PREDICTING BID PRICES IN CONSTRUCTION PROJECTS USING NON-PARAMETRIC STATISTICAL MODELS

A Thesis

by

ROSHAN PAWAR

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

August 2007

Major Subject: Civil Engineering

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Approved by:

Chair of Committee,	Seth Guikema
Committee Members,	Ken Reinshmidt
	J. Eric Bickel
Head of Department,	David Rosowsky

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ABSTRACT

Predicting Bid Prices in Construction Projects Using Non-parametric Statistical Models.

(August 2007)

Roshan Pawar, B.E., University of Mumbai

Chair of Advisory Committee: Dr. Seth Guikema

Bidding is a very competitive process in the construction industry; each competitor's business is based on winning or losing these bids. Contractors would like to predict the bids that may be submitted by their competitors. This will help contractors to obtain contracts and increase their business. Unit prices that are estimated for each quantity differ from contractor to contractor. These unit costs are dependent on factors such as historical data used for estimating unit costs, vendor quotes, market surveys, amount of material estimated, number of projects the contractor is working on, equipment rental costs, the amount of equipment owned by the contractor, and the risk averseness of the estimator. These factors are nearly similar when estimators are estimating cost of similar projects. Thus, there is a relationship between the projects that a particular contractor has bid in previous years and the cost the contractor is likely to quote for future projects. This relationship could be used to predict bids that the contractor might quote for future projects. For example, a contractor may use historical data for a certain year for bidding on certain type of projects, the unit prices may be adjusted for size, time and location, but the basis for bidding on projects of similar types is the same. Statistical tools can be used to model the underlying relationship between the final cost of the project quoted by a contractor to the quantities of materials or amount of tasks performed in a project. There are a number of statistical modeling techniques, but a model used for predicting costs should be flexible enough that it could adjust to depict any underlying pattern.

Data such as amount of work to be performed for a certain line item, material cost index, labor cost index and a unique identifier for each participating contractor is used to predict bids that a contractor might quote for a certain project. To perform the analysis, artificial neural networks and multivariate adaptive regression splines are used. The results obtained from both the techniques are compared, and it is found that multivariate adaptive regression splines are able to predict the cost better than artificial neural networks.

DEDICATION

Dedicated to my parents Suresh and Sharayu Pawar

and brother Abhishek Pawar.

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1. INTRODUCTION

Estimation of cost is carried out during various phases of construction to assess total project cost or to predict costs that may be incurred during different stages (Hendrickson and Au 1998). There are two types of estimates, as described by Faghri (2000), scratch based estimate and bid based estimate. Scratch based estimate uses information such as price, quantity, equipment, manpower and construction procedure, while bid based estimates use data available from similar projects in the past to predict the cost of the project (Faghri 2000). Hendrickson and Au (1998) has classified cost estimation based on its function into three categories viz., design estimates, bid estimates and control estimates. Design estimates are used by owners or design professionals during various stages of the design phase of the project. At the feasibility phase of the project a screening estimate (or an order of magnitude estimate) is prepared to assess the feasibility of the project, followed by a conceptual estimate which is based on the conceptual design of the facility to make a "go/no go" decision (Hendrickson and Au 1998). A detailed estimate is made when the scope of the work is clearly defined followed by an engineer's estimate based on plans and specifications before the project is set out for bidding (Hendrickson and Au 1998). Bid estimates are prepared by contactors for the purpose of competitive bidding.

This thesis follows the style *Journal of Construction Engineering and Management.*

The contractor may either use quantity takeoff for this purpose or base their estimate on the work breakdown structure (Hendrickson and Au 1998). The contractor would like to invest a limited amount of effort in preparing an estimate since this effort is worthless if the work is not awarded to him (Hendrickson and Au 1998).

Cost estimates can also be based on information available from historical and prevailing unit prices of materials used in various construction activities carried out throughout the country. However, every construction project is unique, each project differs due to factors such as location, construction practices, material costs, type of materials used, labor costs, engineering and design, schedule, weather changes, taxes, inflation, budget allocations and legal requirements. Due to these variations, estimating cost of the final facility is difficult and suitable adjustments are made to the final cost estimate to incorporate these variations by including location and time adjustments, contingency, and inflation factors. The goal is to estimate the cost with reasonable accuracy by taking into consideration the sources that introduce such variability, but this is seldom possible due to the limited amount of information available on these factors.

Figure 1 shows the types of estimates prepared during the life cycle of a project. The accuracy of an estimate depends on scope definition and accuracy of information available while preparing the estimate. For an order-of-magnitude estimate, the range of accuracy is +/- 30 to 50%, for factored estimate the range of accuracy is +/- 25 to 30%, for a control estimate the range of accuracy is +/- 10 to 15% and for a detailed or definitive estimate the range of accuracy is +/- < 10% (Oberlender 2000). A statistical model to predict the total cost of a project based on historical data can be developed only if the projects are similar in scope. In the construction industry, roads, highways, bridges, and such other projects have similar scope of work. Statistical models to predict project costs could be developed for such projects which have fairly similar scope of work for example construction of a bridge measuring certain miles in length.

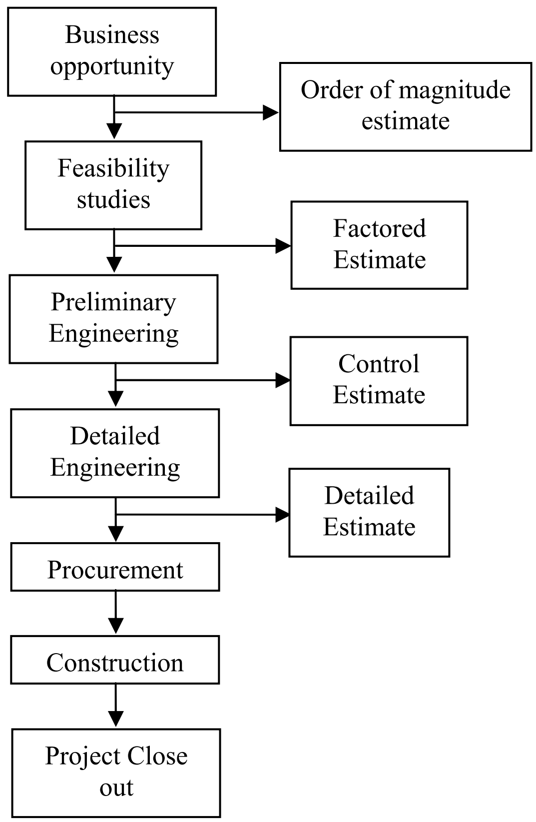

Figure 1: Estimates at various stages of a project life cycle

Predicting a competitors' bid can help a contractor adjust his bid accordingly to win a contract. Scratch based cost estimation is a tedious and time consuming process which not only requires detailed knowledge of the scope of the project but also the unit cost for each activity. There is a need for a quick and reliable technique for estimating project costs. If data from previous bids about projects with similar scope of work are available, statistical models may be developed to predict final bid prices. Neural networks are one such tool that can be used in various applications for such predictions. Some of the fields where neural networks are used are predicting sales (Thiesing and Vornberger 1997), forecasting weather (Maqsood et al. 2004), hand written zip code recognition used in US Postal Service (Hassoun 1994), predicting the flow of rivers (Karunanithi et al. 1994) and pattern recognition (Basheer and Hajmeer 2000). Multivariate Adaptive Regression Splines (MARS), developed by Salford Systems, is another powerful statistical tool that is capable of developing adaptive models. The advantage of using MARS is that it is an adaptive tool that uses the data to determine the function to be fitted to segments of data. Cost estimation using historical data by these statistical models could fasten the estimation process. This process of estimating cost is data driven, when extensive data is available this process is both easy and efficient.

1.1. Background

In the construction industry, neural networks have been a topic of research in fields such as structural engineering, structural condition assessment and monitoring, construction scheduling and management, construction cost estimation, resource allocation and scheduling, environmental and water resource engineering, traffic engineering and highway engineering (Adeli 2001). Maru and Nagpal (2004) have applied neural networks to predict creep and shrinkage deflections in reinforced concrete frames using deflections calculated from an approximate procedure. Artificial neural networks are used in diverse fields for prediction and forecasting using data depicting non-linear behavior. Li et al. (1999) used neural network to extract rules for markup estimation after training the network. Li et al. (1999) developed a neural network to predict the mark-up on estimated project cost which would also provide reasons for selecting the specified mark-up. Factors such as project size, location, market conditions, number of competitors, working cash requirements, overhead rate, contractor's current workload, labor availability and project complexity were used for making a decision for setting up a mark-up percentage from rules extracted from trained neural networks (Li et al. 1999). Adeli and Wu (1998) used a regularization neural network to estimate unit cost for constructing a reinforced concrete pavement. Wilmot and Mei (2005) used neural networks to predict cost escalation in highway construction projects. They used data such as cost of construction materials, labor and equipment along with the characteristics of the contract to predict escalation (Wilmot and Mei 2005). Faghri (2000) used an artificial neural network to estimate transportation project cost with data such as median unit price and the quantity of material used in projects. Neural networks have also been used to forecast escalation in construction cost using historical data available from Engineering News Record (ENR 2005) using parameters such as material, labor and equipment (Sinha and McKim 1997).

Even though a lot of research work is being done in predicting construction cost, it would be useful if it is possible to predict bids submitted by competing contractors. This may inform a contractor of his chances of winning in a competitive bidding process. If a statistical model can be trained with data from past bids submitted by the competing contractors it may be able to predict the bids those contractors will quote in other projects.

Multivariate adaptive regression splines is a relatively new technique used for modeling data depicting non-linear relationship. Riedi (1997) has used multivariate adaptive regression splines in modeling segmental duration in speech synthesis for predicting natural sounding durations for German language. Leathwick et al. (2005) has used MARS to predict the distribution of New Zealand's freshwater diadromous fish by determining relationship between fish species and different environmental variables. Chou et al. (2004) has used artificial neural network and MARS in developing diagnostic techniques that help in identifying breast cancer using a fine needle aspiration cytology dataset. Loizos and Karlaftis (2006) have used an artificial neural network and multivariate adaptive regression spline models for a comparative analysis of pavement condition assessment. Sephton (2005) has used MARS to find a relationship between changes in inflation and interest rate spread. Using MARS, Sephton (2005) estimated models to link changes in inflation rates over a number of policy horizons. The author concludes that tightening the yield spread will reduce inflation when the horizon of study is three to five years as opposed to a three month period.

1.2. Problem statement

The prediction of total project cost is important to determine the investment that a contractor might have to make in a project. To win a bid, a contractor should have information on the estimated cost of the project as well as the bid prices quoted by competing contractors. The aim of this research is to test different models and find out a model which may predict bid prices that other contractors may quote in certain projects. For this to be possible projects with similar scope and construction conditions are required. Highway construction projects are largely similar due to specifications and regulations in place which standardize their scope. The Tennessee Department of Transportation (TDoT) provides information about quantity for each activity performed for a project and the different tasks to be completed for the project. This information can be used to predict bids. Since the data available from TDoT has a lot of variability a statistical tool that is flexible enough to model the variability should be used to perform the analysis. Artificial neural networks and multivariate adaptive regression splines are two such non-parametric, adaptive statistical tools which are data driven. Comparison between the two models will be done using the same dataset on the basis of predicted values. If a model could predict the bid prices reasonably for each of the subcontractors participating in the bid as well as the bid a contractor should submit there would be considerable saving in time and energy in estimating the total cost of the project.

2. DATA DESCRIPTION

Data for the analysis was obtained from the website of the Tennessee Department of Transportation (TDoT 2006). The data obtained consists of highway projects undertaken by TDoT during the year 2005. The information available on the website includes a brief description of work, location of the projects, a unique identifier for each work item involved (referred to as the line item number), quantity of each line item, unit price quoted for each line item by every contractor participating in the bidding process, name of the contractors bidding for the projects and place and date when the bid was opened. Historical cost indices for the entire year are available from Engineering News Record. TDoT has divided the state of Tennessee into four regions for managing the work in each region. Data from all the four regions was used to build the model. TDoT uses unit price bidding for all their projects. The data collected contains information such as unit prices quoted by each contractor for each line item, the contractors participating in the bidding process for a certain project, amount of task performed for each line item and the total bid price quoted by each contractor. Cost indices for the analysis are obtained from Engineering News Record for each month for the year 2005 (refer: Appendix A).

The data obtained from TDoT was sorted on an Excel spreadsheet to collect together all the line items or tasks used in different projects. A standard list of line items, assigned with a uniform identification number for each line item for all the projects under consideration, was used to collect and group the data. Table 1 shows the format in which input was provided to the neural network.

Table 1: A small sample of the input data

	Project Number							
Line Item Number	CND004	CND005	CND005	CND005	CND005	CND006	CND006	CND006
615-02.05	0	0	0	0	0	0	0	0
615-02.12	2428	0	0	0	0	0	0	0
615-02.14	0	0	0	0	0	0	0	0
615-02.75	0	0	0	0	0	0	0	0
615-05	0	0	0	0	0	0	0	0
615M01.03	0	0	0	0	0	0	0	0
615M01.10	0	0	0	0	0	0	0	0
617-01	0	14951	14951	14951	14951	0	0	0
617-02	518	0	0	0	0	598	598	598
617-05	0	0	0	0	0	3	3	3
620-03	0	0	0	0	0	0	0	0
620-03.10	952	0	0	0	0	0	0	0
620-03.10	0	0	0	0	0	0	0	0
620-03.11	0	0	0	0	0	588	588	588

The first column titled line item number represents a unique number which identifies the line item or task for each project. Projects below $6 million were selected for the analysis to reduce computational complexity by reducing the amount of data to be analyzed. The input vector includes quantities for the project, cost indices for the month in which the project was undertaken and a vector that identifies the contractor which bid on the project. The cost indices include construction cost index, which is comprised of common labor and wages per hour, and material cost index which covers fluctuation in the cost of cement, steel and lumber. The vector which identifies various contractors consists of a matrix of binary digits which are unique for each contractor.

The data set comprising of quantities, cost indices and contractor identifiers was then divided into training and validation set. The training set is used to train the model whereas the validation set is used to test the accuracy of the predictions obtained by using inputs from the validation set. A comparison of the predicted values from the testing process and the actual bid prices quoted by the contractors for the data used in the validation set is made to judge the accuracy of the model. The training set comprises of approximately 86% of the observations and the validation set forms the remaining 14%. The split between the training and validation set was selected at random. A random number generator was used to divide the dataset into a training and validation set.

Data was available on the TDoT website in pdf file format, tables were copied from each pdf file onto a spreadsheet. After the data was copied on the spreadsheet the data was filtered to include information that would be used for the analysis. The data was initially sorted according to project numbers, each project included information including date of opening the bid, place where the work is performed, line item number, description of line item, quantity for each line item, contractors who submitted their bid for the project and the amount bid by each contractor. In the next step, a uniform list of line items was used to sort all the activities that were performed in all the projects. Using this list all the projects were collected on a single spreadsheet, if there was an activity performed for a particular line item in a certain project the amount of that activity was included otherwise a zero was used. For example, in Table 1 for project CND004 the line item number 615-02.12 describes a prestressed concrete box beam (42” x 48”), this project requires 2428 linear feet of the prestressed concrete box beam, hence the number

2428 is included whereas line item number 620-03 which describes a concrete parapet is not included in the scope of work hence a zero is put in its place.

Table 2 shows statistics of the data that was used for the training and the validation set.

Table 2: Training and validation set statistic

Training set		Validation set	
Mean	$ 904,530	Mean	$ 583,117
Standard deviation	$ 938,844	Standard deviation	$ 379,565
Highest bid	$5,910,119	Highest bid	$1,859,722
Lowest bid	$ 11,489	Lowest bid	$ 78,179
Number of projects	214	Number of projects	35
Number of bids	517	Number of bids	80

A t-test was carried out on the means of the two datasets to compare the difference in means between the two sets. A t-test was conducted using the means and standard deviations listed in Table 2 using the following equation (Montgomery and Runger 2003):

$$t_0^* = \frac{\overline{x}_1 - \overline{x}_2 - 0}{\sqrt{\frac{\overline{\sigma}_1^2}{n_1} + \frac{\overline{\sigma}_2^2}{n_1}}} \tag{2-1}$$

where,

$\overline{x}_1$ and $\overline{x}_2$ are the means of the training and validation sets respectively

$\overline{\sigma}_1$ and $\overline{\sigma}_2$ are the standard deviations of the training and validation sets respectively and

n_1 and n_2 are the sample sizes of the training and validation sets respectively

The degree of freedom on t_0^* is calculated from the following equation (Montgomery and Runger 2003):

$$\nu = \frac{\left(\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}\right)^2}{\frac{\left(s_1^2/n_1\right)^2}{n_1 - 1} + \frac{\left(s_2^2/n_2\right)^2}{n_2 - 1}} \tag{2-2}$$

From equation (2-1), the value of t_0^* was calculated as 3.541 and the degree of freedom (ν) was equal to 117. Using a significance level of 0.05 and a degree of freedom of 117, the $t_{0.025,117}$ value is found to be equal to 1.981 from the *t*-distribution table. Since $t_0^* = 3.541 > 1.981$, the null hypothesis that the means are equal can be rejected and it can be concluded that the two datasets are drawn from two different populations. This conclusion suggests that a non-parametric model could be used to predict the bid costs using the given data.

The range of data for the training set is from \$11,000 to \$5.9 million whereas for the validation set the range of data is from \$78,000 to \$1.8 million. The following assumptions are made for simplification of the analysis:

1. The size of the contractors bidding on the projects has no effect on the bids submitted by them. This assumption is made because it is not possible to obtain data regarding the financial standing of the participating contractors in 2005.
2. Contract is awarded to the lowest bidder where information about winning bid is not available. This assumption helps in determining the winning bid.

3. Prices quoted for the materials are in accordance with the specifications provided by TDoT. This assumption is made to ensure that there is uniformity of selection of materials.
4. Contingency, profit, management fee and other overheads are included in the bid. This is assumed because the data does not indicate a separate division for such costs.
5. It is assumed that there are no delays in the projects causing cost increase and the projects have been completed successfully.
6. It is assumed that no contractor has been disqualified from the bidding process due to any reasons, this assumption is necessary because there is no information about contractors that have been disqualified from the bidding process.

3. ARTIFICIAL NEURAL NETWORKS

3.1. Introduction

According to Rumelhart et al. (1986), there are eight components of a parallel distributed processing model such as the neural network. These eight components are the processing units or neurons, the activation function, the output function, the connectivity pattern, the propagation rule, the activation rule, the learning rule and the environment in which the system operates. Neural networks are a series of interconnected artificial neurons which are trained using available data to understand the underlying pattern. They consist of a series of layers with a number of processing elements within each layer. The layers can be divided into input layer, hidden layer and output layer. Information is provided to the network through the input layer, the hidden layer processes the information by applying and adjusting the weights and biases and the output layer gives the output (Karna and Breen 1989). Each layer may have a number of processing units called neurons. The inputs are weighted to determine the amount of influence it has on the output (Karna and Breen 1989), input signals with larger weights influence the neurons to a higher extend. An activation function is then applied to the weighted inputs, to produce an output signal by transforming the input. The input can be a single node or it may be multiple nodes depicting different parameters where each of the input nodes acts as an input to the hidden layer. The hidden layer consists of a number of neurons/nodes which calculate the weighted sum of the input data.

Figure 2 shows how neural network adjusts the weights and biases by comparing the output with the target. The weights are not fixed but they change over time by gaining experience after several iterations (Rumelhart et al. 1986). Artificial neural networks are used in pattern classification, clustering/categorizing, function approximation, predicting, optimization, control and content-addressable memory (Jain et al. 1996).

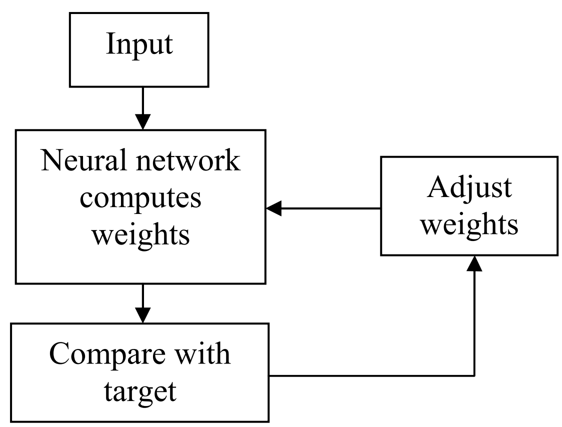

Figure 2: Correction of error using target data
Reference: Demuth H., Beale M., and Hagan M (2006)

Depending upon the type of input data and the output required, there are five types of activation functions used to transform input signal into output viz., linear function, threshold function, sigmoid function, hyperbolic tangent function and radial basis function. The activation functions are described briefly below:

Linear function: The linear function is of the type *f(s) = s* and is used for linear transformation of the input. This type of activation function is used for data that have a linear relationship.

Threshold function: The threshold function is used to output a value of 1 if the value of the function is above a threshold. For example, if s_t is the threshold value then for all $s > s_t$, the neural network will output a value of 1 and for all other values it will output a value of 0. The equation (3-1) shows the threshold function,

$$f(s) = \begin{cases} 1, & if \quad s > s_t \\ 0, & \text{otherwise} \end{cases} \qquad (3\text{-}1)$$

Sigmoid function: The sigmoid function transforms the input into a value between zero and one. A log sigmoid function transforms any value of the input data from + infinity and – infinity to a value between zero and one.

$$f(s) = \left(\frac{1}{(1 + \exp(-s))} \right) \qquad (3\text{-}2)$$

For the data used in this project a log-sigmoid transfer function is used in the input and intermediate layers and a linear transfer function is used in the output layer. A log-sigmoid activation function is used because it transforms any number into a value between zero and one. The equation for the log-sigmoid function is as shown in below:

$$O = \frac{1}{(1 + e^{-X})} \qquad (3\text{-}3)$$

where,

O: is the log-sigmoid transfer function.

X: is the weighted sum of the inputs from the previous layer to a particular neuron/node obtained from equation (3-3)

3.2. Background

According to Pham and Liu (1995), neural networks can be categorized according to the structure and learning algorithm used. According to structure they have classified neural networks into feedforward networks and recurrent networks. Pham and Liu (1995) have classified neural networks according to the learning algorithm used into supervised learning networks and unsupervised learning networks.

In a feedforward neural network, information flows from one layer to the next from the input layer to the hidden layer and then to the output layer. The flow of information is unidirectional. The neurons in one layer are connected to the neurons in the next layer. As shown in Figure 3, feedforward neural networks are further classified into multi-layer perceptron networks (MLP), learning vector quantization networks (LVQ), cerebellar model articulation control networks (CMAC) and group-method of data handling networks (GMDH) network (Pham and Liu 1995).

Multilayer perceptron networks (MLP): A multilayer perceptron network is a neural network with a number of layers consisting of neurons with sigmoid activation function (Pal and Mitra 1992). In a multilayer perceptron network, the information is not exchanged within the layer but neurons from one layer are interconnected with neurons of the adjacent layers with weights determining the degree of correlation between the neurons of the adjacent layers (Pal and Mitra 1992). Multilayer perceptrons uses error back-propagation algorithm to train the network. The error back-propagation technique is a two step process, in the forward step constant weights are assigned to the nodes to compute a response, in the backward step the weights and biases are adjusted to reduce the error between the calculated response and the target values (Haykin 1994).

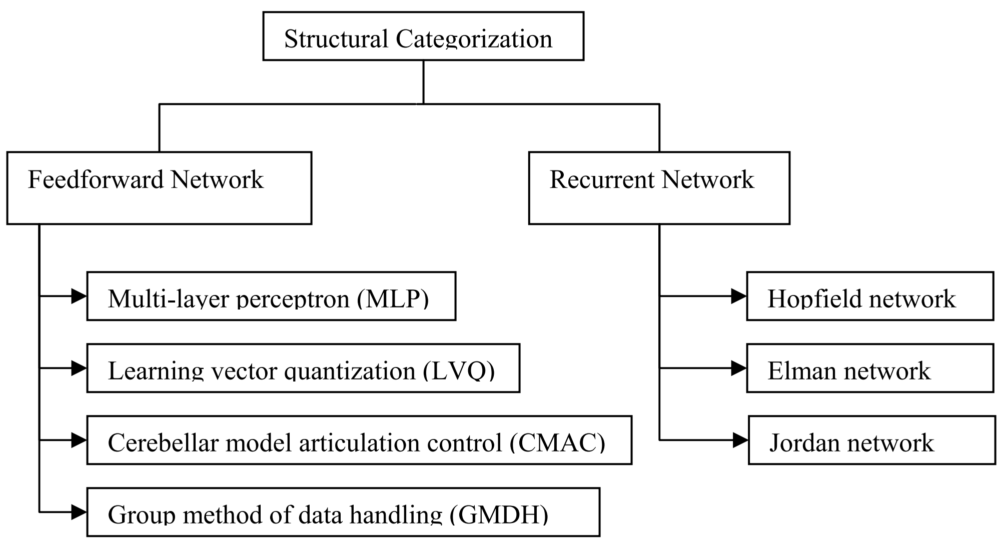

Figure 3: Structural classification of neural networks

Learning vector quantization (LVQ): It is a supervised learning technique in which the input signal is classified into separate classes, these classes are based on similarity in the data structure (Haykin 1994). Vector quantization techniques are used for data compression by utilizing the underlying structure of the input (Haykin 1994).

Cerebellar model articulation control (CMAC): It is a type of supervised learning feedforward network which utilizes fuzzy associative memory (Pham and Liu 1995).

Group method of data handling (GMDH) network: The group method of data handling network has a structure which produces an output which is a linear combination of two inputs (Pham and Liu 1995). For example if the inputs are x_1 and x_2 and the output is given by y, then the output is given by (Pham and Liu 1995)

$$y = w_0 + w_1 x_1 + w_2 x_1^2 + w_3 x_1 x_2 + w_4 x_2^2 + w_5 x_2 \tag{3-4}$$

The GMDH network increases in size during training because in this type of network the weights are adjusted for each neuron, and at the same time, the numbers of layers are increased until required accuracy is achieved.

Hopfield network: Hopfield networks are a type of recurrent network which accepts binary and bipolar inputs (Pham and Liu 1995). These types of network consist of a single layer of neuron which is connected to each others in a recurrent manner (Pham and Liu 1995).

Elman and Jordan networks: These networks are made up of multiple layers which are similar to the multilayer perceptron except in addition to a hidden layer they have a special layer called context. In an Elman net, this context layer receives feedback from the output layer or from a hidden layer. In a Jordan network, the signal is send back from each neuron in the context layer to itself (Pham and Liu 1995).

Neural networks can also be categorized according to the learning methods used to train the network. The most common learning methods used are supervised learning, reinforcement learning and unsupervised learning. In the supervised learning method, the network is provided with input and output, the network adjusts the weights after comparing the results from the network with the output to minimize the error. In reinforcement learning, the network is not provided with the output but it is informed if the output is a good fit or not (Karna and Breen 1989). In the unsupervised learning method, input is provided to the network which adjusts the weights and segregates the input patterns into clusters with similar characteristics eg., the Kohonen learning algorithm (Pham and Liu 1995).

Using the three parameters viz., quantity for each line item, contractor identity matrix and cost indices, an input layer consisting of a single node was constructed as shown in Figure 4. The number of hidden layers can be varied depending upon the accuracy of the output required. The network is trained using data from the training set. This trained network is then used to simulate an output using the input data of the validation set. The output of this simulated network is a vector of predicted bid prices for the input data of the validation set.

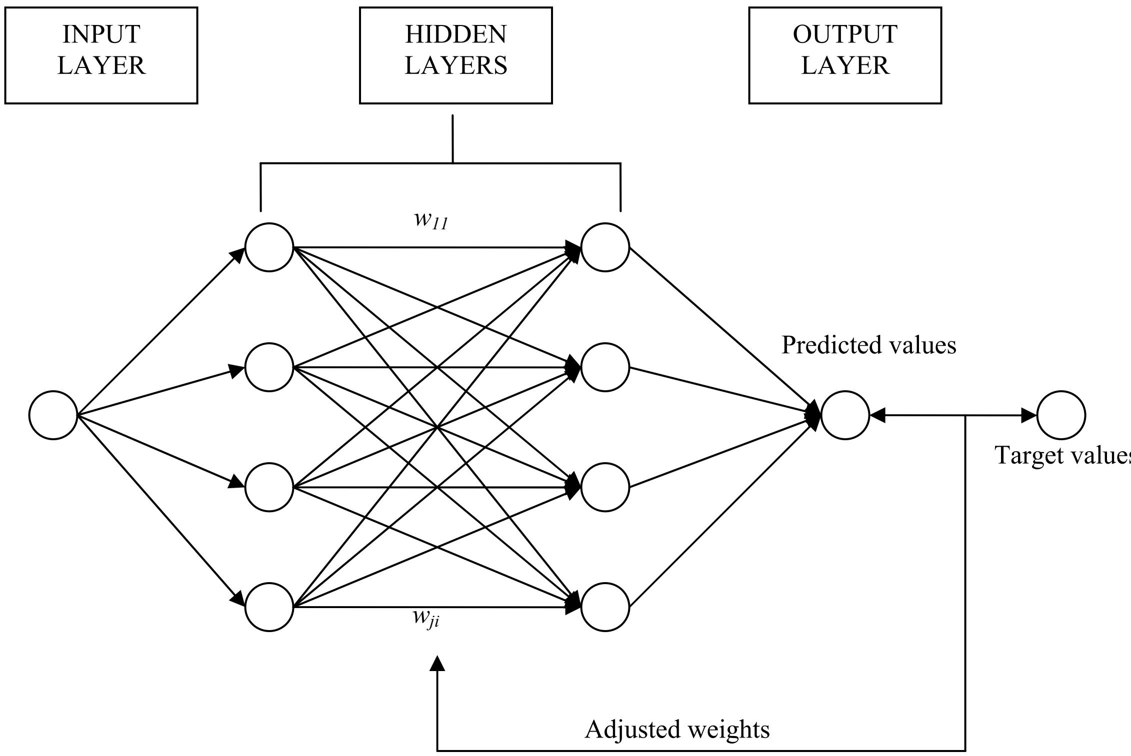

Figure 4: Structure of neural network e.g. [1441] network

The input data was scaled down between zero and one so that it can be used as an input in MATLAB for constructing the network. Scaling down of the dataset was necessary because the inputs for neural network program in MATLAB require that the input be within the range of zero and one. The scaling down was done by subtracting each value with the minimum value of the whole dataset and then dividing this by the difference between the maximum value and the minimum value of the whole dataset.

$$Changed\ Value = \frac{Original\ value - Minimum}{Maximum - Minimum} \qquad (3\text{-}5)$$

Various iterations were performed by changing the number of layers and the number of neurons in each layer. A levenburg-marquardt algorithm was used for training the network. The neural network program in MATLAB uses the levenberg-marquardt algorithm to achieve numerical optimization through nonlinear least squares. The levenberg-marquardt algorithm aims to minimize the least squres error by approximating the Hessian matrix to achieve second order training speed, as follows (Demuth et al. 2006):

$$H = J^T J \tag{3-6}$$

where,

H is the Hessian matrix and

J is the Jacobian matrix of the first derivatives of the errors with respect to the weights and biases (Demuth et al. 2006)

The gradient can be computed using the network error (Demuth et al. 2006)

$$g = J^T e \tag{3-7}$$

where,

J is the first order derivative of the network errors with respect to the biases and weights and *e* is the vector of errors of the network (Demuth et al. 2006).

According to Demuth et al. (2006), this approximation of the Hessian matrix is similar to the Newton's method (Demuth et al. 2006).

$$x_{k+1} = x_k - \left[J^T J + \mu \right]^{-1} J^T e \tag{3-8}$$

The algorithm uses the above form to calculate the performance function. When the value of μ is large the equation (3-8) takes the form of a gradient descent approach whereas if the value of μ is zero the equation (3-8) takes the form of the Newton's method (Demuth et al. 2006). The Hessian matrix approximation using Jacobian transformation is used to arrive at the least squares error faster (Demuth et al. 2006).

In the neural network, the inputs to a node from the previous layer are multiplied by weights and summed as shown in equation (3-9) (Warner and Misra 1996).

$$O = \frac{1}{(1+e^{-X})} \tag{3-9}$$

where,

X: is the weighted sum of the inputs from the previous layer to a particular neuron/node.

w_{ji}: are the weights

x_i: are the inputs from the previous layer

Since the inputs to the neural network are scaled down between zero and one, the output has to be scaled up to get the predicted bid prices. This process is reverse of the scaling down process which is done by using the equation shown below:

$$New\ value = \left[Changed\ value\left(Maximum - Minimum\right)\right] + Minimum \tag{3-10}$$

Using the method described above, a neural network using data from 214 projects was constructed and thirty five projects were used to validate the network. The network was trained using different configurations of the network and different neurons in each layer. The results from different runs of the validation set are as shown in

Appendix B and Table 3. The projects that were used in the training and the validation set are as listed in Appendix C.

The analysis was performed by changing the number of iterations also called epochs and the configuration of the network. The configuration of the network was changed by varying the number of neurons in each layer and/or changing the number of layers. For example, a [1 2 1] configuration denotes that it is a three layered network and there are 1, 2 and 1 neurons in the input, hidden and the output layer of the network respectively. Table 3 shows a summary of the different iterations performed to analyze the data. Root mean square error and coefficient of determination are the two parameters that are used to compare the models. The root mean square error is mathematically expressed as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i}^{n}\left(X_i - \overline{X}\right)^2} \qquad (3\text{-}11)$$

The coefficient of determination is calculated from the regression sum of squares (SS_R) and the total corrected sum of squares (SS_T). The regression sum of squares is given by

$$SS_R = \sum_{i}^{n}(\hat{y}_i - \overline{y})^2 \qquad (3\text{-}12)$$

where,

$\hat{y}_i - \overline{y}$ are the residuals

The total corrected sum of squares (SS_T) is the sum of the regression sum of squares and the error sum of squares (SS_E).

$$SS_T = SS_R + SS_E \tag{3-13}$$

The error sum of square is calculated as follows

$$SS_E = \sum_{i}^{n} (y_i - \hat{y}_i)^2 \tag{3-14}$$

The coefficient of determination is the ratio of regression sum of square (SS_R) and the total corrected sum of squares (SS_T).

$$R^2 = \frac{SS_R}{SS_T} \tag{3-15}$$

The root mean squared error and the coefficient of determination for the validation set, for different configurations of the network and for different epochs are shown in Table 3. The average cost of the projects in the validation set is $583,117. From the results it can be seen that the root mean squared error is large when compared to the average cost of the projects in the validation set.

Table 3: Summary of different iterations for the neural network

		100 epochs		**200 epochs**		**500 epochs**	
	Configuration	RMSE (validation)	R^2 for actual vs. fitted	RMSE (validation)	R^2 for actual vs. fitted	RMSE (validation)	R^2 for actual vs. fitted
3 Layered network	1 2 1	$803,491	13.86%	$448,536	19.29%	$1,222,548	19.33%
	1 3 1	$827,918	1.54%	$1,156,026	0.91%	$1,214,538	0.85%
	1 4 1	$1,245,193	35.52%	$1,293,271	31.38%	$1,074,458	31.31%
	1 5 1	$662,886	7.72%	$2,228,929	2.94%	$431,175	17.89%
	1 6 1	$920,434	18.05%	$1,232,999	7.46%	$1,090,793	10.94%
4 Layered network	1 2 2 1	$827,494	34.96%	$585,738	15.29%	$998,982	9.45%
	1 3 3 1	$829,406	9.84%	$868,846	12.25%	$775,359	14.01%
	1 4 4 1	$877,938	9.79%	$731,104	25.25%	$877,938	9.79%
	1 5 5 1	$886,859	1.23%	$619,733	13.03%	$997,509	5.99%
	1 6 6 1	$886,859	10.72%	$952,016	2.39%	$481,695	13.85%

3.3. Conclusions for neural network

After performing different iterations, the neural network with a [1 2 2 1] configuration and 100 epochs produces the best result. It has a coefficient of determination of 0.34 and a root mean squared error of $827, 494. The plot of actual versus predicted for the neural network with [1 2 2 1] configuration is as shown in Figure 5.

