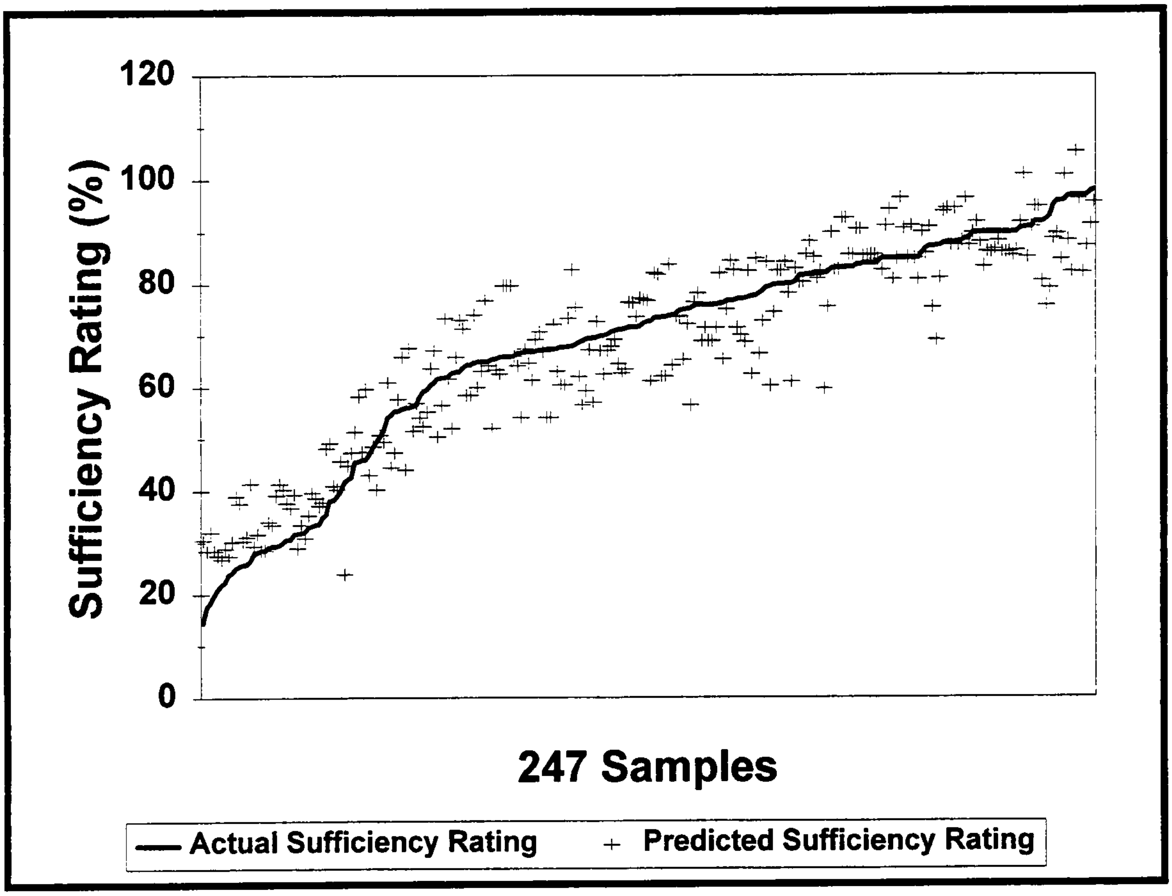

Figure 5.19. Design #3 Testing Results for Multi-Variate Linear Regression Model

inventory items 36, 59, 60 and 66 through 68 (see Table 4.1). The 4N, 3N-2N and 3N-2N-1N networks were used for training to an SSE goal of 1.0227 and another linear regression analysis was performed on the neural network training data.

All networks trained successfully with no significant overfitting (see Figs. 5.20 - 5.22) and testing indicates that the network prediction was better than regression (see Table 5.2 and Figs. 5.23 - 5.26). The networks predicted the data with a maximum error of 64.05% (for 3N-2N-1N). But the error distribution for these networks was larger by comparison to the networks from the third design (see Table 5.2).

Neural Network Design #5

The fifth design also considered a reduced input variable set (see Table 5.1). Variables with the top ten SR correlation coefficients were selected. The four additional variables include inventory items 51, 58, 71, and 72 (see Table 4.1). The 4N, 3N-2N and 3N-2N-1N networks were used for training to an SSE goal of 1.0227 and another linear regression analysis was performed on the neural network training data.

All networks trained successfully with no significant overfitting (see Figs. 5.27 - 5.29) and testing indicates that network prediction was better than regression (see Table 5.2 and Figs. 5.30 - 5.33). The networks predicted the data with a maximum error of 64.80% (for 3N-2N-1N). But, like the fourth design, the error distribution was larger by comparison to the networks from the third design (see Table 5.2).