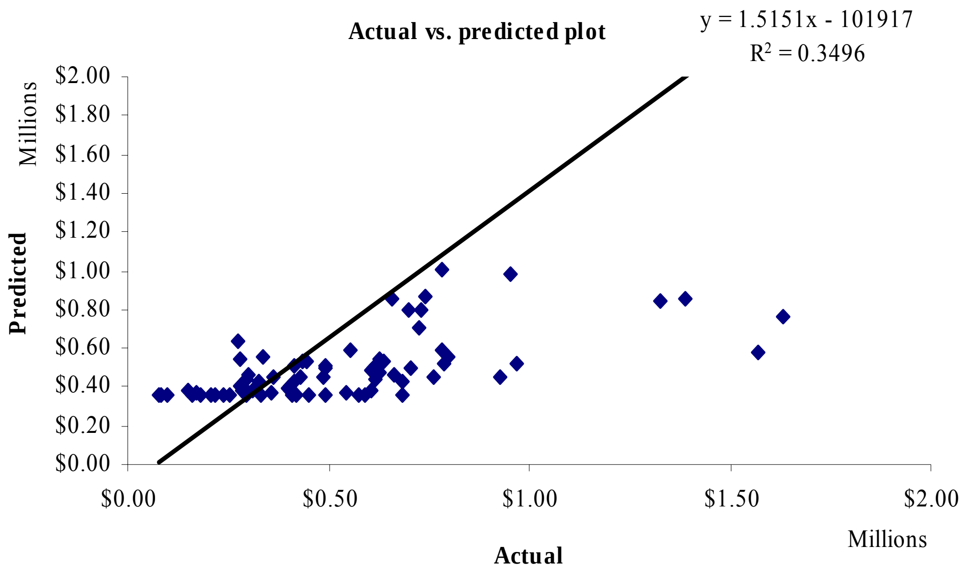

Figure 5: Actual vs. predicted for artificial neural network with [1221] configuration

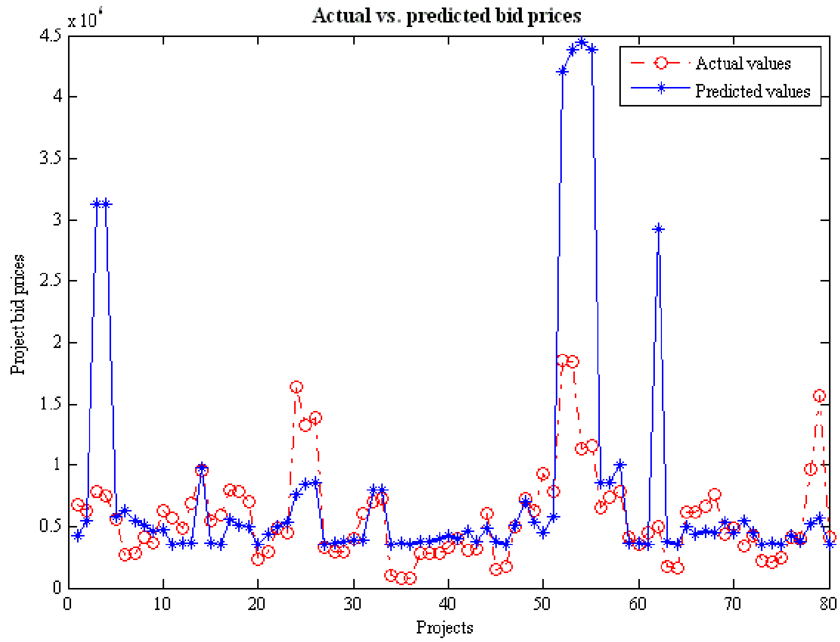

Figure 6: Actual vs. predicted for validation set of ANN with [1221] configuration

Figure 6 shows the ability of the network to predict most of the values for the project except a few projects. Projects number CND055 (3 and 4), CND284 (52, 53, 54 and 55) and CND334 (62) are over estimated by the neural network and these values skew the root mean square values. The average predicted error for the neural network with [1221] configuration is 141%. Though some of the values are close to the actual, there is a lot of variation in the predicted values. The actual and predicted values for neural network with [1221] configuration are as shown in Appendix D. The usefulness of the model developed by neural network can be judged only after comparing it with the model obtained from MARS.

The data transformed using principal component analysis (explained in the next section) was used to train neural network, the results obtained were not promising.

Figure 7 shows the output of the analysis using dataset transformed by principal component analysis. All the predicted values were similar to each other hence further analysis using data transformed by principal component analysis was not done.

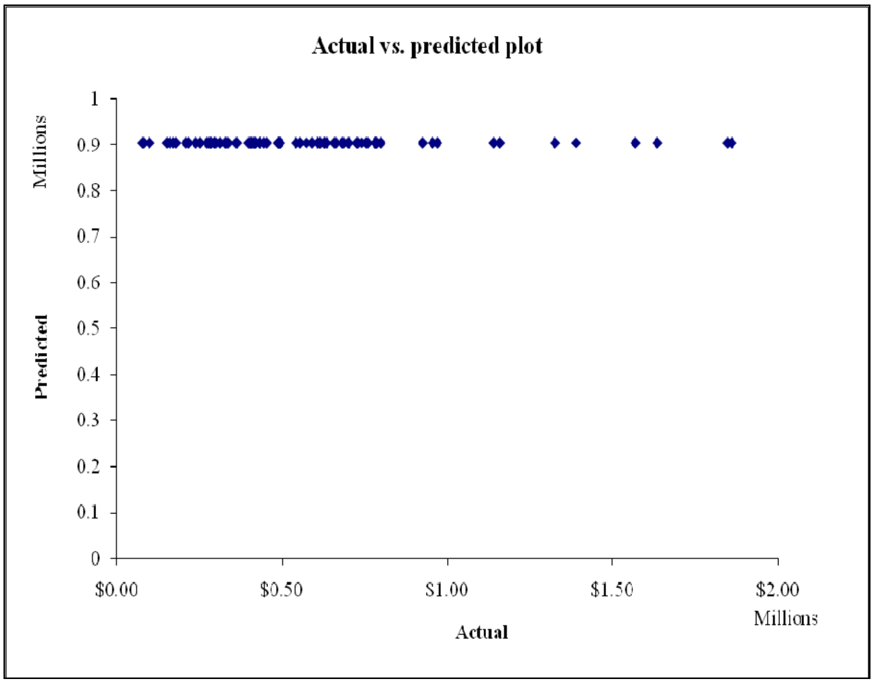

Figure 7: Output of neural network with data transformed using principal component analysis

4. MULTIVARIATE ADAPTIVE REGRESSION SPLINES

4.1. Introduction

Multivariate Adaptive Regression Splines (MARS) is an adaptive modeling process popularized by J. H. Friedman for non-linear relationships. The modeling technique expands product spline basis functions by selecting the number of basis functions, the locations of the knots and the degrees of freedom automatically depending upon the data (Freidman 1995). The aim of the model is to capture the relationship between the dependent variable and the independent variable from the data. According to Leathwick et al. (2005), MARS divides the predictor variables into piece-wise linear segments to describe non-linear relationships between the predictor and the dependent variable.

The MARS software developed by Salford Systems was used and the results were compared with the results obtained from neural network. The MARS software automatically develops and adjusts the model by comparing the target values and the dependent variables supplied as input to the model. This is done by selecting the appropriate variables that contribute to the model fit, determining the degree of interaction between the predictor variables and conducting tests to avoid over fitting to the dataset (MARS 2001). The MARS software has a number of input/output options and is available with a graphical user interface. The data set can be entered in a number of file formats. The problem faced in fitting a model to the dataset is the type of function that will best fit to it. This problem is overcome by MARS by fitting piecewise linear basis functions to small segments of the dataset. The other advantage of the MARS model is that it is adaptive, meaning that the model chooses the locations of the knot points depending upon several strategies. One such strategy is minimization of the least squares criterion given in equation (4-1) (Friedman and Roosen 1995),

$$\sum_{i=1}^{N}\left[y_i - \sum_{k=0}^{K+q} a_k B_k^{(q)}(x) \right]^2 \qquad \text{(4-1)}$$

where,

a_k represents the coefficient of expansion

$B_k^{(q)}(x)$ are the basis functions that are selected for inclusion in the model of order q

4.2. Background

The aim of any regression model is to derive a relationship between the independent variables and the dependent or the predictor variables. A simple linear regression model takes the form given in equation (4-2).

$$\mathrm{y_i} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots\dots\dots\dots + \beta_n x_n + \varepsilon \qquad \text{(4-2)}$$

In equation 4-2, the β's are called regression coefficients and ε is the error term. The x's are the independent variables and the y's are the dependent variables whose values can be estimated using the predictor also known as independent variables. In a MARS model the range of x values are divided into disjoint regions separated by "knot" points (Friedman and Roosen 1995). According to Friedman and Roosen (1995), a q^{th}

degree polynomial is then fitted separately and locally to these disjoint regions and each of the q^{th} order polynomials are then adjusted to fit the disjoint regions locally while satisfying the least squares criterion. Thus, the basis functions are used to determine a relationship between the dependent and the independent variables (Friedman and Roosen 1995). The model iteratively decreases the average squared error, shown in equation (4-3) by attempting to make the predicted values close to the actual values.

$$mse = \sum_{i=1}^{n} \frac{(y_i - \hat{y}_i)^2}{n} \tag{4-3}$$

In equation (4-3), the average sum of squared error term (*mse*) can be minimized if the values of y_i are close to $\hat{y}_i$. This minimization problem is converted into an optimization problem by choosing basis functions of the form $B_k^{(q)}(x)$ for each of the disjoint sets between the knot points (Friedman and Roosen 1995). A linear least squares fit is then performed on each of these basis functions (Friedman and Roosen 1995). The expansion in the piece-wise linear basis function are of the form $(x - t)_+$ and $(t - x)_{+}$,, where + signifies that the equation retains positive values (Hastie 2001). This linear basis function is of the form (Friedman and Roosen 1995)

$$(x - t_k)_+^q \begin{cases} 0 & x \le t_k \\ (x - t_k)^q & x > t_k \end{cases} \tag{4-4}$$

Knots are selected adaptively in a forward/backward stepwise selection approach. A large number of knot locations are selected for the dataset during the forward selection and deleted or retained, depending upon the least squares criterion, in the backward selection process. The advantage of the adaptive knot selection process is that outliers in the independent variables affect the model locally and there is minimal affect on the overall model (Friedman and Roosen 1995).

After the knot locations are selected, the MARS algorithm selects a number of basis functions with the aim to overfit the data. The splines for the disjoint regions separated by knots are tensor products of the splines over the independent variable (Friedman and Roosen 1995). Basis functions are selected locally, depending upon the variable and the contribution of the variable to the overall fit, the basis function is then either retained or deleted to improve the overall fit of the model. The selection of the basis function is a two step process, in the forward stepwise selection a large number of basis functions are selected (Friedman and Roosen 1995). According to Friedman and Roosen (1995), the forward stepwise process is a recursive process and at each step new two basis functions are introduced into the pool of previously entered basis functions. Interactions can be allowed between each of the basis function or for selected variables depending upon the underlying knowledge of the variable. The basis functions selected in the forward step are compared to each other depending upon some lack of fit criterion such as cross-validation. The MARS algorithm uses generalized cross-validation for pruning until the best fit model is obtained. The data used for comparing the lack-of-fit is required to be independent of the training data hence sample reuse techniques such as the cross validation technique or bootstrapping technique is used for comparing the model fit (Friedman and Roosen 1995).

The MARS algorithm implemented by Salford Systems uses the following equation proposed originally by Craven and Wahba for comparing the fit (Friedman 1991)

$$GCV(M) = \frac{1}{N}\sum_{i=1}^{N}\left[y_i - \hat{f}_M(x_i)\right]^2 / \left[1 - \frac{C(M)}{N}\right]^2 \qquad (4\text{-}5)$$

where,

M : number of non constant basis functions

$\hat{f}_M(x_i)$: is the model of the M basis function considered for deletion during the backward step

C(M) : is the cost complexity of the model and is given by

C(M) = *M*.(*d*/2 + 1) + 1 and

d : smoothing parameter

The MARS program however accepts a maximum of 8019 variables hence it was necessary to reduce the dataset. To reduce the dataset and at the same time to retain the variability in the original dataset principal component analysis was used which also makes the dataset uncorrelated. Principal component analysis is discussed in the next section.

4.3. Principal component analysis

The data set from TDoT was found to be correlated. Due to computational constraints the amount of data to be analyzed was required to be reduced. Principal component analysis (PCA) reduces the dataset while retaining most of the variability and at the same time makes the transformed data uncorrelated. Principal component analysis was performed on the whole dataset. Principal component analysis finds orthogonal linear combinations of the original dataset which have the largest variance and at the same time can be used to reduce the dimensionality of the dataset (Fodor 2002). Fodor (2002) has expressed the independent variables as

$$x = (x_1, \ldots\ldots\ldots.., x_p)^T \qquad (4\text{-}6)$$

whose mean values are given by,

$$E(x) = \mu = (\mu_1, \ldots\ldots\ldots.., \mu_p) \qquad (4\text{-}7)$$

The covariance matrix for the data can be represented as (Fodor 2002),

$$E_{p \times p} = E[(x - \mu)(x - \mu)^T] \qquad (4\text{-}8)$$

and its lower dimension or principal components (pc's) are represented by,

$$s = (s_1, \ldots\ldots\ldots.., s_k)^T \qquad (4\text{-}9)$$

where $k \leq p$

Let μ_i *and* σ_i denote the mean and the standard deviation of the i^{th} observation, such that $\sigma_i = \sqrt{\Sigma_{(i,i)}}$. The observations are standardized in order to transform the variables with different units to a set of variables that have zero mean and unit standard deviation (Fodor 2002). The sample mean ($\hat{\mu}_i$) and the standard deviation ($\hat{\sigma}_i$) are given as (Fodor 2002),

$$\hat{\mu}_i = \frac{1}{n}\sum_{j=1}^{n}\left(x_{i,j}\right) \tag{4-10}$$

$$\hat{\sigma}_i = \frac{1}{n}\sum_{j=1}^{n}\left(x_{i,j} - \hat{\mu}_i\right)^2 \tag{4-11}$$

The data is standardized using the mean and the standard deviation as follows (Fodor 2002):

$$\frac{\left(x_{i,j} - \hat{\mu}_i\right)}{\hat{\sigma}_i} \tag{4-12}$$

The principal components are linear combinations of the original variables (Fodor 2002),

$$s_i = w_{i,1}x_1 + \text{..........} + w_{i,p}x_p \tag{4-13}$$

for $i = 1, \ldots\ldots, k$ and $k \leq p$ or

$$s = Wx \tag{4-14}$$

Principal component analysis arranges the transformed variables in descending order of variance with the first few principal components explaining hopefully most of the variability. Mathematically, Fodor (2002) expresses the first principal component as follows:

$$s_1 = x^T w_1 \tag{4-15}$$

where the p dimensional is given by (Fodor 2002)

$$w_1 = \left(w_{1,1} + \dots\dots\dots + w_{1,p}\right)^T \tag{4-16}$$

and

$$w_1 = \arg\max_{\|w=1\|} Var\left(x^T w\right) \tag{4-17}$$

The second principal component explains the second largest variance and is orthogonal to the first principal component (Fodor 2002). Thus a number of principal components are computed which retain the variance of the original data and at the same time reduces the size of the dataset. The data is standardized to have a mean zero and standard deviation of one so that they are comparable even when the variables have different units (Fodor 2002). After the data is standardized the covariance matrix can be given by (Fodor 2002),

$$\Sigma_{pxp} = \frac{1}{n} XX^T \tag{4-18}$$

According to Fodor (2002), $\sum$ can be written using the spectral decomposition theorem as follows:

$$\Sigma = U\Lambda U^T \tag{4-19}$$

where,

$\Lambda = diag(\lambda_1, \dots\dots\dots, \lambda_p)$ is the diagonal matrix of the eigenvalues such that $\lambda_p \geq \dots\dots\dots \geq \lambda_1$ and

U is the orthogonal matrix containing the eigenvectors.

The *p* rows of the *p x n* matrix *S*, in the equation below, gives the principal components (Fodor 2002).

$$S = U^T X \tag{4-20}$$

The eigenvalues are the variances and the eigenvectors are the loadings. MATLAB was used to perform the transformation into principal components. Figure 8 shows the variation explained after principal component analysis is performed on the entire dataset. Figure 9 shows the cumulative percentage of variation explained.

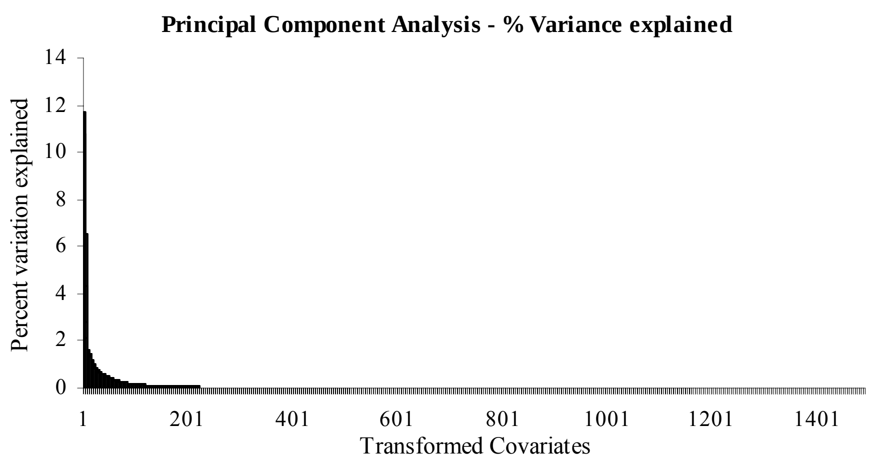

Figure 8: Variance explained for the whole dataset

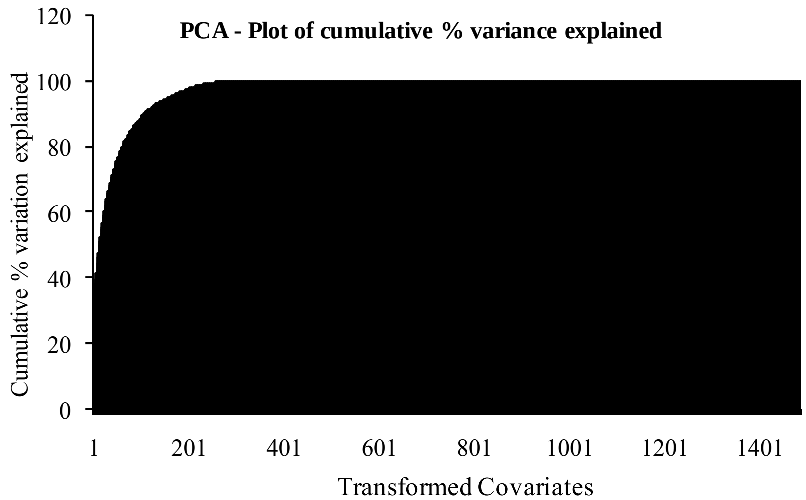

Figure 9: Cumulative variance explained for the whole dataset

Only those principal components that explain 90 percent of the variability are retained for further analysis. The first 108 principal components explain 90 percent of the variability in the whole dataset hence they are used for analyzing using multivariate adaptive regression splines. The components that explain 90 percent of the variability are retained because after this value the percentage variation explained is very small and does not change substantially.

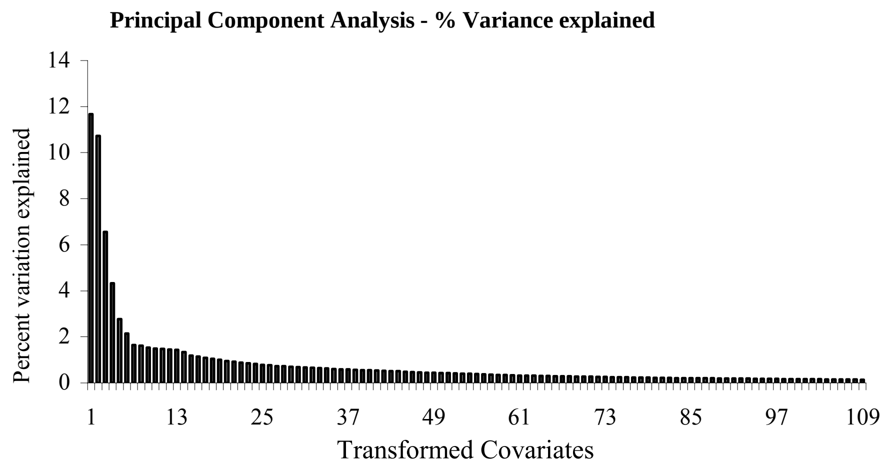

Figure 10: % variance explained for the first 108 principal components

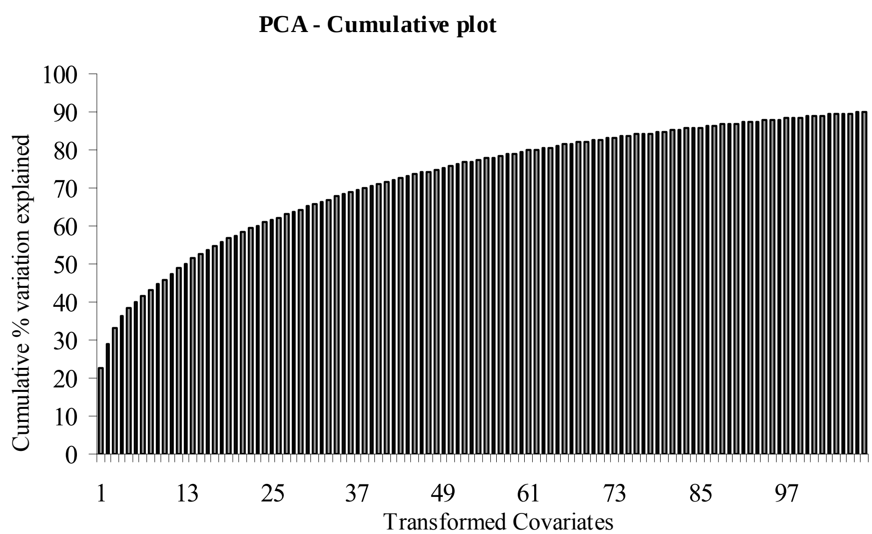

Figure 11: Cumulative % variance explained for the first 108 principal components

Figure 10 and Figure 11 shows the plot of percent variation explained and cumulative percent variation explained for the first 108 principal components.

4.4. Analysis using MARS

The dataset used for training and validation using MARS is the same as that used for analysis using artificial neural networks, except the data used for MARS was transformed using principal component analysis and only the first 108 principal components were retained. The same dataset was used so that comparison between the results using the two methods could be made. Several trials were done by fitting different models by changing various parameters, to the training set and then validating the results. The parameters were changed depending upon the results obtained by testing previous models. Models were fitted by changing certain parameters (discussed below) of the program and comparing the results for the validation set using root mean square error and plotting the predicted values against the actual values. The parameters that were varied are speed factor, penalty on added variable, maximum number of basis functions, maximum interactions, records to process, minimum observations between knots and degree of freedom. These parameters are discussed below:

Maximum number of basis functions: MARS initially constructs a number of models in a bid to over fit the data. The number of models to be fitted is dependent on the number of basis functions allowed. It is advised to have the number of basis functions equal to two to four times of the number of predictors (MARS 2001). The number of basis function is a user specified parameter and affects the speed of the MARS run

(MARS 2001). The maximum number of basis functions is varied from 15 to 200 while performing different iterations.

Penalty on added variables: This parameter directs the MARS model to reuse the available variables i.e. MARS will increase the number of knots for the existing variables or increase interaction between the already present variables rather than generating new variables from combination of the variables already present in the model (MARS 2001).

Minimum number of observations between knots: This parameter allows the user to specify the number of data points between adjacent knots. By default, MARS will generate knots at every observed data point. The default setting allows MARS to select knots depending upon the data (MARS 2001). Increasing the distance between the knots will make the model more global in nature rather than being locally adaptive (MARS 2001).

Speed factor: The speed factor can be adjusted on a scale of one through five, five being the fastest. A speed of one makes the model slower but improves the accuracy of the model. At a speed of one, MARS does intensive search of all the basis functions and chooses the one which contributes the most to the least squares criterion or any other criterion used for evaluating model fit.

Records to process: The records to process option specifies the percent of original data that the program can process, if the option is set to zero it will process the entire dataset, if the option is set to a specific number, the program will process the specified number of observations (MARS 2001).

Maximum interactions: This setting allows the user to specify the amount of interaction between the variables of the model. A value of one for the interaction terms makes the model additive, a value of two allows two way interaction and a value of three or more specifies that the model can be a product of one or more basis functions (MARS 2001).

Degree of freedom: The degree of freedom allows the user to impose a penalty to the knot selection process to avoid over fitting the model to the data. Three methods are available to select the degree of freedom they are: setting it to a particular value, determining by x – fold cross-validation and by using a test sample randomly set aside from every n^{th} observation. Using the first option the user can set the degree of freedom to a particular number, the default is set to 3.00 but it can be set to as high as 200 (MARS 2001). The second option allows the MARS model to select the degree of freedom by fold cross validation, for example if a value of 10 – fold cross-validation is specified, MARS will compute ten more models to optimize the knot selection process. In the third option, the program will set aside a randomly selected sample after every n^{th} observation and estimate the degree of freedom.

4.5. Results

Different models were run by varying the parameters described above. The configurations of the different runs are as shown in Table 4. The parameters were changed depending on results obtained from previous runs. Of the thirteen different models developed, three models showed substantially good results. The results of the different runs are compared using root mean square error and coefficient of determination.

Different models were developed by changing the speed factor, penalty on added variable, maximum basis function, maximum interactions allowed, minimum observations between knots and degree of freedom. The initial model were analyzed using low values for each case, in the first three set of models the number of interactions were changed steadily while keeping the maximum number of basis functions constant. In these three models the penalty on added variable was changed to see if there was any difference in the output. The testing method for determining degree of freedom was kept constant but the value was changed in the third model (Table 4). It was observed that changing the degree of freedom affected the model. Hence, the method of determining degree of freedom was changed in subsequent iterations. It should be noted that changing the method of determining the degree of freedom to "X – cross-validation" gives better results. Other parameters that affected the model significantly are number of maximum basis function and maximum number of interactions. The model prediction improves by increasing the maximum number of basis functions and the number of interactions. MARS selects the degree of freedom by using a generalized cross validation (GCV) criterion as discussed before. There are three methods used to determine the degrees of freedom and the "*x*-fold cross validation" method is the most effective method that improves prediction for this dataset.

Table 4: Parameters for different model runs

Options and Limits							Testing		
							Select method for determining degree of freedom		
Model	**Speed factor**	**Penalty on added variable**	**Max. basis functions**	**Max. Interac tions**	**Records to process**	**Min. observations between knots**	**Set to**	**X - fold Cross validation**	**Use test sample randomly set aside at every n^{th} observation**
Model 1	4	None	15	1	0	0	3.00	-	-
Model 2	1	Moderate	15	2	0	0	3.00	-	-
Model 3	1	Heavy	15	3	0	2	4.00	-	-
Model 4	1	Heavy	20	10	0	0	-	10	-
Model 5	1	None	100	50	0	0	-	110	-
Model 6	1	None	100	100	0	0	-	10	-
Model 7	1	Heavy	200	200	0	0	-	10	-
Model 8	4	None	50	100	0	0	3.0	-	-
Model 9	1	None	100	100	0	50	-	10	
Model 10	1	Moderate	50	50	0	0	-	-	2
Model 11	1	None	100	100	0	110	-	110	-
Model 12	1	None	110	110	0	0	-	110	-
Model 13	1	None	200	200	0	0	-	500	-

The results from the models developed using the different parameters are as shown in Table 5. Model number 5, 12 and 13 have R-square values of 58.27%, 42.53% and 54.17% which are better than the rest of the models. The plot of actual vs. predicted

(Figure 12) shows that the MARS program is able to capture the variability in the data set reasonably well. Model number 5 has the best R-square value of 58.27% while model number 6 has the lowest root mean square error of $1,342,011.

Table 5: MARS results

Model #	**RMSE**	**Coefficient of determination (R^2)**
Model 1	$ 2,535,132	16.78%
Model 2	$ 1,555,689	18.57%
Model 3	$ 1,651,545	23.95%
Model 4	$ 1,489,013	16.68%
Model 5	$ 2,157,533	58.27%
Model 6	$ 1,342,011	13.62%
Model 7	$ 1,162,633	16.94%
Model 8	$ 6,258,412	17.99%
Model 9	$ 2,859,332	14.56%
Model 10	$ 1,340,552	6.67%
Model 11	$ 4,593,369	13.86%
Model 12	$ 1,642,966	42.53%
Model 13	$ 2,467,507	54.17%

Figure 12 and Figure 13 show the plots of the actual and the predicted for the validation set of model 5. The predicted values for model 5 are close to the actual values for the projects in the validation set. The output from the MARS program for model 5 is attached in Appendix G. The level of accuracy achieved depends on the size of the project, the number of contractors participating in the bidding process, the type of project and the total project cost. The predictions from MARS can be improved by providing more information about the location, the total number of projects performed by each contractor bidding on the project, the revenue earned by each contractor, the expected duration required to complete the project etc.

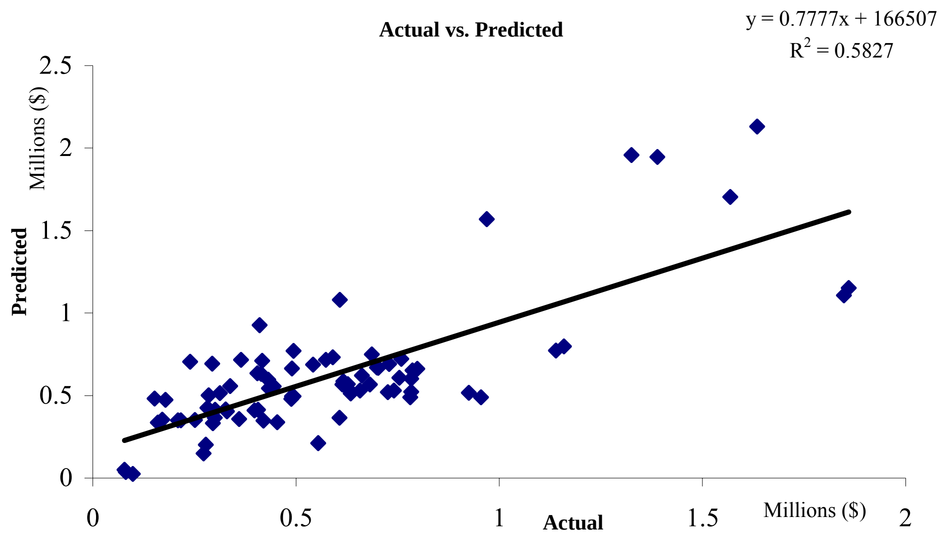

Figure 12: Actual vs. predicted for model 5

The average percent variation of the predicted values from the actual is about 43% with the lowest variation of 0.23% and a highest variation of 217.8%. Figure 14 shows the plot of the percent variation of the predicted values against the actual values. Figure 15 shows the percent variation of the actual bid prices from the predicted values plotted against the actual bid prices.

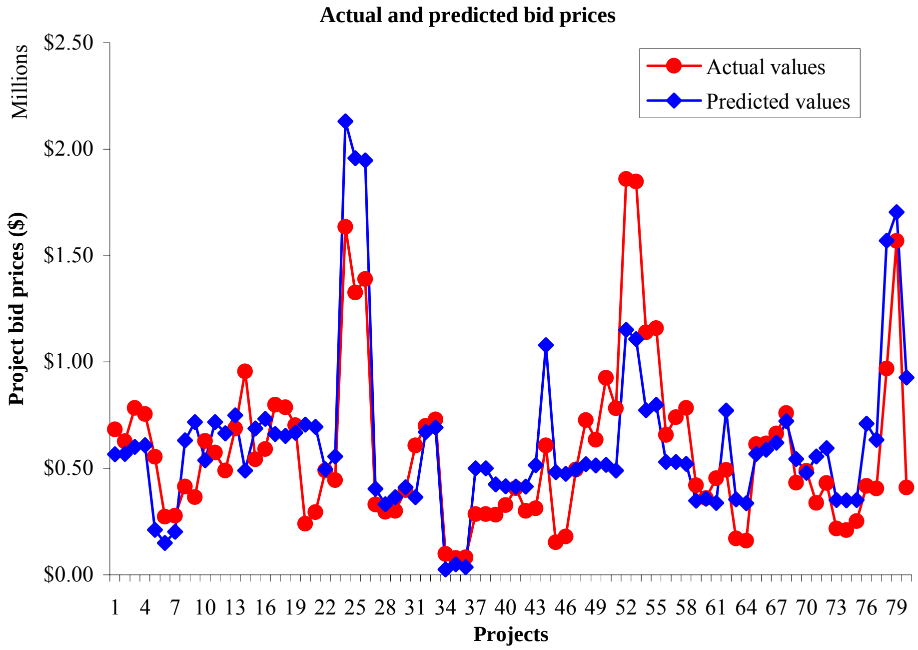

Figure 13: Actual and predicted bid prices for projects in validation set of model 5

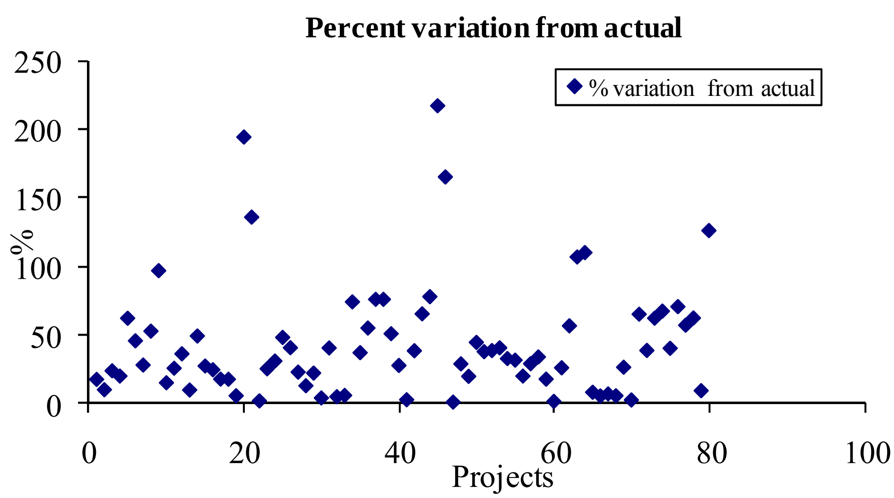

Figure 14: Percent variation of predicted values from actual values

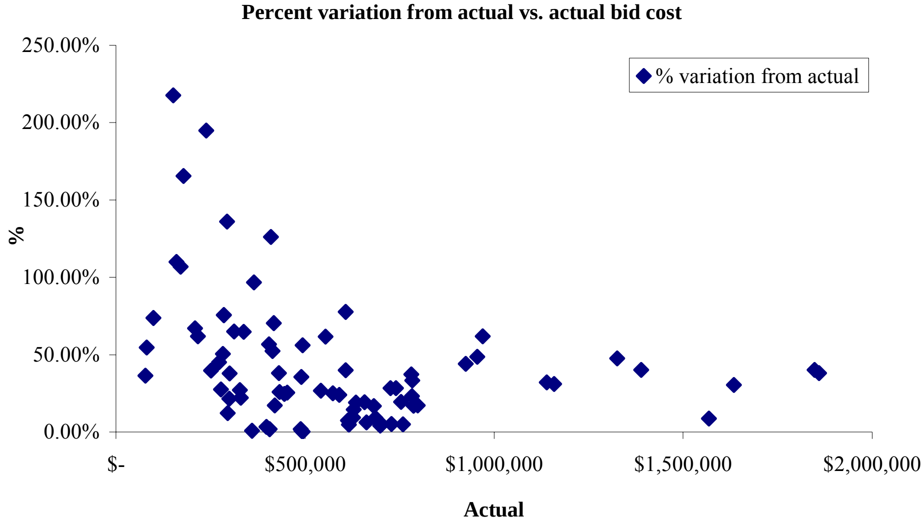

Figure 15: Percent variation of actual from predicted vs. bid costs

5. CONCLUSION

Figure 16 shows the comparison of the best models obtained from both the methods i.e. MARS and ANN with the actual values. The values obtained from MARS are closer to the actual values than those obtained from ANN.

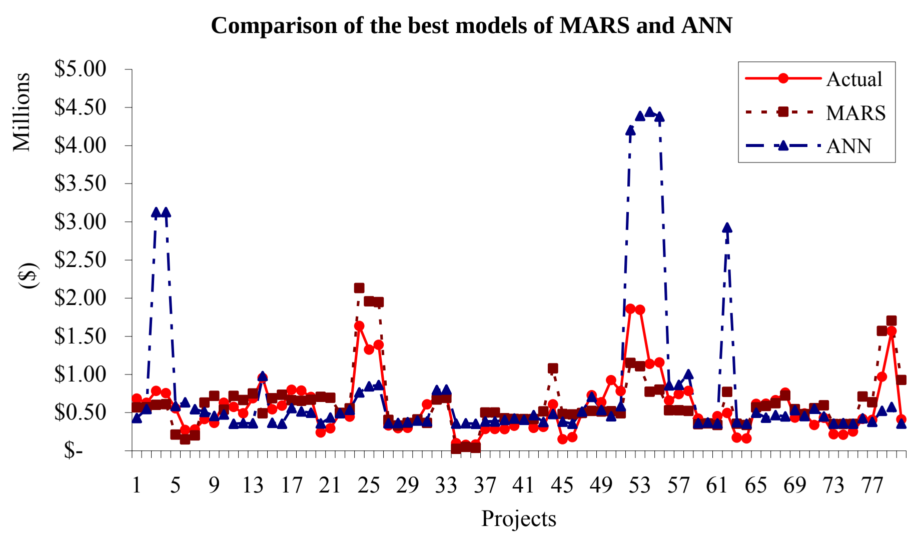

Figure 16: Comparison of best models from MARS and ANN

Bid prices for some of the projects are predicted higher than the actual values by the MARS and ANN model. This is a major drawback of both the models because if the predicted values are higher than the actual values quoted by other contractors, the contractor might lose the contract. If all the contractors bidding on a project use this model to predict the bid prices, then every contractor will know what the other contractors are going to quote on the project. This situation is a problem of decision analysis and game theory. Such a situation is not taken under consideration while developing the model.

After comparing the results from artificial neural networks and multivariate adaptive regression splines, it can be concluded that the MARS model is better than the ANN model for the following reasons:

1) The MARS program requires lesser computational resources whereas ANN requires considerable computational resources.
2) ANN does not provide a functional relationship between the dependent and the independent variables whereas MARS provides a relationship between the basis functions derived from the independent variables and the dependent variable.
3) Since MARS fits sub models to segmented data, outliers do not affect the model globally whereas ANN's are strongly affected by outliers.
4) The MARS model is more stable in terms of prediction i.e. the predictions obtained using the same parameter settings will be fairly similar for several runs, the predictions from ANN are not very stable.
5) ANN does not give useful output when the original dataset is transformed using principal component analysis, this is a major drawback. Principal component analysis reduces the size of the dataset this helps in making the analysis faster and easier to manage when a large amount of data is involved.

6. DISCUSSION

To illustrate the usefulness of the two models, the results from one of the project used in the validation set are discussed below. The project identified as CND374 involves repair of bridges on I-24 over Dodds avenue and Westside drive. The four contractors bidding on the project are General Contractors, Inc., Jamison Construction, LLC., Southern Constructors, Inc. and Williams Restoration & Waterproofing, Inc. Table 6 summarizes the results of the predicted costs for ANN and MARS. For this project, the predicted values for Jamison Construction LLC and Williams restoration and waterproofing, Inc. are very close to the actual values. Figure 17 and Table 6 compare the results of the two methods with the actual values.