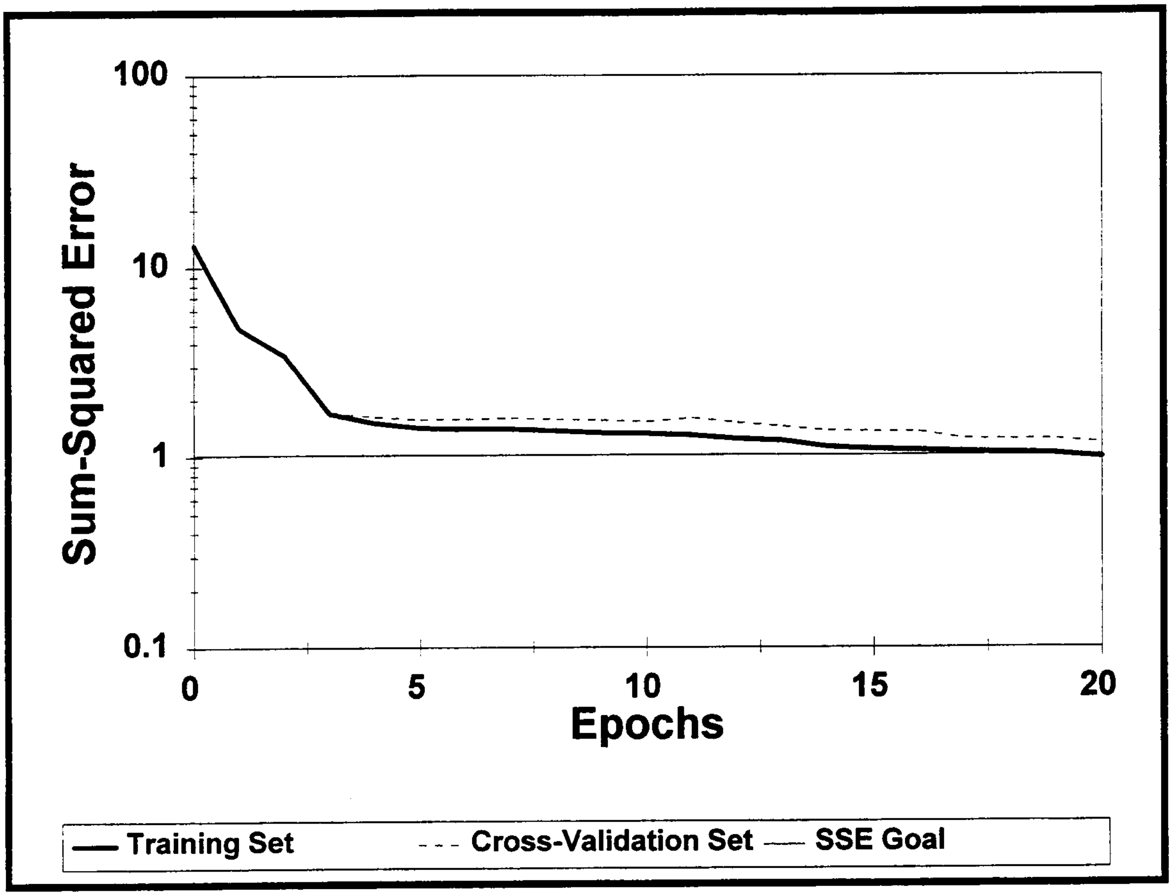

Figure 5.20. Design #4 Training Progress for 4N Network

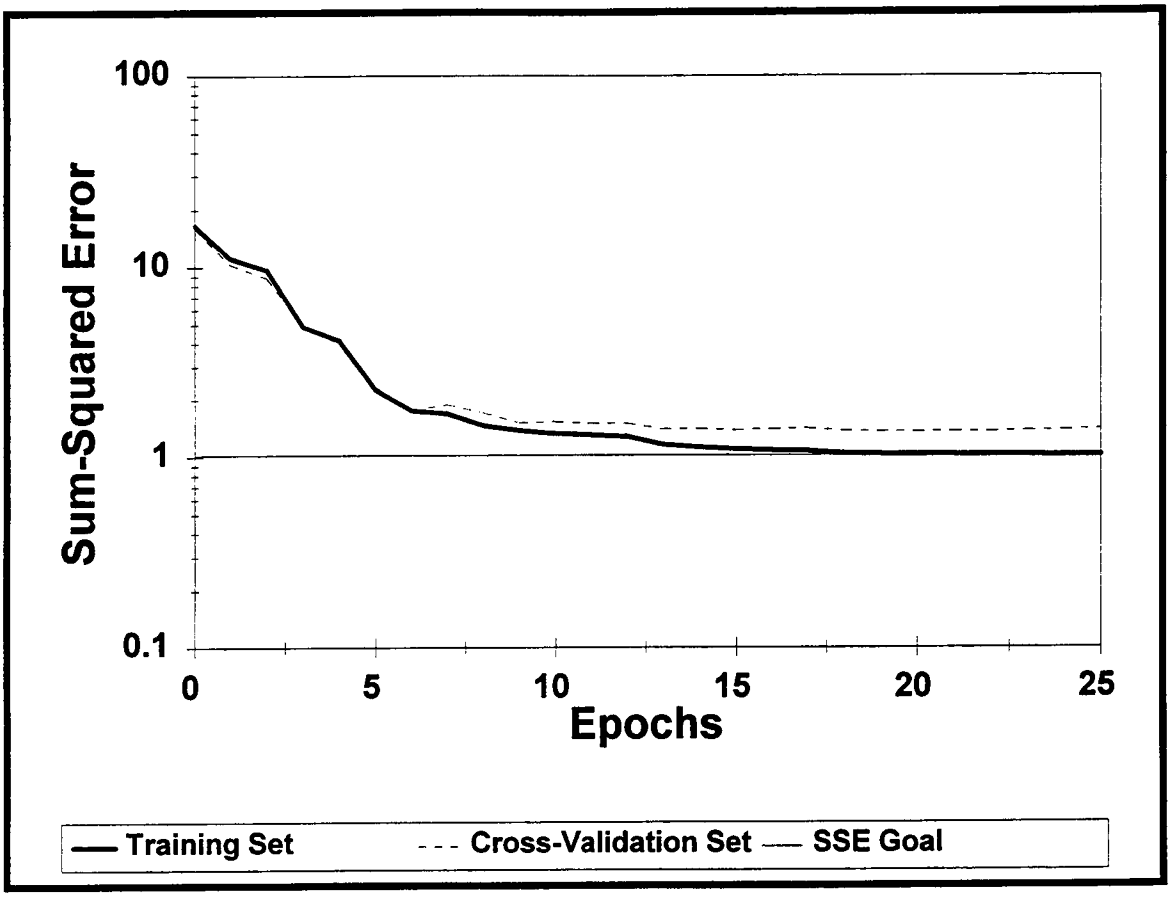

Figure 5.21. Design #4 Training Progress for 3N-2N Network

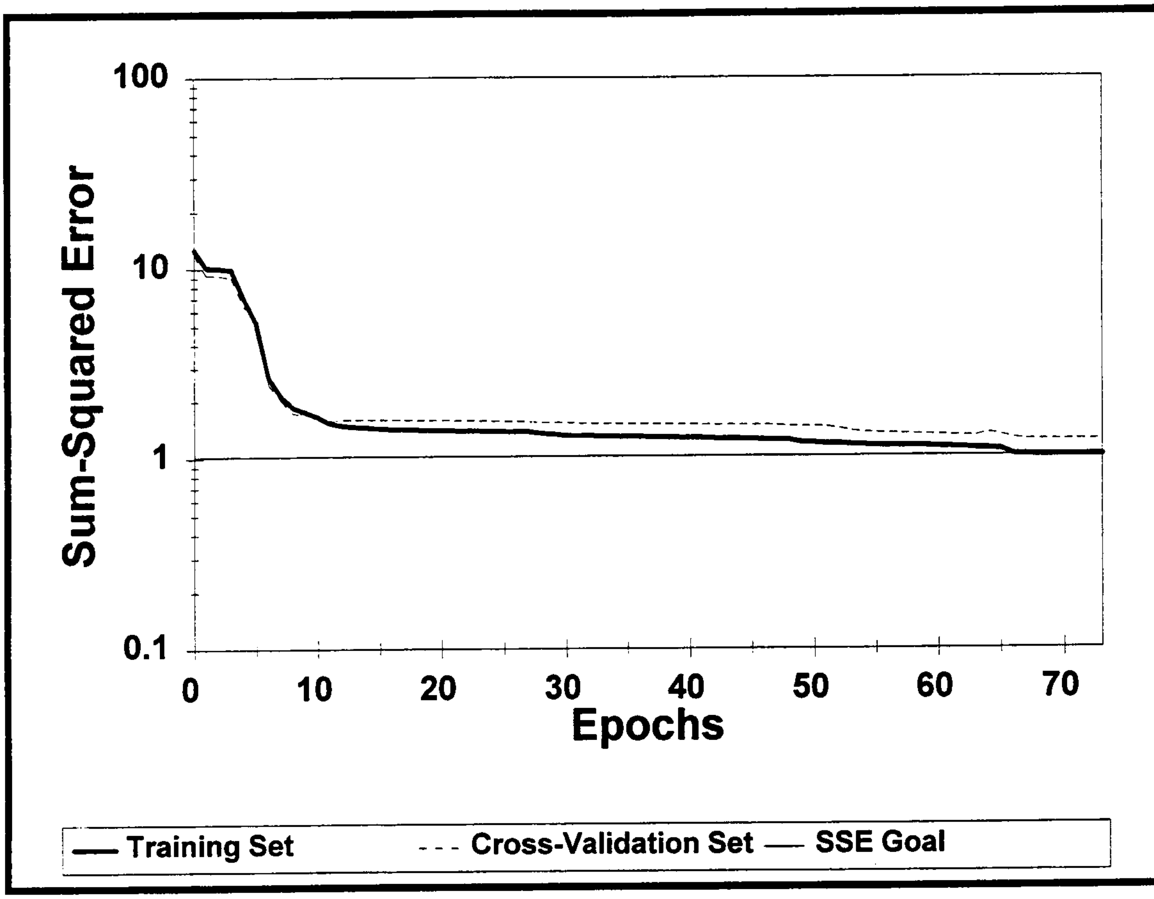

Figure 5.22. Design #4 Training Progress for 3N-2N-1N Network

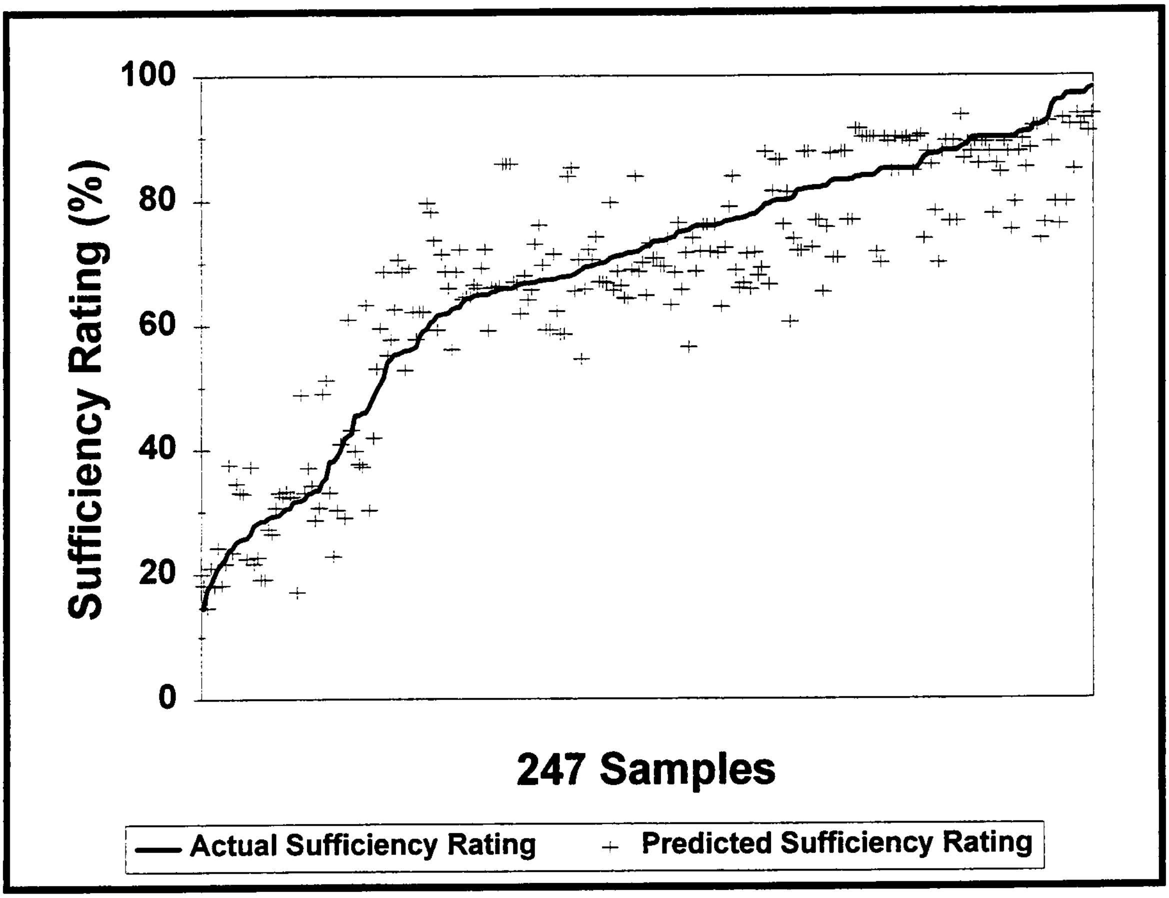

Figure 5.23. Design #4 Testing Results for 4N Network

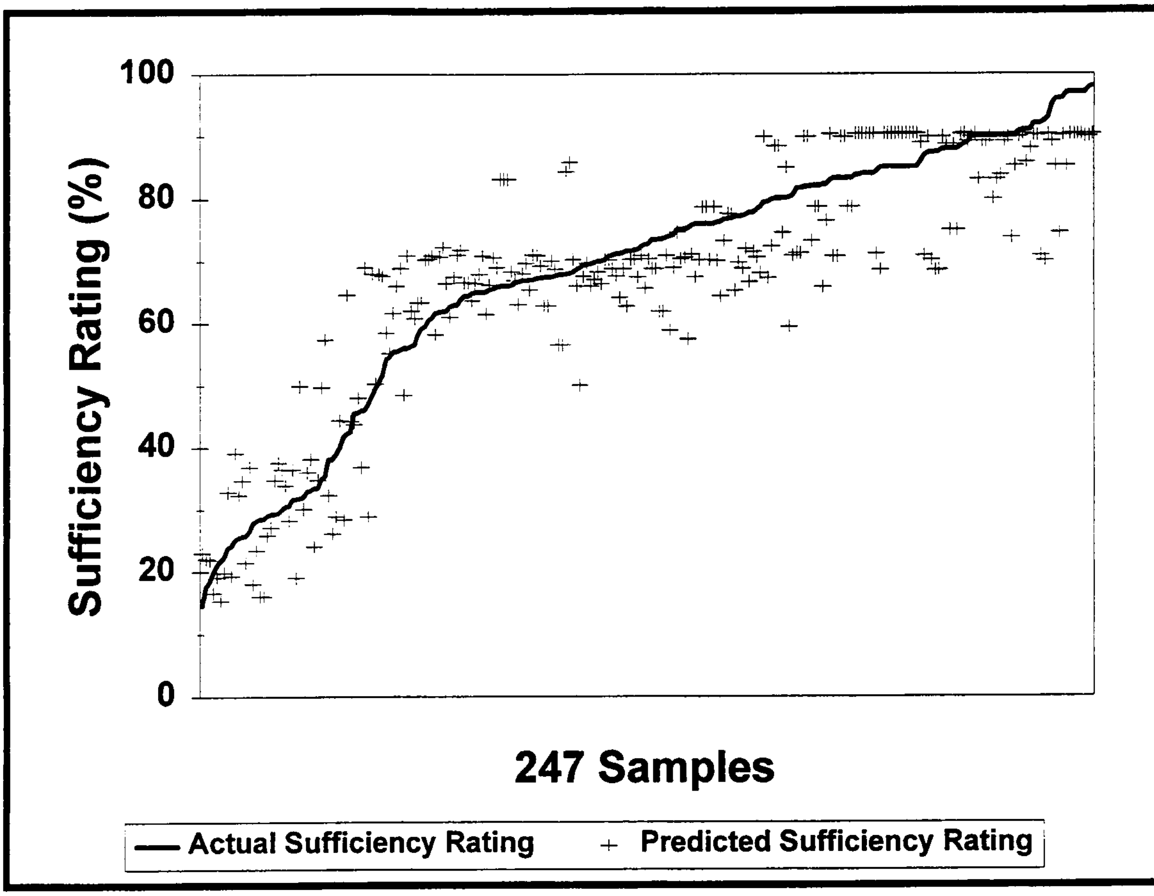

Figure 5.24. Design #4 Testing Results for 3N-2N Network

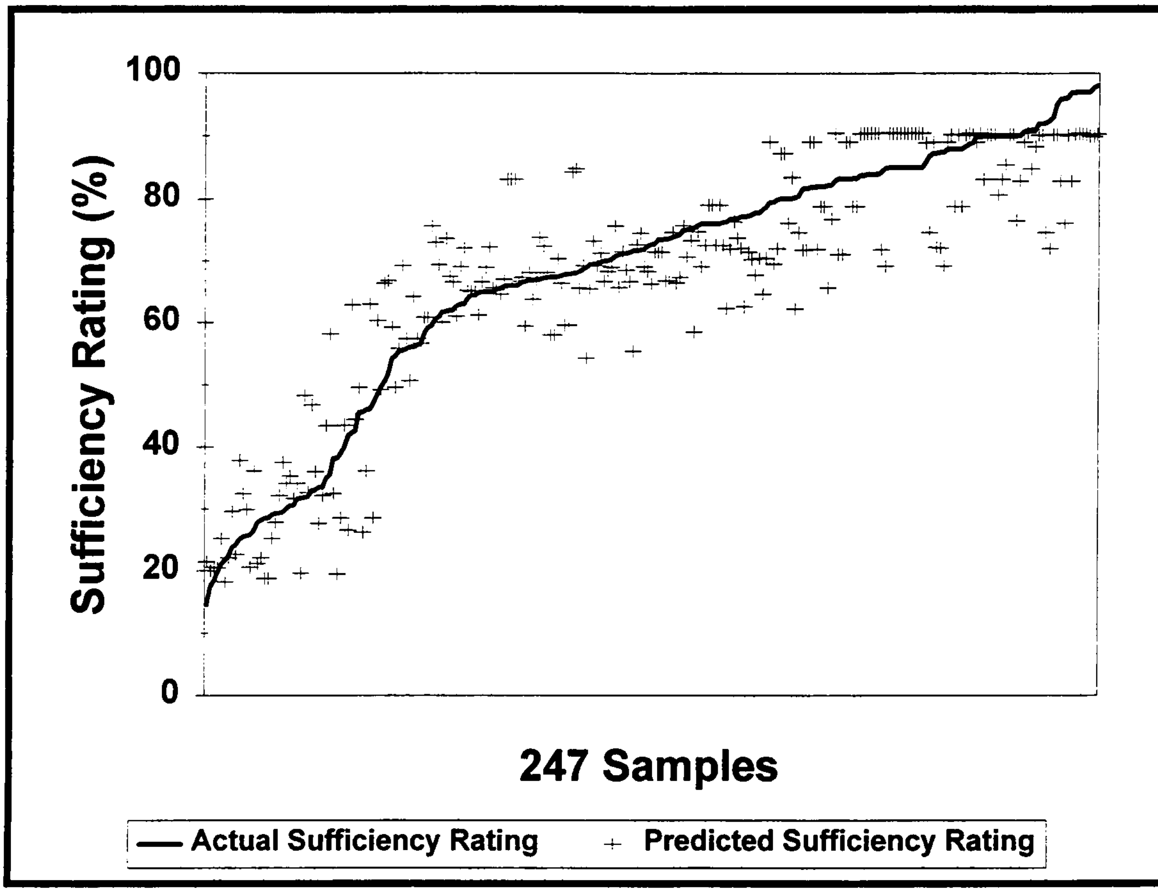

Figure 5.25. Design #4 Testing Results for 3N-2N-1N Network

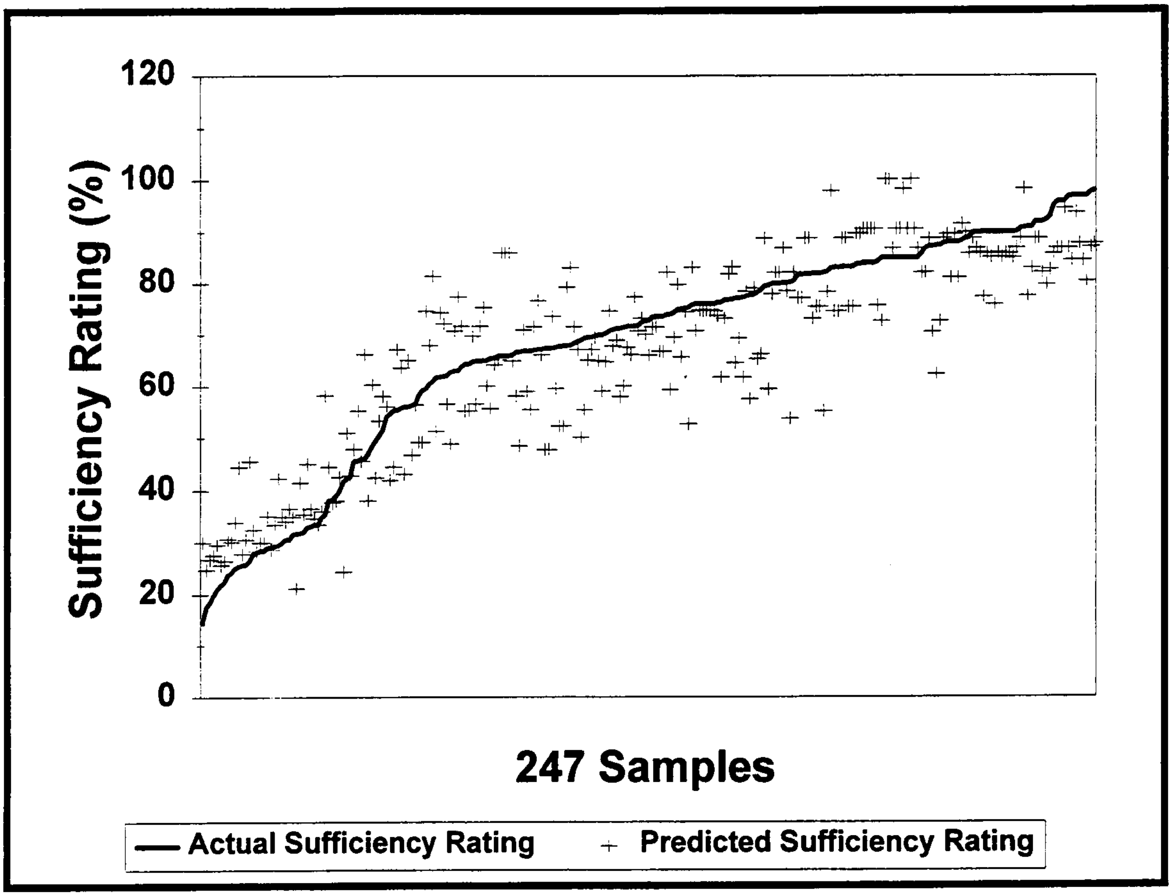

Figure 5.26. Design #4 Testing Results for Multi-Variate Linear Regression Model

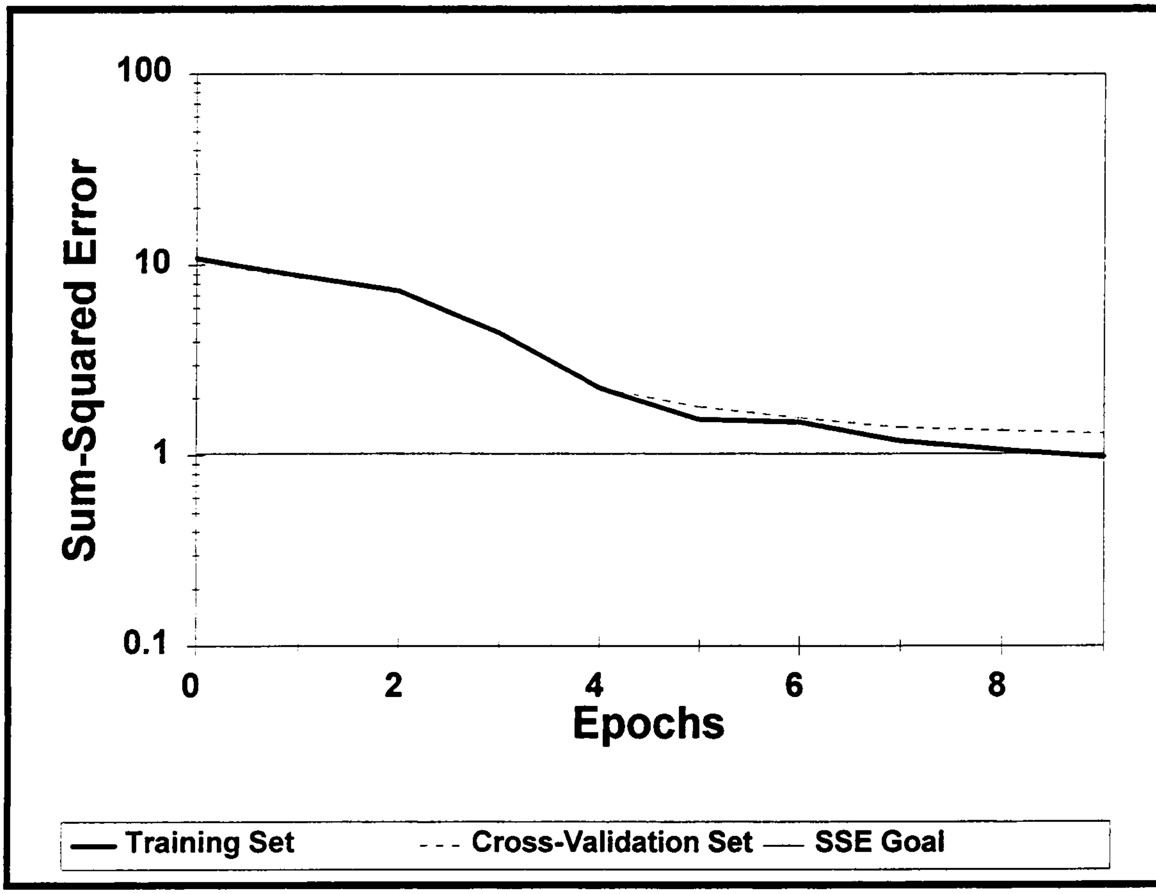

Figure 5.27. Design #5 Training Progress for 4N Network

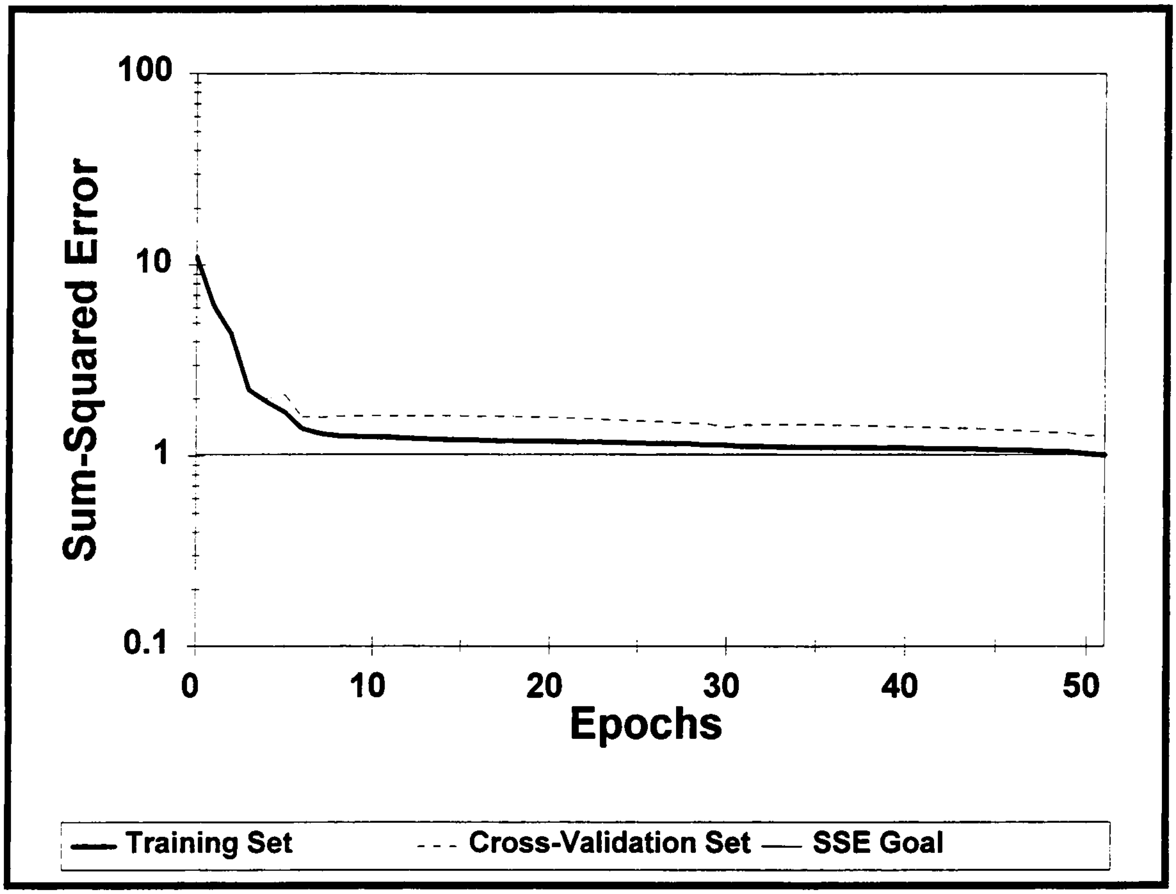

Figure 5.28. Design #5 Training Progress for 3N-2N Network

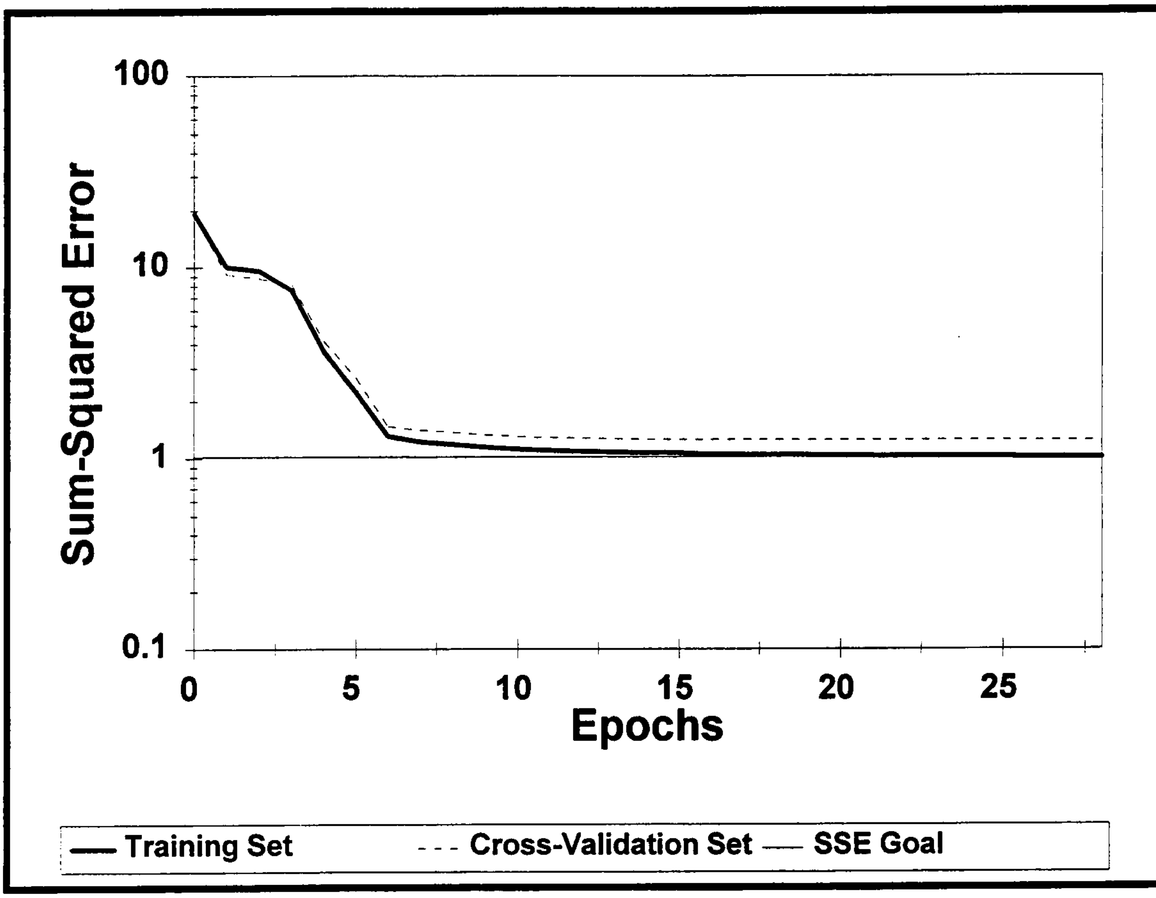

Figure 5.29. Design #5 Training Progress for 3N-2N-1N Network

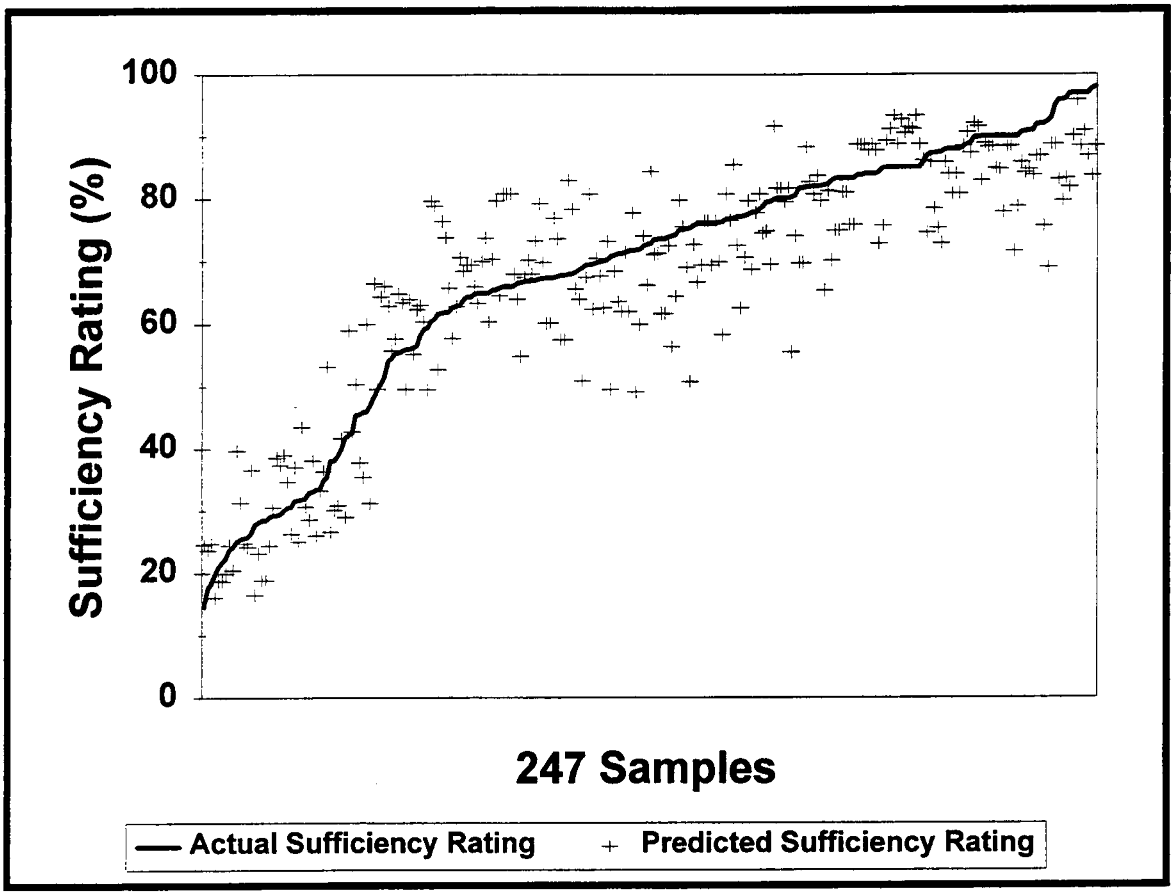

Figure 5.30. Design #5 Testing Results for 4N Network

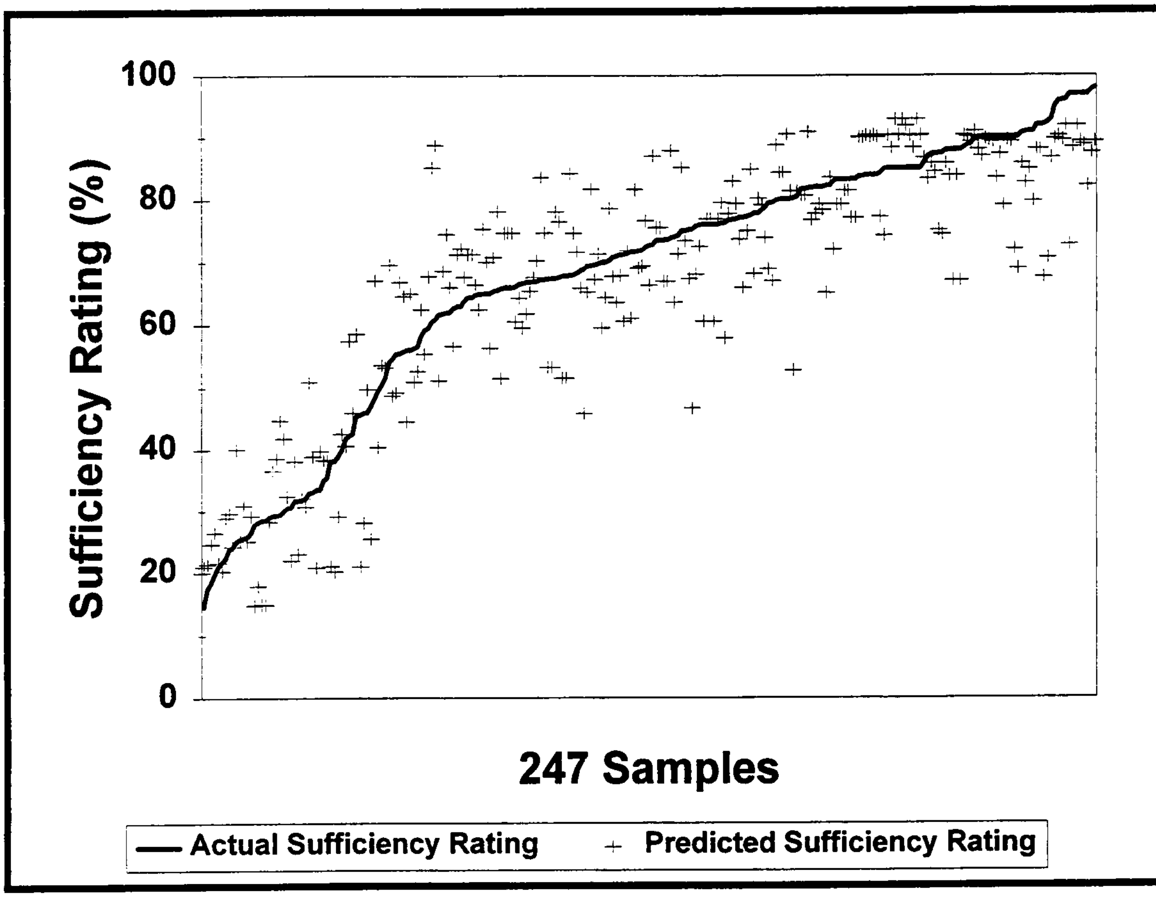

Figure 5.31. Design #5 Testing Results for 3N-2N Network

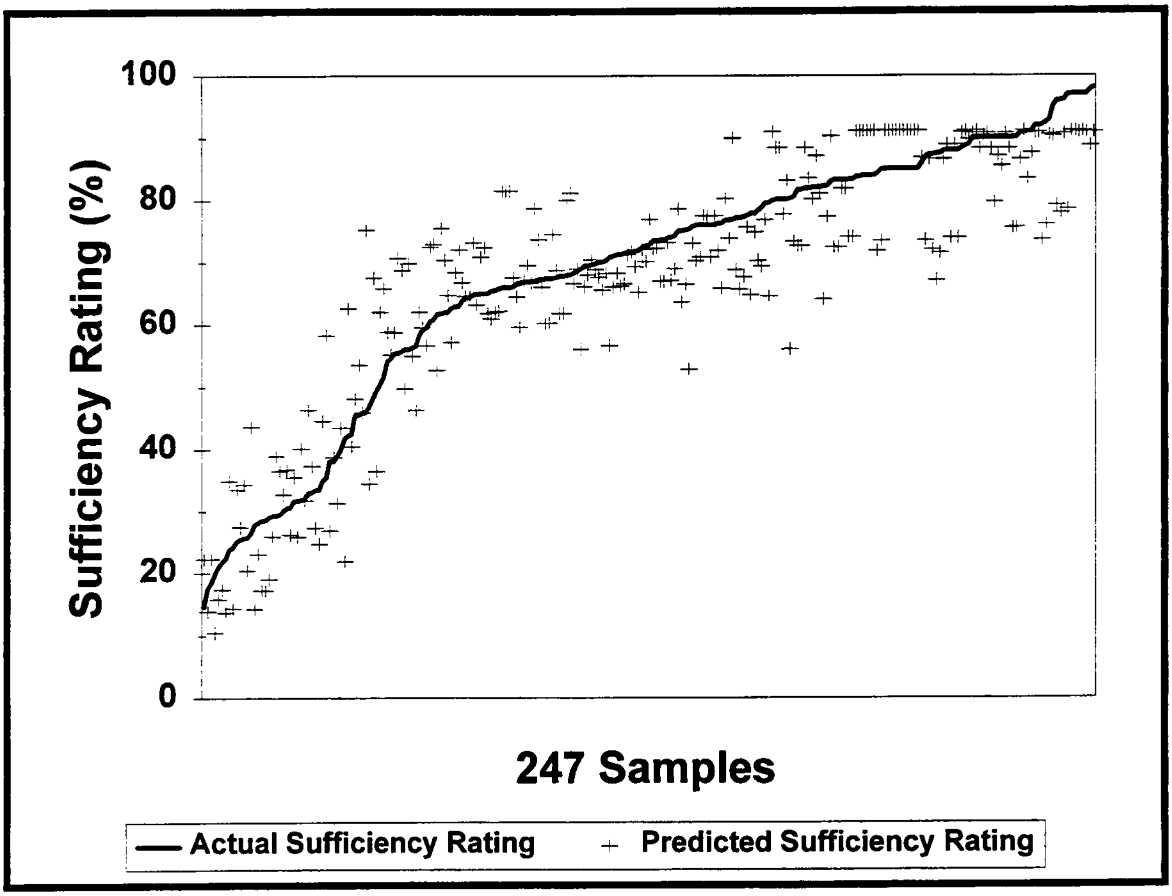

Figure 5.32. Design #5 Testing Results for 3N-2N-1N Network

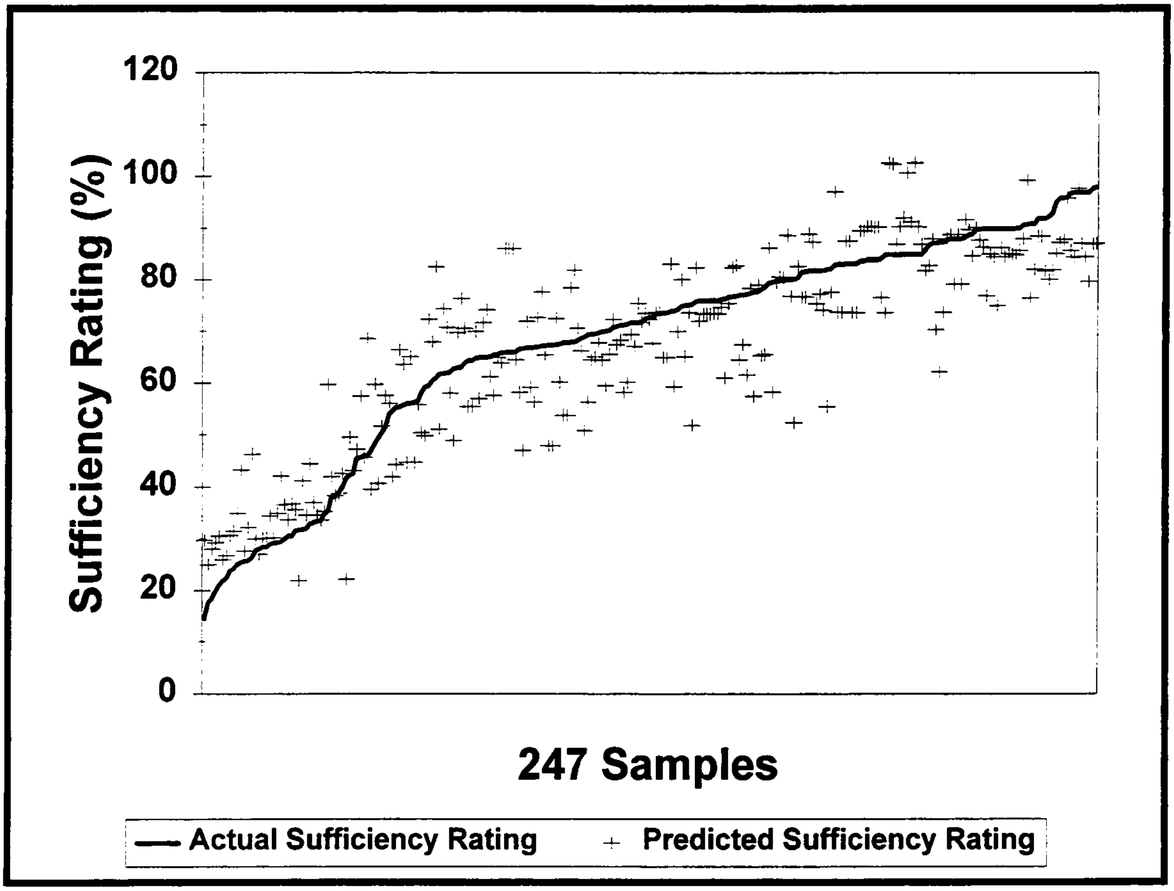

Figure 5.33. Design #5 Testing Results for Multi-Variate Linear Regression Model

Neural Network Design #6

The previous testing results show that the 3N-2N-1N network from the third design produced the best general results (see Table 5.2). This network predicted 68.42% of the test samples within 10% error. A total of 78 samples were predicted with an error greater than 10%. This sample output has a mean SR of 59.84%. The total population mean SR equals 67.99%, suggesting that the network had difficulty predicting small SR values.

For the sixth design, the 3N-2N-1N network was retrained with a new data set that included all nineteen input variables. The new training set consisted of the original two hundred sample set and one half of the samples predicted with more than 10% error; this increased the SSE goal to 1.1840. The thirty-nine additional samples were selected randomly with a mean SR of approximately 59.84% (see Table 5.1). A multi-variate linear regression analysis was also performed on the new neural network training set.

The network trained successfully with no indication of overfitting (see Fig. 5.34). Testing of the network improved with 77.88% of the test samples predicted within 10% error. The regression model also improved by comparison to the previous models but, the neural network still produced better results (see Table 5.2 and Figs. 5.35 and 5.36).