Table 6: Results for CND 374

Sr. No.	Contractors	Actual values	ANN (1 2 2 1 Configuration)	MARS (Model 5)
1	GENERAL CONSTRUCTORS, INC.	$ 613,829.00	$ 499,075.20	$ 567,970.00
2	JAMISON CONSTRUCTION, LLC	$ 616,392.50	$ 433,899.07	$ 587,030.44
3	SOUTHERN CONSTRUCTORS, INC.	$ 662,598.00	$ 466,992.48	$ 621,167.63
4	WILLIAMS RESTORATION & WATERPROOFING, INC.	$ 759,360.25	$ 450,122.17	$ 722,332.50

The comparison between the two models was based on the results from the best models obtained in each of the methods. The neural network model with configuration [1221] and model 5 for MARS was used to compare the predicted values.

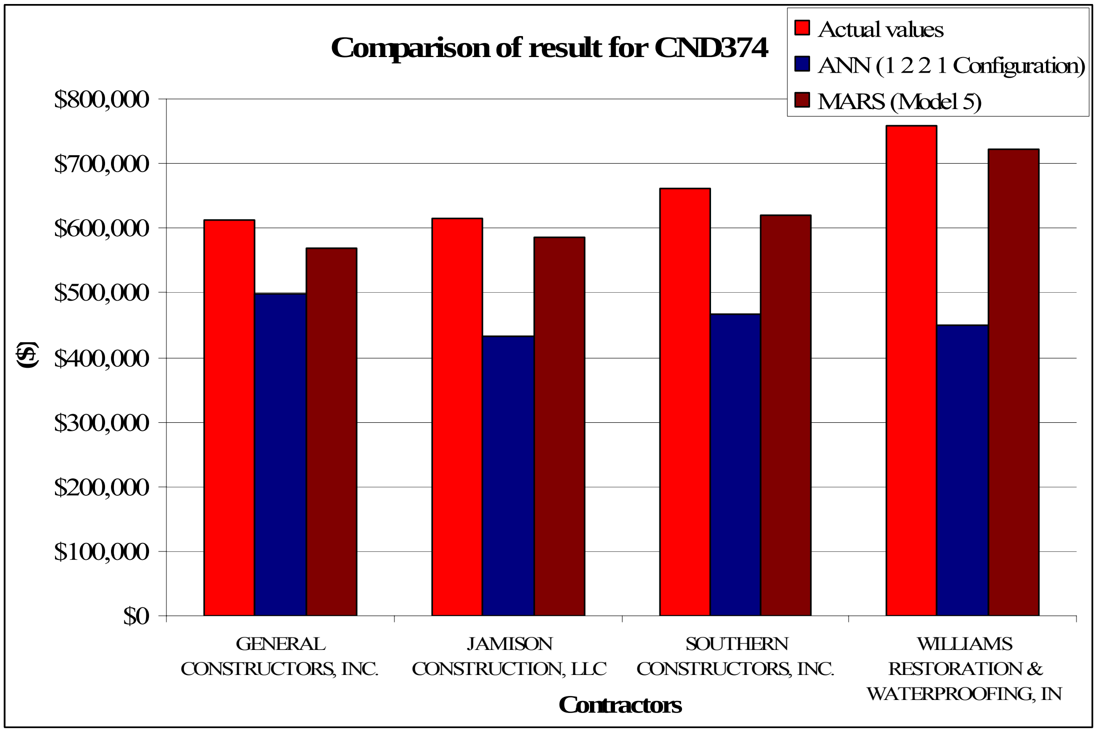

Figure 17: Comparison of results for CND 374

One of the contractors could use MARS to predict what other contractors may bid on the project. For example, if Williams Restoration & Waterproofing, Inc. had information about the bid prices that the other three contractors would quote, the contractor could have adjusted his bid to win the contract. The contractor could then negotiate prices with the suppliers, reduce their profit or utilize some other strategy which would reduce cost of the project. Information about the bid prices quoted by other contractors could also help the contractor determine if bidding on the project is a profitable venture. This decision could be made by the contractor on their expected rate of return on the investment they plan to make on this project.

Table 7 shows the percent variation of the predicted values from the two methods with the actual values for project CND374.

Table 7: Variation of predictions from actual for CND 374

Contractors	**Actual - MARS**	**Variation of MARS results from Actual**	**Actual - ANN**	**Variation of ANN results from Actual**
GENERAL CONSTRUCTORS, INC.	$ 45859.00	7.47%	$ 114753.79	18.69%
JAMISON CONSTRUCTION, LLC	$ 29362.06	4.76%	$ 182493.42	29.61%
SOUTHERN CONSTRUCTORS, INC.	$ 41430.37	6.25%	$ 195605.51	29.52%
WILLIAMS RESTORATION & WATERPROOFING, INC.	$ 37027.75	4.88%	$ 309238.08	40.72%

The above analysis shows the usefulness of the multivariate adaptive regression splines method for predicting bid prices for highway construction project. The MARS method can be used in conjunction to other techniques of cost estimation like a detailed estimate to make decision whether to bid for a project or not.

The model may not be useful when predicting bid prices that may be quoted by a new contractor bidding for a project at TDoT. Future research and model improvement can be done by including more variables in the model. Variables like the amount of equipment owned by the participating contractors, the amount of work performed annually by each contractor, the location where work is being performed, project schedule, fuel cost index and distance of the project site from suppliers would improve the results obtained from the model. Contractors often use their knowledge about competing contractors to bid on projects such practices introduce correlation between bid costs quoted by each contractors, this correlation could also be included in the analysis to improve results.

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APPENDIX A

Cost indices for the year 2005

Table 8: Cost index for the year 2005

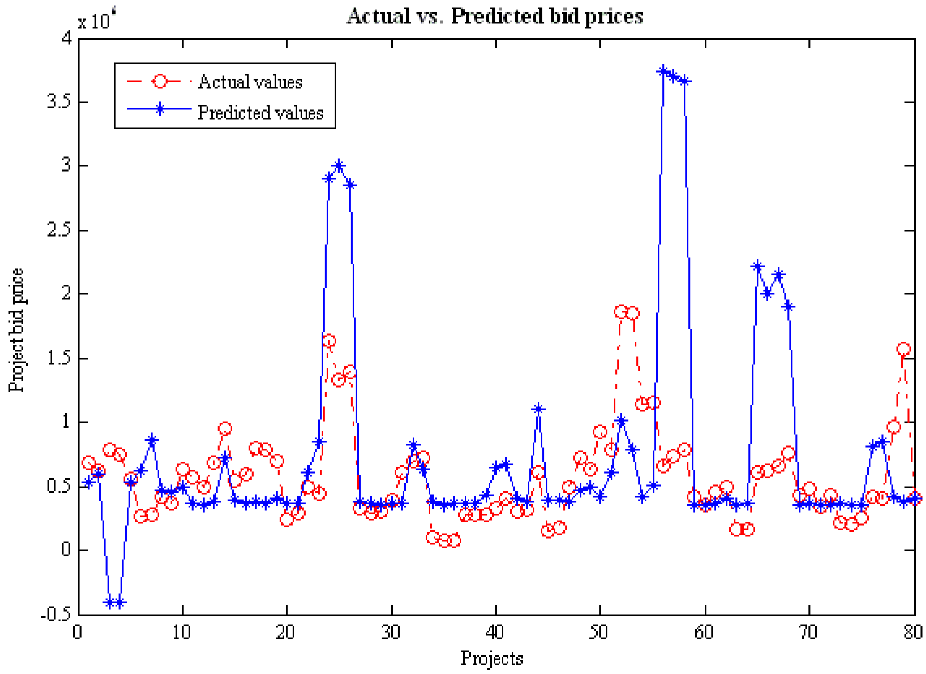
Cost index for 2005 base year 1913 = 100				
	Construction cost	**Building cost**	**Skilled wages**	**Common wages**
JANUARY	7297.24	4112.34	6911.83	15284.21
FEBRUARY	7297.58	4115.73	6925.53	15289.87
MARCH	7308.75	4126.9	6925.53	15289.87
APRIL	7355.38	4167.53	6925.53	15305.66
MAY	7398.03	4188.97	6971.74	15407.63
JUNE	7414.97	4194.65	6981.47	15446.97
JULY	7421.57	4196.87	6997.06	15474.08
AUGUST	7478.51	4209.70	7064.50	15657.50
SEPTEMBER	7540.38	4241.56	7156.97	15828.82
OCTOBER	7562.50	4265.34	7163.96	15831.45
NOVEMBER	7629.95	4311.94	7199.13	15921.45
DECEMBER	7646.87	4328.85	7199.13	15921.45

Reference: www.enr.com (2005)

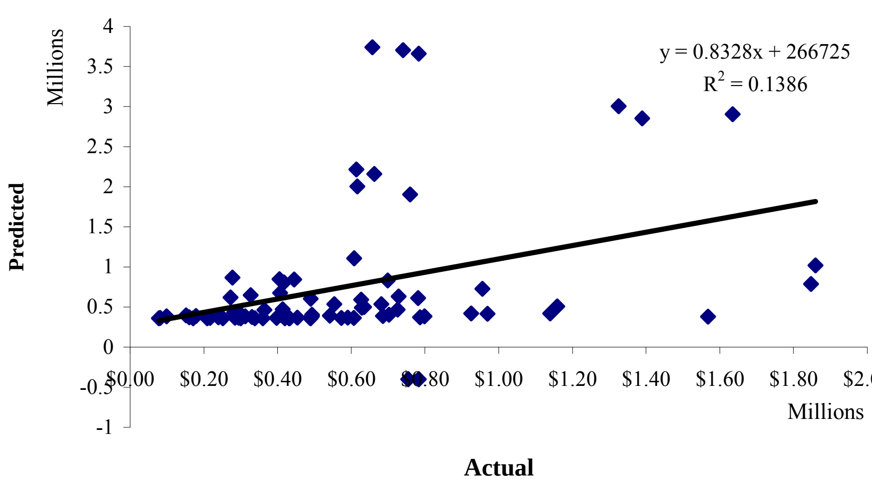
APPENDIX B

Results of different runs using different configurations for ANN.

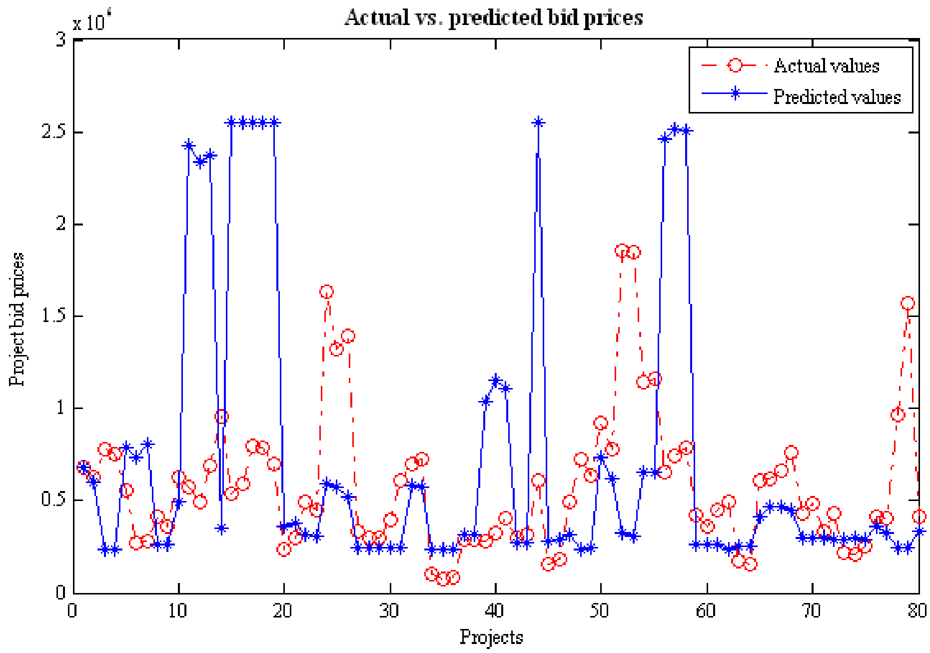
Plots for ANN with 1 2 1 configuration and 100 epochs:



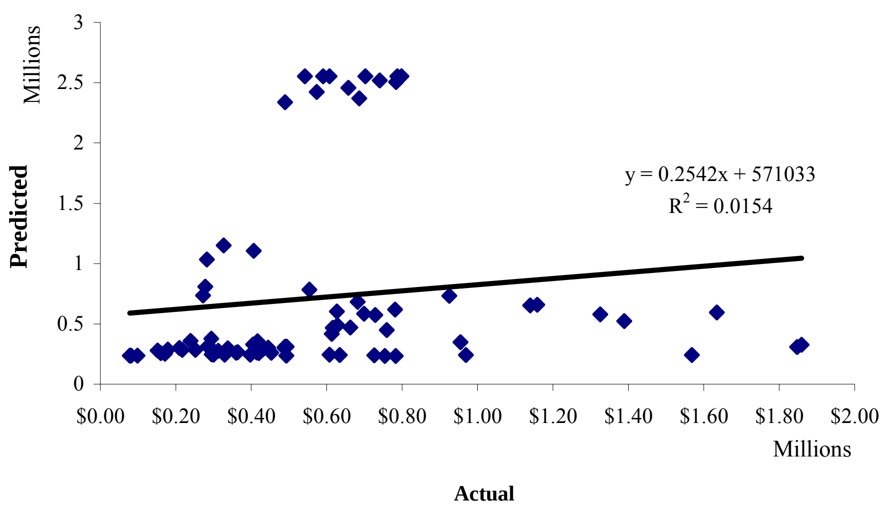
Actual vs. predicted plot



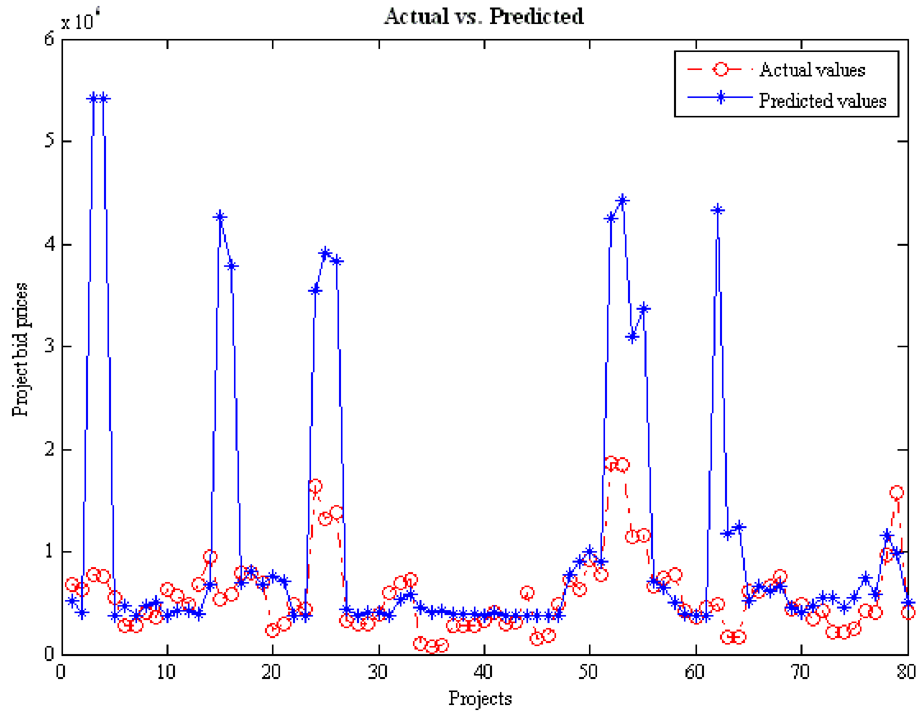
Plots for ANN with 1 3 1 configuration and 100 epochs:

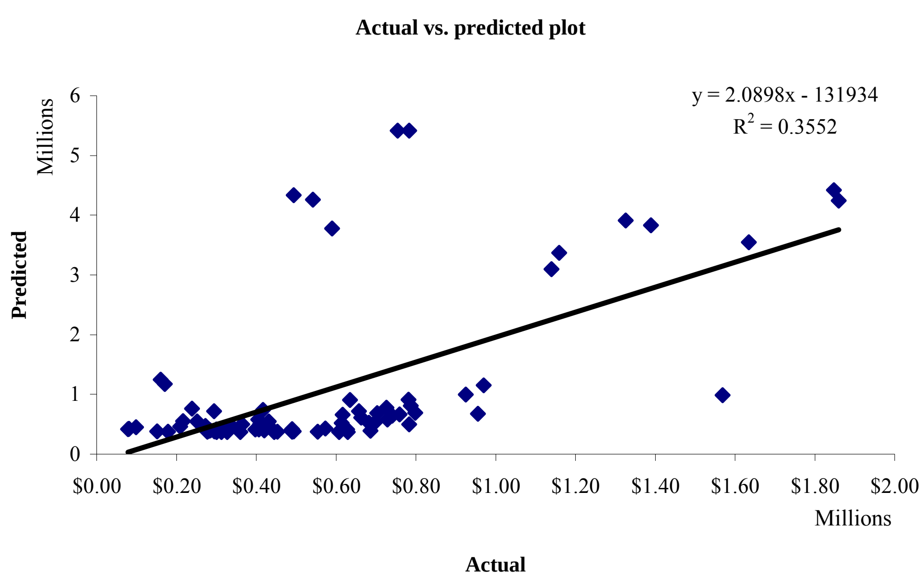


Actual vs. predicted plot

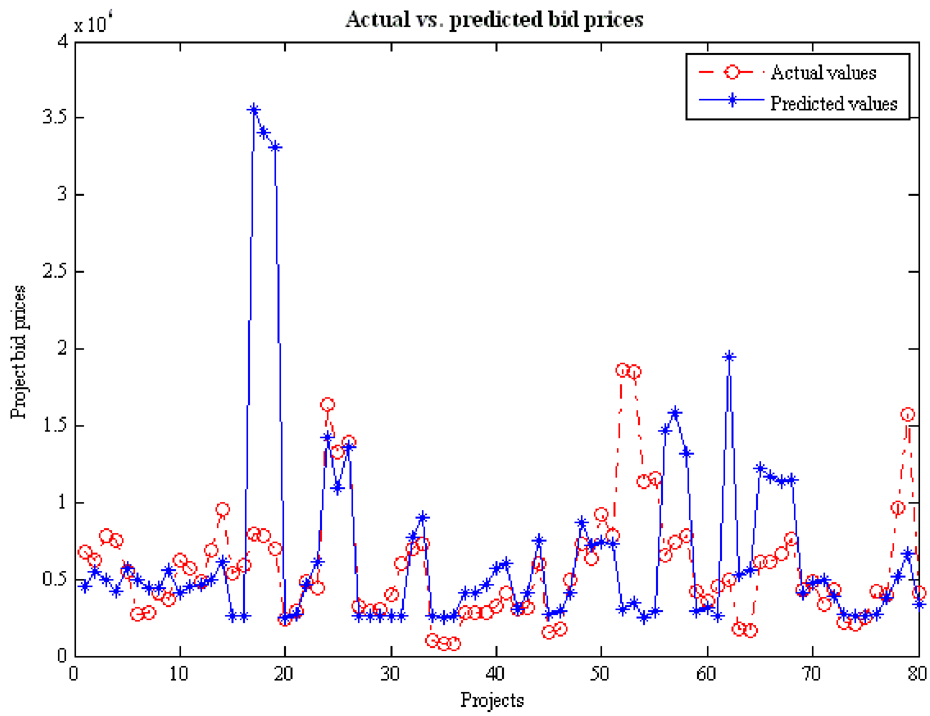


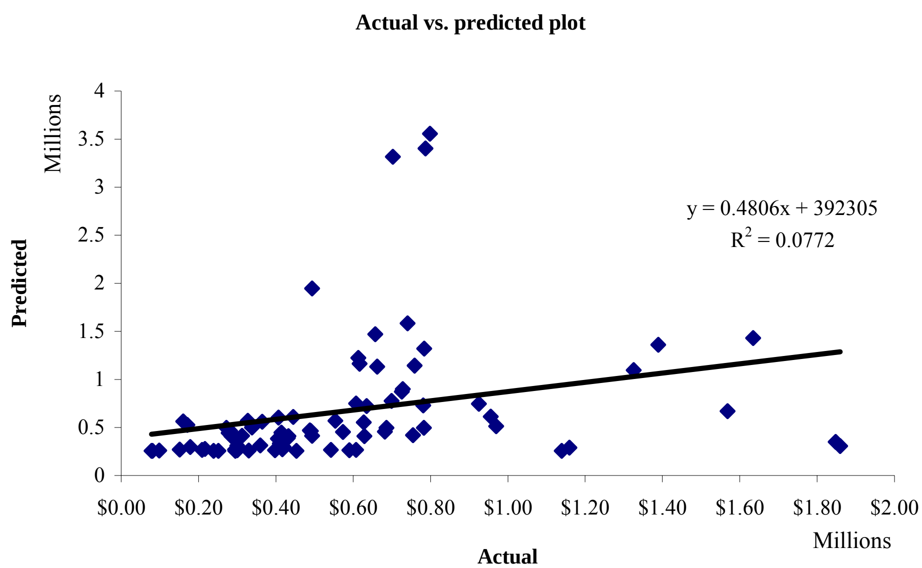
Plots for ANN with 1 4 1 configuration and 100 epochs:



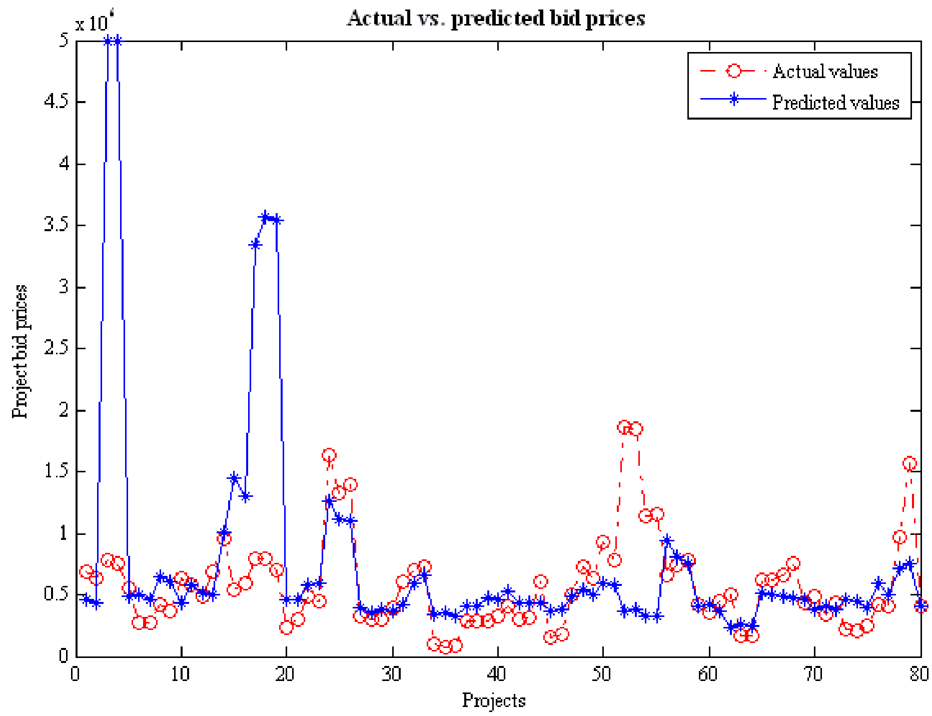


Plots ANN with 1 5 1 configuration and 100 epochs:

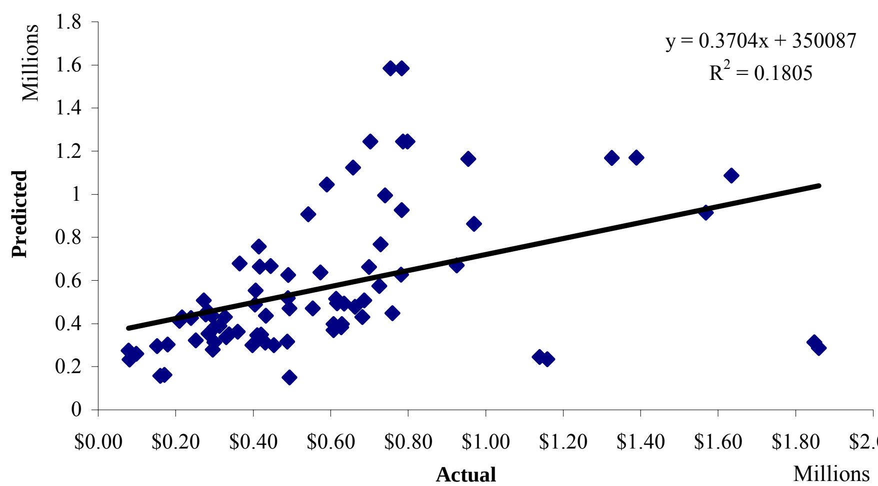




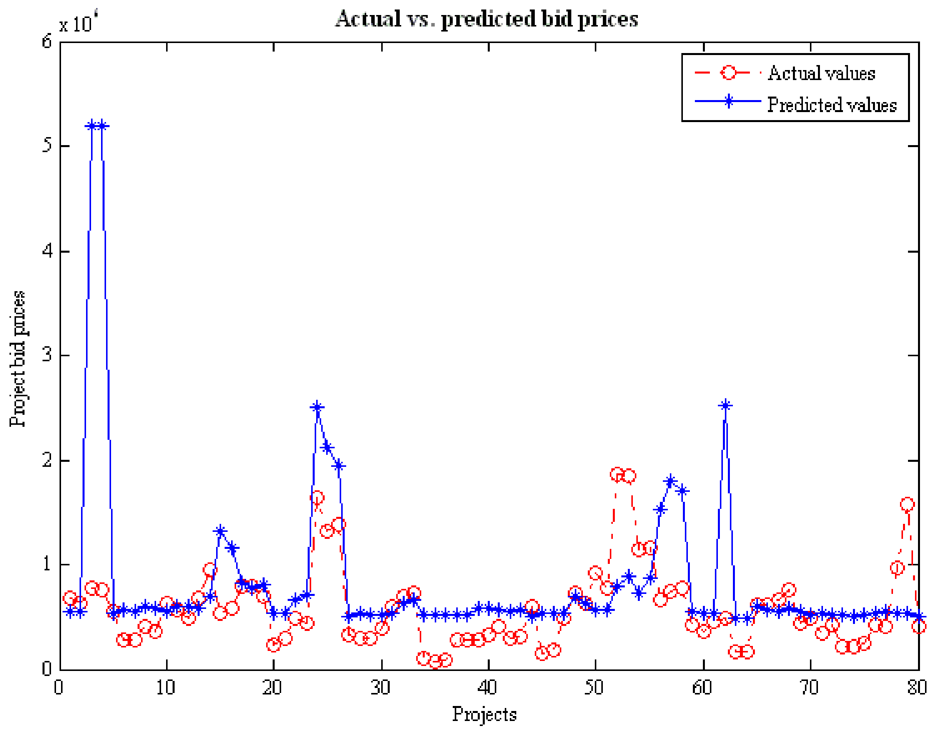
Plots for ANN with 1 6 1 configuration and 100 epochs:

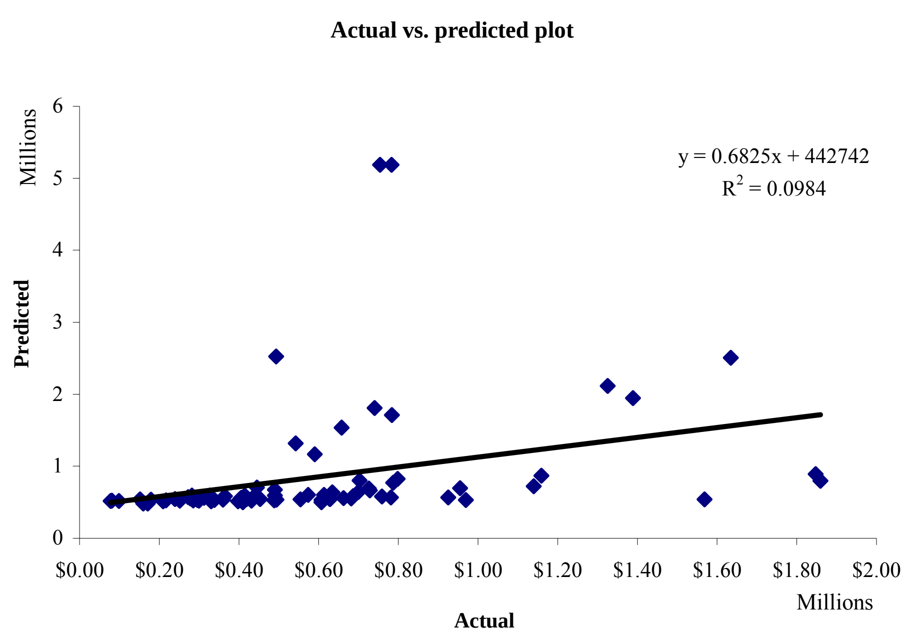


Actual vs. predicted plot

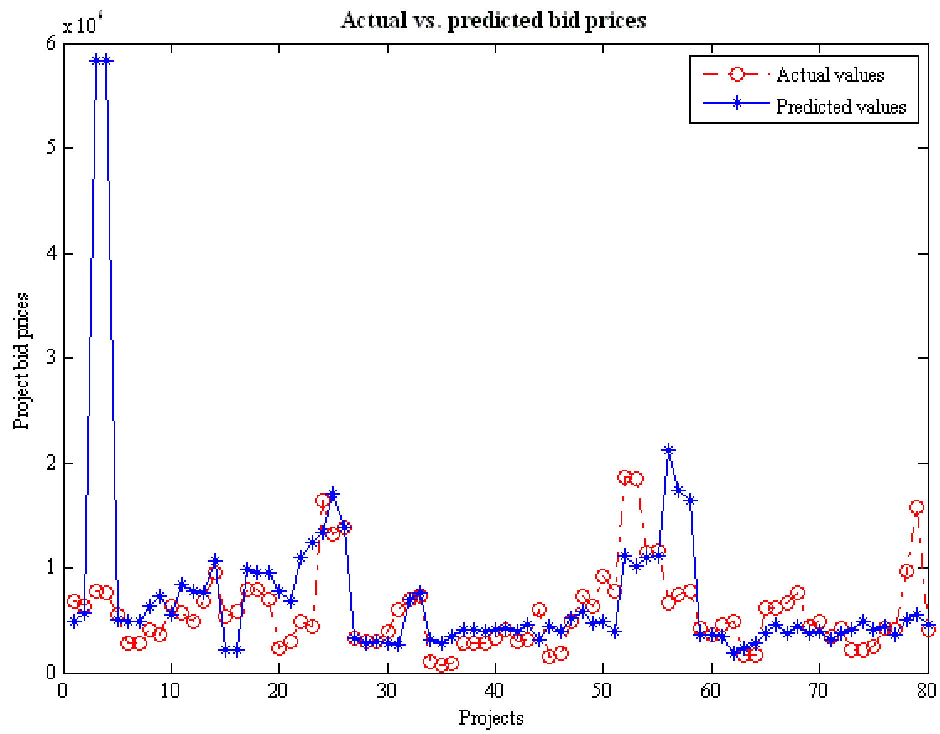


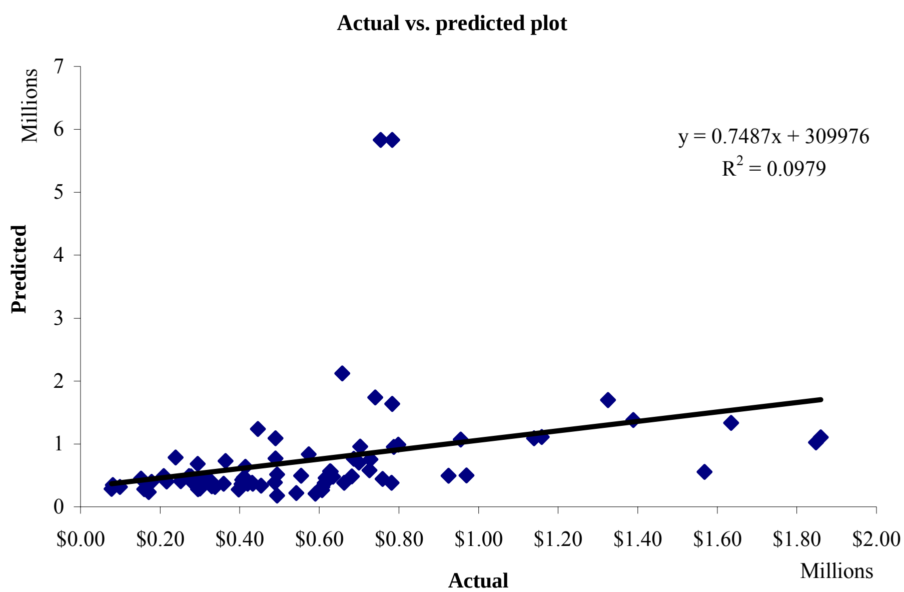
Plots for ANN with 1 3 3 1 configuration and 100 epochs:



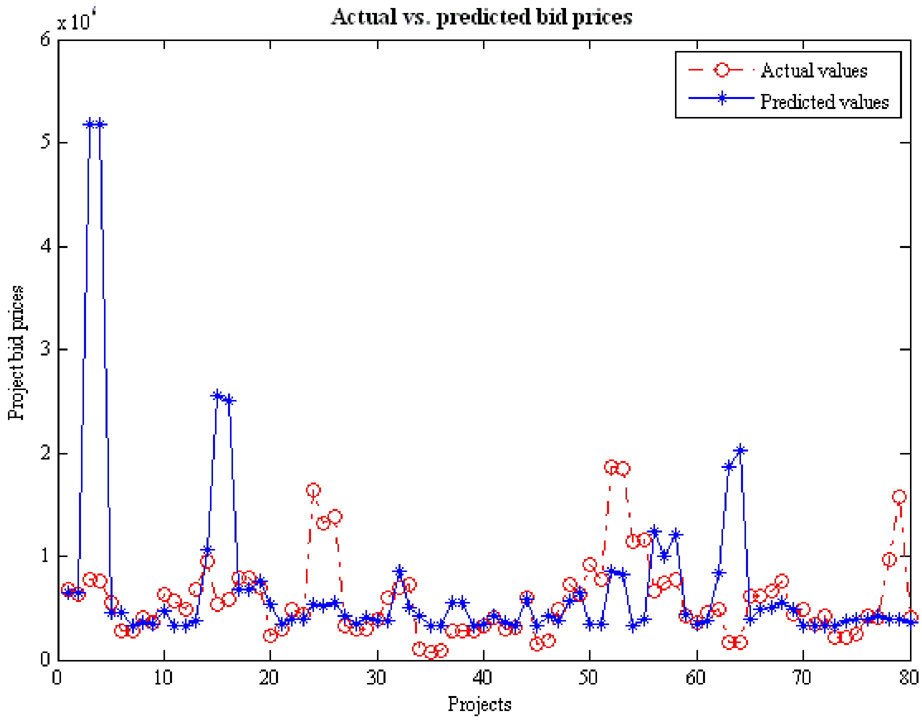


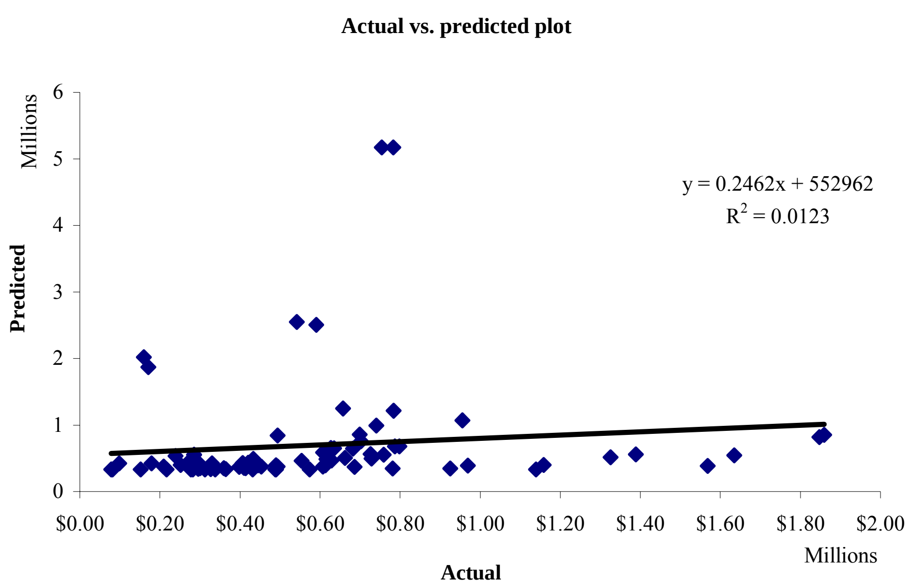
Plots for ANN with 1 4 4 1 configuration and 100 epochs:



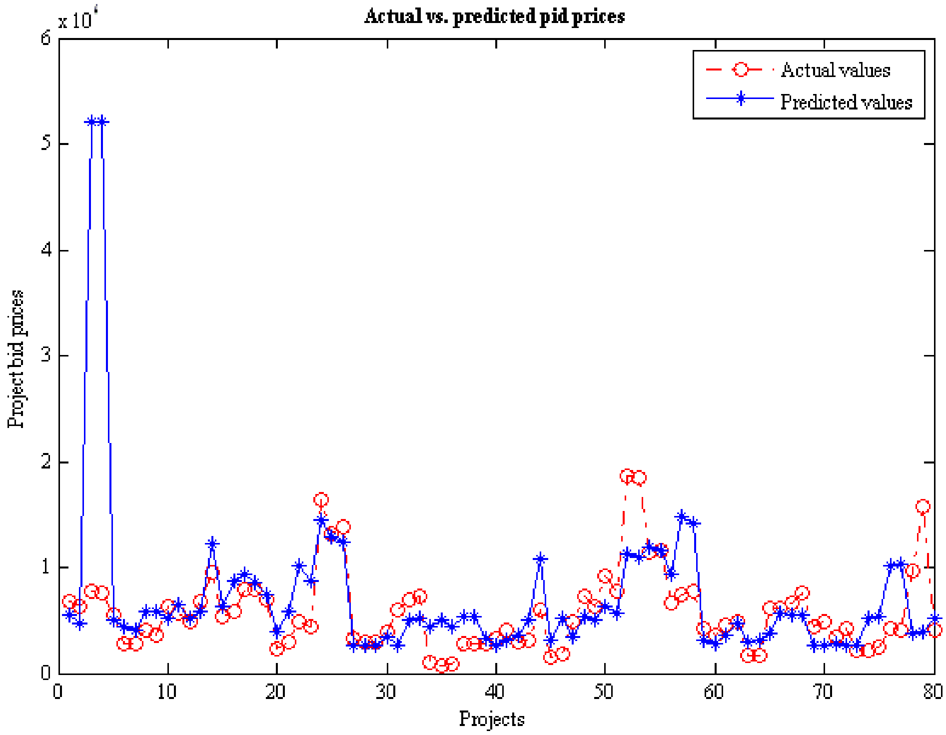


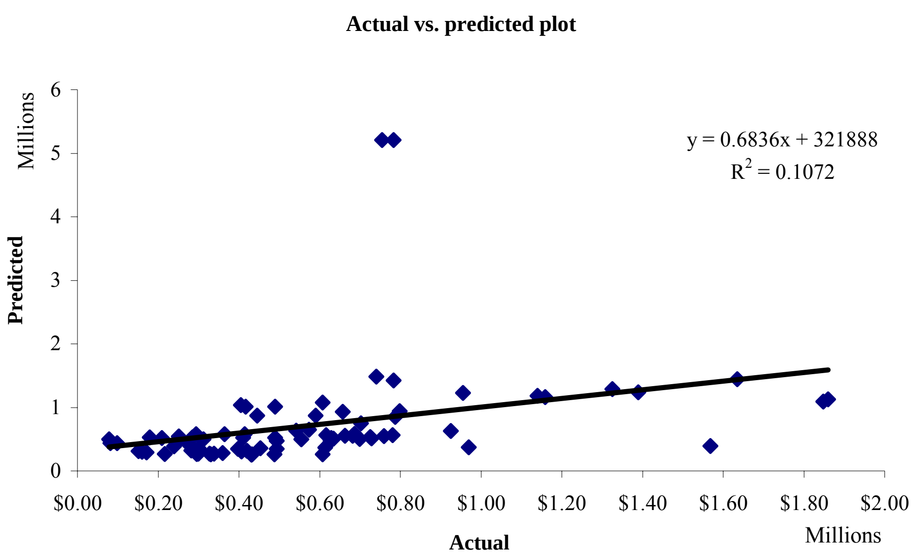
Plots for ANN with 1 5 5 1 configuration and 100 epochs:



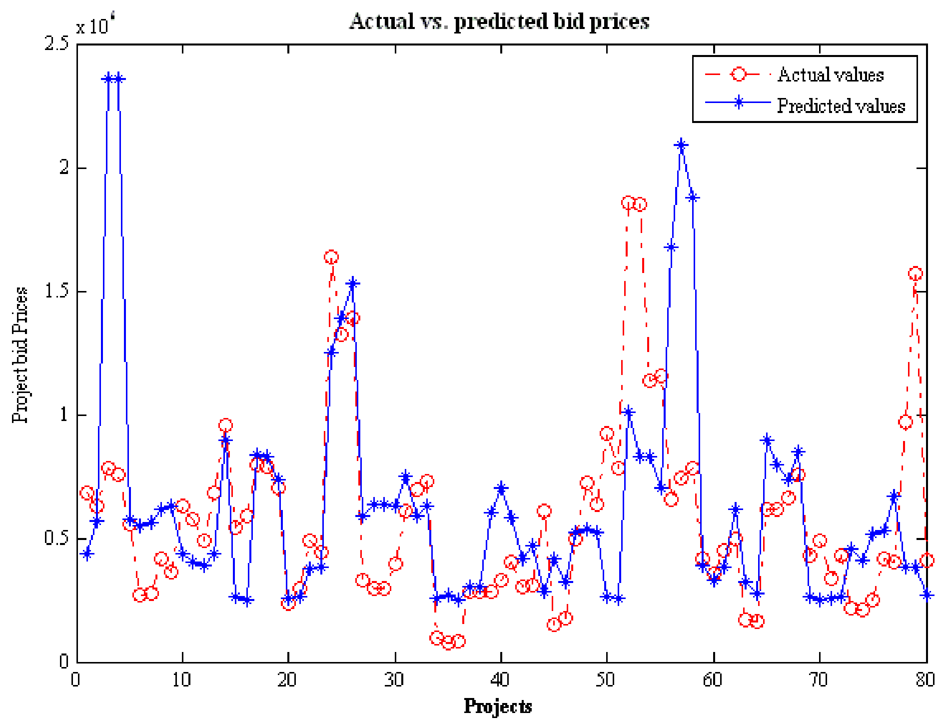


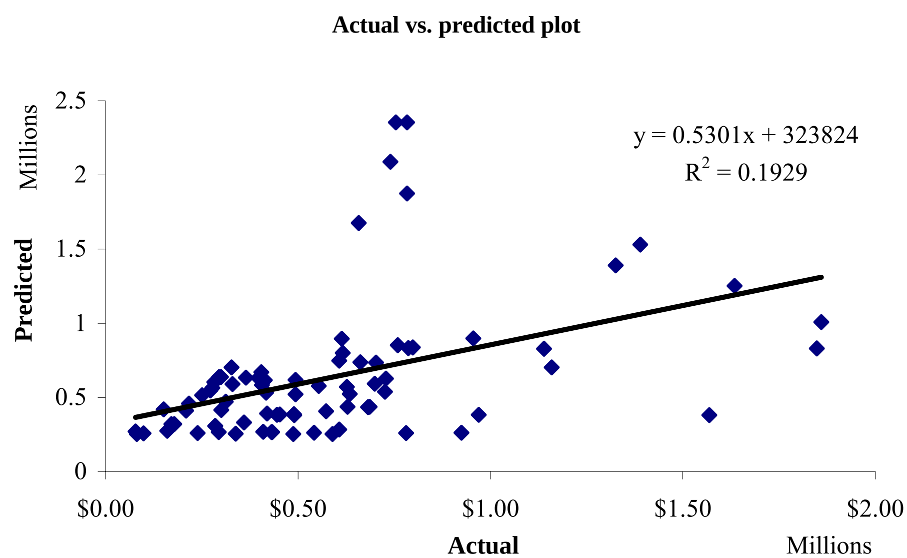
Plots for ANN with 1 6 6 1 configuration and 100 epochs:



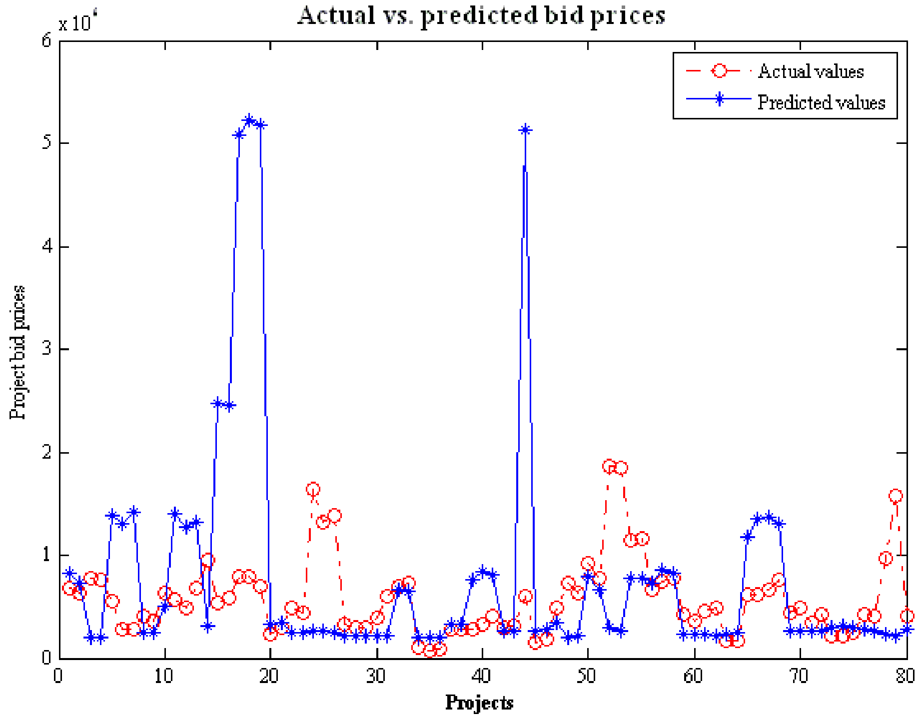


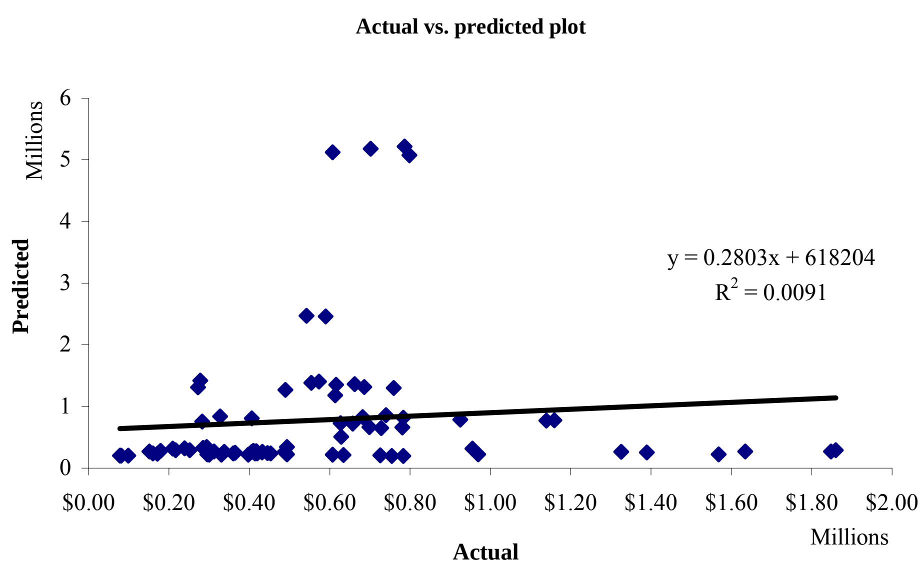
Plots ANN with 1 2 1 configuration and 200 epochs:



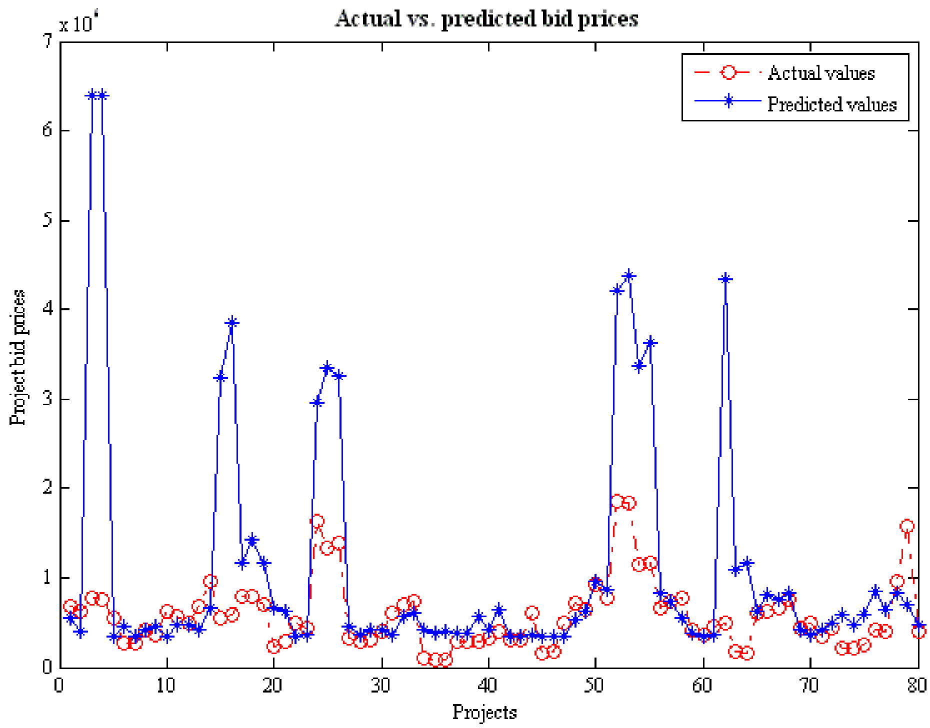


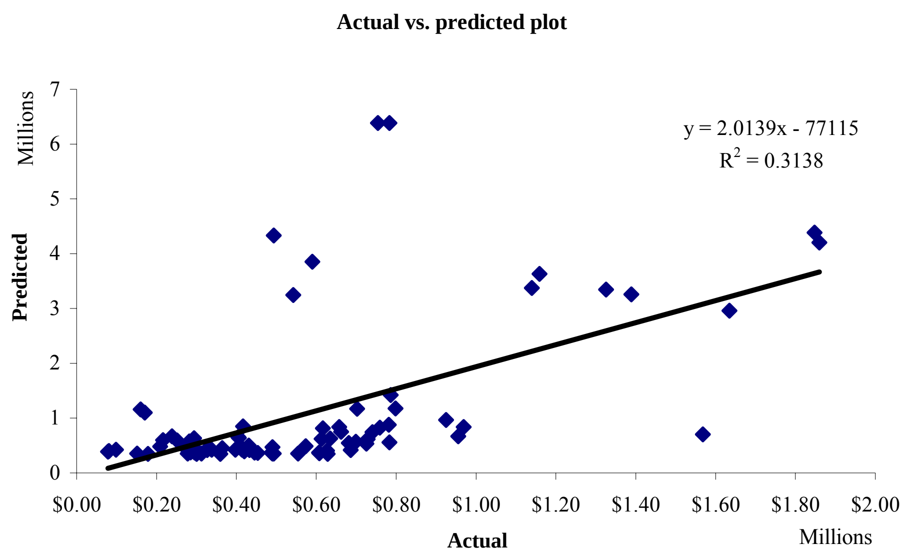
Plots for ANN with 1 3 1 configuration and 200 epochs:



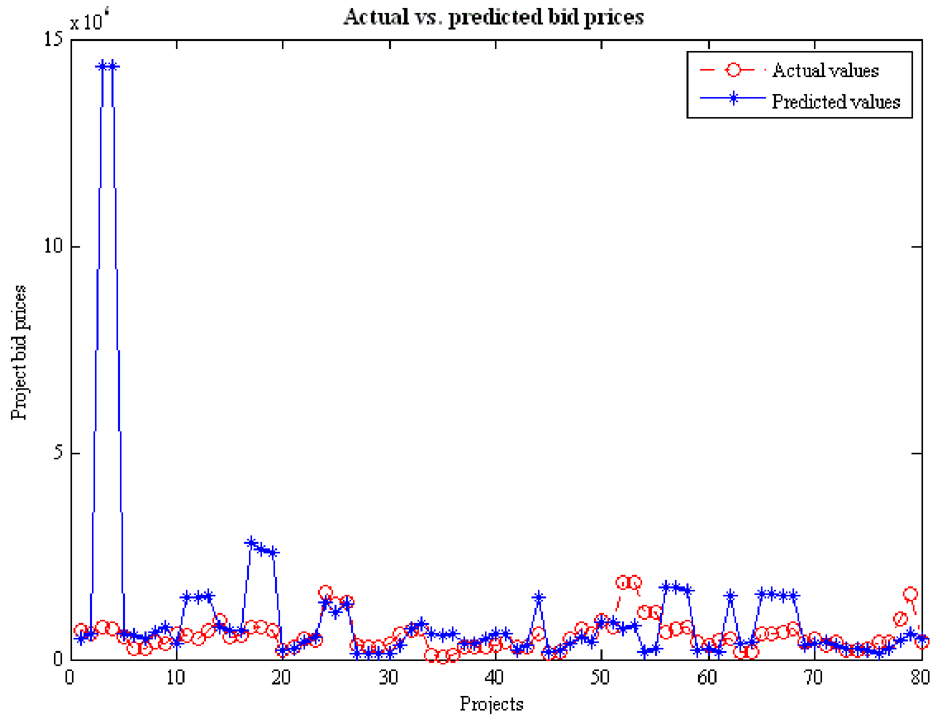


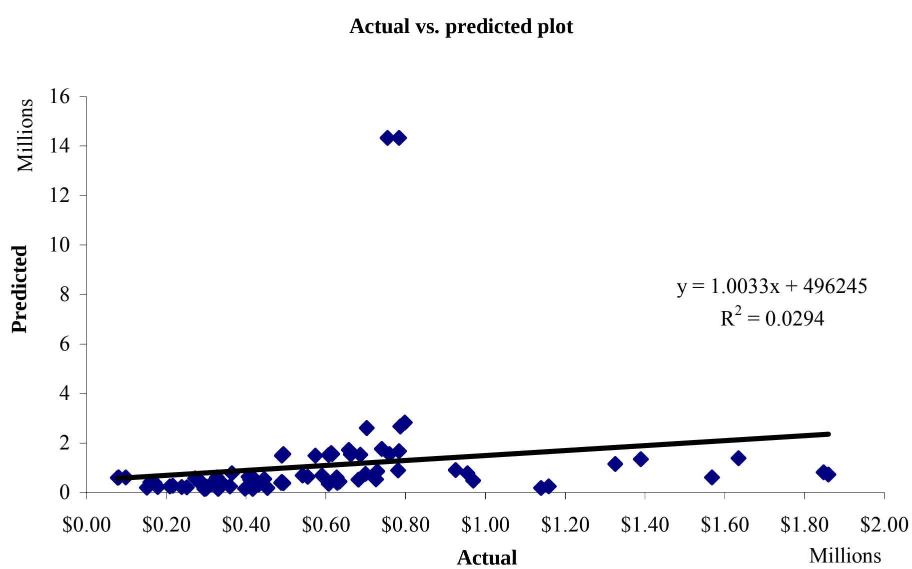
Plots for ANN with 1 4 1 configuration and 200 epochs:



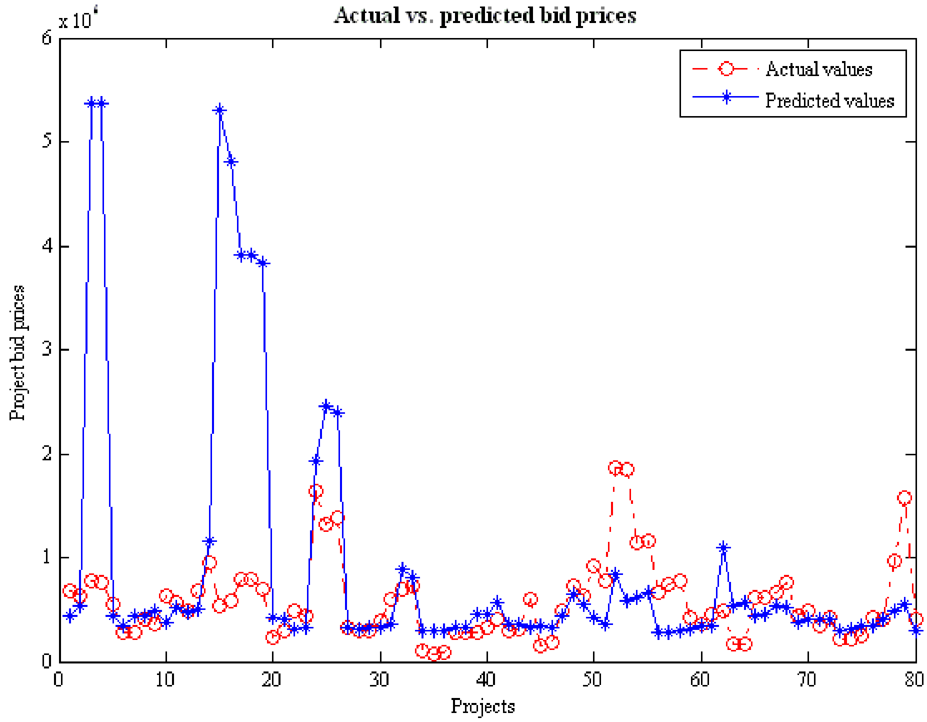


Plots for ANN with 1 5 1 configuration and 200 epochs:

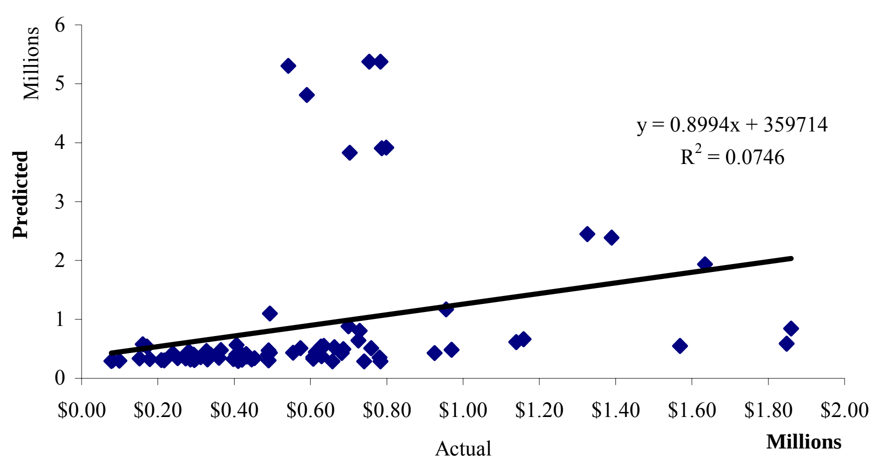




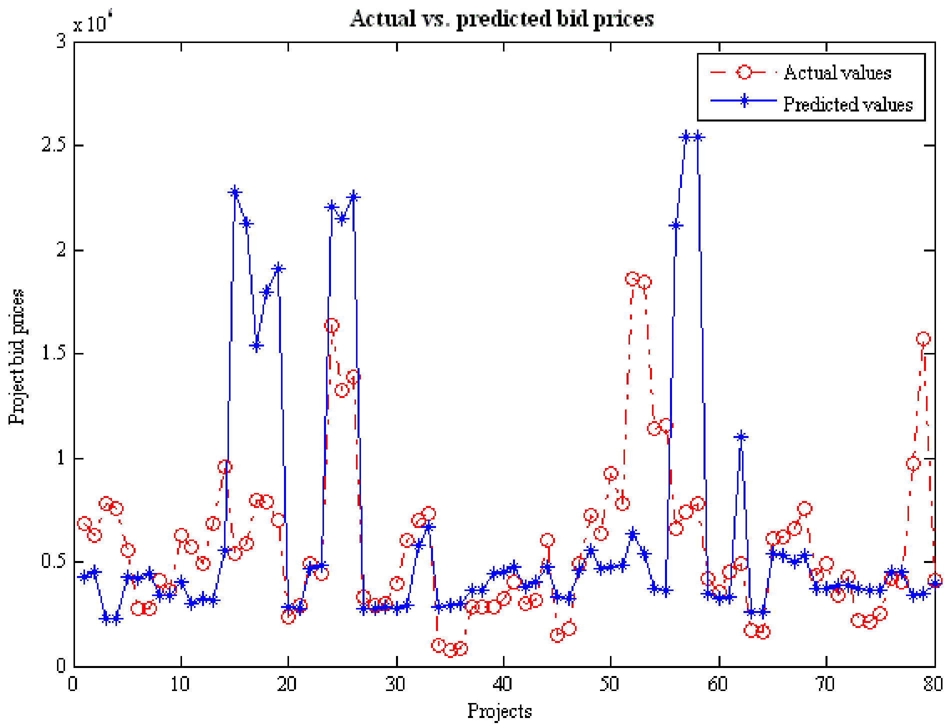
Plots for ANN with 1 6 1 configuration and 200 epochs:

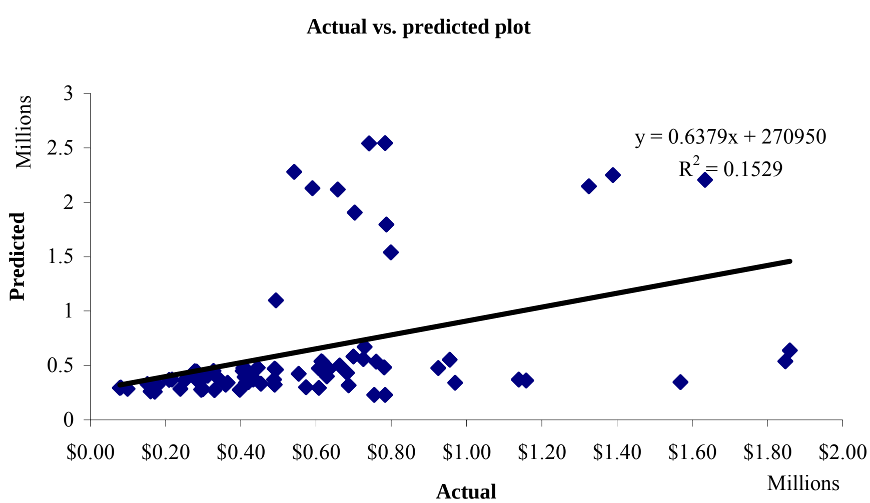


Actual vs. predicted plot

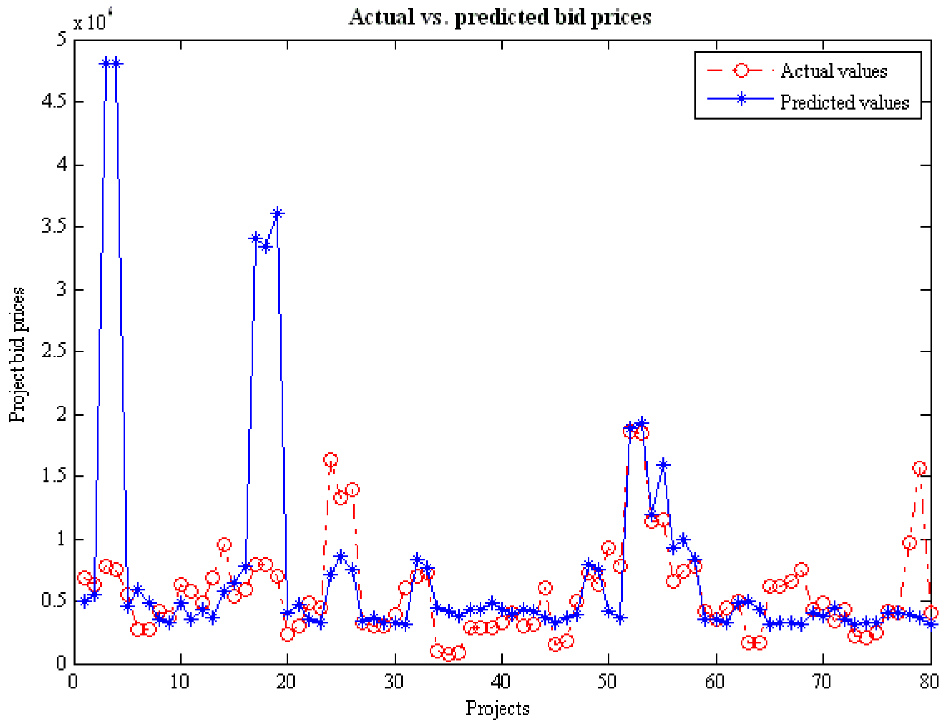


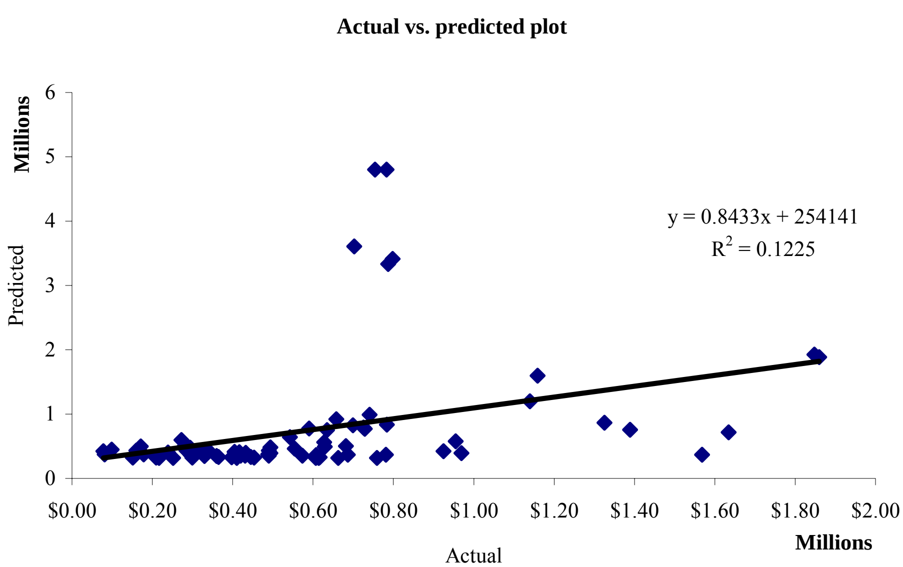
Plots for ANN with 1 2 2 1 configuration and 200 epochs:



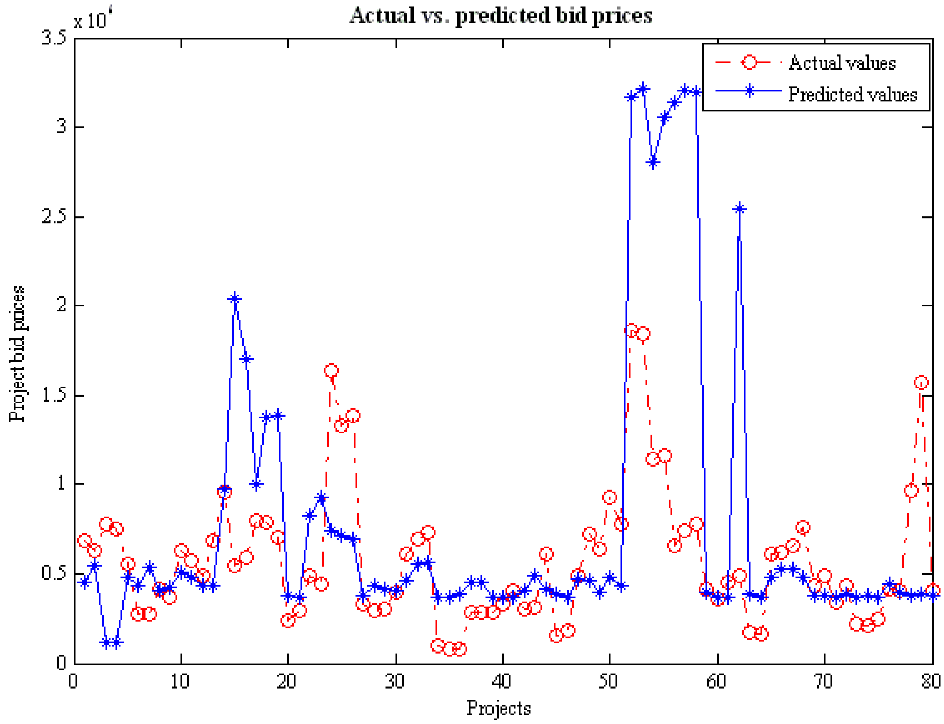


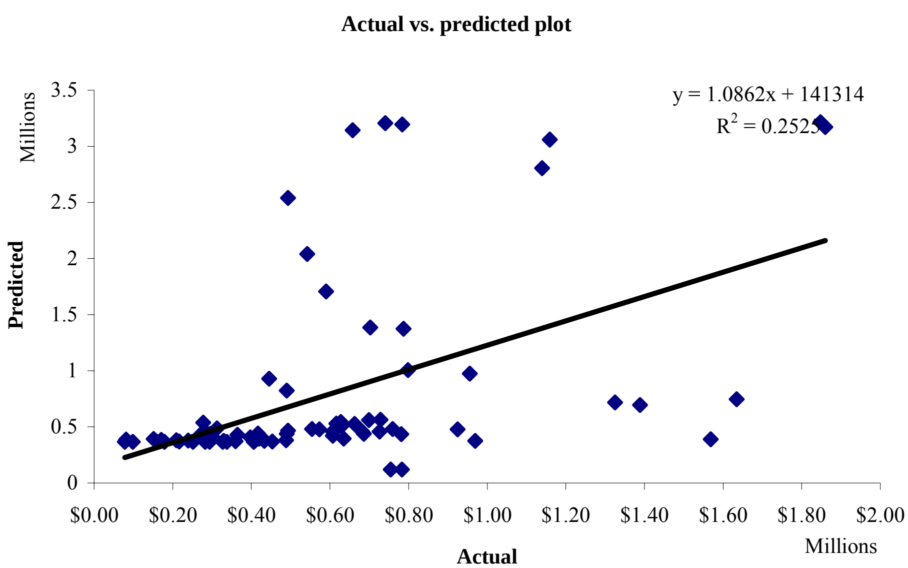
Plots for ANN with 1 3 3 1 configuration and 200 epochs:



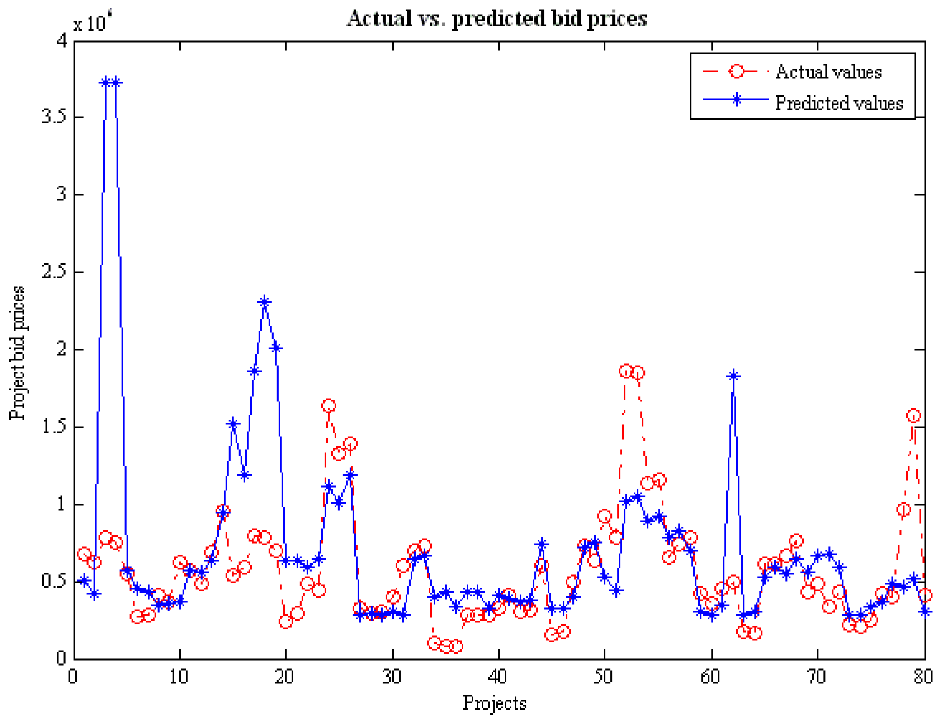


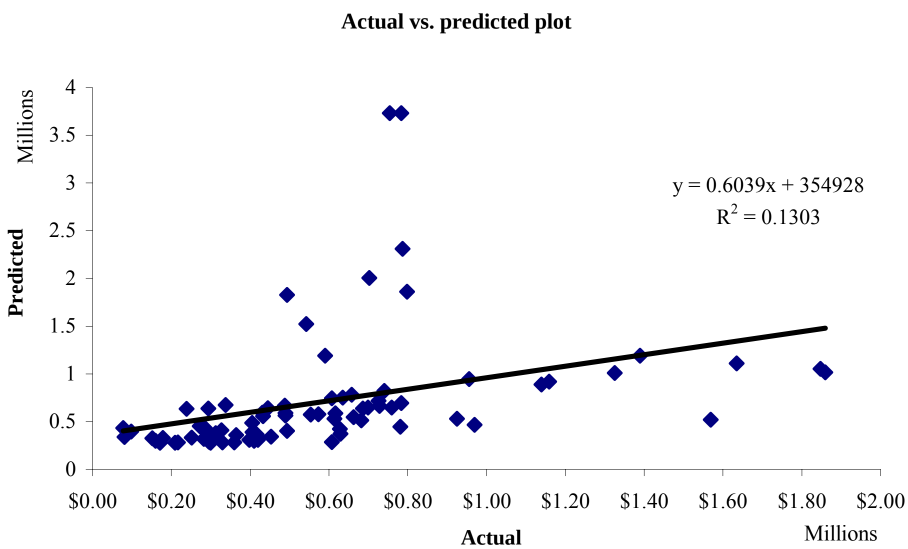
Plots for ANN with 1 4 4 1 configuration and 200 epochs:



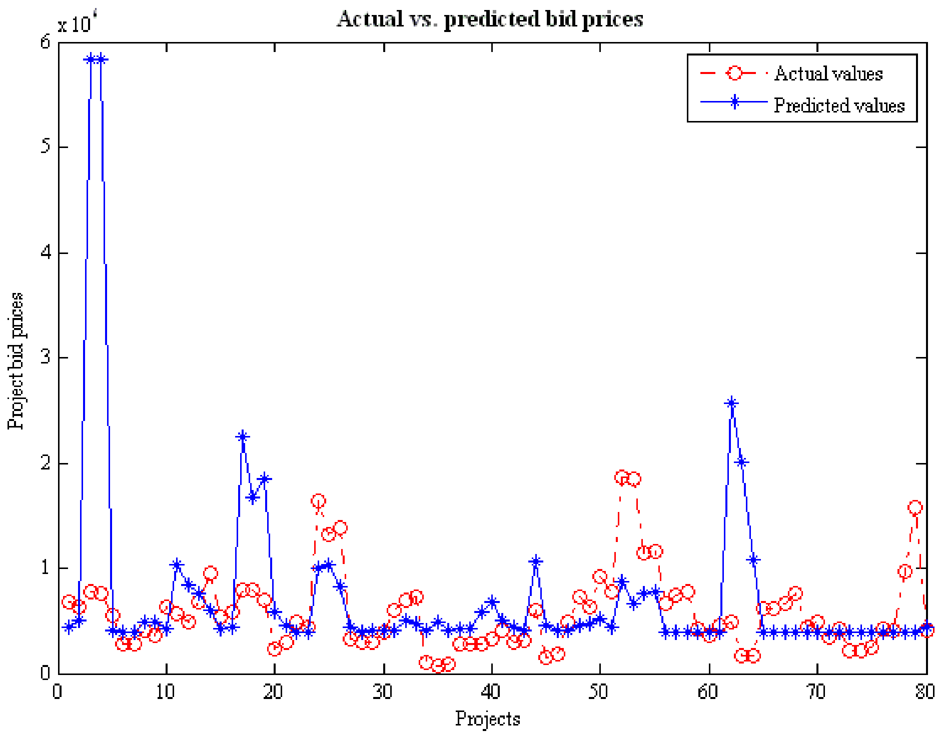


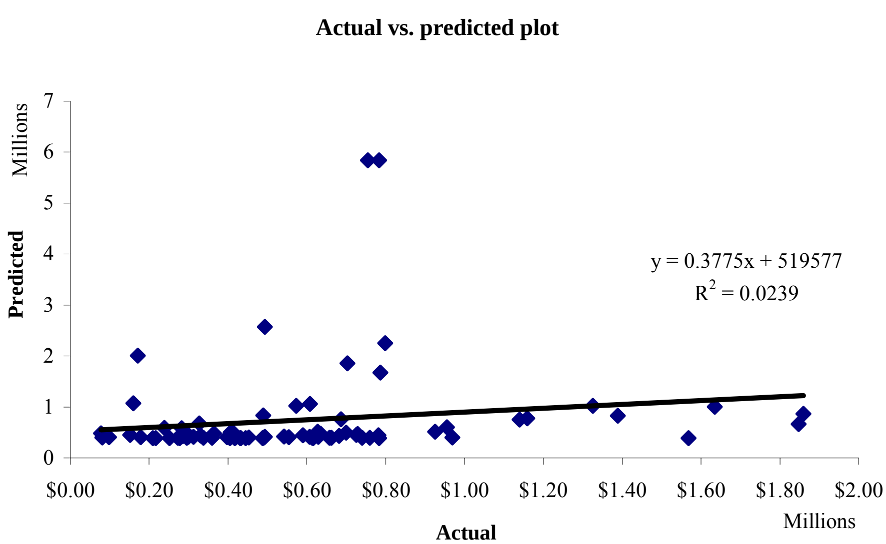
Plots for ANN with 1 5 5 1 configuration and 200 epochs:



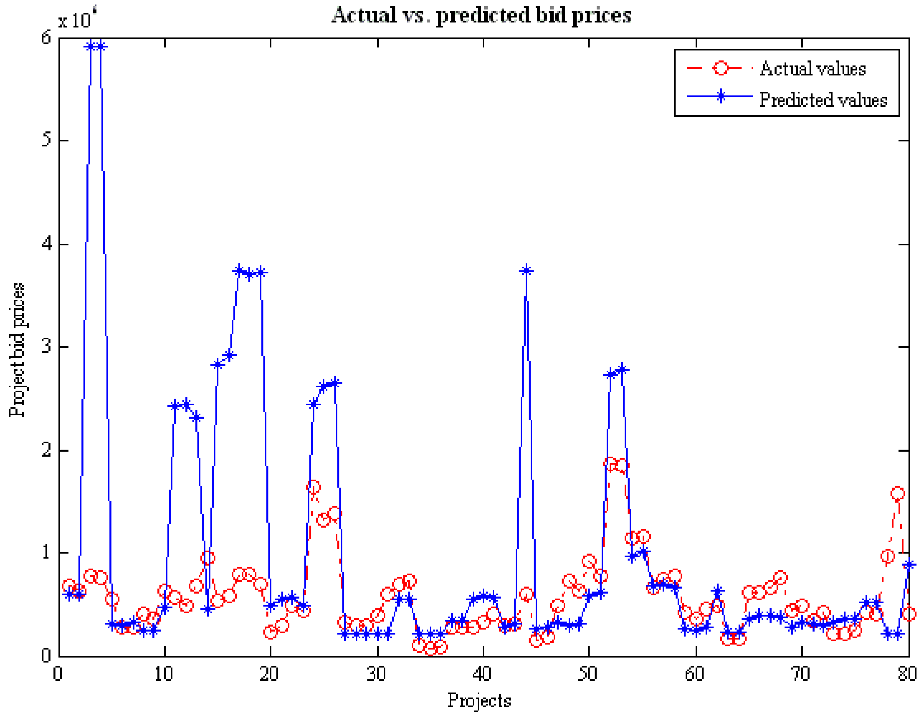


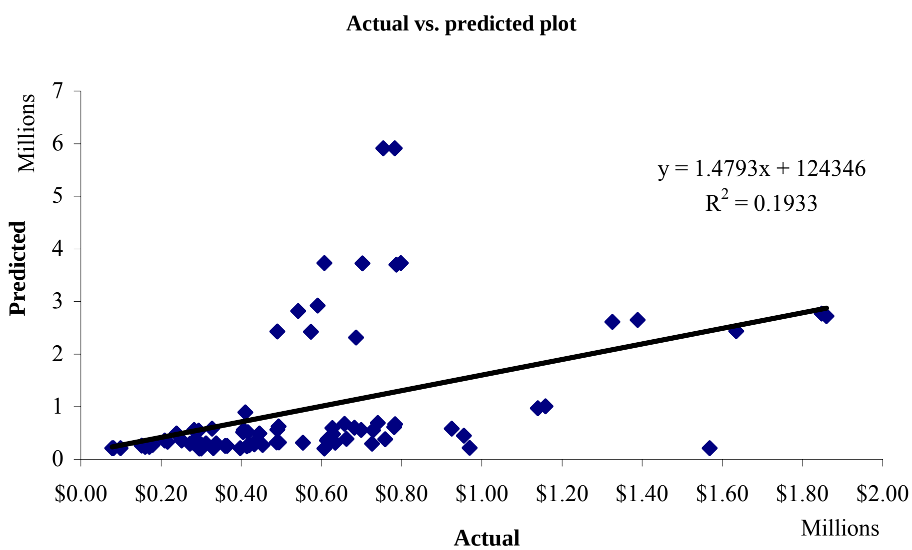
Plots for ANN with 1 6 6 1 configuration and 200 epochs:



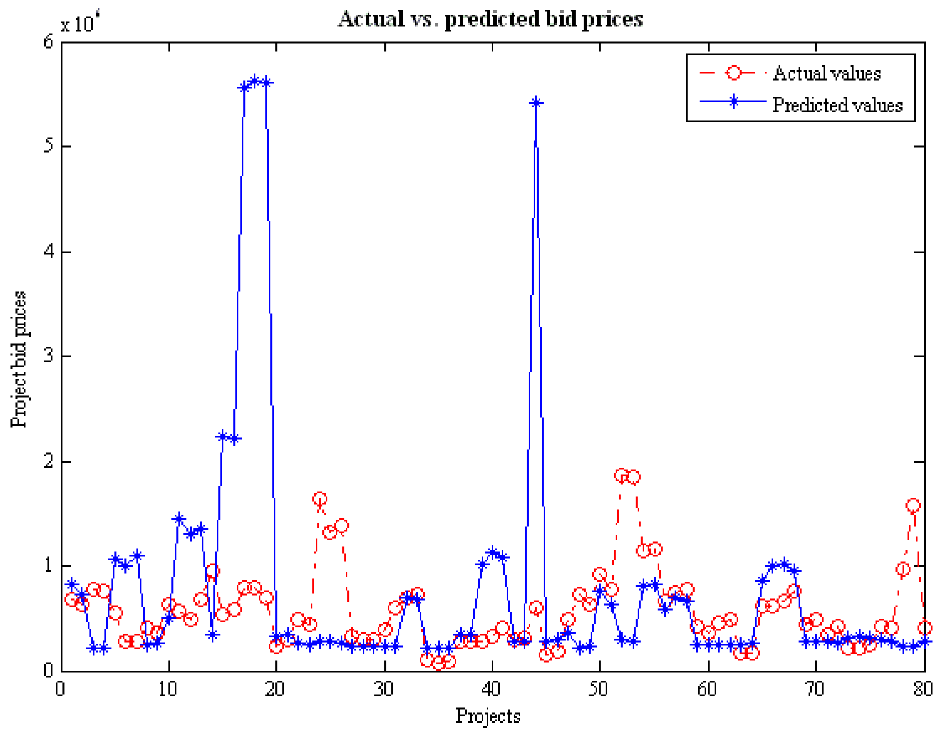


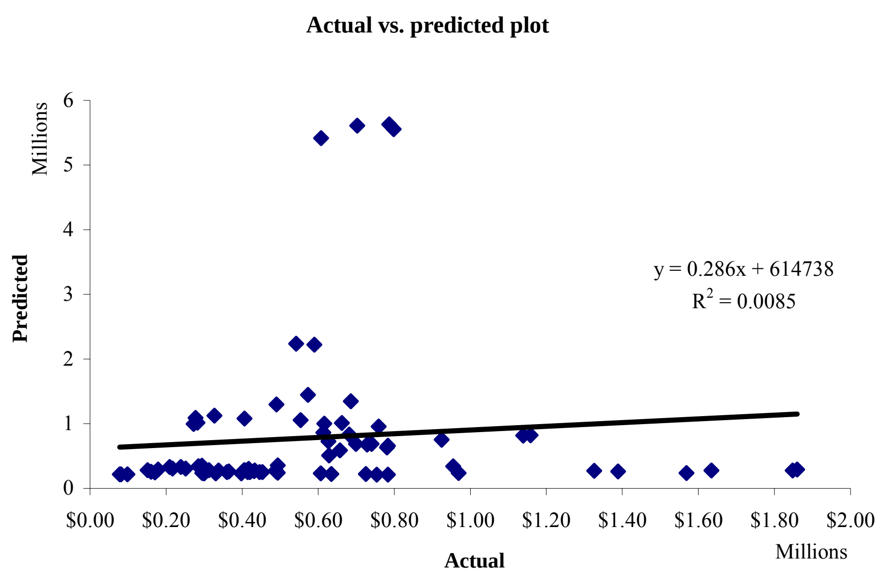
Plots for ANN with 1 2 1 configuration and 500 epochs:



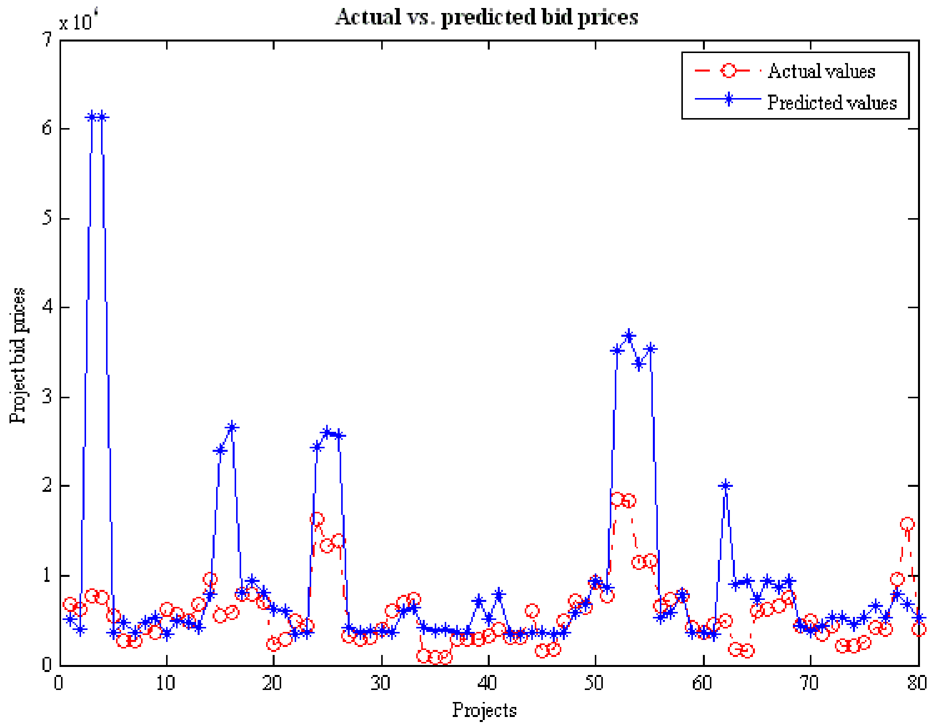


Plots for ANN with 1 3 1 configuration and 500 epochs:

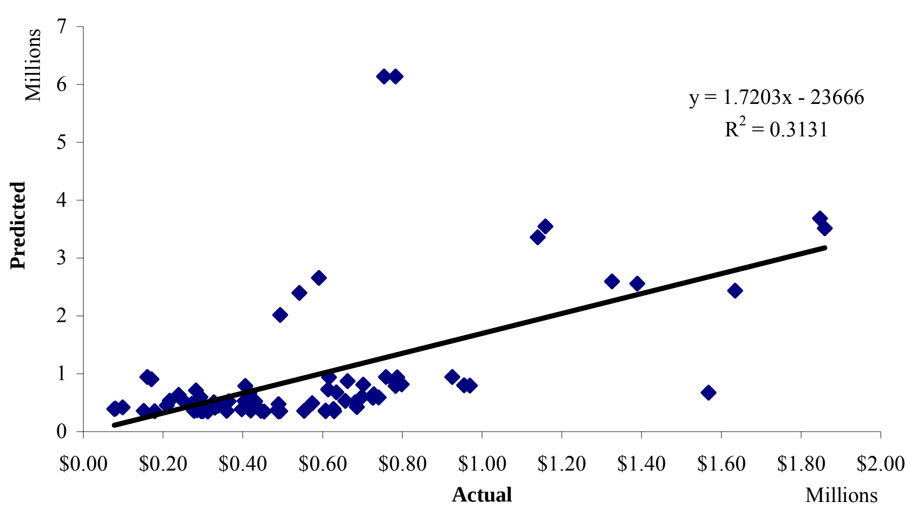




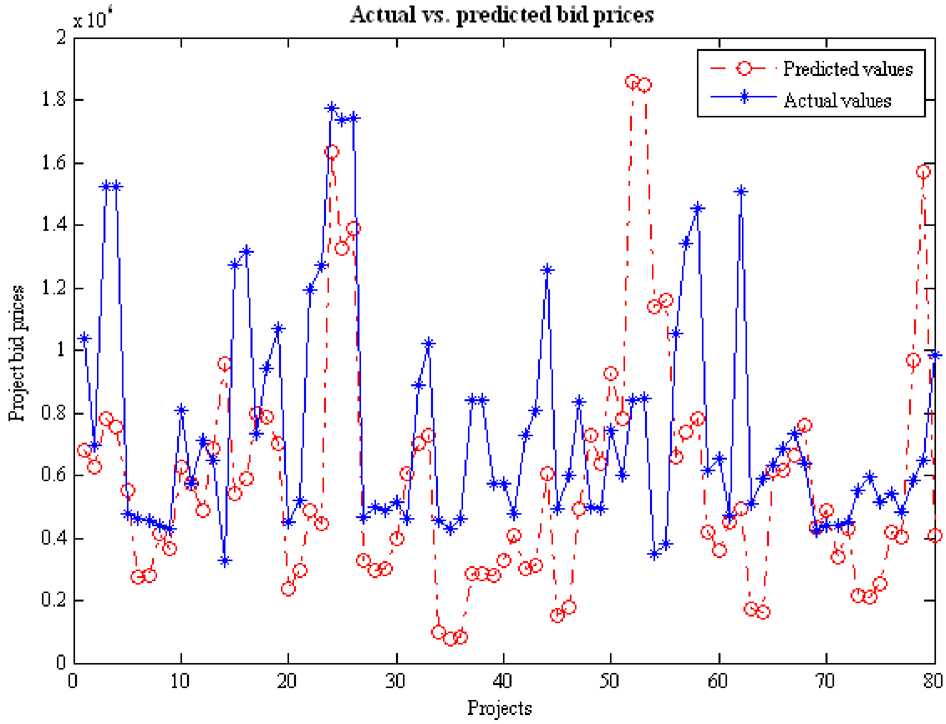
Plots for ANN with 1 4 1 configuration and 500 epochs:

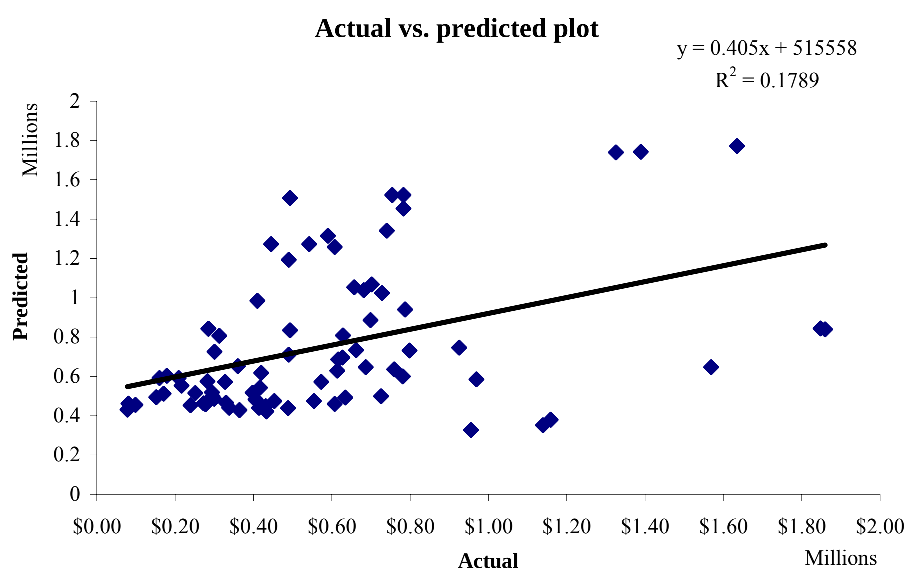


Actual vs. predicted plot



Plots for ANN with 1 5 1 configuration and 500 epochs:





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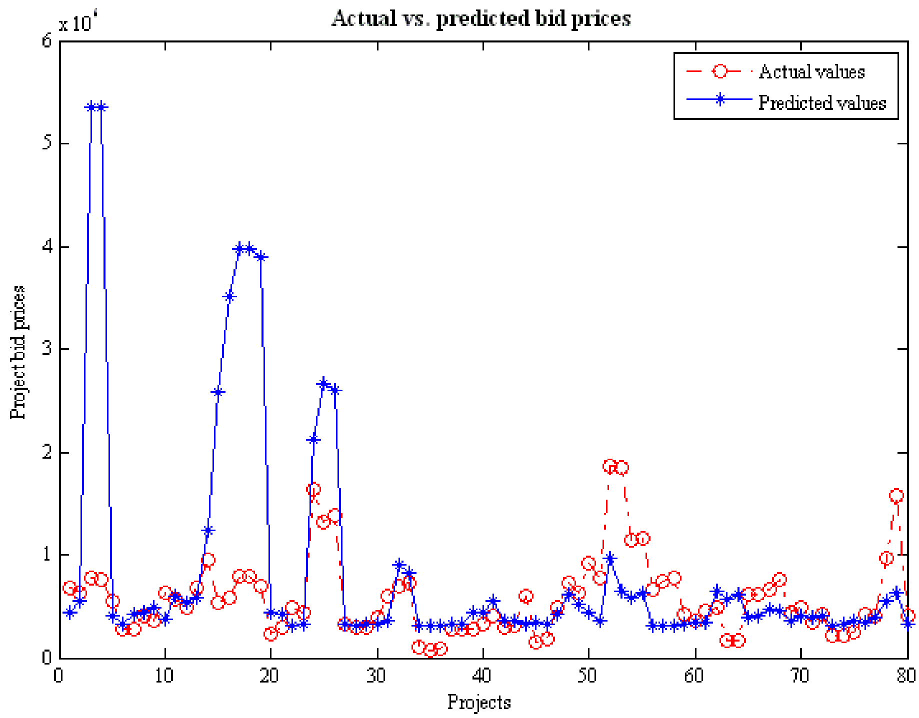

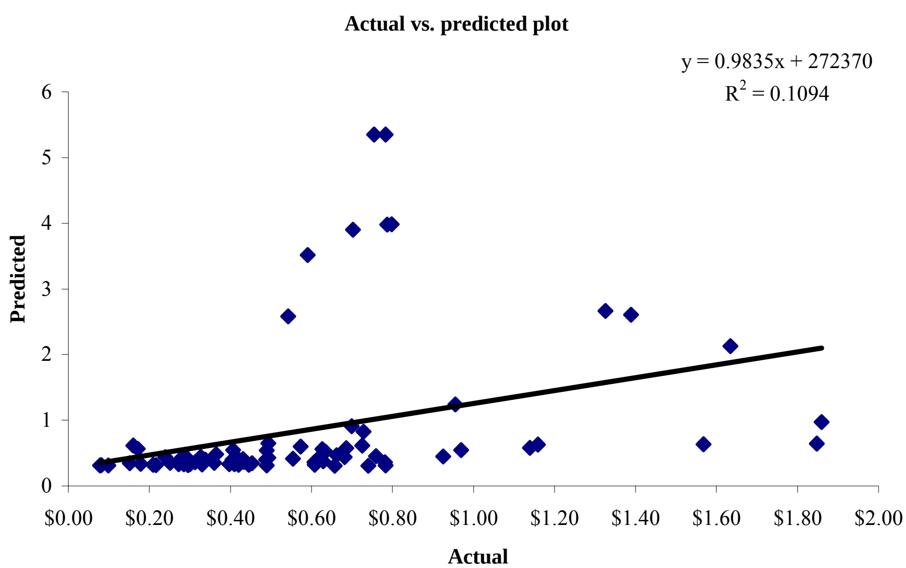

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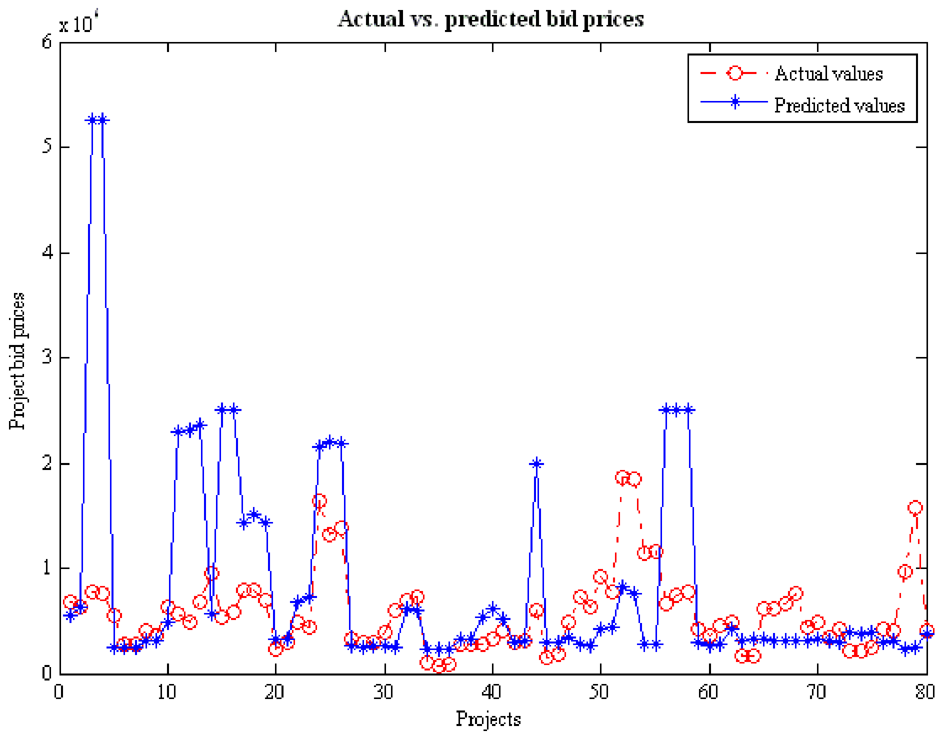

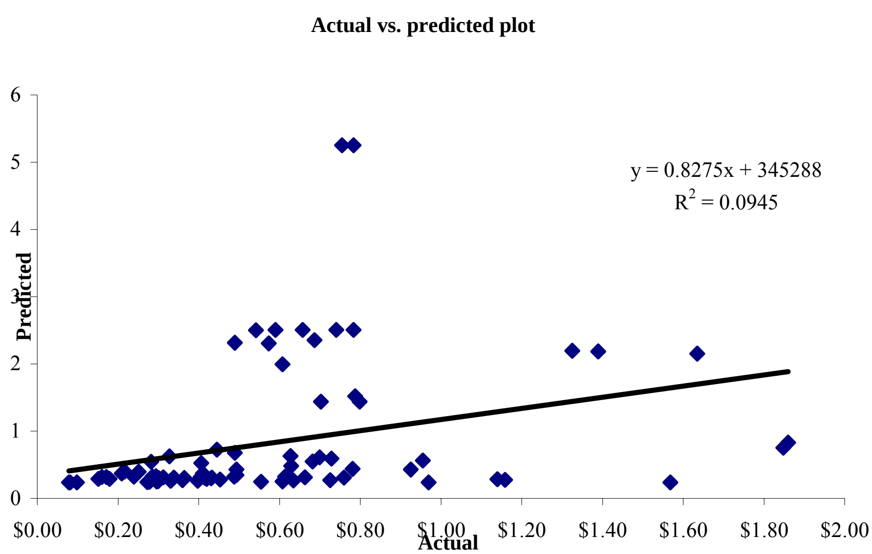

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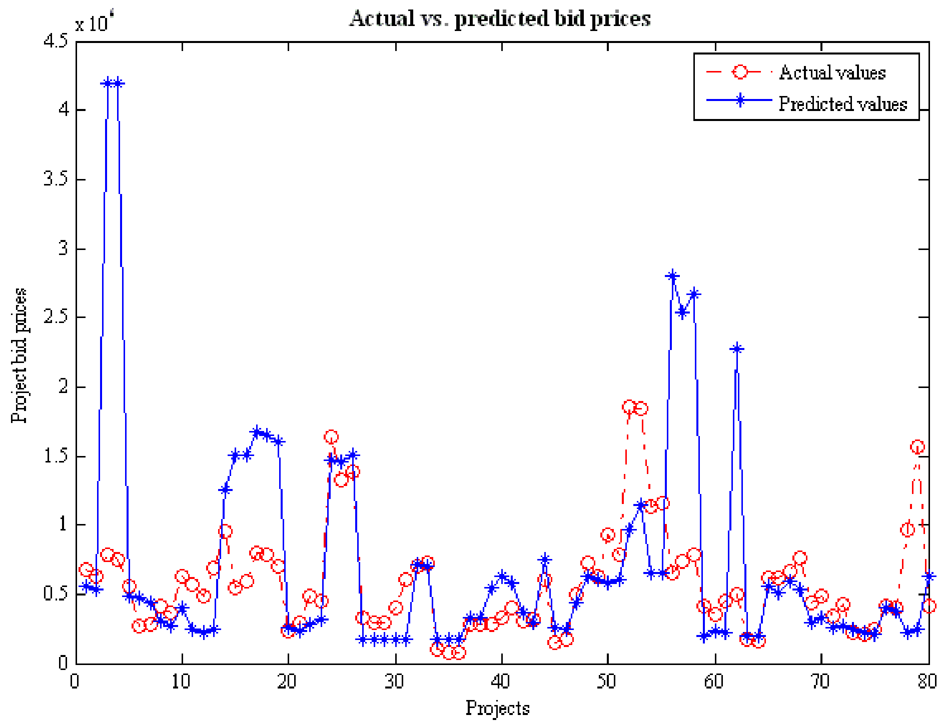

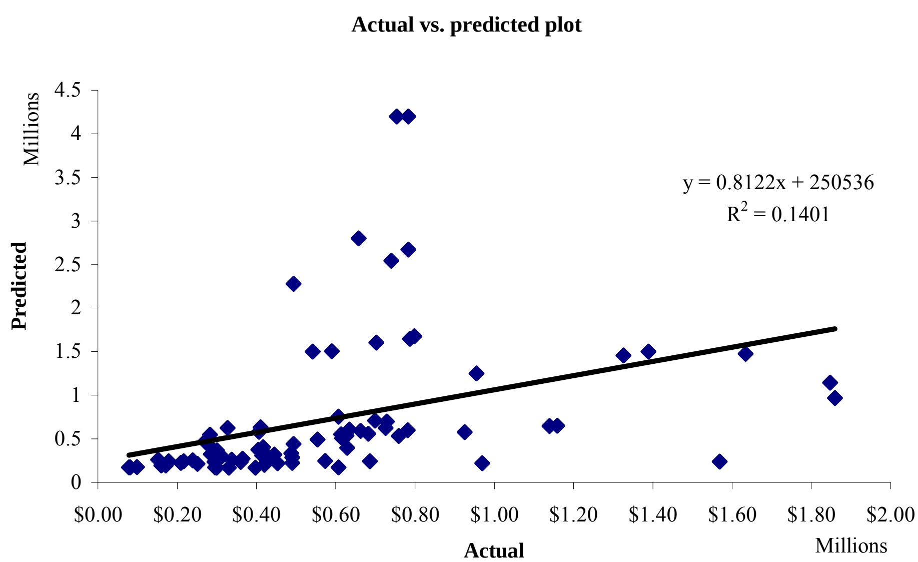

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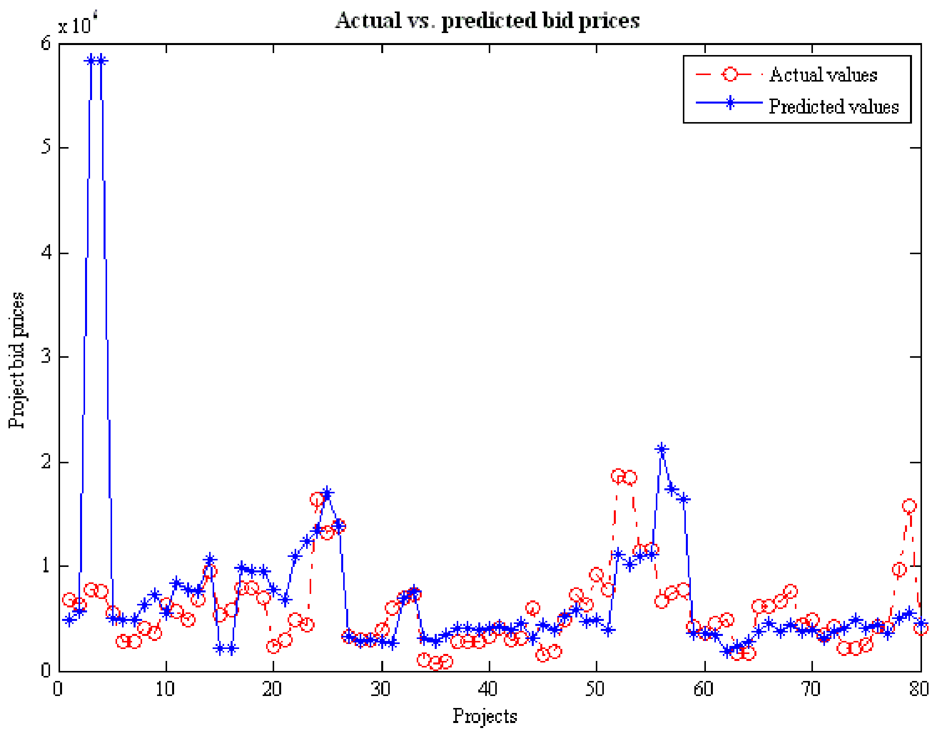
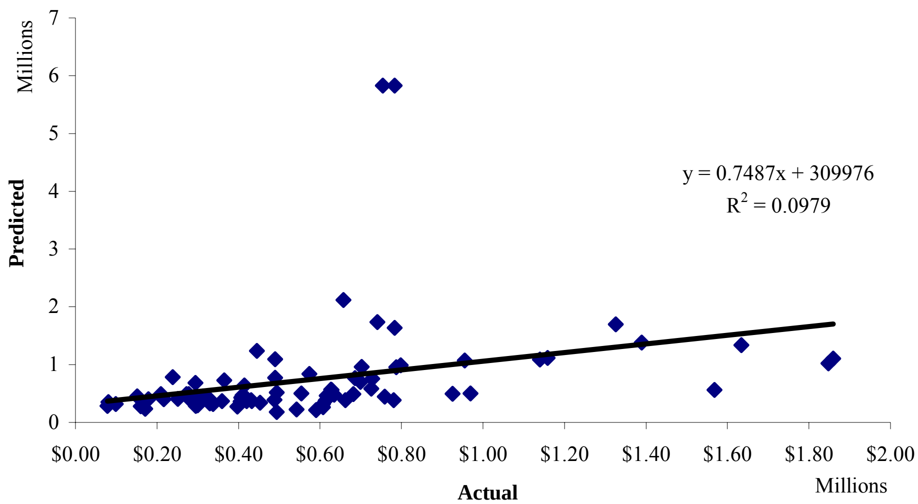


Actual vs. predicted plot



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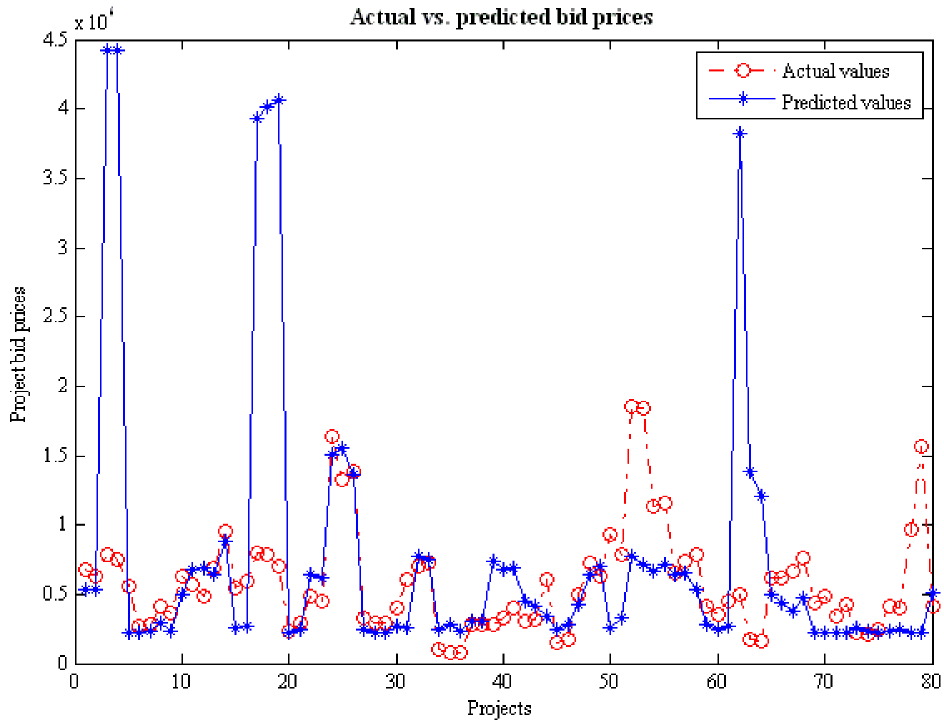

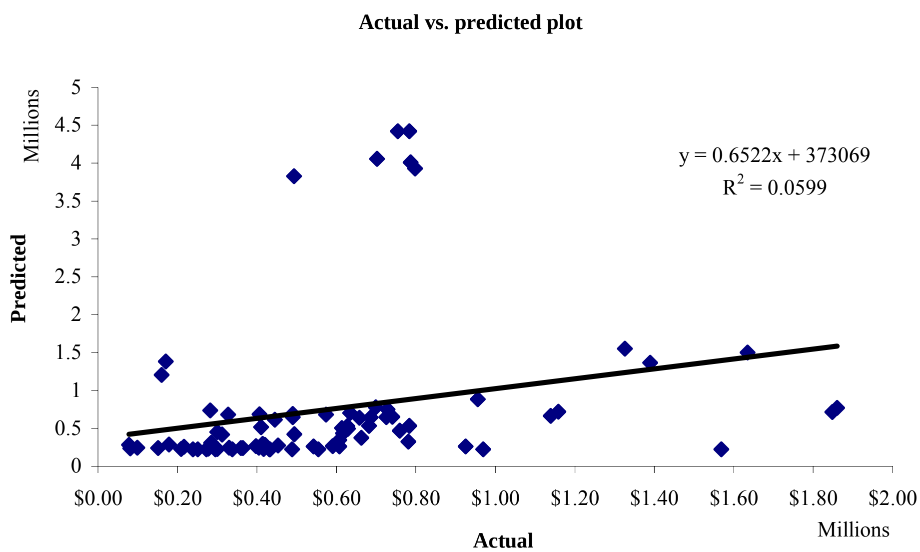

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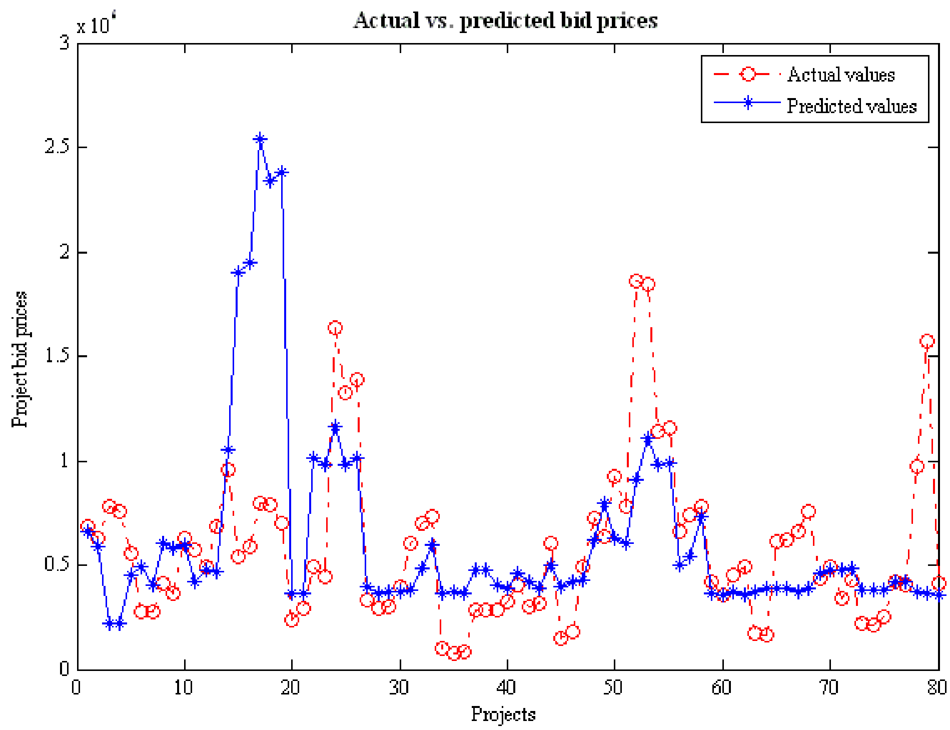
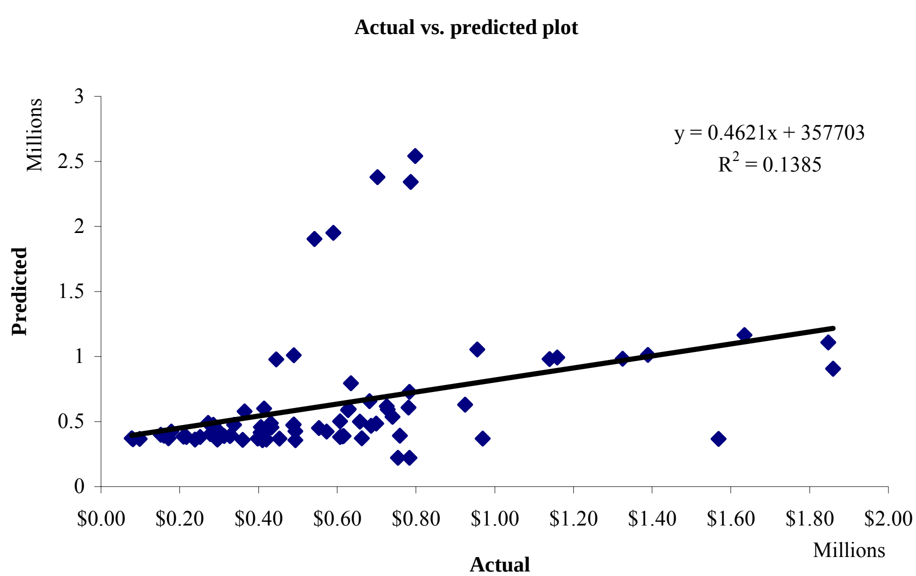




APPENDIX C

Projects used for the training set.