Confidence Interval Calculation

To measure the degree of accuracy provided by the neural network, the confidence interval (CI) of the mean SR was calculated. The samples predicted by the sixth network design were evaluated using a confidence level of 95% ($1-\alpha = 0.95$, where $\alpha = 0.05$). The confidence interval formula is given by (Ang and Tang, 1975)

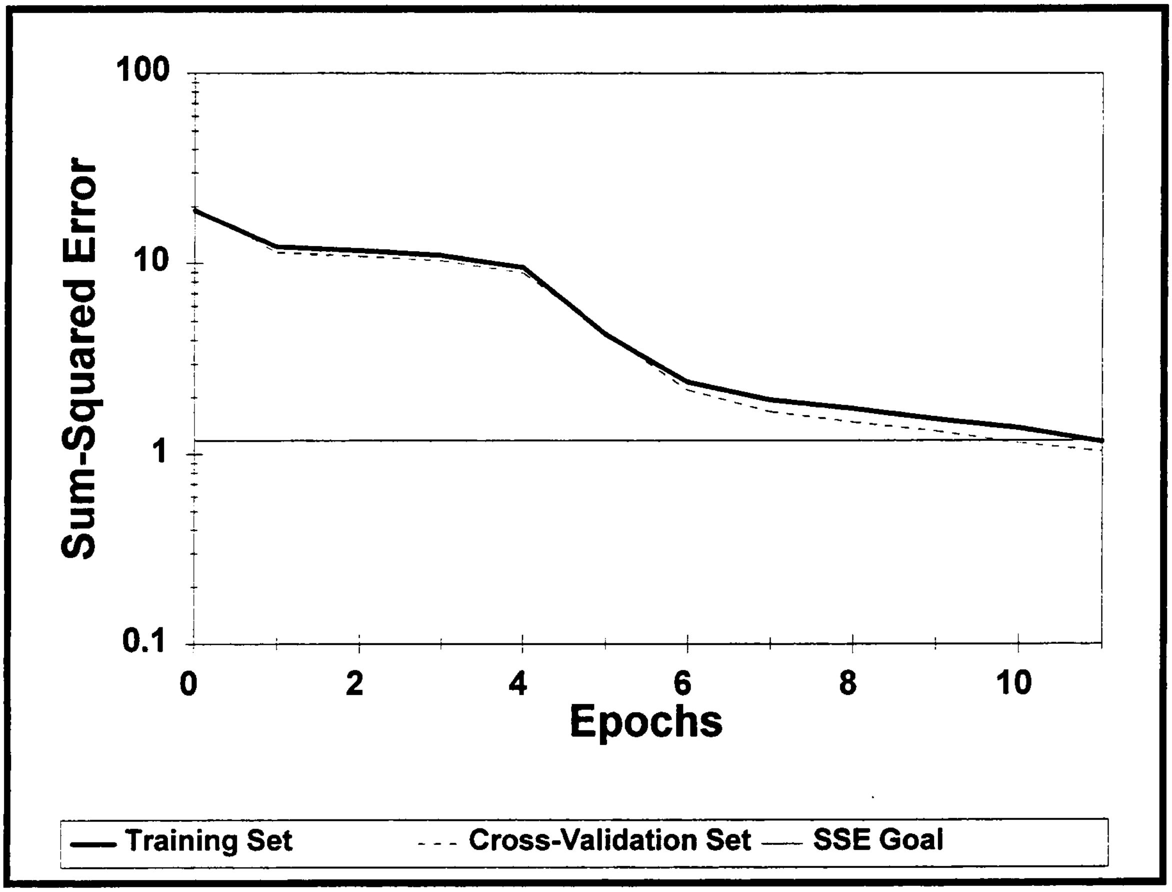

Figure 5.34. Design #6 Training Progress for 3N-2N-1N Network

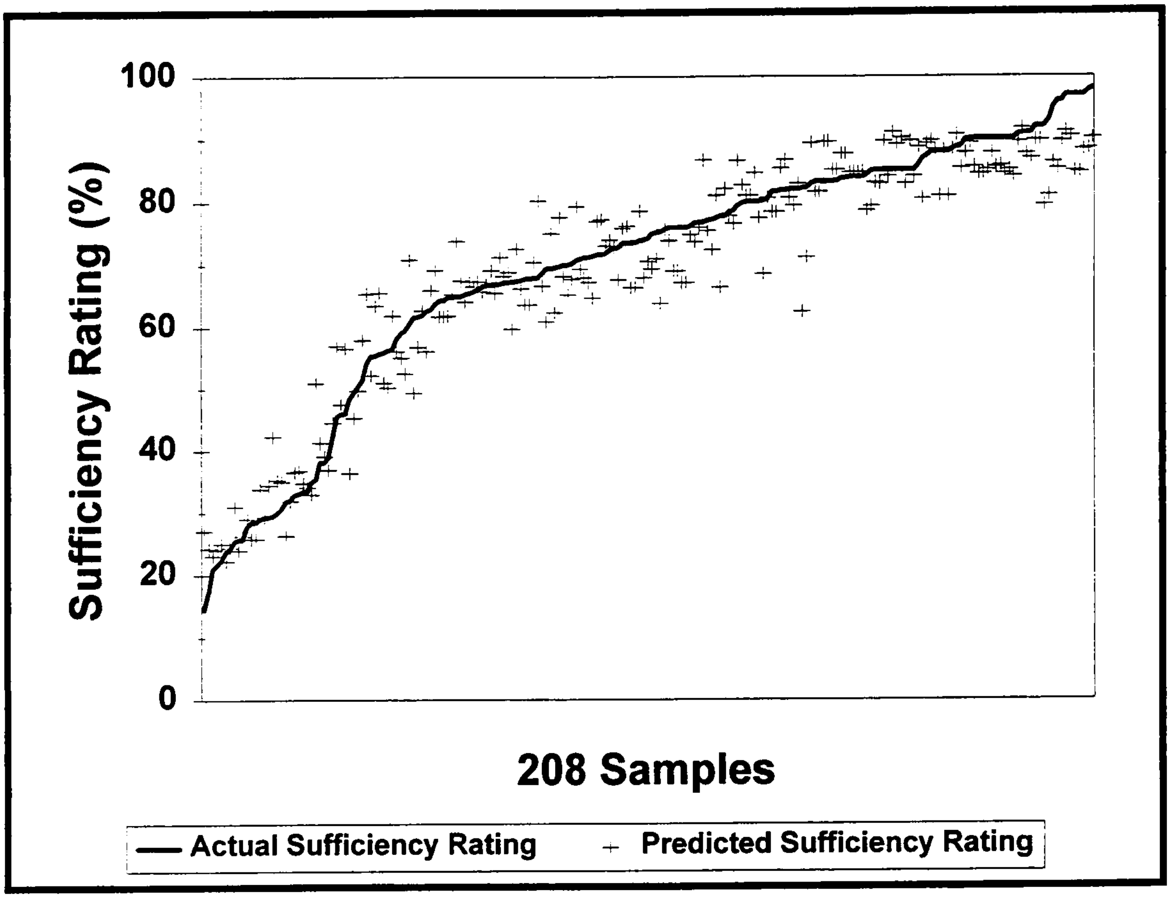

Figure 5.35. Design #6 Testing Results for 3N-2N-1N Network

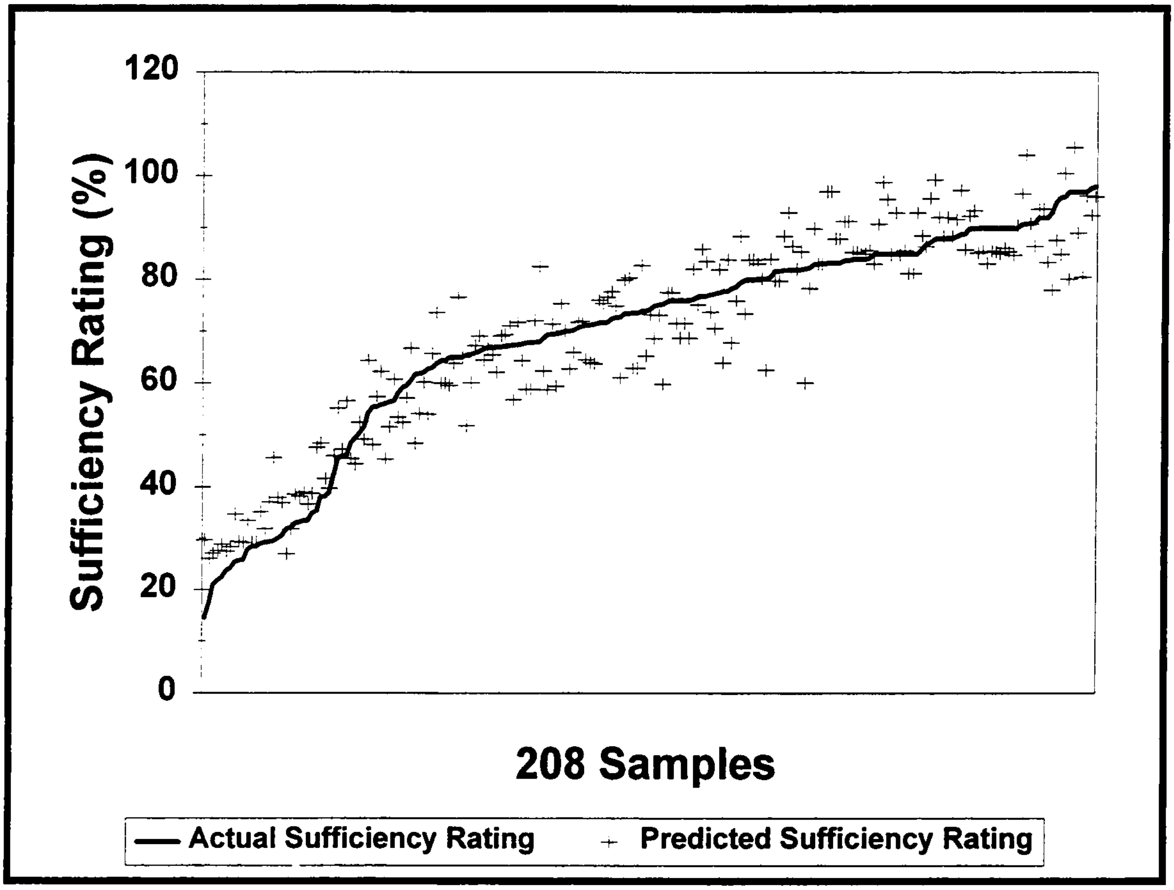

Figure 5.36. Design #6 Testing Results for Multi-Variate Linear Regression Model

$$[m_{SR} - (\sigma_{SR}k_{\alpha/2}) \div (n)^{1/2}] < \mu_{SR} < [m_{SR} + (\sigma_{SR}k_{\alpha/2}) \div (n)^{1/2}] \quad (5.1)$$

Where:

- μ_{SR} = SR mean for the total population
- m_{SR} = SR mean for the predicted samples
- σ_{SR} = SR standard deviation for the total population
- $k_{\alpha/2}$ = Value of the standard normal variate with cumulative probability level of $1 - \alpha/2$
- n = Number of test samples (208)

The mean of the predicted SR and the standard deviation for the total population are 68.77% and 21.68%, respectively. At a 5% confidence level, $k_{\alpha/2}$ equals 1.96, resulting in a confidence interval of 65.82% to 71.72%. These results imply that there is a 95% confidence that μ_{SR} is within the estimated interval (Ang and Tang, 1975). The mean SR for the total population is 67.99% (see Ch. 4), which falls within the CI. Therefore, the network does have a high degree of accuracy.

Summary of Results

Table 5.2 indicates that neural network performance was generally better than the multi-variate linear regression. In network designs #3 to #6, the regression models had the largest maximum error and error distribution. Regression analysis in *Quattro Pro* is based on the assumption of linear relationships between input and output. Neural networks can model non-linear relationships with non-linear transfer functions. Consequently, a neural network can model a set of non-linear data with greater accuracy.

The ability to design networks with different architectures also provides a method for improving accuracy. Testing results from this study showed that the networks with more than one hidden layer tended to produce better results. Increasing the number of hidden layers provides additional transfer functions, which in turn provide more processing capability.

The results have also shown that using neural networks provides a more user-friendly tool for performing calculations. As stated previously in Chapter 4, the sufficiency rating is composed of four variables which represent separate rating categories ($SR = S_1 + S_2 + S_3 - S_4$). Each variable is calculated based on a mathematical formulation of the inventory items. The calculation procedure is found in Appendix A. The neural network provides a relatively simple and accurate prediction model which considers all of the key inventory items and eliminates the need to perform intermediate calculations.

Chapter 6

Conclusions

A study was performed to assess the potential advantages and benefits of using neural networks for evaluating infrastructure systems. Prediction of bridge rating data was used as an example to illustrate this application. Neural network models produced more accurate results than the multi-variate linear regression models. The results from this study show that neural networks can model data relationships that are non-linear and subjective. The results also show that an intricate mathematical formulation can be modeled accurately by a neural network based on a small amount of existing data.

Neural network accuracy was assessed by comparing to multi-variate linear regression analysis. This traditional analysis method is readily available in many spreadsheet programs. Although there are many PC-based programs for data analysis available, most engineering firms and government agencies only use the latest spreadsheet package.

An advantage provided by neural networks is its great design versatility. Network architecture can be easily modified by using different transfer functions and changing the number of hidden neurons and hidden neuron layers. This makes it possible to develop a prediction model suited for a specific type of problem. Networks can be developed for bridges made from a specific material (concrete, steel, timber) or for evaluating specific types of construction (girder, box beam, truss, arch, suspension).

The availability of many PC-based neural network programs makes the use of neural networks simple and affordable. The *Neural Network Toolbox* (which runs with *MATLAB*) provides several different training algorithms that can be used to design a variety of neural network architectures. Its flexibility also enables the user to customize existing training algorithms and create new ones (Beale and Demuth, 1992). More automated packages are also available, such as *NeuralWorks Predict* by NeuralWare, Inc. This program has the advantage of running with *Microsoft Excel*. The use of a spreadsheet program provides a simple and familiar method of supplying input data and receiving output data.

The results of this study show that there is a great potential for using neural networks for infrastructure system evaluation. Other infrastructure systems that may benefit from neural network applications include roads and highways, power plants, airports, railroads, dams and sewer systems. Consistency in future evaluations is just one of the benefits of using neural networks. Their versatility also provides many advantages over other traditional methods of data analysis such as regression analysis and expert systems. The continuing refinement of computer technology also makes neural networks an increasingly attractive tool.

Future studies in infrastructure evaluation can implement the use of other neural network paradigms such as radial basis networks (Beale and Demuth, 1992). Development of several networks for evaluating one system may also be advantageous. The bridge Sufficiency Rating, determined by the U.S. Department of Transportation, is a combination of four distinct rating categories. A neural network could be developed for each category.

As stated previously, networks can also be developed for systems that can be grouped by distinct characteristics.

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Appendices

Appendix A

Sufficiency Rating Calculation Procedure

(Source: U.S. DOT / Federal Highway Administration, 1979)

1. Structural Adequacy and Safety (55% maximum)

If #59 (Superstructure Rating) or #60 (Substructure Rating) is:

	≤ 2	A = 55%
	= 3	B = 40%
	= 4	C = 25%
Or A, B, and C = 0, and #59 or #60 = 5		D = 10%

If #59 and # 60 = NA and #62 (Culvert Rating) is:

	≤ 2	E = 55%
	= 3	F = 40%
	= 4	G = 25%
Or E, F, and G = 0 and #62 = 5		H = 10%

Reduction for Load Capacity:

a) Calculate AIT (Adjusted Inventory Tonnage) as follow:

When the 1st digit of #66 = 1, AIT = the 2nd & 3rd digits multiplied by 1.56

When the 1st digit of #66 = 2, AIT = the 2nd & 3rd digits multiplied by 1.00

When the 1st digit of #66 = 3, AIT = the 2nd & 3rd digits multiplied by 1.56

When the 1st digit of #66 = 4, AIT = the 2nd & 3rd digits multiplied by 1.01

When the 1st digit of #66 = 5, AIT = the 2nd & 3rd digits multiplied by 0.77

When the 1st digit of #66 = 6, AIT = the 2nd & 3rd digits multiplied by 0.67

When the 1st digit of #66 = 9, AIT = the 2nd & 3rd digits multiplied by 1.00

b) $I = (36 - AIT)^{1.5} \times 0.2778$

Note: If $(36 - AIT)^{1.5} \leq 0$, then $I = 0$. Limits: 0% to 55%

$S_1 = 55 - (A + B + C + D + E + F + G + H + I)$

S_1 shall not be less than 0% nor greater than 55%

2. Serviceability and Functional Obsoleteness (30% maximum)

Rating Reductions (13% maximum)

If #58 (Deck Condition) is:	≤ 3	A = 5%
	= 4	A = 3%
	= 5	A = 1%
If #67 (Structural Condition) is:	≤ 3	B = 4%
	= 4	B = 2%
	= 5	B = 1%
If #68 (Deck Geometry) is:	≤ 3	C = 4%
	= 4	C = 2%
	= 5	C = 1%
If #69 (Underclearance) is:	≤ 3	D = 4%
	= 4	D = 2%
	= 5	D = 1%
If #71 (Waterway Adequacy) is:	≤ 3	E = 4%
	= 4	E = 2%
	= 5	E = 1%
If #72 (Approach Road Alignment) is:	≤ 3	F = 4%
	= 4	F = 2%
	= 5	F = 1%

$J = (A + B + C + D + E + F)$

J shall not be less than 0% nor greater than 13%

<u>Width of Roadway Insufficiency</u> (15% maximum)

Note: #1 applies to all bridges

#2 applies to one-lane bridges only

#3 applies to two or more lane bridges

#4 applies to all except one-lane bridges

and

X (ADT ÷ Lane) = #29 (ADT) ÷ First two digits of #28 (Lanes)

Y (Width ÷ Lane) = #51 (Bridge Roadway Width) ÷ First two digits of # 28

#1 - Use when the last two digits of #43 (Structure Type) are not 19 (Culvert):

If (#51 + 2 ft.) < #32 (Approach Roadway Width) G = 5%

#2 - For one-lane bridges only

If the first the first two digits of #28 (Lanes) are equal to 01 and:

If $Y < 14$	$H = 15\%$
If $14 \leq Y < 18$	$H = 15 \times (18 - Y) \div 4\%$
If $Y \geq 18$	$H = 0\%$

#3 - For two or more lane bridges. If these limits apply, do not continue on to #4 as no lane width reductions are allowed.