Project #	Name of Contractor	Bid price quoted	Project #	Name of Contractor	Bid price quoted
CND004	HIGHWAYS, INC.	$ 2,844,235.69	CND065	DEMENT CONSTRUCTION CO., LLC	$ 903,567.61
CND005	BELL & ASSOCIATES CONSTRUCTION, L.P.	$ 3,585,329.22	CND065	MOUNTAIN STATES CONTRACTORS, LLC	$ 1,023,336.77
CND005	MID-STATE CONSTRUCTION COMPANY, INC.	$ 3,926,151.85	CND066	DEMENT CONSTRUCTION COMPANY	$ 986,583.67
CND005	MOUNTAIN STATES CONTRACTORS, LLC	$ 3,794,787.97	CND066	TENNESSEE ASPHALT COMPANY	$ 996,015.48
CND005	SOUTHERN CONSTRUCTORS, INC.	$ 3,413,145.50	CND069	FORD CONSTRUCTION COMPANY	$ 652,850.20
CND006	GENERAL CONSTRUCTORS, INC.	$ 959,691.49	CND069	FORD CONSTRUCTION COMPANY	$ 652,850.20
CND006	JAMISON CONSTRUCTION, LLC	$ 861,767.65	CND070	APAC-TENNESSEE, INC. (M)	$ 1,028,257.00
CND006	SUMMERS-TAYLOR, INC.	$ 1,188,201.30	CND070	LEHMAN-ROBERTS COMPANY	$ 842,100.78
CND048	LINCOLN PAVING, L.L.C.	$ 1,919,209.29	CND073	SHELBY ELECTRIC COMPANY, INC.	$ 156,870.20
CND049	LOJAC ENTERPRISES, INC.	$ 1,192,599.05	CND073	STANSELL ELECTRIC CO., INC.	$ 141,275.40
CND049	ROGERS GROUP, INC.	$ 1,089,595.10	CND073	WADE ELECTRIC COMPANY, INC.	$ 117,496.81
CND053	CHRIS-HILL CONSTRUCTION CO., LLC	$ 281,442.93	CND074	HIGHWAY MARKINGS, INC.	$ 313,355.50
CND053	DEMENT CONSTRUCTION CO., LLC	$ 300,749.65	CND074	HIGHWAYS, INC.	$ 367,024.00
CND053	MOUNTAIN STATES CONTRACTORS, LLC	$ 277,475.40	CND074	TENNESSEE GUARDRAIL, INC.	$ 765,568.00
CND056	FORD CONSTRUCTION COMPANY	$ 3,834,797.48	CND075	APAC-TENNESSEE, INC. (K)	$ 354,817.69
CND059	DEMENT CONSTRUCTION CO., LLC	$ 490,774.80	CND075	RENFRO CONSTRUCTION CO., INC.	$ 336,477.52
CND059	THOMSON & THOMSON, INC.	$ 480,845.50	CND075	TENNESSEE ASPHALT COMPANY	$ 332,772.33
CND060	TENNESSEE ASPHALT COMPANY	$ 518,173.98	CND077	APAC-TENNESSEE, INC. (K)	$ 1,265,257.65
CND063	APAC-TENNESSEE, INC. (K)	$ 142,650.00	CND077	RENFRO CONSTRUCTION CO., INC.	$ 1,290,828.29
CND063	LYONS CONSTRUCTION COMPANY, INC.	$ 154,705.71	CND078	APAC-TENNESSEE, INC. (K)	$ 293,782.18
CND063	RENFRO CONSTRUCTION CO., INC.	$ 139,760.63	CND078	CHARLES BLALOCK & SONS, INC.	$ 326,017.66
CND063	TENNESSEE ASPHALT COMPANY	$ 122,887.26	CND078	RENFRO CONSTRUCTION CO., INC.	$ 312,357.34
CND064	RENFRO CONSTRUCTION CO., INC.	$ 187,497.03			
CND064	TENNESSEE ASPHALT COMPANY	$ 186,262.87			

Project #	Name of Contractor	Bid price quoted	Project #	Name of Contractor	Bid price quoted
CND081	APAC-TENNESSEE, INC. (K)	$ 164,225.93	CND094	HIGHWAYS, INC.	$ 769,440.00
CND081	CHARLES BLALOCK & SONS, INC.	$ 181,879.75	CND094	LOJAC ENTERPRISES, INC.	$ 698,801.25
CND081	RENFRO CONSTRUCTION CO., INC.	$ 177,812.77	CND095	APAC-TENNESSEE, INC. (A)	$ 285,683.00
CND083	RENFRO CONSTRUCTION CO., INC.	$ 1,415,032.78	CND095	ROGERS GROUP, INC.	$ 246,248.71
CND083	ROGERS GROUP, INC.	$ 1,276,057.22	CND095	THOMAS BROTHERS CONSTRUCTION CO., INC.	$ 274,532.00
CND083	TENNESSEE ASPHALT COMPANY	$ 1,815,674.63	CND097	C.W. MATTHEWS CONTRACTING CO., INC.	$ 363,233.35
CND085	STANDARD CONSTRUCTION CO., INC.	$ 612,422.79	CND097	HIGHWAYS, INC.	$ 319,632.00
CND086	DEMENT CONSTRUCTION CO., LLC	$ 251,684.63	CND098	ROGERS GROUP, INC.	$ 334,590.21
CND086	THOMSON & THOMSON, INC.	$ 284,341.95	CND099	ADMAN ELECTRIC INC	$ 633,069.03
CND088	CHRIS-HILL CONSTRUCTION CO., LLC	$ 174,428.90	CND099	DAVIS H. ELLIOT COMPANY, INC.	$ 528,500.00
CND088	DEMENT CONSTRUCTION CO., LLC	$ 142,577.05	CND099	HOLLEY ELECTRIC CONSTRUCTION CO., INC.	$ 530,890.23
CND088	THOMSON & THOMSON, INC.	$ 146,550.05	CND099	NABCO ELECTRIC COMPANY, INC.	$ 640,196.70
CND089	CHRIS-HILL CONSTRUCTION CO., LLC	$ 516,751.99	CND099	STANSELL ELECTRIC CO., INC.	$ 473,628.36
CND089	DEMENT CONSTRUCTION CO., LLC	$ 974,703.15	CND101	ROGERS GROUP, INC.	$ 354,724.55
CND089	GIBSON & ASSOCIATES INC.	$ 713,069.00	CND104	DEMENT CONSTRUCTION CO., LLC	$ 576,059.84
CND089	THOMSON & THOMSON, INC.	$ 385,612.12	CND104	MOUNTAIN STATES CONTRACTORS, LLC	$ 638,487.01
CND090	C.W. MATTHEWS CONTRACTING CO., INC.	$ 406,478.37	CND104	THOMSON & THOMSON, INC.	$ 692,193.37
CND090	RENFRO CONSTRUCTION CO., INC.	$ 349,600.40	CND104	VOLUNTEER BRIDGE CONSTRUCTION, INC.	$ 520,830.25
CND092	ROGERS GROUP, INC.	$ 505,798.48	CND105	DEMENT CONSTRUCTION CO., LLC	$ 794,080.27
CND092	WRIGHT PAVING CONTRACTORS, INC.	$ 559,359.01	CND105	FORD CONSTRUCTION COMPANY	$ 723,305.14
CND093	HIGHWAYS, INC.	$ 369,880.00	CND105	MOUNTAIN STATES CONTRACTORS, LLC	$ 864,809.88
CND093	TENNESSEE ASPHALT COMPANY	$ 350,307.35	CND106	DEMENT CONSTRUCTION CO., LLC	$ 55,587.50
			CND106	JAMISON CONSTRUCTION, LLC	$ 95,295.30
			CND106	THOMSON & THOMSON, INC.	$ 120,119.80

Project #	Name of Contractor	Bid price quoted	Project #	Name of Contractor	Bid price quoted
CND107	FORD CONSTRUCTION COMPANY	$ 619,968.00	CND130	ROGERS GROUP, INC.	$ 312,872.10
CND110	BELL & ASSOCIATES CONSTRUCTION, L.P.	$ 811,144.60	CND131	APAC-TENNESSEE, INC. (A)	$ 803,519.20
CND110	CONCRETE STRUCTURES, INC.	$ 687,054.41	CND133	OGLESBY CONSTRUCTION, INC.	$ 315,686.74
CND110	DEMENT CONSTRUCTION CO., LLC	$ 793,547.21	CND133	SUPERIOR PAVEMENT MARKING, INC.	$ 231,631.92
CND110	MOUNTAIN STATES CONTRACTORS, LLC	$ 654,709.90	CND133	VOLUNTEER HIGHWAY SUPPLY CO., INC.	$ 257,299.20
CND112	APAC-TENNESSEE, INC. (K)	$ 849,690.79	CND135	DEMENT CONSTRUCTION COMPANY	$ 1,548,289.53
CND112	RENFRO CONSTRUCTION CO., INC.	$ 941,478.11	CND135	FORD CONSTRUCTION COMPANY	$ 1,498,907.38
CND112	TENNESSEE ASPHALT COMPANY	$ 976,374.87	CND135	MOUNTAIN STATES CONTRACTORS, LLC	$ 1,546,046.75
CND115	GENERAL CONSTRUCTORS, INC.	$ 557,918.80	CND136	LEHMAN-ROBERTS COMPANY	$ 957,431.91
CND115	JAMISON CONSTRUCTION, LLC	$ 839,361.00	CND137	DEMENT CONSTRUCTION COMPANY	$ 1,035,599.02
CND115	MID-STATE CONSTRUCTION COMPANY, INC.	$ 784,873.50	CND137	FORD CONSTRUCTION COMPANY	$1,228,624.38
CND117	GENERAL CONSTRUCTORS, INC.	$ 435,053.20	CND138	FORD CONSTRUCTION COMPANY	$ 999,658.94
CND117	JAMISON CONSTRUCTION, LLC	$ 315,438.00	CND138	FORD CONSTRUCTION COMPANY	$ 999,658.94
CND117	MOUNTAIN STATES CONTRACTORS, LLC	$ 393,972.00	CND144	LOJAC ENTERPRISES, INC.	$1,034,470.10
CND117	SOUTHERN CONSTRUCTORS, INC.	$ 491,950.00	CND144	MOUNTAIN STATES CONTRACTORS, LLC	$1,123,711.60
CND118	BLUEGRASS CONTRACTING CORPORATION	$ 334,828.00	CND147	ROGERS GROUP, INC.	$ 596,382.00
CND118	CHARLES BLALOCK & SONS, INC.	$ 440,097.80	CND148	BLUEGRASS CONTRACTING CORPORATION	$ 362,639.95
CND118	HINKLE CONTRACTING CORPORATION	$ 334,630.70	CND148	BROWN BUILDERS, INC.	$ 396,590.72
CND118	INTERSTATE CONCRETE CONSTRUCTION, LLC	$ 283,524.00	CND148	MOUNTAIN STATES CONTRACTORS, LLC	$ 410,775.78
CND118	SIMPSON BRIDGE COMPANY, INC.	$ 306,195.36	CND159	DEMENT CONSTRUCTION COMPANY	$2,959,475.63
CND118	SOUTHERN CONSTRUCTORS, INC.	$ 323,999.80	CND159	FORD CONSTRUCTION COMPANY	$3,775,192.67
CND127	APAC-TENNESSEE, INC. (K)	$ 839,391.71	CND160	CIVIL CONSTRUCTORS, INC.	$4,935,044.50
CND127	RENFRO CONSTRUCTION CO., INC.	$ 839,447.52	CND160	SESSIONS PAVING COMPANY	$5,112,023.90
CND127	TENNESSEE ASPHALT COMPANY	$ 831,359.78			

Project #	Name of Contractor	Bid price quoted	Project #	Name of Contractor	Bid price quoted
CND161	BROWN BUILDERS, INC.	$ 386,978.40	CND175	BROWN BUILDERS, INC.	$ 485,254.50
CND161	CIVIL CONSTRUCTORS, INC.	$ 374,873.00	CND175	GENERAL CONSTRUCTORS, INC.	$ 377,633.19
CND161	CONCRETE STRUCTURES, INC.	$ 404,247.87	CND175	MID-STATE CONSTRUCTION COMPANY, INC.	$ 506,174.90
CND161	HINKLE CONTRACTING CORPORATION	$ 445,784.30	CND175	MOUNTAIN STATES CONTRACTORS, LLC	$ 684,231.70
CND161	PUTNAM CONTRACTING SERVICES, LLC.	$ 378,619.00	CND177	DIAMOND SPECIALIZED, INC.	$ 124,950.00
CND161	SESSIONS PAVING COMPANY	$ 333,388.05	CND181	SIMMONS SWEEPING COMPANY	$ 416,087.25
CND163	LAW SIGNS, LLC	$ 421,100.00	CND181	SWEEPING CORPORATION OF AMERICA, INC.	$ 430,610.80
CND163	LOJAC SAFETY, INC.	$ 345,582.65	CND184	SWEEPING CORPORATION OF AMERICA, INC.	$ 573,591.20
CND164	LAW SIGNS, LLC	$ 348,825.00	CND185	SIMMONS SWEEPING COMPANY	$ 437,392.50
CND165	ROGERS GROUP, INC.	$ 199,876.18	CND185	SWEEPING CORPORATION OF AMERICA, INC.	$ 452,269.80
CND168	GREENSTAR, LLC	$ 251,556.35	CND186	SUMMERS-TAYLOR, INC.	$ 1,759,540.15
CND168	MOUNTAIN STATES CONTRACTORS, LLC	$ 297,217.50	CND188	TENNESSEE GUARDRAIL, INC.	$ 248,834.00
CND169	HIGHWAY MARKINGS, INC.	$ 168,837.02	CND189	THOMAS BROTHERS CONSTRUCTION CO., INC.	$ 631,951.80
CND169	INTERSTATE ROAD MANAGEMENT CORP.	$ 84,826.30	CND189	TINSLEY ASPHALT, LLC	$ 650,572.25
CND169	SUPERIOR PAVEMENT MARKING, INC.	$ 171,586.84	CND191	TRAF-MARK, INC.	$ 397,302.00
CND170	LAW SIGNS, LLC	$ 437,615.00	CND192	TENNESSEE GUARDRAIL, INC.	$ 491,846.00
CND172	LAW SIGNS, LLC	$ 234,835.00	CND192	TRAF-MARK, INC.	$ 447,422.00
CND172	LOJAC SAFETY, INC.	$ 201,549.08	CND194	DEMENT CONSTRUCTION COMPANY	$ 483,890.56
CND173	DEMENT CONSTRUCTION COMPANY	$ 371,973.40	CND194	FORD CONSTRUCTION COMPANY	$ 562,317.76
CND174	DEMENT CONSTRUCTION CO., LLC	$ 429,461.77	CND194	DEMENT CONSTRUCTION COMPANY	$ 483,890.56
CND174	FORD CONSTRUCTION COMPANY	$ 387,152.65	CND194	FORD CONSTRUCTION COMPANY	$ 562,317.76
CND174	MOUNTAIN STATES CONTRACTORS, LLC	$ 538,212.97	CND196	BROWN BUILDERS, INC.	$ 870,857.91
			CND196	CONCRETE STRUCTURES, INC.	$ 787,763.38
			CND196	MOUNTAIN STATES CONTRACTORS, LLC	$ 910,448.55

Project #	Name of Contractor	Bid price quoted	Project #	Name of Contractor	Bid price quoted
CND200	LAW SIGNS, LLC	$ 128,959.69	CND214	APAC-TENNESSEE, INC. (A)	$ 586,660.30
CND200	TRI-STATE GUARDRAIL & SIGN CO., INC.	$ 147,367.10	CND215	APAC-TENNESSEE, INC. (A)	$ 652,223.73
CND202	DEMENT CONSTRUCTION COMPANY	$ 969,504.01	CND216	APAC-TENNESSEE, INC. (A)	$ 445,097.00
CND202	J. R. HAYES CONSTRUCTION CO., INC.	$ 1,662,512.76	CND216	LYONS CONSTRUCTION COMPANY, INC.	$ 364,124.50
CND202	PHILLIPS AND JORDAN, INCORPORTATED	$ 1,284,268.59	CND217	APAC-TENNESSEE, INC. (A)	$ 497,960.00
CND203	DEMENT CONSTRUCTION CO., LLC	$ 1,204,486.95	CND217	LYONS CONSTRUCTION COMPANY, INC.	$ 429,311.36
CND203	FORD CONSTRUCTION COMPANY	$ 1,384,288.50	CND218	BELL & ASSOCIATES CONSTRUCTION, L.P.	$ 782,488.00
CND203	THOMSON & THOMSON, INC.	$ 1,079,399.40	CND218	GENERAL CONSTRUCTORS, INC.	$ 1,094,001.00
CND205	DEMENT CONSTRUCTION CO., LLC	$ 479,593.30	CND218	THOMSON & THOMSON, INC.	$ 654,770.00
CND205	FORD CONSTRUCTION COMPANY	$ 459,104.44	CND219	HILL BROS. EXCAVATING, INC.	$ 240,212.74
CND205	MOUNTAIN STATES CONTRACTORS, LLC	$ 509,975.84	CND219	WRIGHT PAVING CONTRACTORS, INC.	$ 227,569.63
CND205	VOLUNTEER BRIDGE CONSTRUCTION, INC.	$ 504,677.80	CND224	TENNESSEE ASPHALT COMPANY	$ 396,107.02
CND206	CHRIS-HILL CONSTRUCTION CO., LLC	$ 470,238.12	CND225	APAC-TENNESSEE, INC. (A)	$ 789,794.00
CND206	DEMENT CONSTRUCTION CO., LLC	$ 448,555.75	CND225	W-L CONSTRUCTION & PAVING, INC.	$ 969,052.95
CND206	FORD CONSTRUCTION COMPANY	$ 389,715.99	CND227	SUPERIOR PAVEMENT MARKING, INC.	$ 242,667.00
CND206	MOUNTAIN STATES CONTRACTORS, LLC	$ 538,552.15	CND228	GENERAL CONSTRUCTORS, INC.	$ 387,089.02
CND206	THOMSON & THOMSON, INC.	$ 524,707.75	CND228	JAMISON CONSTRUCTION, LLC	$ 373,392.80
CND207	APAC-TENNESSEE, INC. (A)	$ 316,806.11	CND228	MOUNTAIN STATES CONTRACTORS, LLC	$ 499,613.80
CND207	TENNESSEE ASPHALT COMPANY	$ 273,065.15	CND229	STANDARD CONSTRUCTION CO., INC.	$ 610,294.15
CND208	ALH CONSTRUCTION COMPANY	$ 559,588.86	CND229	STANDARD CONSTRUCTION CO., INC.	$ 610,294.15
CND208	H. C. LEWIS CONSTRUCTION, INC.	$ 590,443.55	CND234	ENGLAND STRIPING, INC.	$ 211,835.00
CND208	LYONS CONSTRUCTION COMPANY, INC.	$ 532,058.55	CND235	C.W. MATTHEWS CONTRACTING CO., INC.	$ 289,747.34
CND209	APAC-TENNESSEE, INC. (A)	$ 849,709.51	CND235	RENFRO CONSTRUCTION CO., INC.	$ 268,948.60
CND209	TENNESSEE ASPHALT COMPANY	$ 1,003,439.69	CND236	ROGERS GROUP, INC.	$ 398,343.12

Project #	Name of Contractor	Bid price quoted	Project #	Name of Contractor	Bid price quoted
CND237	ROGERS GROUP, INC.	$ 398,343.12	CND255	EUBANK ASPHALT PAVING & SEALING	$ 784,062.25
CND239	ROGERS GROUP, INC.	$ 516,982.59	CND255	LOJAC ENTERPRISES, INC.	$ 728,329.00
CND240	RENFRO CONSTRUCTION CO., INC.	$ 407,658.35	CND255	ROGERS GROUP, INC.	$ 727,801.00
CND240	ROGERS GROUP, INC.	$ 489,713.85	CND256	EUBANK ASPHALT PAVING & SEALING	$ 446,981.31
CND241	ROGERS GROUP, INC.	$ 334,078.30	CND256	MCINTOSH CONSTRUCTION COMPANY, INC.	$ 664,754.00
CND243	HIGHWAYS, INC.	$ 314,830.00	CND256	MOUNTAIN STATES CONTRACTORS, LLC	$ 498,444.55
CND243	LOJAC ENTERPRISES, INC.	$ 341,636.00	CND257	LOJAC ENTERPRISES, INC.	$ 559,699.00
CND245	HIGHWAYS, INC.	$ 369,990.00	CND259	HOOVER, INC.	$ 387,603.29
CND245	LOJAC ENTERPRISES, INC.	$ 388,546.20	CND259	LOJAC ENTERPRISES, INC.	$ 368,156.00
CND247	HIGHWAYS, INC.	$ 369,765.00	CND260	LOJAC ENTERPRISES, INC.	$ 2,728,986.80
CND247	LOJAC ENTERPRISES, INC.	$ 405,915.00	CND260	MOUNTAIN STATES CONTRACTORS, LLC	$ 2,323,337.00
CND248	C & D SAFETY COMPANY, LLC	$ 348,924.00	CND263	TRAF-MARK, INC.	$ 197,101.00
CND248	KERR BROS. & ASSOCIATES, INC.	$ 240,340.00	CND264	APAC-MISSISSIPPI, INC.	$ 1,593,988.32
CND249	C & D SAFETY COMPANY, LLC	$ 716,470.25	CND264	DEMENT CONSTRUCTION COMPANY	$ 1,385,021.34
CND249	MOUNTAIN STATES CONTRACTORS, LLC	$ 859,009.60	CND264	APAC-MISSISSIPPI, INC.	$ 1,593,988.32
CND249	SESSIONS PAVING COMPANY	$ 688,311.20	CND264	DEMENT CONSTRUCTION COMPANY	$ 1,385,021.34
CND250	CUMBERLAND GUARDRAIL, INC.	$ 289,323.50	CND267	TENNESSEE ASPHALT COMPANY	$ 482,846.98
CND250	TENNESSEE GUARDRAIL, INC.	$ 349,340.00	CND267	TENNESSEE ASPHALT COMPANY	$ 482,846.98
CND250	TRI-STATE GUARDRAIL & SIGN CO., INC.	$ 335,998.00	CND268	FORD CONSTRUCTION COMPANY	$ 465,964.90
CND251	LOJAC ENTERPRISES, INC.	$ 968,708.75	CND268	FORD CONSTRUCTION COMPANY	$ 465,964.90
CND251	MOUNTAIN STATES CONTRACTORS, LLC	$ 995,170.35	CND269	DEMENT CONSTRUCTION COMPANY	$ 2,094,551.18
CND251	ROGERS GROUP, INC.	$ 998,330.00	CND269	DEMENT CONSTRUCTION COMPANY	$ 2,094,551.18
CND253	CONCRETE STRUCTURES, INC.	$ 544,159.33	CND272	BAKER'S CONSTRUCTION SERVICES, INC.	$ 498,395.39
CND253	MOUNTAIN STATES CONTRACTORS, LLC	$ 584,940.00	CND272	SUMMERS-TAYLOR, INC.	$ 497,268.95
			CND272	WHALEY & SONS, INC.	$ 677,192.50

Project #	Name of Contractor	Bid price quoted
CND273	GENERAL CONSTRUCTORS, INC.	$ 678,592.29
CND273	JAMISON CONSTRUCTION, LLC	$ 780,691.10
CND273	MID-STATE CONSTRUCTION COMPANY, INC.	$ 927,988.38
CND273	MOUNTAIN STATES CONTRACTORS, LLC	$ 1,022,616.20
CND273	SIMPSON BRIDGE COMPANY, INC.	$ 927,242.94
CND274	CHRIS-HILL CONSTRUCTION CO., LLC	$ 583,652.00
CND274	DEMENT CONSTRUCTION CO., LLC	$ 562,311.67
CND274	FORD CONSTRUCTION COMPANY	$ 479,419.14
CND274	MOUNTAIN STATES CONTRACTORS, LLC	$ 638,868.35
CND275	J & M INCORPORATED	$ 1,346,373.50
CND275	SIMPSON BRIDGE COMPANY, INC.	$ 979,832.07
CND275	WRIGHT BROTHERS CONSTRUCTION CO., INC.	$ 1,086,242.10
CND276	DEMENT CONSTRUCTION CO., LLC	$ 1,255,979.18
CND276	HIGHWAYS, INC.	$ 1,149,796.18
CND276	MOUNTAIN STATES CONTRACTORS, LLC	$ 1,066,541.48
CND276	SIMPSON CONSTRUCTION COMPANY, INC.	$ 1,087,562.28
CND276	WRIGHT BROTHERS CONSTRUCTION CO., INC.	$ 1,138,402.60
CND278	HOLLEY ELECTRIC CONSTRUCTION CO., INC.	$ 19,317.00
CND278	PROGRESSION ELECTRIC, LLC	$ 11,489.00
CND283	HIGHWAYS, INC.	$ 414,660.00
CND283	LOJAC ENTERPRISES, INC.	$ 306,234.90
CND285	DEMENT CONSTRUCTION COMPANY	$ 1,299,244.46
CND285	FORD CONSTRUCTION COMPANY	$ 1,385,043.25
CND285	DEMENT CONSTRUCTION COMPANY	$ 1,299,244.46
CND285	FORD CONSTRUCTION COMPANY	$ 1,385,043.25
CND286	EUBANK ASPHALT PAVING & SEALING	$ 573,495.45
CND287	HIGHWAYS, INC.	$ 524,985.00
CND287	TENNESSEE ASPHALT COMPANY	$ 556,449.50
CND288	APAC-TENNESSEE, INC. (A)	$ 325,887.70
CND288	HIGHWAYS, INC.	$ 259,900.00
CND288	LOJAC ENTERPRISES, INC.	$ 285,037.50
CND289	LINCOLN PAVING, L.L.C.	$ 1,346,951.08
CND289	WRIGHT PAVING CONTRACTORS, INC.	$ 1,216,024.11
CND291	APAC-TENNESSEE, INC. (A)	$ 336,173.16
CND291	HIGHWAYS, INC.	$ 427,620.00
CND291	LOJAC ENTERPRISES, INC.	$ 388,664.50
CND294	INTERSTATE CONCRETE CONSTRUCTION, LLC	$ 400,039.15
CND294	SUMMERS-TAYLOR, INC.	$ 384,825.20
CND295	CUMBERLAND GUARDRAIL, INC.	$ 248,433.20
CND295	KRD CORPORATION	$ 285,506.75
CND295	TENNESSEE GUARDRAIL, INC.	$ 297,925.00
CND295	TRI-STATE GUARDRAIL & SIGN CO., INC.	$ 487,717.50
CND296	DEMENT CONSTRUCTION COMPANY	$ 604,340.50
CND296	ROGERS GROUP, INC.	$ 721,682.00
CND299	TENNESSEE ASPHALT COMPANY	$ 584,655.18
CND303	EUBANK ASPHALT PAVING & SEALING	$ 1,238,495.45
CND303	LOJAC ENTERPRISES, INC.	$ 1,132,807.10
CND303	ROGERS GROUP, INC.	$ 1,245,512.00

Project #	Name of Contractor	Bid price quoted	Project #	Name of Contractor	Bid price quoted
CND305	APAC-TENNESSEE, INC. (M)	$ 599,997.05	CND329	DEMENT CONSTRUCTION CO., LLC	$ 690,196.45
CND305	LEHMAN-ROBERTS COMPANY	$ 551,706.83	CND329	MID-STATE CONSTRUCTION COMPANY, INC.	$ 907,065.81
CND305	STANDARD CONSTRUCTION CO., INC.	$ 569,487.73	CND329	SIMPSON CONSTRUCTION COMPANY, INC.	$ 824,467.56
CND305	APAC-TENNESSEE, INC. (M)	$ 599,997.05	CND329	SOUTHERN CONSTRUCTORS, INC.	$ 1,135,225.00
CND305	LEHMAN-ROBERTS COMPANY	$ 551,706.83	CND330	APAC-TENNESSEE, INC. (A)	$ 593,165.58
CND305	STANDARD CONSTRUCTION CO., INC.	$ 569,487.73	CND330	LYONS CONSTRUCTION COMPANY, INC.	$ 514,470.29
CND311	S & W CONTRACTING CO., INC.	$ 53,473.00	CND330	SUMMERS-TAYLOR, INC.	$ 492,761.50
CND311	STANSELL ELECTRIC CO., INC.	$ 50,660.00	CND332	FREISTHLER PAVING, INC.	$ 266,168.50
CND312	CIVIL CONSTRUCTORS, INC.	$ 1,326,813.88	CND332	TENNESSEE ASPHALT COMPANY	$ 307,510.00
CND312	MOUNTAIN STATES CONTRACTORS, LLC	$ 1,891,495.79	CND340	CHARLES BLALOCK & SONS, INC.	$ 491,282.00
CND314	DEMENT CONSTRUCTION COMPANY	$ 333,687.94	CND343	JAMISON CONSTRUCTION, LLC	$ 2,228,938.00
CND314	FORD CONSTRUCTION COMPANY	$ 251,295.00	CND343	SOUTHERN CONSTRUCTORS, INC.	$ 2,701,682.50
CND315	HILL BROS. EXCAVATING, INC.	$ 621,495.18	CND346	ROGERS GROUP, INC.	$ 387,159.76
CND315	MARCUM EXCAVATING	$ 735,893.50	CND346	WRIGHT PAVING CONTRACTORS, INC.	$ 439,334.03
CND315	WRIGHT BROTHERS CONSTRUCTION CO., INC.	$ 646,987.18	CND347	EUBANK ASPHALT PAVING & SEALING	$ 519,256.60
CND316	DEMENT CONSTRUCTION COMPANY	$ 231,757.20	CND348	FORD CONSTRUCTION COMPANY	$ 1,114,797.24
CND316	DEMENT CONSTRUCTION COMPANY	$ 231,757.20	CND348	FORD CONSTRUCTION COMPANY	$ 1,114,797.24
CND320	DEMENT CONSTRUCTION COMPANY	$ 539,597.15	CND351	RENFRO CONSTRUCTION CO., INC.	$ 845,435.20
CND320	FORD CONSTRUCTION COMPANY	$ 370,596.47	CND351	SIMPSON CONSTRUCTION COMPANY, INC.	$ 695,038.18
CND320	VOLUNTEER BRIDGE CONSTRUCTION, INC.	$ 450,806.00	CND351	WRIGHT BROTHERS CONSTRUCTION CO., INC.	$ 773,548.59
CND321	FORD CONSTRUCTION COMPANY	$ 453,068.30	CND356	TENNESSEE GUARDRAIL, INC.	$ 4,320,390.00
CND321	FORD CONSTRUCTION COMPANY	$ 453,068.30	CND357	GERALD DAVID ORR CONTRACTING , INC.	$ 337,950.00
CND328	GENERAL CONSTRUCTORS, INC.	$ 421,941.00	CND357	ORR CONTRACTING, INC.	$ 338,935.00
CND328	JAMISON CONSTRUCTION, LLC	$ 270,966.00	CND358	CUMBERLAND GUARDRAIL, INC.	$ 3,591,462.50
CND328	MID-STATE CONSTRUCTION COMPANY, INC.	$ 183,344.05	CND358	TENNESSEE GUARDRAIL, INC.	$ 3,963,300.00

Project #	Name of Contractor	Bid price quoted	Project #	Name of Contractor	Bid price quoted
CND360	GENERAL CONSTRUCTORS, INC.	$ 978,505.74	CND378	DEMENT CONSTRUCTION CO., LLC	$ 910,904.25
CND360	MID-STATE CONSTRUCTION COMPANY, INC.	$ 1,129,693.11	CND378	MOUNTAIN STATES CONTRACTORS, LLC	$ 880,326.50
CND360	SOUTHERN CONSTRUCTORS, INC.	$ 1,999,942.00	CND378	THOMSON & THOMSON, INC.	$ 654,431.25
CND361	APEX CONTRACTING, INC OF KY	$ 197,208.45	CND378	VOLUNTEER BRIDGE CONSTRUCTION, INC.	$ 631,650.00
CND361	DAVIS H. ELLIOT COMPANY, INC.	$ 225,008.30	CND379	DEMENT CONSTRUCTION CO., LLC	$ 538,044.90
CND361	S & W CONTRACTING CO., INC.	$ 154,796.32	CND379	FORD CONSTRUCTION COMPANY	$ 391,038.50
CND361	STANSELL ELECTRIC CO., INC.	$ 160,227.08	CND380	CHRIS-HILL CONSTRUCTION CO., LLC	$ 621,388.65
CND365	DAVIS H. ELLIOT COMPANY, INC.	$ 83,331.00	CND380	DEMENT CONSTRUCTION CO., LLC	$ 446,008.90
CND365	S & W CONTRACTING CO., INC.	$ 81,716.25	CND380	THOMSON & THOMSON, INC.	$ 427,670.40
CND365	STANSELL ELECTRIC CO., INC.	$ 64,692.00	CND384	MID-STATE CONSTRUCTION COMPANY, INC.	$ 540,431.51
CND370	GENERAL CONSTRUCTORS, INC.	$ 531,753.38	CND384	SOUTHERN CONSTRUCTORS, INC.	$ 2,806,087.15
CND370	JAMISON CONSTRUCTION, LLC	$ 589,418.00	CND415	CBM ENTERPRISES, INC.	$ 634,267.06
CND370	MID-STATE CONSTRUCTION COMPANY, INC.	$ 639,677.36	CND415	CIVIL CONSTRUCTORS, INC.	$ 681,816.20
CND370	SOUTHERN CONSTRUCTORS, INC.	$ 687,585.00	CND415	JENCO CONSTRUCTION, INC.	$ 688,677.72
CND372	TENNESSEE GUARDRAIL, INC.	$ 3,826,860.00	CND415	LOJAC ENTERPRISES, INC.	$ 686,011.05
CND373	TRI-STATE GUARDRAIL & SIGN CO., INC.	$ 2,688,500.00	CND415	ROGERS GROUP, INC.	$ 766,531.50
CND376	HIGHWAYS, INC.	$ 807,641.60	CND415	SESSIONS PAVING COMPANY	$ 698,087.00
CND376	THOMAS BROTHERS CONSTRUCTION CO., INC.	$ 984,278.00	CND416	DEMENT CONSTRUCTION CO., LLC	$ 316,929.31
CND377	DEMENT CONSTRUCTION CO., LLC	$ 943,487.00	CND416	FORD CONSTRUCTION COMPANY	$ 353,319.06
CND377	JAMISON CONSTRUCTION, LLC	$ 734,646.48	CND416	MOUNTAIN STATES CONTRACTORS, LLC	$ 419,591.84
CND377	MOUNTAIN STATES CONTRACTORS, LLC	$ 950,292.42	CND416	VOLUNTEER BRIDGE CONSTRUCTION, INC.	$ 348,867.74
CND377	THOMSON & THOMSON, INC.	$ 857,578.90	CND419	DEMENT CONSTRUCTION CO., LLC	$ 286,909.62
CND377	VOLUNTEER BRIDGE CONSTRUCTION, INC.	$ 811,344.00	CND419	FORD CONSTRUCTION COMPANY	$ 272,314.00
			CND419	MOUNTAIN STATES CONTRACTORS, LLC	$ 385,770.59
			CND419	THOMSON & THOMSON, INC.	$ 341,909.80