	If the first two digits of #28 = 02 and $Y \geq 16$	$H = 0\%$
	If the first two digits of #28 = 03 and $Y \geq 15$	$H = 0\%$
	If the first two digits of #28 = 04 and $Y \geq 14$	$H = 0\%$
	If the first two digits of #28 = 05 and $Y \geq 12$	$H = 0\%$

#4 - For all except one-lane bridges

	If $Y < 9$ and $X > 50$	$H = 15\%$
	If $Y < 9$ and $X \leq 50$	$H = 7.5\%$
	If $Y \geq 9$ and $X \leq 50$	$H = 0\%$
If $50 < X \leq 125$ and:	$Y < 10$	$H = 15\%$
	$10 \leq Y < 13$	$H = 15 \times (13 - Y) \div 3\%$
	$Y \geq 13$	$H = 0\%$
If $125 < X \leq 375$ and:	$Y < 11$	$H = 15\%$
	$11 \leq Y < 14$	$H = 15 \times (14 - Y) \div 3\%$
	$Y \geq 14$	$H = 0\%$
If $375 < X \leq 1350$ and:	$Y < 12$	$H = 15\%$
	$12 \leq Y < 16$	$H = 15 \times (16 - Y) \div 4\%$
	$Y \geq 16$	$H = 0\%$
If $X > 1350$ and:	$Y < 15$	$H = 15\%$
	$15 \leq Y < 16$	$H = 15 \times (16 - Y)\%$
	$Y \geq 16$	$H = 0\%$

"Width of Roadway Insufficiency" shall not be less than 0% nor greater than 15%

Vertical Clearance Insufficiency (2% maximum)

If #12 (Defense Road) > 0 and:

#53 (VC over Deck) $\geq$ 1600	I = 0%
#53 (VC over Deck) < 1600	I = 2%

If #12 (Defense Road) = 0 and:

#53 (VC over Deck) $\geq$ 1400	I = 0%
#53 (VC over Deck) < 1400	I = 2%

"Vertical Clearance Insufficiency" shall not be less than 0% nor greater than 2%

$\mathbf{S_2 = 30 - [J + (G + H) + I]}$

Where J shall not exceed 13% and (G + H) shall not exceed 15%

S_2 shall not be less than 0% nor greater than 30%

3. Essential Public Use (15% maximum)

$K = (S_1 + S_2) \div 85$

$A = [\#29\ (ADT) \times \#19\ (Detour\ Length) \times 15] \div [200{,}000 \times K]$

A shall not be less than 0% nor greater than 15%

If #12 > 0, then B = 2%

If #12 = 0, then B = 0%

$S_3 = 15 - (A + B)$

S_3 shall not be less than 0% nor greater than 15%

4. Special Reductions (Use only when $S_1 + S_2 + S_3 \geq 50\%$)

a) Detour Length Reduction: $A = (\#19)^4 \times (5.205 \times 10^{-8})$ Maximum = 5%

b) If the 2nd and 3rd digits of #43 (Structure Type, Main) are 10, 12, 13, 14, 15, 16 ,17:

$$B = 5\%$$

c)	If two digits of # 36 (Highway Safety Features)	= 0	C = 1%
	If three digits of #36	= 0	C = 2%
	If Four digits of #36	= 0	C = 3%

$\mathbf{S_4 = A + B + C}$

Sufficiency Rating = $\mathbf{S_1 + S_2 + S_3 - S_4}$

The Sufficiency Rating shall not be less than 0% nor greater than 100%

Appendix B

Tennessee DOT Bridge Rating Data

SR	Item Number:																								
	12*	19	28	29	32	36				43		51	53		58	59	60	62	66		67	68	69	71	72
(%)		(Miles)			(Feet)	(1)	(2)	(3)	(4)	(1)	(2)	(Feet)	(1) (Feet)	(2) (Inches)					(1)	(2) (Tons)					
2.0	0	99	2	250	18	0	0	0	0	1	2	20.0	99	99	4	4	4	NA	2	12	4	3	4	NA	3
3.0	0	35	2	8760	26	0	0	0	0	7	10	21.0	99	99	4	3	4	NA	2	10	4	3	5	NA	4
3.0	0	6	2	1200	24	0	0	0	0	1	2	19.2	99	99	4	3	7	NA	2	7	3	3	NA	5	8
6.3	0	99	2	300	20	0	0	0	0	3	2	22.1	99	99	5	3	3	NA	2	16	4	5	NA	3	5
9.0	0	99	2	1000	29	0	0	0	0	3	2	19.1	99	99	6	4	3	NA	2	14	4	3	NA	8	8
9.1	0	99	1	900	15	0	0	0	0	7	2	15.9	99	99	4	3	4	NA	2	18	4	3	5	NA	3
14.5	0	4	2	700	17	0	0	0	0	1	11	20.2	99	99	5	3	7	NA	2	18	4	3	NA	6	2
14.6	0	5	1	150	15	0	0	0	0	3	2	12.0	99	99	4	4	4	NA	2	10	3	2	NA	2	2
14.9	0	1	1	6000	17	0	0	0	0	1	2	15.1	99	99	3	3	4	NA	2	7	4	3	NA	3	8
16.9	0	1	2	3900	20	0	0	0	0	2	2	20.3	99	99	4	4	6	NA	2	13	4	2	NA	8	8
17.6	0	4	2	220	21	0	0	0	0	1	1	19.1	99	99	7	3	8	NA	2	14	4	3	NA	5	3
18.5	0	1	1	700	14	0	0	0	0	1	1	14.3	99	99	6	4	6	NA	2	14	5	3	NA	3	3
19.8	0	1	3	4620	26	0	0	0	0	3	2	40.5	99	99	7	4	5	NA	2	14	4	5	NA	3	5
21.0	0	7	2	200	22	0	0	0	0	1	2	18.1	99	99	6	5	4	NA	2	15	4	3	NA	3	5
21.6	0	1	2	3900	23	0	0	0	0	2	2	20.0	99	99	4	4	7	NA	2	15	4	3	NA	8	8
21.8	0	1	2	2000	27	0	0	0	0	1	2	23.1	99	99	5	4	5	NA	2	14	4	3	NA	5	8
22.4	0	1	2	2800	24	0	0	0	0	1	1	23.5	99	99	7	4	6	NA	2	14	4	3	NA	5	8
22.5	0	1	2	15000	30	0	0	0	0	1	11	30.0	99	99	4	4	5	NA	2	20	4	3	3	NA	6
22.6	0	4	2	500	20	0	0	0	0	5	6	18.0	99	99	7	4	7	NA	2	12	4	3	NA	6	8
23.3	0	2	2	700	19	0	0	0	0	1	1	20.5	99	99	6	4	5	NA	2	15	5	3	NA	3	8
23.8	0	2	2	150	20	1	0	0	0	1	19	15.9	99	99	6	3	6	NA	2	17	4	3	NA	6	6
24.2	0	9	2	350	23	0	0	0	0	1	2	20.2	99	99	7	4	5	NA	2	17	4	3	NA	3	5
24.8	0	1	1	600	13	0	0	0	0	2	2	13.0	99	99	3	5	6	NA	2	10	3	3	NA	5	5
25.0	0	2	2	250	20	1	0	0	0	1	11	20.0	99	99	7	4	5	NA	2	15	4	3	NA	4	6
25.1	0	3	2	370	19	0	0	0	0	1	2	21.0	99	99	7	4	8	NA	2	18	4	3	NA	3	3
25.5	Def Hwy	5	4	15500	47	0	0	0	0	1	2	46.1	99	99	5	4	4	NA	2	27	4	3	3	NA	5
25.5	Def Hwy	10	5	36380	74	0	0	0	0	1	11	54.4	99	99	4	4	6	NA	2	27	6	3	3	8	5
25.7	0	4	2	110	20	1	0	0	0	1	1	20.0	99	99	6	3	7	NA	2	14	4	4	NA	6	6
25.8	0	10	2	230	25	0	0	0	0	1	2	20.0	99	99	7	4	5	NA	2	17	5	3	NA	3	5
25.8	0	5	1	800	18	0	0	0	0	8	11	11.8	99	99	6	4	7	NA	2	18	4	2	NA	5	2

*Bridges on designated defense highways are identified by "Def Hwy"

SR	Item Number:																								
	12*	19	28	29	32	36				43		51	53		58	59	60	62	66		67	68	69	71	72
(%)		(Miles)			(Feet)	(1)	(2)	(3)	(4)	(1)	(2)	(Feet)	(1) (Feet)	(2) (Inches)					(1)	(2) (Tons)					
26.5	Def Hwy	5	4	17230	60	0	0	0	0	1	2	38.1	99	99	5	4	5	NA	2	27	5	3	2	6	5
27.8	0	3	1	800	30	0	0	0	0	7	10	15.7	99	99	4	4	4	NA	2	19	4	3	NA	NA	3
28.2	0	5	1	200	21	0	0	0	0	1	2	15.7	99	99	5	4	6	NA	2	15	5	3	NA	8	6
28.5	0	4	1	490	23	0	0	0	0	1	11	16.3	99	99	4	4	4	NA	2	18	4	2	NA	5	2
28.5	0	4	1	490	23	0	0	0	0	1	11	16.3	99	99	4	4	4	NA	2	18	4	2	NA	5	2
29.0	0	8	2	3000	33	0	0	0	0	1	2	25.1	99	99	7	4	5	NA	2	20	5	3	NA	8	5
29.2	0	10	2	900	24	0	0	0	0	1	1	20.1	99	99	6	4	6	NA	2	22	4	3	NA	3	3
29.3	0	1	2	11400	42	0	0	0	0	1	2	34.4	99	99	7	4	7	NA	2	15	4	3	NA	3	8
29.4	0	2	2	480	26	0	0	0	0	3	2	20.0	99	99	7	4	7	NA	2	18	5	3	NA	3	8
29.5	0	1	2	2000	29	0	0	0	0	1	1	24.0	99	99	4	NA	5	NA	2	12	4	4	NA	3	5
29.9	0	3	2	250	25	0	0	0	0	1	1	22.0	99	99	4	NA	5	NA	2	10	4	4	NA	5	8
30.0	0	3	2	1300	25	0	0	0	0	1	2	20.2	99	99	8	4	7	NA	2	19	5	3	NA	3	8
30.0	0	3	2	1300	25	0	0	0	0	1	2	20.2	99	99	8	4	7	NA	2	19	5	3	NA	3	8
30.6	0	1	2	3120	30	0	0	0	0	1	11	30.0	99	99	4	4	7	NA	2	18	4	4	NA	6	7
30.6	0	5	1	300	14	0	0	0	0	1	1	12.0	99	99	5	5	4	NA	2	20	5	2	NA	5	2
31.6	0	2	2	2800	25	0	0	0	0	1	1	23.7	99	99	7	4	7	NA	2	19	5	3	NA	5	5
31.8	0	3	1	200	16	0	0	0	0	1	1	18.3	99	99	4	4	7	NA	2	10	4	3	NA	3	8
31.9	Def Hwy	10	4	39750	60	0	0	0	0	3	10	40.2	15	1	4	5	7	NA	2	21	6	3	4	8	5
32.1	0	1	4	10000	36	0	0	0	0	1	2	35.5	99	99	5	4	6	NA	2	20	4	3	NA	8	8
32.9	0	1	2	10330	29	1	0	0	0	1	11	34.7	99	99	5	3	5	NA	2	14	4	2	NA	6	4
33.0	0	99	2	1000	30	0	0	0	0	1	1	29.7	99	99	4	NA	7	NA	2	11	4	7	NA	3	3
33.1	0	7	2	950	28	0	0	0	0	1	2	20.0	99	99	7	4	7	NA	2	20	5	3	NA	5	5
33.5	0	2	1	360	20	0	0	0	0	1	1	16.0	99	99	4	4	5	NA	2	20	4	3	NA	5	5
33.5	0	6	2	120	20	0	0	0	0	1	1	19.1	99	99	8	4	7	NA	2	18	5	3	NA	6	8
34.9	0	6	1	180	21	1	0	0	0	1	11	16.0	99	99	7	4	7	NA	2	18	4	3	NA	7	6
35.1	0	4	2	120	19	0	0	0	0	1	2	20.2	99	99	7	4	7	NA	2	18	5	4	NA	5	8
35.4	0	99	1	100	21	0	0	0	0	1	1	17.0	99	99	6	7	3	NA	2	30	6	3	NA	3	5
38.1	0	3	1	1800	21	0	0	0	0	7	2	15.0	99	99	4	4	4	NA	2	27	4	3	2	NA	4
38.2	0	7	1	700	13	0	0	0	0	2	2	11.6	99	99	5	4	4	NA	2	22	6	3	NA	5	8
38.2	0	1	4	2500	48	0	0	0	0	1	2	40.0	99	99	6	4	6	NA	2	21	5	8	NA	3	8

*Bridges on designated defense highways are identified by "Def Hwy"

SR	Item Number:																								
	12*	19	28	29	32	36				43		51	53		58	59	60	62	66		67	68	69	71	72
(%)		(Miles)			(Feet)	(1)	(2)	(3)	(4)	(1)	(2)	(Feet)	(1) (Feet)	(2) (Inches)					(1)	(2) (Tons)					
38.9	0	4	2	500	22	0	0	0	0	1	1	20.3	99	99	7	4	5	NA	2	22	5	3	NA	5	8
39.0	0	3	2	1300	25	0	0	0	0	1	1	19.3	99	99	7	4	7	NA	2	23	5	3	NA	4	6
39.5	0	8	2	1550	30	0	0	0	0	1	2	28.2	99	99	6	4	6	NA	2	19	5	7	NA	3	5
39.7	0	2	2	500	16	0	0	0	0	1	1	20.5	99	99	7	4	6	NA	2	23	5	3	NA	4	8
39.9	0	8	2	800	19	0	0	0	0	1	1	20.1	99	99	7	4	7	NA	2	24	5	3	NA	6	4
41.8	0	3	2	80	21	0	0	0	0	3	2	18.0	99	99	3	6	7	NA	2	8	4	3	NA	8	5
42.2	0	4	2	380	25	0	0	0	0	5	2	18.5	99	99	4	5	6	NA	2	19	5	3	NA	3	3
42.2	Def Hwy	17	2	23000	98	0	0	0	0	3	10	24.0	16	3	7	8	8	NA	2	20	6	4	NA	8	6
42.6	0	11	2	150	23	0	0	0	0	1	1	20.3	99	99	7	4	7	NA	2	23	5	5	NA	5	5
44.6	0	99	2	80	12	0	0	0	0	1	1	20.3	99	99	4	4	8	NA	2	20	3	4	NA	4	6
45.5	0	4	2	1020	24	0	0	0	0	1	1	24.0	99	99	4	NA	8	NA	2	14	5	4	NA	4	4
45.5	0	4	2	1020	24	0	0	0	0	1	1	24.0	99	99	4	NA	8	NA	2	14	5	4	NA	4	4
45.6	0	8	2	350	21	0	0	0	0	3	2	20.1	99	99	4	4	4	NA	2	34	5	3	NA	2	5
45.9	0	5	2	550	20	0	0	0	0	1	2	20.6	99	99	5	4	5	NA	2	27	5	3	NA	6	6
45.9	0	5	2	550	20	0	0	0	0	1	2	20.6	99	99	5	4	5	NA	2	27	5	3	NA	6	6
46.0	0	99	2	3000	30	1	0	0	0	1	1	30.0	99	99	5	5	5	NA	2	36	6	4	NA	3	8
46.4	0	5	2	1100	18	0	0	0	0	1	11	19.8	99	99	6	5	4	NA	2	27	6	3	NA	7	5
47.0	0	4	1	150	15	0	0	0	0	3	2	17.9	99	99	6	4	5	NA	2	22	5	3	NA	3	3
48.2	0	1	1	280	16	0	0	0	0	1	1	18.2	99	99	7	4	7	NA	2	20	5	3	NA	3	8
48.4	Def Hwy	33	2	34820	98	0	0	0	0	3	10	24.2	14	4	7	6	6	NA	2	24	6	6	NA	7	6
48.4	Def Hwy	60	2	13300	32	1	1	1	1	1	2	24.0	99	99	8	7	8	NA	2	22	6	2	5	NA	4
48.6	0	2	2	750	24	0	0	0	0	1	1	20.1	99	99	7	7	4	NA	2	31	6	2	NA	2	8
49.4	0	2	2	500	19	0	0	0	0	1	1	20.2	99	99	5	7	7	NA	2	19	6	3	NA	3	3
49.4	0	1	2	12000	30	0	0	0	0	1	11	30.1	99	99	4	7	7	NA	2	18	4	3	NA	8	3
50.4	0	8	2	31000	84	0	0	1	0	3	2	23.3	99	99	6	7	7	NA	2	22	7	4	5	NA	6
50.6	0	3	2	1300	20	0	0	0	0	1	1	20.1	99	99	7	8	8	NA	2	20	4	3	NA	2	2
50.6	0	3	2	1300	20	0	0	0	0	1	1	20.1	99	99	7	8	8	NA	2	20	4	3	NA	2	2
51.0	0	10	2	1460	23	0	0	0	0	1	11	20.0	99	99	7	6	6	NA	2	20	4	2	NA	2	5
51.4	0	20	4	21040	48	0	0	0	0	1	2	48.3	99	99	7	6	6	NA	2	24	6	4	4	NA	6
51.5	Def Hwy	60	2	11000	32	0	0	0	0	1	2	26.5	99	99	8	8	8	NA	2	26	6	2	NA	7	4

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SR	Item Number:																								
	12*	19	28	29	32	36				43		51	53		58	59	60	62	66		67	68	69	71	72
						(1)	(2)	(3)	(4)	(1)	(2)		(1)	(2)					(1)	(2)					
(%)		(Miles)			(Feet)							(Feet)	(Feet)	(Inches)						(Tons)					
51.8	0	2	4	5500	41	0	0	0	0	1	2	40.3	99	99	5	5	5	NA	2	27	5	3	2	NA	5
52.6	0	5	2	440	20	0	0	0	0	1	1	20.2	99	99	7	5	7	NA	2	23	5	3	NA	5	8
52.6	0	5	2	440	20	0	0	0	0	1	1	20.2	99	99	7	5	7	NA	2	23	5	3	NA	5	8
53.9	0	3	2	600	25	0	0	0	0	1	2	21.1	99	99	7	7	6	NA	2	20	5	3	NA	3	5
54.1	0	1	2	500	22	0	0	0	0	1	1	22.0	99	99	4	NA	7	NA	2	20	5	4	NA	3	8
54.5	0	4	2	450	22	0	0	0	0	3	2	20.0	99	99	7	7	7	NA	2	18	5	2	NA	5	8
55.3	0	2	4	10600	44	0	0	0	0	1	1	36.0	99	99	7	7	5	NA	2	26	5	4	NA	5	5
55.4	0	5	2	1630	24	0	0	0	0	3	2	20.2	99	99	7	7	8	NA	2	19	6	2	NA	6	4
55.4	0	5	2	1630	24	0	0	0	0	3	2	20.2	99	99	7	7	8	NA	2	19	6	2	NA	6	4
55.4	0	32	2	5250	24	0	0	0	0	1	1	21.6	99	99	8	NA	NA	6	2	27	6	2	NA	6	6
55.7	Def Hwy	10	2	24940	29	0	0	1	0	4	2	40.0	99	99	7	4	7	NA	2	35	5	5	6	8	6
56.0	0	1	2	1700	28	0	0	0	0	1	19	20.5	99	99	5	6	6	NA	2	20	8	3	NA	4	5
56.0	Def Hwy	10	2	24940	30	0	0	1	0	4	2	40.3	99	99	7	4	7	NA	2	36	5	5	6	8	6
56.0	0	99	2	1600	24	0	0	0	0	1	1	24.0	99	99	6	6	6	NA	2	36	8	5	NA	3	5
56.3	0	1	2	3900	27	0	0	0	0	1	2	20.2	99	99	7	7	7	NA	2	21	6	2	2	NA	5
56.3	0	5	2	1280	18	0	0	0	0	1	1	20.7	99	99	7	7	5	NA	2	26	7	2	NA	5	5
56.3	0	5	2	1280	18	0	0	0	0	1	1	20.7	99	99	7	7	5	NA	2	26	7	2	NA	5	5
56.6	0	4	2	1600	20	0	0	0	0	1	1	23.0	99	99	4	NA	6	NA	2	22	5	2	NA	5	5
57.4	0	4	2	180	20	0	0	0	0	1	1	20.0	99	99	5	7	8	NA	2	19	5	4	NA	5	8
57.5	0	15	2	500	20	1	0	1	0	1	1	20.4	99	99	4	NA	7	NA	2	19	5	5	NA	5	6
58.0	Def Hwy	5	4	62540	30	0	0	1	0	4	2	26.0	99	99	3	7	6	NA	2	36	6	2	5	7	6
58.0	Def Hwy	5	4	62540	30	0	0	1	0	4	2	26.0	99	99	3	7	6	NA	2	36	6	2	5	7	6
58.1	0	3	2	800	17	0	0	0	0	1	1	20.5	99	99	7	7	7	NA	2	22	6	3	NA	3	5
59.1	0	9	2	300	21	0	0	0	0	1	1	19.3	99	99	6	7	7	NA	2	22	6	3	NA	4	4
59.5	Def Hwy	10	4	30670	54	0	0	0	0	1	19	0.0	99	99	NA	NA	NA	8	2	27	6	NA	NA	6	NA
60.5	0	10	4	29680	70	1	0	0	0	1	11	52.5	99	99	8	8	8	NA	2	27	6	8	NA	7	8
60.7	0	6	2	700	17	0	0	0	0	1	19	20.0	99	99	NA	NA	NA	7	2	20	6	4	NA	5	NA
60.8	0	2	2	1800	30	0	0	0	0	1	2	30.0	99	99	6	6	6	NA	2	17	5	2	NA	2	8
60.9	0	99	2	800	21	0	0	0	0	1	19	22.0	99	99	NA	NA	NA	7	2	36	6	3	NA	3	NA
61.7	0	1	4	12000	40	0	0	0	0	1	2	40.0	99	99	6	6	6	NA	2	26	6	3	4	8	3

*Bridges on designated defense highways are identified by "Def Hwy"

SR	Item Number:																								
	12*	19	28	29	32	36				43		51	53		58	59	60	62	66		67	68	69	71	72
(%)		(Miles)			(Feet)	(1)	(2)	(3)	(4)	(1)	(2)	(Feet)	(1) (Feet)	(2) (Inches)					(1)	(2) (Tons)					
61.8	Def Hwy	60	3	7980	32	1	1	1	1	1	11	31.0	99	99	7	7	NA	7	2	27	7	7	NA	8	7
61.8	Def Hwy	60	3	7980	32	1	1	1	1	1	11	31.0	99	99	8	NA	8	7	2	27	6	6	NA	7	6
62.0	Def Hwy	17	3	23000	98	0	0	0	0	3	10	28.2	99	99	6	6	6	NA	2	36	8	6	NA	8	6
62.0	0	8	2	24110	26	0	0	1	0	4	2	23.3	15	2	7	7	6	NA	2	36	6	3	5	NA	5
62.1	0	1	2	3320	22	0	0	0	0	1	1	22.0	99	99	7	7	7	NA	2	27	6	3	NA	3	3
62.6	Def Hwy	5	2	54910	44	0	0	1	0	4	2	28.0	99	99	6	8	8	NA	2	33	7	3	6	NA	6
62.6	Def Hwy	5	2	54910	44	0	0	1	0	4	2	28.0	99	99	6	8	8	NA	2	33	7	3	6	NA	6
62.7	0	3	2	400	27	0	0	0	0	5	2	22.2	99	99	6	7	6	NA	2	21	6	5	NA	5	5
63.0	Def Hwy	5	2	54910	34	0	0	1	0	2	2	30.0	99	99	5	8	8	NA	2	36	8	3	7	NA	8
63.0	Def Hwy	5	2	55350	40	0	0	0	0	2	2	30.0	99	99	6	7	7	NA	2	36	8	3	6	NA	6
63.0	Def Hwy	5	2	55350	40	0	0	0	0	2	2	30.0	99	99	6	7	7	NA	2	36	8	3	6	NA	6
63.0	Def Hwy	5	2	55350	40	0	0	0	0	2	2	30.0	99	99	7	8	8	NA	2	36	8	3	6	NA	6
63.0	Def Hwy	5	2	54910	34	0	0	1	0	2	2	30.0	99	99	5	8	8	NA	2	36	8	3	7	NA	8
63.0	Def Hwy	5	2	55350	40	0	0	0	0	2	2	30.0	99	99	7	8	8	NA	2	36	8	3	6	NA	6
63.2	0	32	2	4000	24	0	0	0	0	1	2	20.3	99	99	7	7	7	NA	2	36	8	2	NA	6	4
63.8	0	6	2	300	17	0	0	0	0	1	1	18.0	99	99	7	8	5	NA	2	36	6	3	NA	8	3
63.8	0	5	2	280	20	0	0	0	0	1	1	20.2	99	99	7	8	7	NA	2	23	5	4	NA	4	6
64.0	Def Hwy	15	2	13570	700	0	0	0	0	3	2	28.9	99	99	7	7	7	NA	2	36	8	4	5	NA	6
64.0	Def Hwy	5	2	54910	34	0	0	1	0	2	2	30.0	99	99	6	8	8	NA	2	36	8	3	7	NA	8
64.0	Def Hwy	5	2	54910	34	0	0	1	0	2	2	30.0	99	99	6	8	8	NA	2	36	8	3	7	NA	8
64.3	0	10	2	4220	23	1	0	0	0	4	10	24.4	15	0	6	6	6	NA	2	28	7	4	7	8	5
64.4	0	10	2	920	21	0	0	0	0	1	2	20.5	99	99	8	8	7	NA	2	24	6	3	NA	5	8
64.4	0	10	2	920	21	0	0	0	0	1	2	20.5	99	99	8	8	7	NA	2	24	6	3	NA	5	8
64.4	0	4	1	150	21	0	0	0	0	1	1	16.3	99	99	7	8	8	NA	2	21	6	3	NA	8	5
64.9	0	10	4	13580	40	0	0	0	0	1	2	40.0	99	99	6	6	6	NA	2	36	8	6	2	8	7
64.9	0	4	2	1200	21	0	0	0	0	1	1	20.0	99	99	7	7	7	NA	2	27	6	3	NA	5	2
65.0	Def Hwy	20	2	28280	308	0	0	0	0	1	2	28.4	99	99	6	6	6	NA	2	36	8	4	NA	8	6
65.0	Def Hwy	20	2	28280	308	0	0	0	0	1	2	30.1	99	99	7	7	7	NA	2	36	8	4	NA	8	6
65.0	0	5	2	24110	26	0	0	1	0	4	2	23.3	15	5	7	7	7	NA	2	36	6	3	6	NA	4
65.0	0	8	4	31000	84	0	0	1	0	3	2	28.2	99	99	6	7	7	NA	2	36	8	4	6	NA	5

*Bridges on designated defense highways are identified by "Def Hwy"

SR	Item Number:																									
	12*	19	28	29	32	36				43		51	53		58	59	60	62	66		67	68	69	71	72
(%)		(Miles)			(Feet)	(1)	(2)	(3)	(4)	(1)	(2)	(Feet)	(1) (Feet)	(2) (Inches)					(1)	(2) (Tons)					
65.0	0	8	2	31000	84	0	0	1	0	3	2	23.3	99	99	7	7	8	NA	2	36	8	4	5	NA	6
65.0	Def Hwy	8	2	31000	25	0	0	1	0	1	2	21.6	99	99	8	8	8	NA	2	36	8	4	6	NA	5
65.1	0	1	2	5000	25	0	0	0	0	1	1	30.5	99	99	6	7	5	NA	2	30	7	3	NA	5	5
65.5	Def Hwy	30	4	20500	90	0	0	0	0	1	2	86.3	99	99	7	7	7	NA	2	27	6	2	NA	7	6
65.6	0	5	2	3470	22	1	1	1	1	1	10	22.3	18	1	5	6	6	NA	2	27	6	3	NA	7	6
65.6	Def Hwy	22	2	6000	600	0	0	0	0	1	2	28.4	99	99	7	7	7	NA	2	36	8	6	4	NA	6
65.8	0	1	2	1460	27	0	0	0	0	1	19	28.0	99	99	NA	NA	NA	5	2	27	5	3	NA	5	NA
65.8	0	8	2	700	18	0	0	0	0	1	19	19.5	99	99	NA	NA	NA	7	2	27	6	3	NA	3	NA
65.9	0	5	2	1100	16	0	0	0	0	1	11	17.6	99	99	6	NA	6	NA	2	27	6	3	NA	7	3
66.0	Def Hwy	25	2	32300	42	1	1	1	1	2	2	30.5	99	99	8	8	8	NA	2	36	8	3	7	NA	6
66.0	Def Hwy	25	2	32300	44	1	1	1	1	2	2	30.5	99	99	8	8	8	NA	2	36	8	3	6	NA	6
66.0	Def Hwy	25	2	32300	44	1	1	1	1	2	2	30.5	99	99	8	8	8	NA	2	36	8	3	6	NA	6
66.0	Def Hwy	25	2	32300	42	1	1	1	1	2	2	30.5	99	99	8	8	8	NA	2	36	8	3	6	NA	6
66.0	Def Hwy	10	2	24940	42	0	0	1	0	6	2	28.0	99	99	7	8	8	NA	2	36	8	6	4	NA	6
66.0	Def Hwy	10	2	24940	42	0	0	1	0	5	2	28.0	99	99	7	8	8	NA	2	36	8	6	4	NA	6
66.1	0	5	2	8000	20	0	0	0	0	1	1	21.6	99	99	7	NA	7	NA	2	27	6	2	NA	6	6
66.3	Def Hwy	60	2	5450	30	0	0	0	0	1	19	0.0	99	99	NA	NA	NA	8	2	36	8	NA	NA	8	NA
66.4	0	4	2	4800	20	0	0	0	0	3	2	21.0	99	99	7	7	7	NA	2	33	6	3	NA	3	3
66.6	0	1	1	1120	22	0	0	0	0	1	2	12.2	99	99	7	7	7	NA	2	28	6	3	NA	5	3
66.6	0	4	1	300	15	0	0	0	0	1	1	16.4	99	99	7	8	5	NA	2	32	6	3	NA	3	3
66.7	0	2	1	370	22	0	0	0	0	1	2	17.8	99	99	8	8	8	NA	2	19	6	3	NA	8	5
66.7	0	2	1	370	22	0	0	0	0	1	2	17.8	99	99	8	8	8	NA	2	19	6	3	NA	8	5
66.9	Def Hwy	10	2	24940	102	0	0	0	0	3	2	40.0	99	99	3	7	7	NA	2	29	8	8	6	NA	7
66.9	0	5	2	4500	27	1	1	1	1	8	11	20.5	99	99	8	8	8	NA	2	27	6	2	NA	6	2
66.9	0	5	2	4500	27	1	1	1	1	8	11	20.5	99	99	8	8	8	NA	2	27	6	2	NA	6	2
66.9	0	3	2	1000	21	0	0	0	0	1	1	22.4	99	99	7	8	8	NA	2	26	6	3	NA	5	5
66.9	Def Hwy	33	2	34820	98	0	0	0	0	6	2	28.2	99	99	7	7	7	NA	2	36	8	6	NA	8	6
67.0	0	5	2	2200	19	0	0	0	0	1	1	22.5	99	99	7	7	7	NA	2	26	7	3	NA	5	8
67.0	Def Hwy	10	4	26000	54	0	0	0	0	1	2	54.3	99	99	7	7	6	NA	2	36	8	8	NA	7	7
67.0	Def Hwy	10	4	26000	54	0	0	0	0	1	2	53.3	99	99	7	6	6	NA	2	36	8	8	NA	7	7

*Bridges on designated defense highways are identified by "Def Hwy"

SR	Item Number:																								
	12*	19	28	29	32	36				43		51	53		58	59	60	62	66		67	68	69	71	72
(%)		(Miles)			(Feet)	(1)	(2)	(3)	(4)	(1)	(2)	(Feet)	(1) (Feet)	(2) (Inches)					(1)	(2) (Tons)					
67.0	Def Hwy	10	4	26000	54	0	0	0	0	1	2	54.2	99	99	7	6	6	NA	2	36	8	8	NA	7	7
67.2	Def Hwy	60	2	5450	30	1	1	1	0	1	2	30.4	99	99	8	8	8	NA	2	31	8	4	NA	7	6
67.3	0	5	2	9850	17	0	0	0	0	1	1	24.3	99	99	6	NA	6	NA	2	27	6	4	NA	6	6
67.4	0	4	1	370	22	0	0	0	0	1	2	18.0	99	99	8	8	7	NA	2	19	6	3	NA	5	8
67.4	0	4	1	370	22	0	0	0	0	1	2	18.0	99	99	8	8	7	NA	2	19	6	3	NA	5	8
67.5	Def Hwy	10	4	12470	48	0	0	0	0	1	5	37.0	99	99	7	7	7	NA	2	36	8	6	5	NA	8
67.5	0	6	2	2000	32	1	0	0	0	1	1	26.5	99	99	7	7	6	NA	2	29	6	5	NA	2	2
67.6	0	5	2	500	19	1	0	0	0	1	2	21.4	99	99	7	8	7	NA	2	25	6	3	NA	5	8
67.8	0	7	2	570	26	0	0	0	0	1	1	26.3	99	99	5	5	7	NA	2	27	6	5	NA	3	5
67.8	0	7	2	570	26	0	0	0	0	1	1	26.3	99	99	5	5	7	NA	2	27	6	5	NA	3	5
67.9	0	10	2	16020	32	1	1	1	1	4	2	40.8	99	99	7	7	7	NA	2	21	6	8	5	NA	7
67.9	0	10	2	16020	32	1	1	1	1	4	2	40.8	99	99	8	8	8	NA	2	21	6	8	5	NA	7
67.9	Def Hwy	33	2	31930	98	0	0	1	1	6	2	27.9	99	99	7	7	7	NA	2	36	8	6	5	NA	6
68.0	Def Hwy	10	2	24940	102	0	0	1	1	4	2	28.0	99	99	6	8	8	NA	2	36	8	6	5	NA	6
68.0	Def Hwy	10	2	24940	102	0	0	1	1	4	2	28.0	99	99	6	8	8	NA	2	36	8	6	5	NA	6
68.3	0	5	1	2750	18	1	0	1	0	1	1	15.7	99	99	7	NA	7	NA	2	27	6	2	NA	6	2
68.3	0	10	2	8690	25	0	0	1	0	2	2	28.2	99	99	5	7	6	NA	2	36	7	2	5	NA	7
68.3	0	10	2	8690	25	0	0	1	0	2	2	28.2	99	99	5	7	6	NA	2	36	7	2	5	NA	7
68.7	0	5	2	3260	19	0	0	0	0	1	1	20.0	99	99	6	NA	NA	6	2	27	6	2	NA	6	6
68.9	0	3	2	4970	30	0	0	0	0	1	1	28.3	99	99	7	7	7	NA	2	27	6	3	NA	6	6
68.9	0	1	2	2500	40	0	0	0	0	3	2	32.0	99	99	5	5	6	NA	2	26	6	5	NA	5	5
68.9	Def Hwy	33	2	31930	98	0	0	1	1	1	2	28.2	99	99	6	7	8	NA	2	36	8	6	NA	8	6
68.9	Def Hwy	33	2	31930	98	0	0	1	1	6	2	27.9	99	99	6	6	6	NA	2	36	8	6	6	NA	6
68.9	Def Hwy	33	2	31930	98	0	0	1	1	6	2	28.2	99	99	7	7	8	NA	2	36	8	6	NA	8	6
69.0	0	5	2	2700	17	0	0	0	0	1	2	20.3	99	99	7	7	7	NA	2	27	6	2	NA	6	6
69.2	0	5	2	4250	19	1	0	0	0	1	1	20.8	99	99	7	NA	7	NA	2	27	6	2	NA	6	6
69.4	0	5	2	1990	30	1	0	0	0	1	1	19.7	99	99	6	6	7	NA	2	27	6	2	NA	5	8
69.5	Def Hwy	10	4	17140	108	0	0	0	0	1	1	86.3	99	99	8	8	8	NA	2	27	6	8	NA	NA	8
69.6	0	5	2	1700	19	0	0	0	0	3	19	0.0	99	99	7	NA	NA	7	2	27	6	2	NA	7	6
69.8	Def Hwy	10	2	24940	102	0	0	0	0	3	2	40.0	99	99	3	7	7	NA	2	32	8	8	6	NA	7

*Bridges on designated defense highways are identified by "Def Hwy"

SR	Item Number: 12*	19	28	29	32	36				43		51	53		58	59	60	62	66		67	68	69	71	72
(%)		(Miles)			(Feet)	(1)	(2)	(3)	(4)	(1)	(2)	(Feet)	(1) (Feet)	(2) (Inches)					(1)	(2) (Tons)					
69.8	0	5	2	1200	18	0	0	0	0	1	2	20.0	99	99	7	7	7	NA	2	27	6	2	NA	6	6
70.0	0	5	2	880	19	0	0	0	0	1	1	19.8	99	99	7	NA	7	NA	2	27	6	2	NA	6	6
70.1	0	5	2	1430	23	0	0	0	0	1	2	19.7	99	99	7	7	7	NA	2	29	7	2	NA	6	4
70.1	0	5	2	1430	23	0	0	0	0	1	2	19.7	99	99	7	7	7	NA	2	29	7	2	NA	6	4
70.3	0	3	2	1360	19	1	0	1	0	1	1	20.9	99	99	7	7	7	NA	2	28	6	4	NA	5	2
70.8	0	5	2	7300	28	0	0	0	0	1	19	0.0	99	99	NA	NA	NA	7	2	27	6	NA	NA	6	NA
71.0	0	5	2	910	20	1	0	0	0	1	1	20.1	99	99	6	NA	7	NA	2	27	6	2	NA	6	6
71.2	0	5	2	2550	18	0	0	0	0	1	1	22.0	99	99	NA	NA	NA	6	2	27	6	4	NA	6	6
71.2	0	5	2	880	19	0	0	0	0	4	2	22.1	99	99	7	7	7	NA	2	28	8	2	NA	7	6
71.4	0	4	2	180	22	1	0	0	0	1	1	20.4	99	99	6	7	7	NA	2	27	5	4	NA	5	5
71.5	0	5	2	6600	18	1	0	1	0	1	1	22.0	99	99	7	6	6	NA	2	30	8	2	5	NA	6
71.7	0	2	2	800	32	1	0	0	0	1	1	26.1	99	99	7	8	8	NA	2	29	7	4	NA	3	8
71.7	0	1	2	1800	25	0	0	0	0	1	1	25.0	99	99	6	5	7	NA	2	36	7	5	NA	5	8
71.7	0	5	2	1540	18	0	0	0	0	1	1	23.4	99	99	7	NA	7	NA	2	27	6	4	NA	6	7
71.8	Def Hwy	46	4	11210	72	0	0	0	0	1	19	72.0	99	99	NA	NA	NA	5	2	36	6	6	NA	6	NA
71.8	0	5	2	7280	24	0	0	1	0	1	1	0.0	99	99	NA	NA	NA	7	2	27	6	NA	NA	6	NA
71.9	0	6	2	200	19	0	0	0	0	5	2	20.0	99	99	5	7	7	NA	2	36	8	3	NA	5	3
72.0	0	5	2	2760	20	1	0	0	0	1	1	24.2	99	99	7	NA	7	NA	2	27	6	4	NA	6	7
72.4	0	10	2	6830	42	0	0	1	0	1	2	26.2	99	99	6	7	7	NA	2	36	7	3	NA	7	7
72.8	0	5	2	450	17	0	0	0	0	1	1	20.6	99	99	7	7	6	NA	2	36	8	3	NA	3	5
72.8	Def Hwy	60	4	13300	32	1	1	1	0	1	2	80.0	99	99	7	7	8	NA	2	24	6	8	NA	7	8
73.0	Def Hwy	2	4	54910	92	1	1	1	1	1	1	46.0	99	99	NA	NA	NA	8	2	36	8	NA	NA	8	NA
73.0	Def Hwy	2	4	54910	92	1	1	1	1	1	1	46.0	99	99	NA	NA	NA	8	2	36	8	NA	NA	8	NA
73.5	0	5	2	920	21	0	0	0	0	1	1	22.0	99	99	7	7	8	NA	2	36	8	3	NA	3	8
73.5	0	5	2	920	21	0	0	0	0	1	1	20.0	99	99	7	7	8	NA	2	36	8	3	NA	3	8
73.6	0	5	1	3300	18	0	0	0	0	1	1	16.6	99	99	6	NA	NA	6	2	27	5	2	NA	7	2
73.6	0	5	1	3300	18	0	0	0	0	1	1	16.6	99	99	6	NA	NA	6	2	27	5	2	NA	7	2
73.7	0	1	2	2720	27	0	0	0	0	1	1	27.4	99	99	7	8	7	NA	2	36	8	3	NA	3	8
73.8	0	99	2	500	35	0	0	1	0	1	1	27.7	99	99	6	7	6	NA	2	36	8	5	NA	3	3
74.0	0	4	1	100	17	0	0	0	0	4	11	0.0	99	99	NA	NA	NA	7	2	36	8	3	NA	3	NA