Project #	Name of Contractor	Bid price quoted	Project #	Name of Contractor	Bid price quoted
CND420	DEMENT CONSTRUCTION CO., LLC	$ 602,918.04	CND452	BELL & ASSOCIATES CONSTRUCTION, L.P.	$ 2,422,544.46
CND420	JAMISON CONSTRUCTION, LLC	$ 507,007.00	CND452	DEMENT CONSTRUCTION CO., LLC	$ 2,639,592.75
CND420	MID-STATE CONSTRUCTION COMPANY, INC.	$ 549,163.70	CND452	MOUNTAIN STATES CONTRACTORS, LLC	$ 2,726,906.75
CND420	MOUNTAIN STATES CONTRACTORS, LLC	$ 676,131.00	CND452	THOMSON & THOMSON, INC.	$ 2,151,332.66
CND427	HAINES ELECTRIC CO., INC.	$ 54,903.10	CND452	W. L. SHARPE CONTRACTING COMPANY, L. P.	$ 2,843,282.48
CND427	TRI-STATE GUARDRAIL & SIGN CO., INC.	$ 87,053.00	CND900	GENERAL CONSTRUCTORS, INC.	$ 1,294,021.10
CND429	CHARLES BLALOCK & SONS, INC.	$ 315,140.00	CND900	JAMISON CONSTRUCTION, LLC	$ 1,209,804.30
CND429	SIMPSON CONSTRUCTION COMPANY, INC.	$ 326,495.00	CND900	LYONS CONSTRUCTION COMPANY, INC.	$ 2,174,227.13
CND432	ROGERS GROUP, INC.	$ 5,910,119.49	CND900	SOUTHERN CONSTRUCTORS, INC.	$ 1,316,572.50
CND433	CHARLES BLALOCK & SONS, INC.	$ 2,259,070.45	CND901	DEMENT CONSTRUCTION COMPANY	$ 1,620,054.94
CND433	SIMPSON CONSTRUCTION COMPANY, INC.	$ 1,835,707.46	CND901	DEMENT CONSTRUCTION COMPANY	$ 1,620,054.94
CND436	TENNESSEE ASPHALT COMPANY	$ 5,606,840.87	CND902	H. C. LEWIS CONSTRUCTION, INC.	$ 373,527.10
CND439	APAC-TENNESSEE, INC. (A)	$ 2,866,062.21	CND902	SUMMERS-TAYLOR, INC.	$ 388,516.07
CND439	RENFRO CONSTRUCTION CO., INC.	$ 2,534,761.21	CND903	DEMENT CONSTRUCTION COMPANY	$ 596,243.92
CND441	JAMISON CONSTRUCTION, LLC	$ 157,113.75	CND903	MOUNTAIN STATES CONTRACTORS, LLC	$ 825,391.31
CND441	MID-STATE CONSTRUCTION COMPANY, INC.	$ 218,705.28	CND904	CHARLES BLALOCK & SONS, INC.	$ 4,923,307.56
CND441	SOUTHERN CONSTRUCTORS, INC.	$ 141,316.50	CND904	SIMPSON CONSTRUCTION COMPANY, INC.	$ 5,091,566.64
CND442	HIGHWAYS, INC.	$ 1,898,665.00	CND906	MOUNTAIN STATES CONTRACTORS, LLC	$ 745,405.72
CND442	ROGERS GROUP, INC.	$ 1,537,050.02	CND906	SIMPSON CONSTRUCTION COMPANY, INC.	$ 919,976.75
CND446	LOJAC ENTERPRISES, INC.	$ 3,266,013.35	CND907	DEMENT CONSTRUCTION COMPANY	$ 1,685,317.47
CND446	MOUNTAIN STATES CONTRACTORS, LLC	$ 4,180,238.46	CND916	CUMBERLAND GUARDRAIL, INC.	$ 2,996,023.50
CND448	ROGERS GROUP, INC.	$ 2,649,480.00	CND916	TENNESSEE GUARDRAIL, INC.	$ 2,692,787.50
CND448	WRIGHT PAVING CONTRACTORS, INC.	$ 3,258,485.64	CND916	TRI-STATE GUARDRAIL & SIGN CO., INC.	$ 4,185,900.00
CND449	DEMENT CONSTRUCTION COMPANY	$ 3,547,458.80			
CND449	DEMENT CONSTRUCTION COMPANY	$ 3,547,458.80			

Project #	Name of Contractor	Bid price quoted	Project #	Name of Contractor	Bid price quoted
CND919	COFFEY CONSTRUCTION COMPANY, INC.	$ 1,696,596.91	CND934	C.W. MATTHEWS CONTRACTING CO., INC.	$ 498,712.71
CND919	CONSTRUCTION COMPANY	$ 1,643,422.70	CND936	CIVIL CONSTRUCTORS, INC.	$ 798,614.30
CND919	CONSTRUCTION COMPANY	$ 2,136,277.50	CND936	SESSIONS PAVING COMPANY	$ 741,155.30
CND920	CHARLES BLALOCK & SONS, INC.	$ 794,395.55	CND937	APAC-TENNESSEE, INC. (A)	$ 1,714,250.00
CND922	CHARLES BLALOCK & SONS, INC.	$ 2,299,299.99	CND937	SUMMERS-TAYLOR, INC.	$ 1,457,122.50
CND922	MOUNTAIN STATES CONTRACTORS, LLC	$ 1,890,671.80	CND939	ERBY CONTRACTORS, INC.	$ 815,634.01
CND922	SIMPSON CONSTRUCTION COMPANY, INC.	$ 2,142,060.63	CND939	H. C. LEWIS CONSTRUCTION, INC.	$ 801,644.85
CND923	CIVIL CONSTRUCTORS, INC.	$ 1,093,834.10	CND939	SIMPSON CONSTRUCTION COMPANY, INC.	$ 832,952.62
CND923	HIGHWAYS, INC.	$ 1,251,083.00	CND948	MOUNTAIN STATES CONTRACTORS, LLC	$ 3,772,564.11
CND923	HILL BROS. EXCAVATING, INC.	$ 1,382,080.90	CND948	SIMPSON CONSTRUCTION COMPANY, INC.	$ 3,780,858.30
CND923	JENCO CONSTRUCTION, INC.	$ 1,226,574.28	CND949	B & W EXCAVATION, LLC	$ 1,270,691.00
CND923	MOUNTAIN STATES CONTRACTORS, LLC	$ 1,560,539.84	CND949	CIVIL CONSTRUCTORS, INC.	$ 1,323,751.10
CND923	SESSIONS PAVING COMPANY	$ 1,074,054.50	CND949	HIGHWAYS, INC.	$ 1,263,678.00
CND924	OCCI, INC.	$ 428,000.00	CND949	JENCO CONSTRUCTION, INC.	$ 1,347,052.17
CND925	FIRST RESPONSE, INC.	$ 363,925.00	CND949	MOUNTAIN STATES CONTRACTORS, LLC	$ 2,054,706.89
CND925	ORCHARD FENCE COMPANY	$ 369,100.00	CND949	PHILLIPS AND JORDAN, INCORPORTATED	$ 1,445,877.00
CND927	EAST TENNESSEE TURF AND LANDSCAPE	$ 212,025.00	CND949	SESSIONS PAVING COMPANY	$ 2,222,192.00
CND927	ORCHARD FENCE COMPANY	$ 223,100.00			
CND928	DEMENT CONSTRUCTION CO., LLC	$ 924,167.06			
CND928	FORD CONSTRUCTION COMPANY	$ 787,130.65			
CND928	MOUNTAIN STATES CONTRACTORS, LLC	$ 972,653.58			
CND930	THOMAS BROTHERS CONSTRUCTION CO., INC.	$ 844,253.60			
CND931	DIXIELAND CONTRACTORS, INC.	$ 201,441.64			
CND931	FERRELL PAVING, INC.	$ 189,206.83			

APPENDIX D

Output of neural network for [1221] configuration.

Sr. No.	Project #	Actual Bid Costs	Predicted Bid Costs	Sr. No.	Project #	Actual Bid Costs	Predicted Bid Costs	Sr. No.	Project #	Actual Bid Costs	Predicted Bid Costs
1	CND009	$682,000	$428,917	30	CND146	$397,551	$395,101	59	CND318	$419,929	$362,860
2	CND009	$627,289	$546,607	31	CND146	$607,280	$384,226	60	CND318	$359,853	$371,133
3	CND055	$783,320	$3,128,377	32	CND152	$699,358	$796,327	61	CND318	$453,202	$357,346
4	CND055	$754,477	$3,128,377	33	CND152	$728,773	$802,701	62	CND334	$493,517	$2,926,535
5	CND057	$554,129	$587,307	34	CND162	$98,612	$355,288	63	CND352	$170,948	$373,087
6	CND057	$272,363	$634,073	35	CND162	$78,179	$360,930	64	CND352	$160,196	$353,825
7	CND057	$277,659	$543,389	36	CND162	$81,206	$354,016	65	CND374	$613,829	$499,075
8	CND076	$414,125	$507,930	37	CND193	$284,896	$383,305	66	CND374	$616,392	$433,899
9	CND076	$364,617	$456,352	38	CND193	$284,896	$383,305	67	CND374	$662,598	$466,992
10	CND084	$629,043	$475,360	39	CND211	$282,282	$403,799	68	CND374	$759,360	$450,122
11	CND096	$573,456	$353,970	40	CND211	$327,140	$422,041	69	CND381	$432,697	$531,361
12	CND096	$489,790	$362,629	41	CND211	$406,367	$406,827	70	CND381	$488,066	$453,951
13	CND096	$686,410	$360,247	42	CND223	$300,425	$465,989	71	CND381	$337,904	$549,909
14	CND102	$955,381	$979,301	43	CND223	$312,445	$376,526	72	CND381	$431,139	$449,312
15	CND109	$542,058	$366,868	44	CND226	$607,589	$482,406	73	CND417	$216,576	$355,706
16	CND109	$590,354	$354,592	45	CND242	$151,605	$380,174	74	CND417	$209,310	$361,188
17	CND116	$798,420	$559,135	46	CND242	$178,766	$353,363	75	CND417	$251,342	$353,363
18	CND116	$786,930	$515,040	47	CND252	$493,652	$511,974	76	CND421	$416,849	$424,582
19	CND116	$702,622	$498,819	48	CND258	$725,934	$705,466	77	CND421	$404,867	$379,616
20	CND128	$239,008	$358,442	49	CND258	$634,845	$534,287	78	CND908	$969,543	$524,467
21	CND128	$294,030	$436,505	50	CND282	$925,094	$451,660	79	CND908	$1,568,489	$572,936
22	CND129	$489,894	$493,031	51	CND282	$781,350	$585,080	80	CND932	$409,948	$355,557
23	CND129	$445,196	$536,737	52	CND284	$1,859,722	$4,202,236				
24	CND140	$1,634,599	$764,358	53	CND284	$1,847,741	$4,389,446				
25	CND140	$1,325,497	$843,951	54	CND306	$1,139,495	$4,443,723				
26	CND140	$1,389,030	$859,675	55	CND306	$1,158,879	$4,381,200				
27	CND146	$330,050	$359,573	56	CND309	$657,700	$857,309				
28	CND146	$295,310	$363,994	57	CND309	$740,638	$863,292				
29	CND146	$299,797	$375,496	58	CND309	$783,562	$1,005,348				

APPENDIX E

Projects used for the validation set.

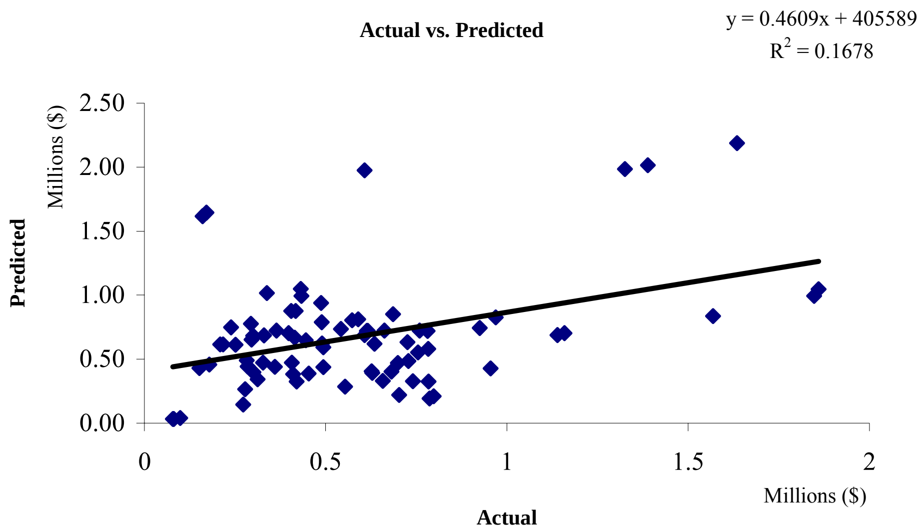
Project #	Name of Contractor	Bid price quoted	Project #	Name of Contractor	Bid price quoted
CND009	ROGERS GROUP, INC.	$ 682,000.00	CND140	APAC-MISSISSIPPI, INC.	$ 1,634,598.62
CND009	WRIGHT PAVING CONTRACTORS, INC.	$ 627,289.17	CND140	DEMENT CONSTRUCTION COMPANY	$ 1,325,497.03
CND055	APAC-TENNESSEE, INC. (K)	$ 783,320.00	CND140	MOUNTAIN STATES CONTRACTORS, LLC	$ 1,389,029.85
CND055	RENFRO CONSTRUCTION CO., INC.	$ 754,477.50	CND146	CUMBERLAND GUARDRAIL, INC.	$ 330,050.62
CND057	DEMENT CONSTRUCTION CO., LLC	$ 554,129.20	CND146	DIXIELAND CONTRACTORS, INC.	$ 295,310.19
CND057	FORD CONSTRUCTION COMPANY	$ 272,363.00	CND146	LTS CONSTRUCTION, LLC	$ 299,797.50
CND057	THOMSON & THOMSON, INC.	$ 277,659.30	CND146	TENNESSEE ASPHALT COMPANY	$ 397,551.68
CND076	APAC-TENNESSEE, INC. (A)	$ 414,125.70	CND146	VOLUNTEER BRIDGE CONSTRUCTION, INC.	$ 607,280.00
CND076	PATTY DRILLING, INC.	$ 364,616.95	CND152	HOOVER, INC.	$ 699,358.80
CND084	SUMMERS-TAYLOR, INC.	$ 629,043.00	CND152	LOJAC ENTERPRISES, INC.	$ 728,773.50
CND096	C.W. MATTHEWS CONTRACTING CO., INC.	$ 573,456.09	CND162	ADMAN ELECTRIC INC	$ 98,612.17
CND096	HIGHWAYS, INC.	$ 489,790.00	CND162	S & W CONTRACTING CO., INC.	$ 78,179.45
CND096	TALLEY CONSTRUCTION COMPANY, INC.	$ 686,410.40	CND162	STANSELL ELECTRIC CO., INC.	$ 81,206.40
CND102	APAC-TENNESSEE, INC. (A)	$ 955,380.95	CND193	STANDARD CONSTRUCTION CO., INC.	$ 284,895.95
CND109	FERRELL PAVING, INC.	$ 542,058.49	CND193	STANDARD CONSTRUCTION CO., INC.	$ 284,895.95
CND109	WHITE CONTRACTING, INC.	$ 590,354.65	CND211	HIGHWAYS, INC.	$ 282,282.00
CND116	BLUEGRASS CONTRACTING CORPORATION	$ 798,420.24	CND211	HILL BROS. EXCAVATING, INC.	$ 327,139.97
CND116	EATHERLY GROUP, INC.	$ 786,930.76	CND211	MARCUM EXCAVATING	$ 406,367.50
CND116	HIGHWAYS, INC.	$ 702,621.95	CND223	APAC-TENNESSEE, INC. (A)	$ 300,425.00
CND128	RENFRO CONSTRUCTION CO., INC.	$ 239,008.40	CND223	CHARLES BLALOCK & SONS, INC.	$ 312,445.70
CND128	ROGERS GROUP, INC.	$ 294,030.25	CND226	ROGERS GROUP, INC.	$ 607,589.20
CND129	HIGHWAYS, INC.	$ 489,894.00	CND242	RENFRO CONSTRUCTION CO., INC.	$ 151,605.79
CND129	LOJAC ENTERPRISES, INC.	$ 445,196.25	CND242	ROGERS GROUP, INC.	$ 178,765.96

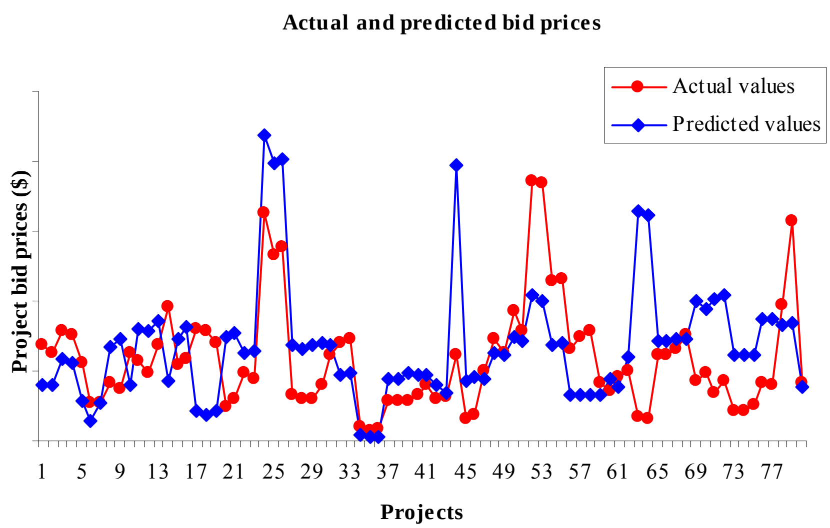
Project #	Name of Contractor	Bid price quoted	Project #	Name of Contractor	Bid price quoted
CND252	EUBANK ASPHALT PAVING & SEALING	$ 493,652.00	CND381	CHRIS-HILL CONSTRUCTION CO., LLC	$ 432,697.25
CND258	LOJAC ENTERPRISES, INC.	$ 725,934.60	CND381	DEMENT CONSTRUCTION CO., LLC	$ 488,066.75
CND258	ROGERS GROUP, INC.	$ 634,845.50	CND381	THOMSON & THOMSON, INC.	$ 337,904.20
CND282	BELL & ASSOCIATES CONSTRUCTION, L.P.	$ 925,094.90	CND381	W. L. SHARPE CONTRACTING COMPANY, L. P.	$ 431,139.06
CND282	GENERAL CONSTRUCTORS, INC.	$ 781,349.96	CND417	GENERAL CONSTRUCTORS, INC.	$ 216,576.00
CND284	DEMENT CONSTRUCTION COMPANY	$ 1,859,722.45	CND417	JAMISON CONSTRUCTION, LLC	$ 209,310.00
CND284	FORD CONSTRUCTION COMPANY	$ 1,847,741.44	CND417	MID-STATE CONSTRUCTION COMPANY, INC.	$ 251,342.38
CND306	EUBANK ASPHALT PAVING & SEALING	$ 1,139,495.45	CND421	JAMISON CONSTRUCTION, LLC	$ 416,849.70
CND306	LOJAC ENTERPRISES, INC.	$ 1,158,879.29	CND421	MID-STATE CONSTRUCTION COMPANY, INC.	$ 404,867.10
CND309	CUMBERLAND GUARDRAIL, INC.	$ 657,700.00	CND908	HIGHWAYS, INC.	$ 969,543.00
CND309	TENNESSEE GUARDRAIL, INC.	$ 740,638.00	CND908	LOJAC ENTERPRISES, INC.	$ 1,568,488.70
CND309	TRI-STATE GUARDRAIL & SIGN CO., INC.	$ 783,562.00	CND932	SUMMERS-TAYLOR, INC.	$ 409,948.20
CND318	CHARLES BLALOCK & SONS, INC.	$ 419,929.50			
CND318	HINKLE CONTRACTING CORPORATION	$ 359,853.90			
CND318	PHILLIPS AND JORDAN, INCORPORTATED	$ 453,202.00			
CND334	GREENSTAR, LLC	$ 493,517.76			
CND352	S & W CONTRACTING CO., INC.	$ 170,948.70			
CND352	STANSELL ELECTRIC CO., INC.	$ 160,196.25			
CND374	GENERAL CONSTRUCTORS, INC.	$ 613,829.00			
CND374	JAMISON CONSTRUCTION, LLC	$ 616,392.50			
CND374	SOUTHERN CONSTRUCTORS, INC.	$ 662,598.00			
CND374	WILLIAMS RESTORATION & WATERPROOFING, IN	$ 759,360.25			

APPENDIX F

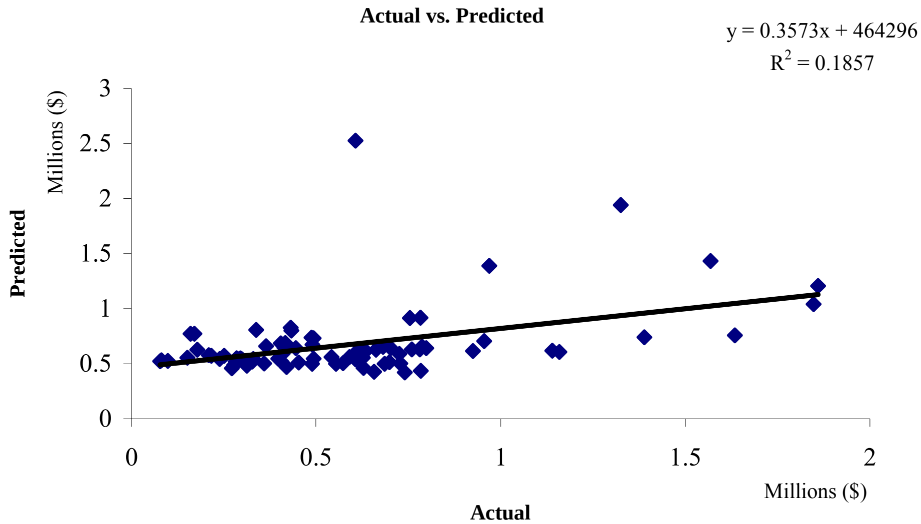
Results from Multivariate Adaptive Regression Splines analysis.