*Bridges on designated defense highways are identified by "Def Hwy"

	Item Number:																								
SR	12*	19	28	29	32	36				43		51	53		58	59	60	62	66		67	68	69	71	72
						(1)	(2)	(3)	(4)	(1)	(2)		(1)	(2)					(1)	(2)					
(%)		(Miles)			(Feet)							(Feet)	(Feet)	(Inches)						(Tons)					
74.0	Def Hwy	0	2	69080	40	0	0	1	1	2	2	30.5	99	99	8	8	8	NA	2	36	8	3	2	NA	6
74.0	Def Hwy	0	2	69080	40	0	0	1	1	2	2	30.5	99	99	8	8	8	NA	2	36	8	3	2	NA	6
74.0	0	5	2	1670	18	0	0	0	0	1	2	20.0	99	99	7	6	7	NA	2	31	8	2	NA	8	7
74.3	0	5	2	3430	24	0	0	0	0	2	2	20.2	99	99	7	7	7	NA	2	36	7	2	NA	6	4
74.3	0	5	2	3430	24	0	0	0	0	2	2	20.2	99	99	7	7	7	NA	2	36	7	2	NA	6	4
74.4	0	2	2	550	23	0	0	0	0	1	1	22.8	99	99	6	NA	6	NA	2	27	6	5	NA	5	6
75.0	0	7	2	1550	30	0	0	0	0	1	1	30.5	99	99	4	NA	8	NA	2	25	5	7	NA	3	8
75.0	Def Hwy	0	2	69080	37	1	1	1	1	2	2	30.5	99	99	6	6	8	NA	2	36	8	3	2	NA	6
75.0	Def Hwy	0	2	69080	37	1	1	1	1	2	2	30.5	99	99	6	6	8	NA	2	36	8	3	2	NA	6
75.0	0	3	2	650	19	0	0	0	0	1	1	22.2	99	99	7	8	7	NA	2	35	6	4	NA	3	5
75.1	Def Hwy	2	2	31270	56	0	0	1	1	4	2	41.2	99	99	5	7	7	NA	2	29	7	3	5	NA	8
75.1	Def Hwy	2	2	31270	56	0	0	1	1	4	2	41.2	99	99	5	7	7	NA	2	29	7	3	5	NA	8
75.2	Def Hwy	5	2	54910	42	0	0	1	0	4	2	40.0	99	99	4	8	8	NA	2	34	8	3	6	NA	8
75.2	Def Hwy	5	2	54910	42	0	0	1	0	4	2	40.0	99	99	4	8	8	NA	2	34	8	3	6	NA	8
75.3	0	4	2	420	38	0	0	0	0	1	2	38.4	99	99	5	6	5	NA	2	27	5	4	NA	8	7
75.8	0	5	2	9000	24	0	0	0	0	1	19	0.0	99	99	NA	NA	NA	7	2	36	8	4	NA	6	NA
75.9	0	1	2	1500	30	0	0	0	0	1	1	23.8	99	99	7	8	7	NA	2	36	8	3	NA	5	5
75.9	0	1	4	11250	46	0	0	0	0	1	1	25.3	99	99	7	7	6	NA	2	36	8	3	NA	5	8
75.9	0	2	2	300	24	0	0	0	0	1	1	20.3	99	99	7	7	7	NA	2	36	8	3	NA	5	5
76.0	Def Hwy	0	3	55350	45	0	0	1	0	4	2	42.0	99	99	4	7	7	NA	2	36	6	5	5	NA	7
76.0	Def Hwy	0	2	54910	34	0	0	0	0	2	2	30.0	99	99	6	7	7	NA	2	36	8	3	6	NA	6
76.0	Def Hwy	0	3	55350	45	0	0	1	0	4	2	42.0	99	99	4	7	7	NA	2	36	6	5	5	NA	7
76.0	Def Hwy	0	3	55350	45	0	0	1	0	4	2	42.0	99	99	4	7	7	NA	2	36	6	5	5	NA	7
76.0	Def Hwy	0	3	55350	45	0	0	1	0	4	2	42.0	99	99	4	7	7	NA	2	36	6	5	5	NA	7
76.0	Def Hwy	0	2	54910	34	0	0	0	0	2	2	30.0	99	99	7	8	8	NA	2	36	8	3	6	NA	6
76.0	Def Hwy	0	2	54910	34	0	0	0	0	2	2	30.0	99	99	7	8	8	NA	2	36	8	3	6	NA	6
76.0	Def Hwy	0	2	54910	34	0	0	0	0	2	2	30.0	99	99	6	7	7	NA	2	36	8	3	6	NA	6
76.1	0	7	2	7280	24	1	1	1	0	4	2	28.2	99	99	7	7	7	NA	2	36	8	2	NA	8	8
76.3	0	3	2	2530	20	0	0	0	0	1	1	20.1	99	99	7	8	8	NA	2	36	8	2	NA	5	8
76.3	0	5	2	520	22	0	0	0	0	1	1	20.0	99	99	6	6	6	NA	2	33	6	3	NA	8	8

*Bridges on designated defense highways are identified by "Def Hwy"

Item Number:

SR	12*	19	28	29	32	36				43		51	53		58	59	60	62	66		67	68	69	71	72
(%)		(Miles)			(Feet)	(1)	(2)	(3)	(4)	(1)	(2)	(Feet)	(1) (Feet)	(2) (Inches)					(1)	(2) (Tons)					
76.3	0	60	2	5450	33	0	0	0	0	1	19	33.0	99	99	NA	NA	NA	6	2	36	6	8	NA	5	0
76.6	0	3	2	1200	24	0	0	0	0	1	19	0.0	99	99	NA	NA	NA	7	2	36	8	3	NA	5	NA
76.8	Def Hwy	46	4	11100	108	0	0	0	0	1	2	98.5	99	99	7	7	7	NA	2	36	7	6	NA	7	7
76.8	Def Hwy	46	4	11100	108	0	0	0	0	1	2	98.3	99	99	7	7	7	NA	2	36	7	6	NA	7	7
76.8	0	4	2	460	20	1	0	0	0	1	1	20.0	99	99	7	NA	6	NA	2	36	7	3	NA	5	5
76.8	0	4	2	460	20	1	0	0	0	1	1	20.0	99	99	7	NA	6	NA	2	36	7	3	NA	5	5
76.9	Def Hwy	5	2	32000	56	1	1	1	1	5	2	40.0	99	99	8	8	8	NA	2	31	8	8	7	NA	8
76.9	Def Hwy	5	2	32000	55	1	1	1	1	5	2	40.0	99	99	8	8	8	NA	2	31	8	8	7	NA	8
76.9	0	1	2	990	22	0	0	0	0	1	1	20.3	99	99	7	7	7	NA	2	36	8	3	NA	5	8
76.9	0	2	2	400	25	0	0	0	0	4	11	0.0	99	99	NA	NA	NA	7	2	36	8	3	NA	5	NA
77.0	0	1	2	150	20	0	0	0	0	1	19	0.0	99	99	NA	NA	NA	7	2	36	8	3	NA	5	NA
77.1	0	5	2	2020	20	0	0	0	0	4	2	24.1	99	99	7	7	7	NA	2	30	8	6	NA	7	6
77.1	Def Hwy	33	1	4000	21	0	0	0	0	3	2	22.3	99	99	6	7	6	NA	2	36	6	3	5	NA	4
77.3	0	8	2	520	20	0	0	0	0	1	1	24.2	99	99	7	8	8	NA	2	26	6	6	NA	5	6
77.5	0	5	2	7280	25	0	1	1	1	5	2	28.3	99	99	7	7	7	NA	2	36	8	2	6	NA	7
77.8	0	5	2	500	21	0	0	0	0	1	2	24.2	99	99	7	7	7	NA	2	27	6	4	NA	6	6
77.8	0	5	2	6600	27	0	1	1	1	1	2	28.3	99	99	7	7	8	NA	2	36	8	2	6	NA	7
78.4	0	5	2	6530	43	1	1	1	1	4	2	44.3	99	99	6	6	5	NA	2	27	6	5	7	NA	6
78.7	0	1	2	900	31	0	0	0	0	1	5	26.2	99	99	7	7	7	NA	2	32	7	5	NA	8	8
79.4	0	5	2	5650	22	0	0	0	0	1	19	0.0	99	99	NA	NA	NA	7	2	36	8	NA	NA	8	NA
79.6	0	41	2	2900	28	0	0	0	0	1	2	32.0	99	99	6	7	7	NA	2	27	6	6	NA	8	6
79.9	Def Hwy	20	4	43000	90	1	1	1	1	4	2	90.0	99	99	7	7	7	NA	2	30	8	8	5	NA	7
80.0	Def Hwy	2	2	54910	40	0	0	1	0	4	2	36.4	99	99	5	8	8	NA	2	36	8	8	5	NA	8
80.0	Def Hwy	2	2	54910	40	0	0	1	0	4	2	36.4	99	99	5	8	8	NA	2	36	8	8	5	NA	8
80.1	0	4	2	400	28	0	0	1	0	3	19	22.9	99	99	NA	NA	NA	6	2	36	8	5	NA	3	NA
80.1	Def Hwy	2	2	54910	40	0	0	0	0	4	2	36.4	99	99	6	8	7	NA	2	36	8	8	5	NA	8
80.1	Def Hwy	2	2	54910	40	0	0	0	0	4	2	36.4	99	99	6	8	7	NA	2	36	8	8	5	NA	8
80.2	0	99	2	80	21	0	0	0	0	1	1	23.1	99	99	7	8	8	NA	2	30	8	5	NA	4	3
80.3	0	1	2	2500	50	0	0	0	0	1	2	39.9	99	99	6	6	6	NA	2	27	6	4	5	NA	5
80.6	0	10	1	200	15	0	0	0	0	3	19	15.0	99	99	NA	NA	NA	7	2	36	8	3	NA	5	NA

*Bridges on designated defense highways are identified by "Def Hwy"

SR	Item Number: 12*	19	28	29	32	36				43		51	53		58	59	60	62	66		67	68	69	71	72
(%)		(Miles)			(Feet)	(1)	(2)	(3)	(4)	(1)	(2)	(Feet)	(1) (Feet)	(2) (Inches)					(1)	(2) (Tons)					
81.0	0	8	2	31000	30	0	0	0	0	6	2	40.0	99	99	5	7	7	NA	2	36	8	8	6	NA	8
81.7	Def Hwy	2	2	31270	40	0	1	1	0	4	2	39.0	99	99	3	7	8	NA	2	36	8	3	5	NA	8
81.7	Def Hwy	2	2	31270	40	0	1	1	0	4	2	39.0	99	99	3	7	8	NA	2	36	8	3	5	NA	8
81.7	Def Hwy	48	4	12330	78	0	0	0	0	1	19	75.2	99	99	7	NA	NA	7	2	36	8	8	NA	8	7
81.9	Def Hwy	40	2	17000	52	0	0	0	0	1	19	62.4	99	99	NA	NA	NA	7	2	36	8	NA	NA	7	NA
81.9	0	35	2	8760	30	0	0	0	0	1	19	32.8	99	99	NA	NA	NA	8	2	36	8	NA	NA	8	NA
82.0	Def Hwy	20	2	18000	78	0	0	0	0	1	1	98.0	99	99	7	7	7	NA	2	36	7	6	NA	7	7
82.0	Def Hwy	17	4	13570	86	0	0	0	0	1	2	86.8	99	99	7	7	7	NA	2	36	8	8	NA	7	8
82.0	0	8	2	31000	30	0	0	0	0	6	2	40.0	99	99	6	7	7	NA	2	36	8	8	6	NA	8
82.2	0	2	2	30	22	0	0	0	0	1	1	20.2	99	99	7	7	7	NA	2	26	6	3	NA	5	5
82.3	0	99	2	600	38	0	0	0	0	5	5	32.9	99	99	7	8	8	NA	2	36	8	7	NA	8	8
82.3	0	7	2	300	22	0	0	0	0	1	1	25.9	99	99	7	8	8	NA	2	28	5	5	NA	5	8
82.3	0	10	2	13450	48	1	0	0	0	6	5	40.7	99	99	7	8	8	NA	2	36	8	6	6	NA	6
82.9	0	2	2	5770	37	1	1	1	1	1	19	24.0	99	99	8	8	8	NA	2	36	8	7	NA	5	NA
83.0	Def Hwy	1	1	500	24	1	1	1	1	1	19	0.0	99	99	NA	NA	NA	7	2	36	7	8	NA	7	7
83.0	0	5	2	3500	35	0	0	0	0	1	11	38.0	99	99	7	7	7	NA	2	27	6	4	NA	5	4
83.2	0	5	2	1000	38	0	0	1	0	1	2	28.6	99	99	7	7	7	NA	2	36	8	4	5	NA	6
83.2	0	5	2	1000	38	0	0	1	0	1	2	28.6	99	99	7	7	7	NA	2	36	8	4	5	NA	6
83.2	0	5	2	630	25	0	0	0	0	1	19	22.6	99	99	NA	NA	NA	8	2	36	8	NA	NA	7	NA
83.2	0	5	2	630	25	0	0	0	0	1	19	22.6	99	99	NA	NA	NA	8	2	36	8	NA	NA	7	NA
83.2	0	5	2	1000	33	0	0	0	0	2	2	28.1	99	99	6	7	7	NA	2	36	8	8	6	NA	5
83.2	0	5	2	1000	33	0	0	0	0	2	2	28.1	99	99	6	7	7	NA	2	36	8	8	6	NA	5
83.5	0	3	4	600	48	0	0	0	0	3	19	48.5	99	99	NA	NA	NA	8	2	36	8	6	NA	3	NA
83.7	0	5	4	2760	30	1	1	1	1	5	2	38.0	99	99	8	8	8	NA	2	36	8	7	8	NA	8
83.7	0	5	4	2760	30	1	1	1	1	5	2	38.0	99	99	8	8	8	NA	2	36	8	7	8	NA	8
84.0	Def Hwy	5	2	69080	40	1	1	1	1	2	2	40.3	99	99	6	8	8	NA	2	36	8	8	5	NA	8
84.0	Def Hwy	5	2	69080	40	1	1	1	1	2	2	40.3	99	99	7	8	8	NA	2	36	8	8	5	NA	8
84.0	Def Hwy	5	2	69080	40	1	1	1	1	2	2	40.3	99	99	6	8	8	NA	2	36	8	8	5	NA	8
84.0	Def Hwy	5	2	69080	40	1	1	1	1	2	2	40.3	99	99	7	8	8	NA	2	36	8	8	5	NA	8
84.3	0	1	2	2000	27	0	0	0	0	1	1	26.9	99	99	6	8	7	NA	2	36	8	5	NA	5	5

*Bridges on designated defense highways are identified by "Def Hwy"

SR	Item Number:																								
	12*	19	28	29	32	36				43		51	53		58	59	60	62	66		67	68	69	71	72
						(1)	(2)	(3)	(4)	(1)	(2)		(1)	(2)					(1)	(2)					
(%)		(Miles)			(Feet)							(Feet)	(Feet)	(Inches)						(Tons)					
84.3	0	2	2	4000	39	1	1	1	1	2	5	30.0	99	99	7	8	8	NA	2	36	8	7	8	NA	7
84.8	0	5	2	1800	38	1	0	1	0	3	2	29.1	99	99	8	7	7	NA	2	36	8	5	5	NA	5
84.8	0	5	2	1800	38	1	0	1	0	3	2	29.1	99	99	8	7	7	NA	2	36	8	5	5	NA	5
84.8	0	5	2	1000	36	0	0	0	0	2	2	30.0	99	99	6	7	7	NA	2	36	8	8	5	NA	4
85.0	0	1	2	260	24	0	0	0	0	1	1	24.0	99	99	7	7	7	NA	2	36	8	5	NA	5	8
85.0	Def Hwy	10	4	26000	90	1	1	1	1	1	19	99.9	99	99	NA	NA	NA	7	2	36	8	8	NA	8	7
85.0	Def Hwy	10	4	26000	90	1	1	1	1	1	19	99.9	99	99	NA	NA	NA	7	2	36	8	NA	NA	8	NA
85.0	0	8	2	31000	30	1	1	1	1	2	5	60.3	99	99	7	8	8	NA	2	36	8	8	NA	8	8
85.0	Def Hwy	5	2	60580	42	1	1	1	1	1	2	40.3	99	99	7	8	8	NA	2	36	8	8	NA	8	8
85.0	Def Hwy	5	2	69080	49	1	1	1	1	2	2	48.4	99	99	6	7	7	NA	2	36	8	8	7	NA	8
85.0	Def Hwy	5	2	69080	40	1	1	1	1	2	2	40.3	99	99	6	8	7	NA	2	36	8	8	7	NA	8
85.0	Def Hwy	5	2	69080	40	1	1	1	1	2	2	40.3	99	99	6	7	8	NA	2	36	8	8	6	NA	8
85.0	Def Hwy	5	2	60580	42	1	1	1	1	1	2	40.3	99	99	7	8	8	NA	2	36	8	8	NA	8	8
85.0	Def Hwy	5	4	69080	80	1	1	1	1	1	19	108.0	99	99	NA	NA	NA	8	2	36	8	NA	NA	8	NA
85.0	Def Hwy	5	2	69080	40	1	1	1	1	2	2	40.3	99	99	7	8	8	NA	2	36	8	8	6	NA	8
85.0	Def Hwy	5	2	69080	40	1	1	1	1	2	2	40.3	99	99	6	7	8	NA	2	36	8	8	6	NA	8
85.0	Def Hwy	5	2	60580	42	1	1	1	1	1	2	40.3	99	99	7	8	8	NA	2	36	8	8	NA	8	8
85.0	Def Hwy	5	2	60580	42	1	1	1	1	1	2	40.3	99	99	7	8	8	NA	2	36	8	8	NA	8	8
85.0	Def Hwy	5	2	69080	40	1	1	1	1	2	2	40.3	99	99	6	8	7	NA	2	36	8	8	7	NA	8
85.0	Def Hwy	5	2	69080	40	1	1	1	1	2	2	40.3	99	99	7	8	8	NA	2	36	8	8	6	NA	8
85.0	Def Hwy	5	2	69080	49	1	1	1	1	2	2	48.4	99	99	6	7	7	NA	2	36	8	8	7	NA	8
85.0	Def Hwy	5	4	69080	80	1	1	1	1	1	19	108.0	99	99	NA	NA	NA	8	2	36	8	NA	NA	8	NA
85.9	Def Hwy	1	1	24940	36	1	1	1	1	4	2	22.3	99	99	6	7	7	NA	2	36	8	4	5	NA	4
86.0	0	5	2	12000	42	1	1	1	0	4	2	34.6	99	99	7	7	7	NA	2	36	8	6	2	NA	6
86.0	0	5	2	12000	42	1	1	1	0	4	2	34.6	99	99	7	7	7	NA	2	36	8	6	2	NA	6
86.0	Def Hwy	5	4	32000	132	1	1	1	1	1	19	127.0	99	99	NA	NA	NA	7	2	36	7	7	NA	7	7
86.9	0	5	1	320	22	0	0	0	0	4	11	19.0	99	99	NA	NA	NA	7	2	36	8	3	NA	5	NA
87.2	0	10	2	13000	40	0	0	0	0	1	19	50.0	99	99	NA	NA	NA	7	2	36	8	NA	NA	8	NA
87.2	0	10	2	13000	40	0	0	0	0	1	19	50.0	99	99	NA	NA	NA	7	2	36	8	NA	NA	8	NA
87.3	0	5	4	5350	39	0	0	0	0	1	1	67.0	99	99	7	NA	7	NA	2	27	6	8	NA	7	7

*Bridges on designated defense highways are identified by "Def Hwy"

Item Number:

SR	12*	19	28	29	32	36				43		51	53		58	59	60	62	66		67	68	69	71	72
(%)		(Miles)			(Feet)	(1)	(2)	(3)	(4)	(1)	(2)	(Feet)	(1) (Feet)	(2) (Inches)					(1)	(2) (Tons)					
87.4	0	1	2	9520	51	1	0	0	0	1	2	51.1	99	99	6	7	6	NA	2	26	7	8	NA	8	5
87.5	0	1	2	260	25	0	0	0	0	5	5	25.4	99	99	7	7	7	NA	2	36	8	5	NA	5	5
87.9	0	10	2	12130	40	0	0	0	0	1	19	50.0	99	99	NA	NA	NA	8	2	36	8	NA	NA	8	NA
88.0	Def Hwy	1	2	0	40	1	1	1	1	3	2	30.0	99	99	9	9	9	NA	2	36	5	4	4	9	8
88.0	Def Hwy	1	2	0	47	0	0	1	0	3	2	40.0	99	99	9	9	9	NA	2	36	5	4	7	NA	6
88.0	Def Hwy	1	2	0	40	1	1	1	1	3	2	30.0	99	99	9	9	9	NA	2	36	5	4	4	9	8
88.0	Def Hwy	1	2	0	40	1	1	1	1	3	2	30.0	99	99	9	9	9	NA	2	36	5	4	4	9	8
88.0	Def Hwy	1	2	0	47	0	0	1	0	3	2	40.0	99	99	9	9	9	NA	2	36	5	4	7	NA	6
88.0	Def Hwy	1	2	0	40	1	1	1	1	3	2	30.0	99	99	9	9	9	NA	2	36	5	4	4	9	8
88.1	0	1	2	5000	28	0	0	0	0	1	1	31.0	99	99	7	8	6	NA	2	36	8	7	NA	5	8
88.4	0	8	4	16000	30	0	0	1	0	1	19	64.0	99	99	NA	NA	NA	7	2	36	8	NA	NA	8	NA
88.8	0	10	2	13450	24	1	1	1	1	6	2	40.6	99	99	8	8	7	NA	2	36	8	8	5	NA	8
88.8	0	10	2	13450	24	1	1	1	1	6	2	40.6	99	99	8	8	7	NA	2	36	8	8	5	NA	8
89.0	Def Hwy	10	2	0	40	1	1	1	1	4	2	30.0	99	99	8	8	8	NA	2	36	5	4	5	NA	8
89.0	Def Hwy	10	2	0	40	1	1	1	1	4	2	30.0	99	99	8	8	8	NA	2	36	5	4	5	NA	8
89.0	Def Hwy	10	2	0	40	1	1	1	1	4	2	30.0	99	99	8	8	8	NA	2	36	5	4	5	NA	8
89.0	Def Hwy	10	2	0	40	1	1	1	1	4	2	30.0	99	99	8	8	8	NA	2	36	5	4	5	NA	8
89.6	0	2	2	2500	44	0	0	0	0	5	5	40.0	99	99	6	6	7	NA	2	36	6	7	5	NA	5
89.9	Def Hwy	18	4	3780	98	0	0	0	0	1	19	98.0	99	99	NA	NA	NA	7	2	36	8	NA	NA	7	NA
89.9	0	10	2	13450	24	1	1	1	1	6	2	40.5	99	99	7	7	7	NA	2	36	8	8	NA	8	8
89.9	0	10	2	13450	24	1	1	1	1	6	2	40.5	99	99	7	7	7	NA	2	36	8	8	NA	8	8
90.0	0	8	2	0	35	0	1	1	1	2	2	28.0	99	99	4	6	6	NA	2	36	8	5	5	NA	6
90.0	0	8	2	0	35	0	1	1	1	2	2	28.0	99	99	4	6	6	NA	2	36	8	5	5	NA	6
90.0	Def Hwy	5	2	0	54	1	0	0	0	5	2	36.7	99	99	8	6	8	NA	2	36	8	8	5	NA	8
90.0	Def Hwy	5	4	0	54	1	0	0	0	5	2	36.7	99	99	8	8	8	NA	2	36	8	8	5	NA	8
90.0	Def Hwy	1	3	0	45	1	1	1	1	3	2	42.0	99	99	7	8	8	NA	2	36	5	4	7	NA	8
90.0	Def Hwy	1	2	0	47	1	1	1	1	3	2	40.0	99	99	9	8	7	NA	2	36	5	4	7	NA	6
90.0	Def Hwy	1	3	0	45	1	1	1	1	3	2	42.0	99	99	7	8	8	NA	2	36	5	4	7	NA	8
90.0	Def Hwy	1	3	0	45	1	1	1	1	3	2	42.0	99	99	8	8	8	NA	2	36	5	4	7	NA	8
90.0	Def Hwy	1	2	0	47	1	1	1	1	3	2	40.0	99	99	9	8	7	NA	2	36	5	4	7	NA	6

*Bridges on designated defense highways are identified by "Def Hwy"

Item Number:

SR	12*	19	28	29	32	36				43		51	53		58	59	60	62	66		67	68	69	71	72
(%)		(Miles)			(Feet)	(1)	(2)	(3)	(4)	(1)	(2)	(Feet)	(1) (Feet)	(2) (Inches)					(1)	(2) (Tons)					
90.0	Def Hwy	1	3	0	45	1	1	1	1	3	2	42.0	99	99	8	8	8	NA	2	36	5	4	7	NA	8
90.0	Def Hwy	0	2	32300	40	1	1	1	1	2	2	40.3	99	99	8	8	8	NA	2	36	8	3	2	NA	8
90.0	Def Hwy	0	2	32300	40	1	1	1	1	2	2	40.3	99	99	7	8	8	NA	2	36	8	3	2	NA	8
90.0	Def Hwy	0	2	32300	40	1	1	1	1	2	2	40.3	99	99	8	8	8	NA	2	36	8	3	2	NA	8
90.0	Def Hwy	0	2	32300	40	1	1	1	1	2	2	40.3	99	99	7	8	8	NA	2	36	8	3	2	NA	8
90.1	0	5	2	4220	22	0	0	0	0	1	19	31.3	99	99	7	NA	NA	7	2	36	8	6	NA	6	7
90.1	0	1	2	1200	31	0	0	0	0	1	1	30.5	99	99	7	7	7	NA	2	36	8	7	NA	3	8
90.1	0	32	2	2350	24	0	0	0	0	1	19	31.4	99	99	NA	NA	NA	8	2	36	8	8	NA	8	8
90.7	0	10	2	8400	40	0	0	0	0	1	19	50.0	99	99	NA	NA	NA	7	2	36	8	NA	NA	8	NA
90.9	0	8	2	15180	30	1	1	1	1	1	19	63.0	99	99	8	NA	NA	8	2	36	8	8	NA	8	8
91.0	Def Hwy	2	2	0	40	0	0	1	0	4	2	36.0	99	99	7	7	6	NA	2	36	8	8	6	NA	8
91.0	Def Hwy	2	2	0	40	0	0	1	0	4	2	36.0	99	99	7	7	6	NA	2	36	8	8	6	NA	8
91.0	Def Hwy	0	2	0	40	0	0	1	1	3	2	30.2	99	99	8	8	8	NA	2	36	8	6	5	NA	8
91.0	Def Hwy	0	2	0	40	0	0	1	1	3	2	30.2	99	99	8	8	8	NA	2	36	8	6	5	NA	8
91.6	0	5	4	14400	78	0	0	0	0	1	19	116.0	99	99	7	NA	NA	7	2	36	8	8	NA	7	7
92.0	Def Hwy	2	2	0	40	0	0	1	1	4	2	32.0	99	99	6	8	8	NA	2	36	8	6	6	NA	8
92.0	Def Hwy	2	2	0	40	0	0	1	1	4	2	32.0	99	99	6	8	8	NA	2	36	8	6	6	NA	8
92.0	Def Hwy	0	2	0	40	1	1	1	1	3	2	30.2	99	99	8	8	8	NA	2	36	8	6	5	NA	8
92.0	Def Hwy	0	2	0	40	1	1	1	1	3	2	30.2	99	99	8	8	8	NA	2	36	8	6	5	NA	8
92.0	0	2	2	6100	32	0	0	0	0	1	19	32.0	99	99	NA	NA	NA	7	2	36	8	3	NA	8	NA
92.5	0	3	2	150	26	1	1	1	0	1	19	26.0	99	99	NA	NA	NA	7	2	27	7	6	NA	6	NA
93.0	Def Hwy	5	4	0	132	1	0	1	1	5	2	37.0	99	99	7	7	7	NA	2	36	7	7	6	NA	7
93.8	0	5	2	500	54	1	1	1	1	4	2	51.0	99	99	7	8	8	NA	2	36	8	8	5	NA	6
95.0	Def Hwy	10	2	0	40	1	1	1	1	2	2	40.3	99	99	8	8	8	NA	2	36	5	4	6	NA	8
95.0	Def Hwy	10	2	0	40	1	1	1	1	2	2	40.0	99	99	8	8	8	NA	2	36	5	4	6	NA	8
95.0	Def Hwy	10	2	0	40	1	1	1	1	2	2	40.3	99	99	8	8	8	NA	2	36	5	4	6	NA	8
95.0	Def Hwy	10	2	0	40	1	1	1	1	2	2	40.0	99	99	8	8	8	NA	2	36	5	4	6	NA	8
95.0	Def Hwy	0	4	0	40	1	0	0	0	1	2	38.0	99	99	8	8	8	NA	2	36	8	8	5	NA	8
95.0	Def Hwy	0	4	0	40	1	0	0	0	1	2	38.0	99	99	8	8	8	NA	2	36	8	8	5	NA	8
95.5	0	2	4	10000	66	1	0	0	0	1	19	66.0	99	99	NA	NA	NA	6	2	36	8	8	NA	5	NA

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SR	Item Number:																								
	12*	19	28	29	32	36				43		51	53		58	59	60	62	66		67	68	69	71	72
(%)		(Miles)			(Feet)	(1)	(2)	(3)	(4)	(1)	(2)	(Feet)	(1) (Feet)	(2) (Inches)					(1)	(2) (Tons)					
95.6	0	10	2	5920	40	1	1	1	1	1	19	50.0	99	99	NA	NA	NA	6	2	36	8	NA	NA	8	NA
95.8	0	7	2	290	30	0	0	0	0	1	19	32.8	99	99	NA	NA	NA	7	2	36	8	8	NA	5	NA
96.0	0	1	2	60	28	1	0	0	0	1	19	28.0	99	99	NA	NA	NA	6	2	36	8	5	NA	5	NA
96.0	0	5	2	7830	44	1	1	1	1	6	2	44.3	99	99	7	7	7	NA	2	36	8	5	6	NA	6
96.1	0	2	2	800	31	1	0	1	1	1	1	30.5	99	99	NA	NA	NA	8	2	36	8	7	NA	5	NA
96.6	0	5	2	6210	44	1	1	1	1	6	6	47.0	99	99	8	8	8	NA	2	36	8	5	7	NA	7
96.9	0	5	2	300	33	0	0	0	0	1	19	33.0	99	99	NA	NA	NA	7	2	36	8	8	NA	8	NA
97.0	Def Hwy	5	2	0	37	1	0	1	1	5	2	37.0	99	99	8	8	8	NA	2	36	8	8	5	NA	8
97.0	Def Hwy	2	2	0	40	0	0	1	1	4	2	40.0	99	99	6	7	6	NA	2	36	8	8	7	NA	8
97.0	Def Hwy	2	2	0	40	0	0	1	1	4	2	40.0	99	99	6	7	6	NA	2	36	8	8	7	NA	8
97.0	Def Hwy	0	2	65630	40	1	1	1	1	2	2	40.3	99	99	7	8	8	NA	2	36	8	8	5	NA	8
97.0	Def Hwy	0	2	65630	40	1	1	1	1	2	2	40.3	99	99	7	7	8	NA	2	36	8	8	5	NA	8
97.0	Def Hwy	0	4	62540	183	1	1	1	1	1	2	183.0	99	99	9	9	9	NA	2	36	6	8	5	NA	6
97.0	Def Hwy	0	2	65630	40	1	1	1	1	2	2	40.3	99	99	7	7	8	NA	2	36	8	8	5	NA	8
97.0	Def Hwy	0	2	65630	40	1	1	1	1	2	2	40.3	99	99	7	8	8	NA	2	36	8	8	5	NA	8
97.0	Def Hwy	0	2	62600	40	1	1	1	1	2	2	40.3	99	99	6	6	8	NA	2	36	8	8	5	NA	8
97.0	Def Hwy	0	4	62540	183	1	1	1	1	1	2	183.0	99	99	9	9	9	NA	2	36	6	8	5	NA	6
97.0	Def Hwy	0	2	62600	40	1	1	1	1	2	2	40.3	99	99	7	6	8	NA	2	36	8	8	5	NA	8
97.0	Def Hwy	0	2	62600	40	1	1	1	1	2	2	40.3	99	99	6	6	8	NA	2	36	8	8	5	NA	8
97.0	Def Hwy	0	2	62600	40	1	1	1	1	2	2	40.3	99	99	7	6	8	NA	2	36	8	8	5	NA	8
97.0	0	1	2	13220	37	1	0	0	0	5	6	37.0	99	99	8	8	8	NA	2	36	8	6	NA	6	6
97.8	0	3	2	1000	34	1	1	1	1	5	5	32.6	99	99	7	8	7	NA	2	36	8	5	7	NA	5
98.0	Def Hwy	10	2	0	80	1	1	1	1	1	19	99.9	99	99	NA	NA	NA	8	2	36	8	NA	NA	8	NA
98.0	Def Hwy	5	2	0	37	1	0	1	1	5	2	37.0	99	99	8	8	8	NA	2	36	8	8	6	NA	8
98.5	0	1	2	6210	42	1	1	1	1	6	5	47.0	99	99	7	8	7	NA	2	36	8	5	6	NA	6
99.8	0	5	2	510	22	1	1	1	0	5	5	32.4	99	99	8	8	8	NA	2	36	8	6	6	NA	7
99.8	0	5	2	510	22	1	1	1	0	5	5	32.4	99	99	8	8	8	NA	2	36	8	6	6	NA	7

*Bridges on designated defense highways are identified by "Def Hwy"

Vita

Augusto V. Molina was born on April 21, 1969 in Queens, NY. He attended public school in Dumont, NJ and graduated from Dumont High School in June, 1987. In the fall of 1987, he entered Villanova University, in Villanova, Pennsylvania. He received the Bachelor of Civil Engineering degree in May, 1991 and accepted a position as a structural engineer with Ebasco Services Incorporated.

He relocated to Knoxville, Tennessee in August, 1991 and began a long term assignment with Ebasco Services Incorporated at the Watts Bar Nuclear Plant in Spring City, Tennessee. In January of 1994 he entered the University of Tennesse on a part-time basis to pursue the Master of Science degree in Civil Engineering with a concentration in structural engineering. He left Ebasco Services Incorporated in August of 1995 and continued his Master's degree education on a full-time basis. In July, 1996 he completed his Master's thesis and received his degree in August, 1996.