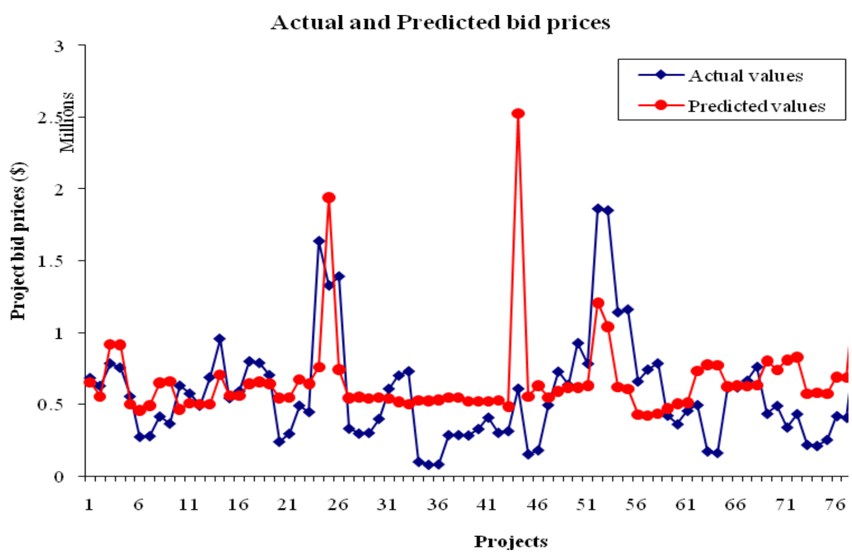
MODEL 1: RESULTS



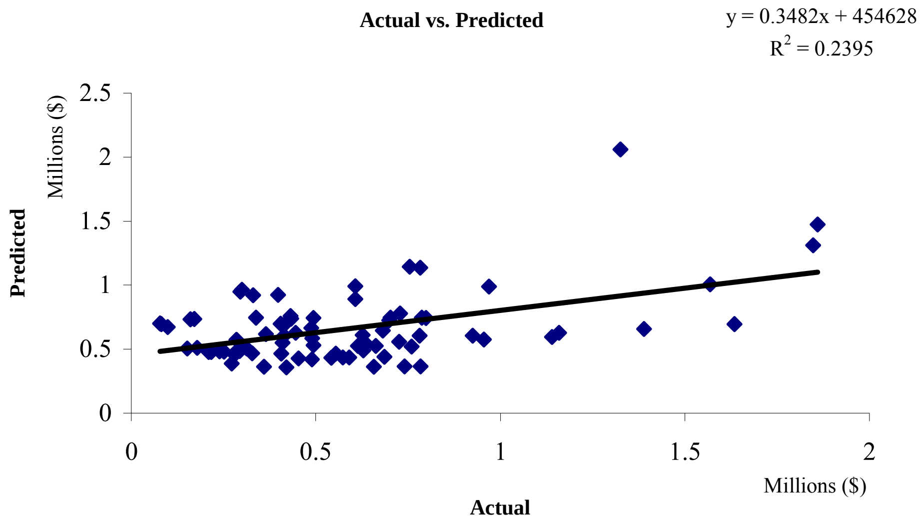


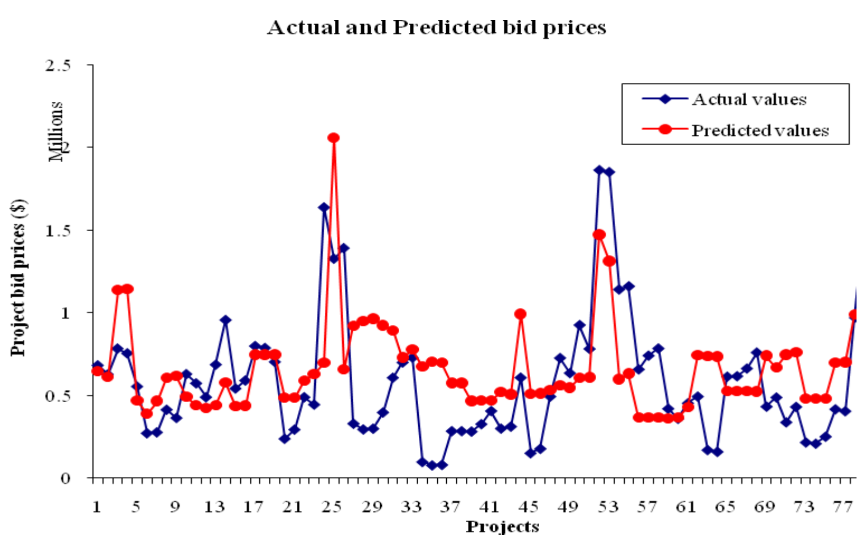
MODEL 2: RESULTS



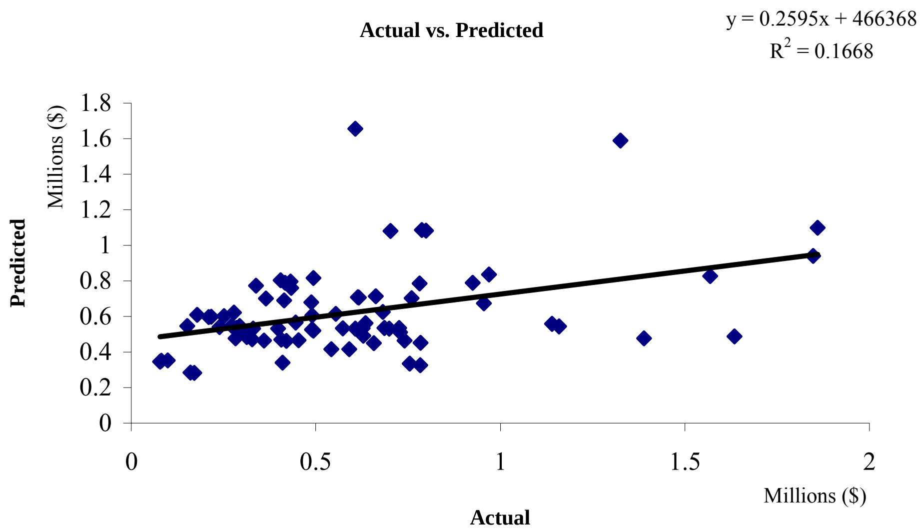


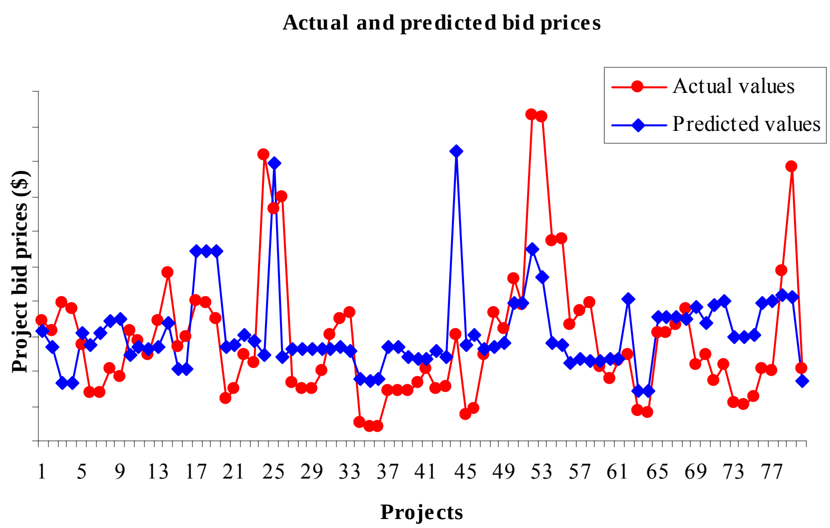
MODEL 3: RESULTS



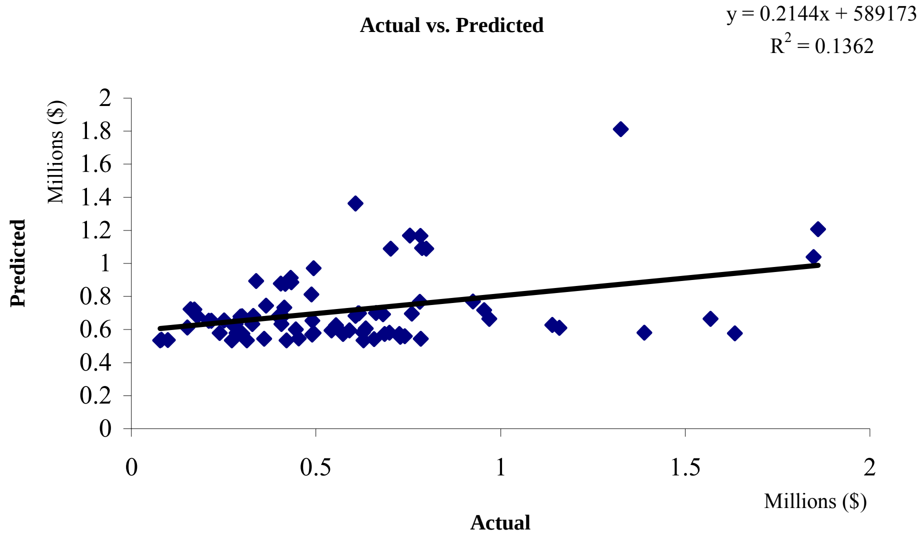


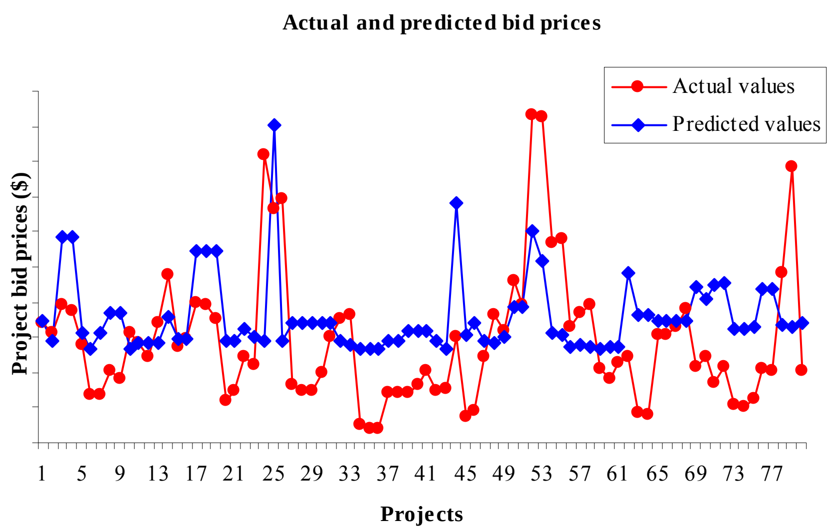
MODEL 4: RESULTS



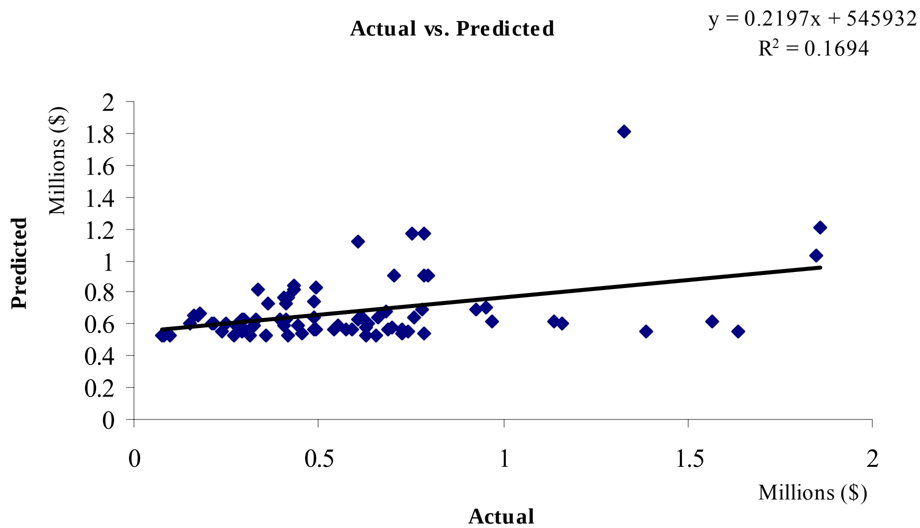


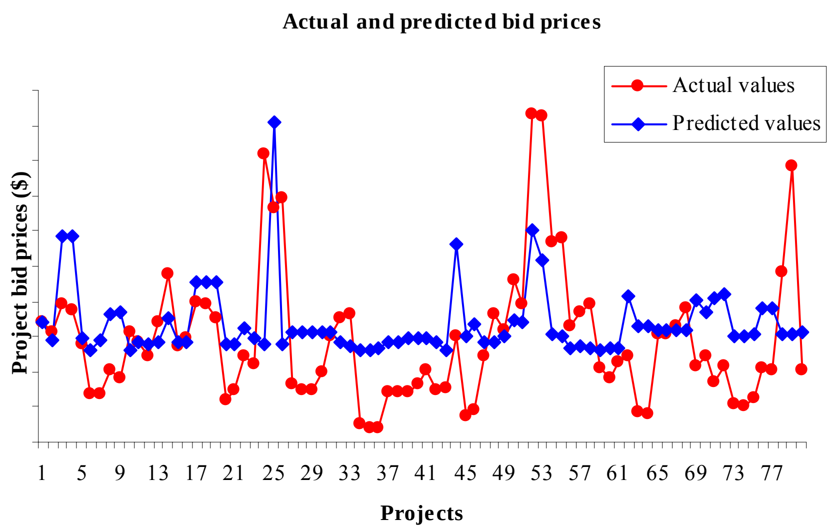
MODEL 6: RESULTS



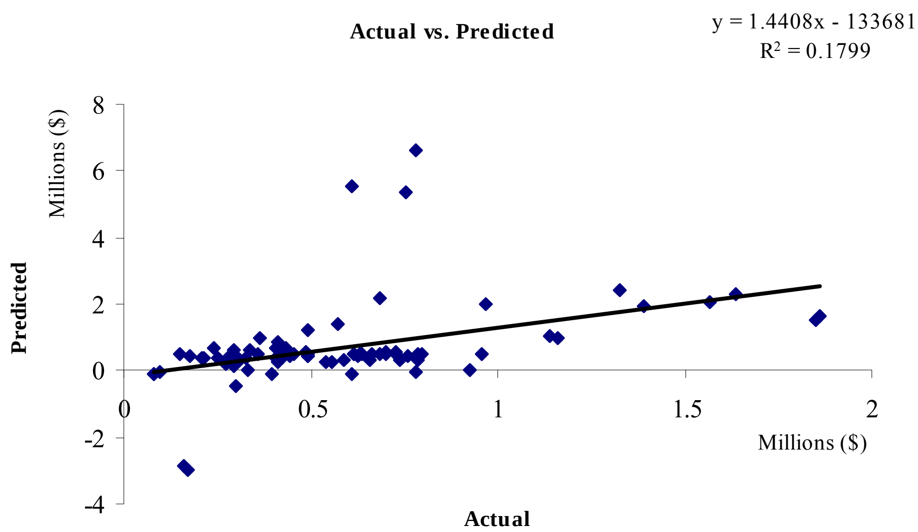


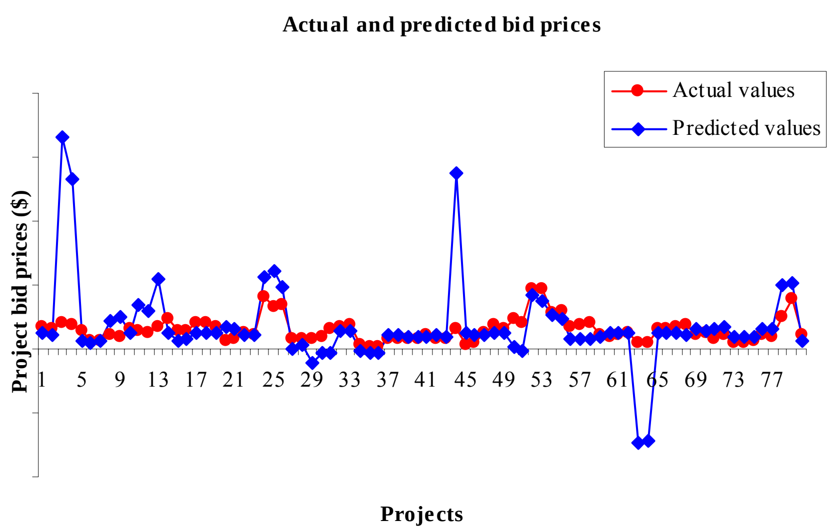
MODEL 7: RESULTS



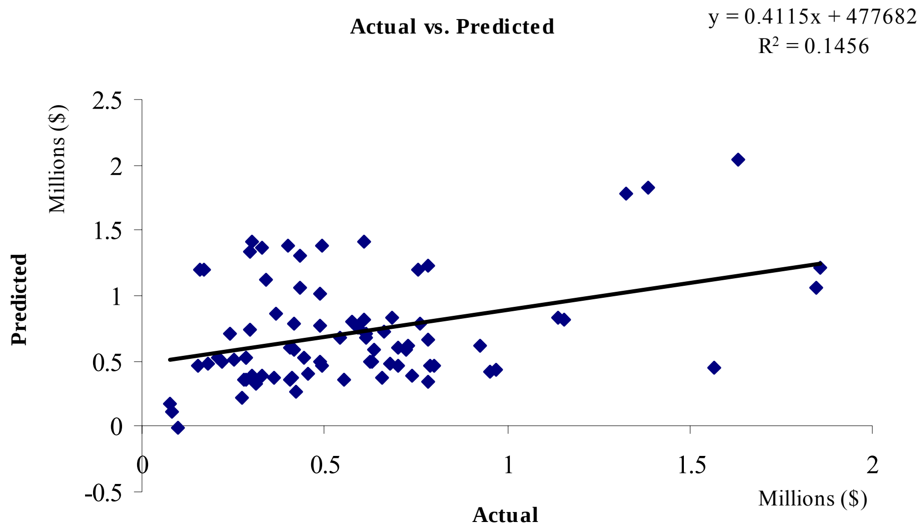


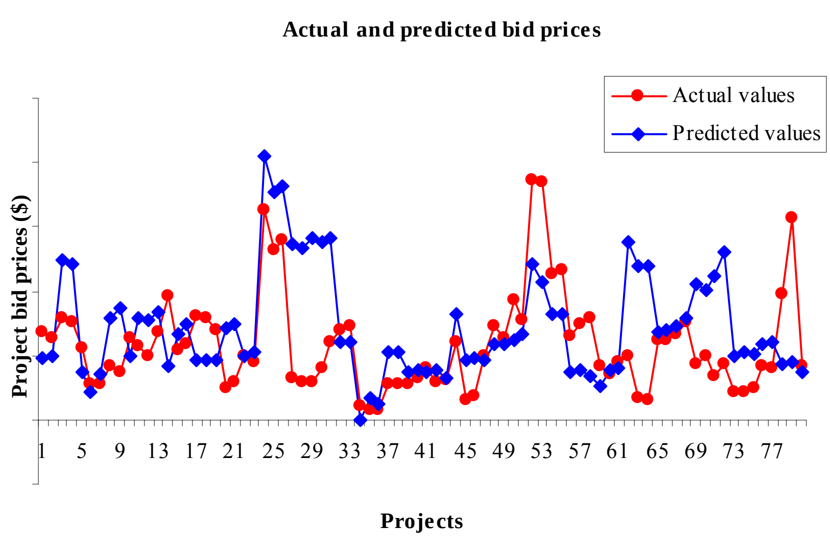
MODEL 8: RESULTS



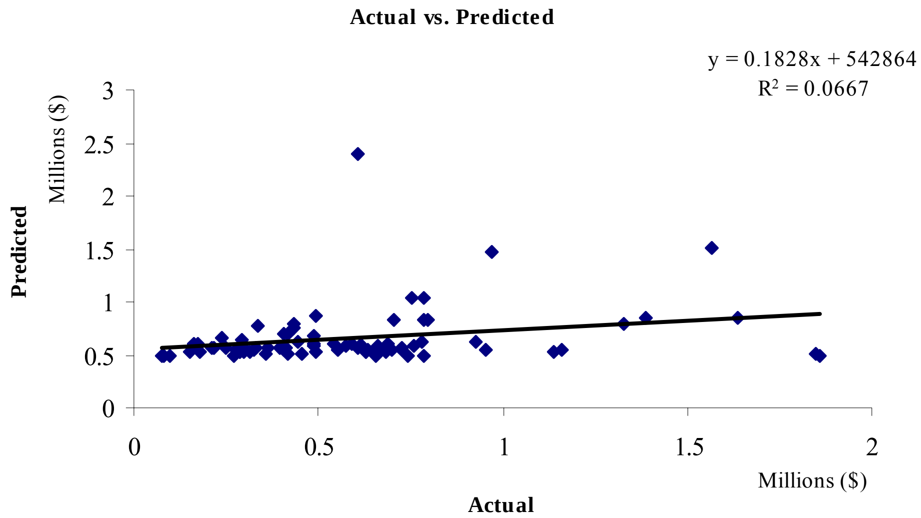


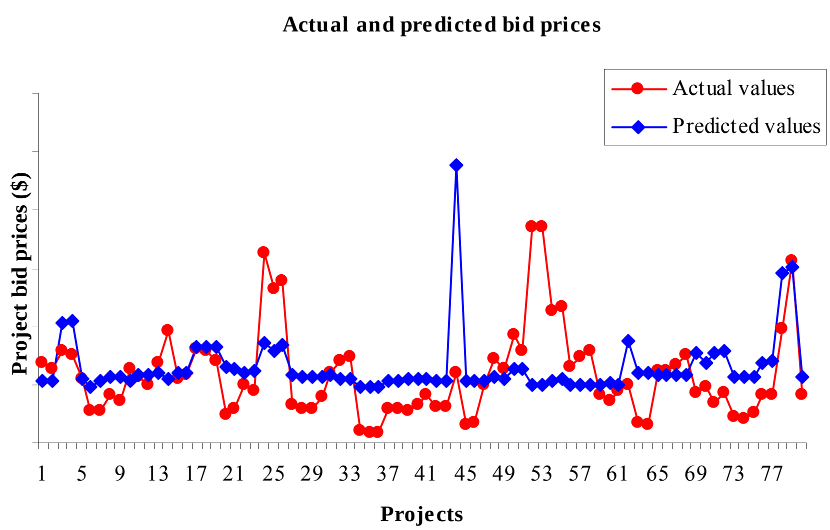
MODEL 9: RESULTS



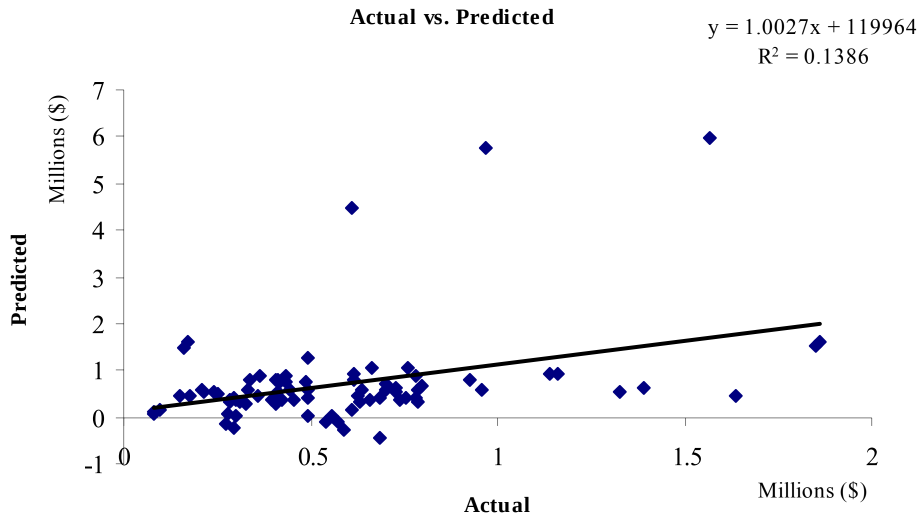


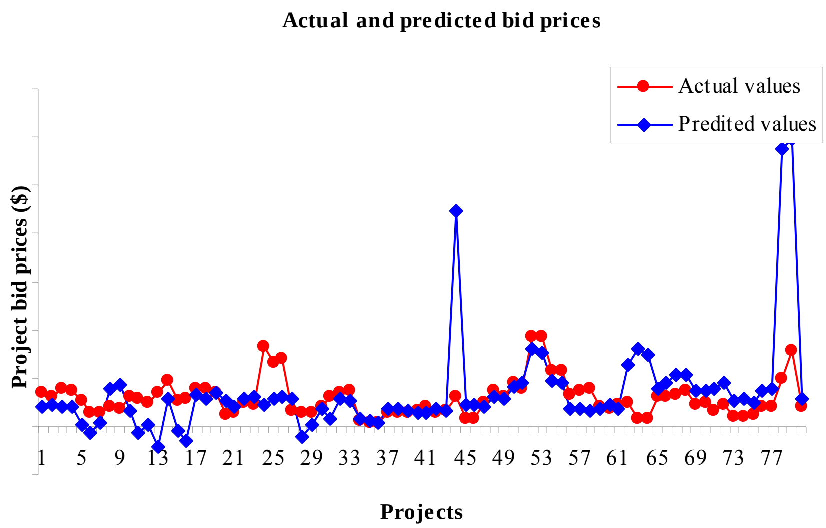
MODEL 10: RESULTS



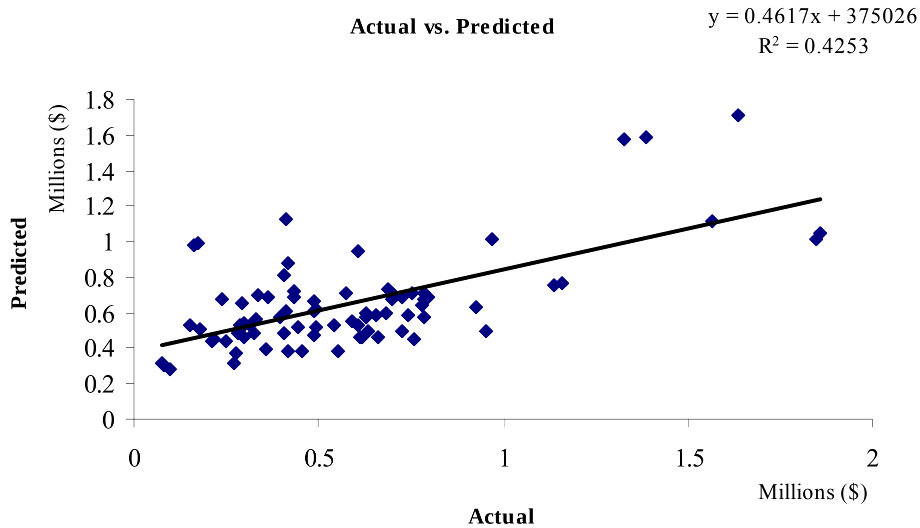


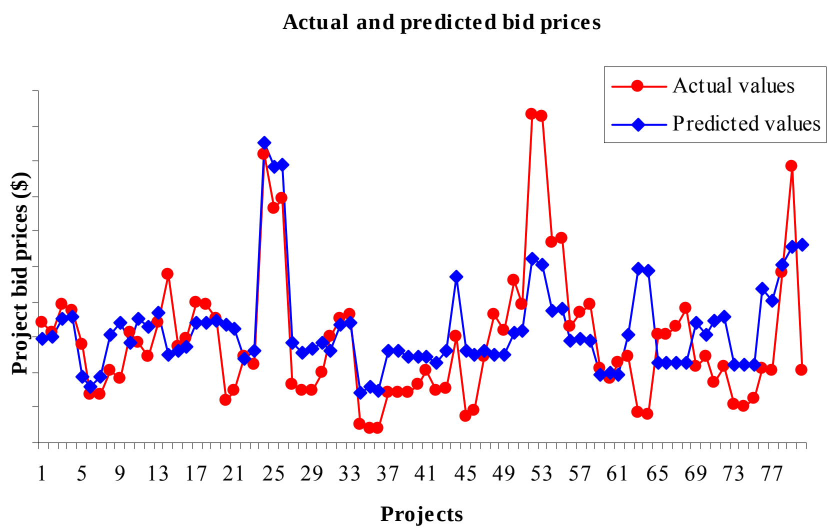
MODEL 11: RESULTS



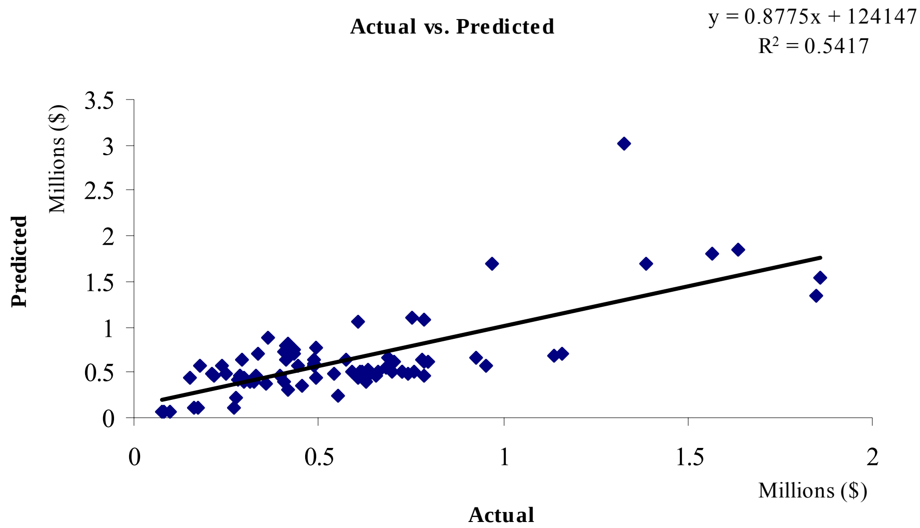


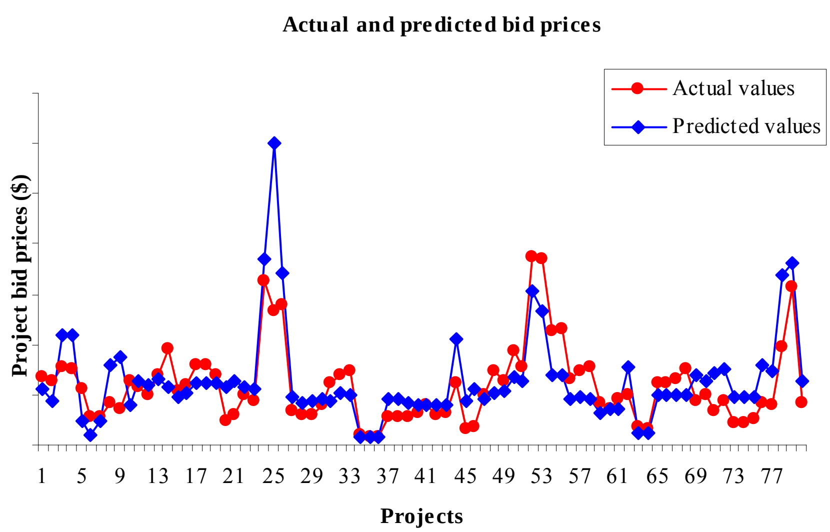
MODEL 12: RESULTS





MODEL 13: RESULTS





APPENDIX G

Results from the MARS model 5

Model 1: nr. basis func. = 14, GCV = 297086250089.684450, eff. params = 217.999725

File: train.SAV
Target Variable: V109
Predictor Variables: V1, V2, V3, V4, V5, V6, V7, V8, V9, V10, V11, V12, V13, V14, V15, V16, V17, V18, V19, V20, V21, V22, V23, V24, V25, V26, V27, V28, V29, V30, V31, V32, V33, V34, V35, V36, V37, V38, V39, V40, V41, V42, V43, V44, V45, V46, V47, V48, V49, V50, V51, V52, V53, V54, V55, V56, V57, V58, V59, V60, V61, V62, V63, V64, V65, V66, V67, V68, V69, V70, V71, V72, V73, V74, V75, V76, V77, V78, V79, V80, V81, V82, V83, V84, V85, V86, V87, V88, V89, V90, V91, V92, V93, V94, V95, V96, V97, V98, V99, V100, V101, V102, V103, V104, V105, V106, V107, V108
Predictor Missings: No variables created for missings

Anova Decomposition

Function	Standard Deviation	Cost of Omission	No. of Basis Functions	No. of Effective Parameters	Variables	Variables	Variables	Variables
1	350663.785	4.87162230E+011	1	15.500	V3			
2	154971.292	3.00680905E+011	1	15.500	V4			
3	281409.506	4.71261138E+011	1	15.500	V64			
4	185200.917	3.57699339E+011	1	15.500	V3	V37		
5	233343.526	3.52453961E+011	1	15.500	V4	V29		
6	411541.519	3.33011996E+011	1	15.500	V6	V53		
7	212509.020	3.81635668E+011	1	15.500	V7	V9		
8	229570.837	4.01336288E+011	1	15.500	V4	V29	V44	
9	213678.605	3.26721719E+011	1	15.500	V6	V35	V53	
10	305532.581	4.53068717E+011	2	31.000	V3	V11	V81	
11	618639.215	4.47758426E+011	1	15.500	V1	V6	V53	
12	187427.122	3.61303802E+011	1	15.500	V4	V29	V44	V70
13	118457.863	3.02994481E+011	1	15.500	V3	V11	V42	V81

Variable Importance

<table>
<tr><th>Variable</th><th>Cost of Omission</th><th>Importance</th><th></th></tr>
<tr><td>V3</td><td>6.95862493E+011</td><td>100.000</td><td>||||||||||||||||||||||||||||||||||||||||||||||||||</td></tr>
<tr><td>V6</td><td>5.93241899E+011</td><td>86.178</td><td>|||||||||||||||||||||||||||||||||||||||||||</td></tr>
<tr><td>V53</td><td>5.93241899E+011</td><td>86.178</td><td>|||||||||||||||||||||||||||||||||||||||||||</td></tr>
<tr><td>V64</td><td>4.71261184E+011</td><td>66.089</td><td>|||||||||||||||||||||||||||||||||</td></tr>
<tr><td>V11</td><td>4.65476780E+011</td><td>64.982</td><td>||||||||||||||||||||||||||||||||</td></tr>
<tr><td>V81</td><td>4.65476780E+011</td><td>64.982</td><td>||||||||||||||||||||||||||||||||</td></tr>
<tr><td>V29</td><td>4.52977623E+011</td><td>62.524</td><td>|||||||||||||||||||||||||||||||</td></tr>
<tr><td>V1</td><td>4.47758434E+011</td><td>61.468</td><td>|||||||||||||||||||||||||||||||</td></tr>
<tr><td>V44</td><td>4.35520504E+011</td><td>58.919</td><td>|||||||||||||||||||||||||||||</td></tr>
<tr><td>V4</td><td>4.15597560E+011</td><td>54.515</td><td>|||||||||||||||||||||||||||</td></tr>
<tr><td>V7</td><td>3.81635658E+011</td><td>46.046</td><td>|||||||||||||||||||||||</td></tr>
<tr><td>V9</td><td>3.81635658E+011</td><td>46.046</td><td>|||||||||||||||||||||||</td></tr>
<tr><td>V70</td><td>3.61303835E+011</td><td>40.129</td><td>||||||||||||||||||||</td></tr>
<tr><td>V37</td><td>3.57699322E+011</td><td>38.987</td><td>|||||||||||||||||||</td></tr>
<tr><td>V35</td><td>3.26721700E+011</td><td>27.261</td><td>|||||||||||||</td></tr>
<tr><td>V42</td><td>3.02994555E+011</td><td>12.172</td><td>||||||</td></tr>
<tr><td>V2</td><td>2.97085960E+011</td><td>0.000</td><td></td></tr>
<tr><td>V5</td><td>2.97085960E+011</td><td>0.000</td><td></td></tr>
<tr><td>V8</td><td>2.97085960E+011</td><td>0.000</td><td></td></tr>
<tr><td>V10</td><td>2.97085960E+011</td><td>0.000</td><td></td></tr>
<tr><td>V12</td><td>2.97085960E+011</td><td>0.000</td><td></td></tr>
<tr><td>V13</td><td>2.97085960E+011</td><td>0.000</td><td></td></tr>
<tr><td>V14</td><td>2.97085960E+011</td><td>0.000</td><td></td></tr>
<tr><td>V15</td><td>2.97085960E+011</td><td>0.000</td><td></td></tr>
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Variable	Cost of Omission	Importance	
V16	2.97085960E+011	0.000	
V17	2.97085960E+011	0.000	
V18	2.97085960E+011	0.000	
V19	2.97085960E+011	0.000	
V20	2.97085960E+011	0.000	
V21	2.97085960E+011	0.000	
V22	2.97085960E+011	0.000	
V23	2.97085960E+011	0.000	
V24	2.97085960E+011	0.000	
V25	2.97085960E+011	0.000	
V26	2.97085960E+011	0.000	
V27	2.97085960E+011	0.000	
V28	2.97085960E+011	0.000	
V30	2.97085960E+011	0.000	
V31	2.97085960E+011	0.000	
V32	2.97085960E+011	0.000	
V33	2.97085960E+011	0.000	
V34	2.97085960E+011	0.000	
V36	2.97085960E+011	0.000	
V38	2.97085960E+011	0.000	
V39	2.97085960E+011	0.000	
V40	2.97085960E+011	0.000	
V41	2.97085960E+011	0.000	
V43	2.97085960E+011	0.000	
V45	2.97085960E+011	0.000	
V46	2.97085960E+011	0.000	
V47	2.97085960E+011	0.000	
V48	2.97085960E+011	0.000	
V49	2.97085960E+011	0.000	
V50	2.97085960E+011	0.000	
V51	2.97085960E+011	0.000	
V52	2.97085960E+011	0.000	
V54	2.97085960E+011	0.000	
V55	2.97085960E+011	0.000	
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V60	2.97085960E+011	0.000	
V61	2.97085960E+011	0.000	
V62	2.97085960E+011	0.000	
V63	2.97085960E+011	0.000	
V65	2.97085960E+011	0.000	
V66	2.97085960E+011	0.000	
V67	2.97085960E+011	0.000	
V68	2.97085960E+011	0.000	
V69	2.97085960E+011	0.000	
V71	2.97085960E+011	0.000	
V72	2.97085960E+011	0.000	
V73	2.97085960E+011	0.000	
V74	2.97085960E+011	0.000	
V75	2.97085960E+011	0.000	
V76	2.97085960E+011	0.000	
V77	2.97085960E+011	0.000	
V78	2.97085960E+011	0.000	
V79	2.97085960E+011	0.000	
V80	2.97085960E+011	0.000	
V82	2.97085960E+011	0.000	
V83	2.97085960E+011	0.000	
V84	2.97085960E+011	0.000	
V85	2.97085960E+011	0.000	
V86	2.97085960E+011	0.000	
V87	2.97085960E+011	0.000	
V88	2.97085960E+011	0.000	
V89	2.97085960E+011	0.000	
V90	2.97085960E+011	0.000	

Variable	Cost of Omission	Importance	
V91	2.97085960E+011	0.000	
V92	2.97085960E+011	0.000	
V93	2.97085960E+011	0.000	
V94	2.97085960E+011	0.000	
V95	2.97085960E+011	0.000	
V96	2.97085960E+011	0.000	
V97	2.97085960E+011	0.000	
V98	2.97085960E+011	0.000	
V99	2.97085960E+011	0.000	
V100	2.97085960E+011	0.000	
V101	2.97085960E+011	0.000	
V102	2.97085960E+011	0.000	
V103	2.97085960E+011	0.000	
V104	2.97085960E+011	0.000	
V105	2.97085960E+011	0.000	
V106	2.97085960E+011	0.000	
V107	2.97085960E+011	0.000	
V108	2.97085960E+011	0.000	

Final Model

Basis Function	Coefficient	Variable	Parent	Knot
0	347729.313			
1	2160884.75	V3		0.549
4	-161361.938	V4		3.010
6	143573.984	V37	V3	0.114
8	296869.188	V64		-2.442
10	18109.969	V29	V4	6.760
14	9289.705	V44	V29	-0.317
15	7624.673	V70	V44	1.956
22	-231047.984	V6	V53	2.233
23	39573.816	V35	V6	-2.422
25	1140948.38	V81	V11	1.449
26	269260.594	V81	V11	1.449
28	40768.789	V7	V9	0.009
29	27609.434	V1	V6	-12.629
31	345902.313	V42	V81	0.166

Basis Functions

```
BF1 = max(0, V3 - 0.549);
BF2 = max(0, 0.549 - V3 );
BF4 = max(0, 3.010 - V4 );
BF6 = max(0, 0.114 - V37 ) * BF2;
BF8 = max(0, - 2.442 - V64 );
BF10 = max(0, 6.760 - V29 ) * BF4;
BF12 = max(0, - 0.217 - V11 ) * BF1;
BF13 = max(0, V44 + 0.317) * BF10;
BF14 = max(0, - 0.317 - V44 ) * BF10;
BF15 = max(0, V70 - 1.956) * BF13;
BF18 = max(0, 6.319 - V9 );
BF20 = max(0, 0.261 - V53 );
BF22 = max(0, 2.233 - V6 ) * BF20;
BF23 = max(0, V35 + 2.422) * BF22;
BF25 = max(0, V81 - 1.449) * BF12;
BF26 = max(0, 1.449 - V81 ) * BF12;
BF28 = max(0, 0.009 - V7 ) * BF18;
BF29 = max(0, V1 + 12.629) * BF22;
BF31 = max(0, 0.166 - V42 ) * BF26;

Y = 347729.313 + 2160884.750 * BF1 - 161361.938 * BF4
               + 143573.984 * BF6 + 296869.188 * BF8 + 18109.969 * BF10
               + 9289.705 * BF14 + 7624.673 * BF15 - 231047.984 * BF22
```

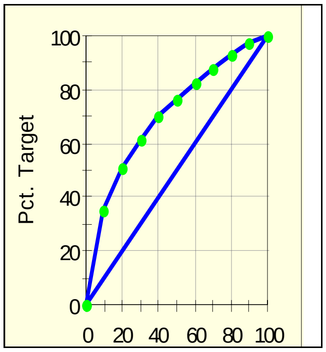
```
          + 39573.816 * BF23 + 1140948.375 * BF25
          + 269260.594 * BF26 + 40768.789 * BF28
          + 27609.434 * BF29 + 345902.313 * BF31;

model V109 = BF1 BF4 BF6 BF8 BF10 BF14 BF15 BF22 BF23 BF25 BF26 BF28 BF29
             BF31
```

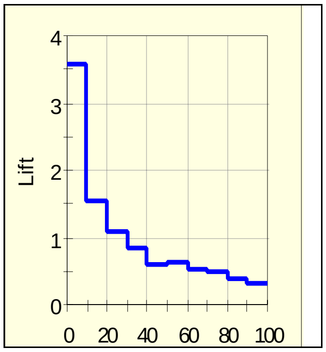
Gains Data

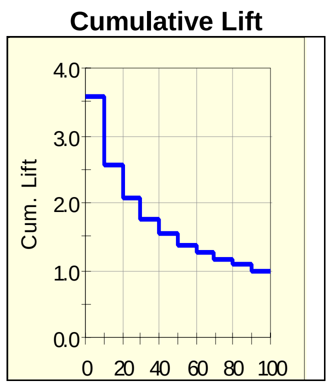
Bin	Target Bin Avg.	% Target in Bin	Cum. % Target	Cum. % Pop.	% Pop	Cases in Bin	Cum. Lift	Lift
1	3.23188E+006	35.25	35.25	9.86	9.86	51	3.573	3.573
2	1.39139E+006	15.47	50.72	19.92	10.06	52	2.546	1.538
3	997664.	11.09	61.81	29.98	10.06	52	2.062	1.103
4	772006.	8.42	70.23	39.85	9.86	51	1.763	0.853
5	548664.	6.10	76.33	49.90	10.06	52	1.530	0.607
6	557813.	6.20	82.53	59.96	10.06	52	1.376	0.617
7	490756.	5.35	87.89	69.83	9.86	51	1.259	0.543
8	460156.	5.12	93.00	79.88	10.06	52	1.164	0.509
9	353154.	3.93	96.93	89.94	10.06	52	1.078	0.390
10	276078.	3.07	100.00	100.00	10.06	52	1.000	0.305

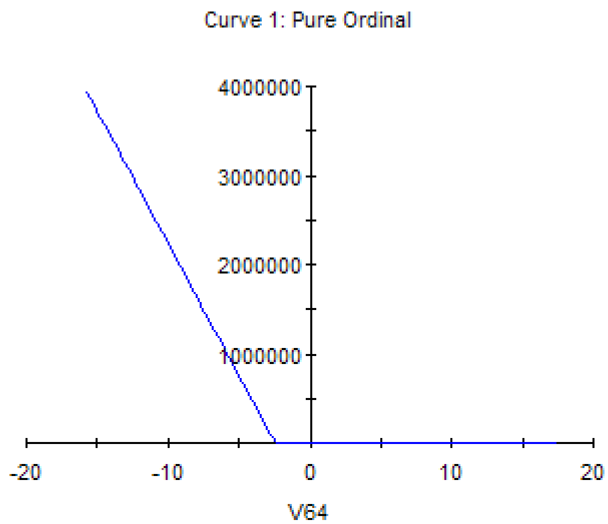
Gains

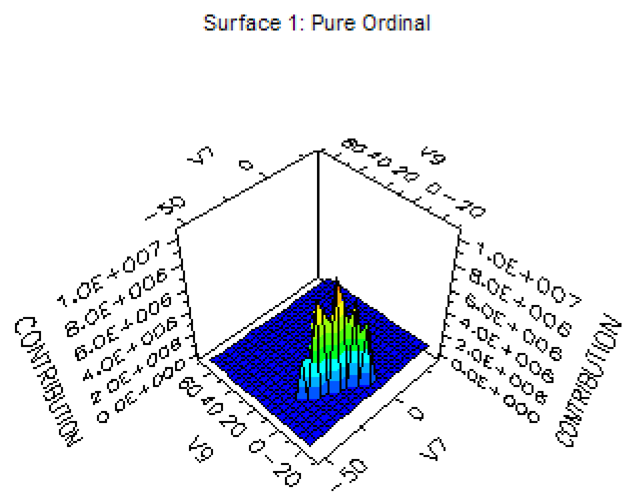


Lift




Cumulative Lift
Cum. Lift
4.0
3.0
2.0
1.0
0.0
0
20
40
60
80
100


Curve 1: Pure Ordinal
4000000
3000000
2000000
1000000
-20
-10
0
10
20
V64


Surface 1: Pure Ordinal
CONTRIBUTION
V5
V9

```
>

 MARS VERSION 2.0.0.20 (8192 Variables)
 COPYRIGHT, 1991-1999, SALFORD SYSTEMS, SAN DIEGO, CALIFORNIA, U.S.A.

>LOPTIONS MEANS = YES, PLOTS = YES
>FORMAT = 3/UNDERFLOW
>LOPTIONS MEANS = YES, PLOTS = YES
>FORMAT = 3/UNDERFLOW
>USE 'C:\Mars run 5\train.SAV[spsswin]'
 VARIABLES IN RECT FILE ARE:
        V1           V2          V3              V4              V5
        V6           V7          V8              V9             V10
       V11          V12         V13             V14             V15
       V16          V17         V18             V19             V20
       V21          V22         V23             V24             V25
       V26          V27         V28             V29             V30
       V31          V32         V33             V34             V35
       V36          V37         V38             V39             V40
       V41          V42         V43             V44             V45
       V46          V47         V48             V49             V50
       V51          V52         V53             V54             V55
       V56          V57         V58             V59             V60
       V61          V62         V63             V64             V65
       V66          V67         V68             V69             V70
       V71          V72         V73             V74             V75
       V76          V77         V78             V79             V80
       V81          V82         V83             V84             V85
       V86          V87         V88             V89             V90
       V91          V92         V93             V94             V95
       V96          V97         V98             V99            V100
      V101         V102        V103            V104            V105
      V106         V107        V108            V109

 C:\Mars run 5\train.SAV[spsswin]: 517 RECORDS.

>USE "C:\Mars run 5\valid.SAV[spsswin]"
 VARIABLES IN RECT FILE ARE:
        V1           V2          V3              V4              V5
        V6           V7          V8              V9             V10
       V11          V12         V13             V14             V15
       V16          V17         V18             V19             V20
       V21          V22         V23             V24             V25
       V26          V27         V28             V29             V30
       V31          V32         V33             V34             V35
       V36          V37         V38             V39             V40
       V41          V42         V43             V44             V45
       V46          V47         V48             V49             V50
       V51          V52         V53             V54             V55
       V56          V57         V58             V59             V60
       V61          V62         V63             V64             V65
       V66          V67         V68             V69             V70
       V71          V72         V73             V74             V75
       V76          V77         V78             V79             V80
```

```
      V81          V82          V83          V84          V85
      V86          V87          V88          V89          V90
      V91          V92          V93          V94          V95
      V96          V97          V98          V99         V100
     V101         V102         V103         V104         V105
     V106         V107         V108

 C:\Mars run 5\valid.SAV[spsswin]: 80 RECORDS.

>RETRIEVE "C:\Mars run 5\Model5.mdl"
>SAVE "C:\Mars run 5\new2.XLS[xls7]"
>APPLY

 Dependent variable: V109 not found on your dataset.

 READING DATA, UP TO 8865 RECORDS.

 RECORDS READ: 80
 RECORDS KEPT IN LEARNING SAMPLE: 80

<a name="0"></a>

 LEARNING SAMPLE STATISTICS
 ==========================

 VARIABLE         MEAN            SD             N           SUM
 ----------------------------------------------------------------
       V1       -0.492         1.075        80.000       -39.346
       V2        1.044         0.083        80.000        83.545
       V3        0.575         0.066        80.000        45.965
       V4       -0.687         0.739        80.000       -54.934
       V5       -0.343         0.372        80.000       -27.426
       V6        0.637         0.740        80.000        50.960
       V7       -1.172         8.719        80.000       -93.770
       V8        0.850         4.730        80.000        68.022
       V9       -0.100         2.609        80.000        -7.977
      V10        0.155         1.254        80.000        12.400
      V11       -0.045         1.534        80.000        -3.637
      V12       -0.250         1.145        80.000       -20.007
      V13       -0.175         1.072        80.000       -13.970
      V14        0.556         2.133        80.000        44.449
      V15        0.554         1.934        80.000        44.307
      V16       -0.018         1.065        80.000        -1.411
      V17       -0.622         0.955        80.000       -49.764
      V18       -0.856         0.961        80.000       -68.450
      V19        0.782         0.982        80.000        62.586
      V20        0.600         1.746        80.000        48.011
      V21        0.540         1.178        80.000        43.218
      V22        0.305         6.669        80.000        24.439
      V23       -1.146         7.093        80.000       -91.643
      V24        1.307         4.450        80.000       104.542
      V25       -0.128         1.223        80.000       -10.220
      V26       -0.059         2.091        80.000        -4.734
      V27        0.630         1.529        80.000        50.382
      V28        0.032         2.907        80.000         2.560
      V29        0.010         2.828        80.000         0.809
      V30       -0.557         2.309        80.000       -44.530
```

V31	0.277	1.290	80.000	22.152
V32	0.737	3.610	80.000	58.949
V33	0.411	2.985	80.000	32.842
V34	0.268	2.090	80.000	21.447
V35	-0.480	3.304	80.000	-38.390
V36	0.336	2.625	80.000	26.874
V37	-0.424	5.360	80.000	-33.939
V38	-0.402	3.635	80.000	-32.171
V39	-0.077	3.272	80.000	-6.125
V40	0.118	1.369	80.000	9.420
V41	-0.020	0.762	80.000	-1.630
V42	0.265	0.821	80.000	21.214
V43	-0.094	0.965	80.000	-7.535
V44	-0.353	0.959	80.000	-28.229
V45	-0.137	2.200	80.000	-10.949
V46	0.271	2.663	80.000	21.658
V47	0.213	1.809	80.000	17.011
V48	0.412	3.011	80.000	32.935
V49	0.244	2.403	80.000	19.550
V50	-0.663	3.492	80.000	-53.077
V51	0.159	1.194	80.000	12.747
V52	-0.475	4.053	80.000	-38.012
V53	-0.186	0.447	80.000	-14.844
V54	0.461	2.731	80.000	36.902
V55	0.125	2.072	80.000	10.033
V56	-0.300	1.127	80.000	-24.007
V57	0.345	1.262	80.000	27.599
V58	0.065	1.670	80.000	5.200
V59	0.075	1.131	80.000	5.976
V60	-0.324	1.552	80.000	-25.884
V61	-0.007	0.825	80.000	-0.542
V62	0.596	4.070	80.000	47.699
V63	0.153	2.960	80.000	12.213
V64	0.169	1.370	80.000	13.542
V65	0.132	2.693	80.000	10.555
V66	-0.251	2.957	80.000	-20.073
V67	-0.194	1.441	80.000	-15.551
V68	0.711	2.623	80.000	56.869
V69	0.630	2.492	80.000	50.395
V70	0.209	2.323	80.000	16.745
V71	0.070	1.494	80.000	5.575
V72	0.432	2.672	80.000	34.564
V73	-1.008	4.502	80.000	-80.613
V74	-0.035	0.100	80.000	-2.818
V75	0.194	2.042	80.000	15.498
V76	0.064	1.833	80.000	5.158
V77	-0.503	1.452	80.000	-40.206
V78	0.119	2.409	80.000	9.505
V79	0.015	1.080	80.000	1.187
V80	0.227	1.254	80.000	18.124
V81	-0.204	3.544	80.000	-16.327
V82	0.245	1.972	80.000	19.639
V83	0.089	1.468	80.000	7.113
V84	-0.079	0.382	80.000	-6.334
V85	-0.179	1.521	80.000	-14.345
V86	0.090	1.710	80.000	7.204
V87	0.039	0.760	80.000	3.083

```
     V88        -0.119        2.128        80.000        -9.495
     V89         0.367        2.121        80.000        29.323
     V90        -0.533        2.573        80.000       -42.635
     V91         0.430        2.314        80.000        34.429
     V92         0.423        1.474        80.000        33.852
     V93         0.020        1.613        80.000         1.615
     V94         0.132        1.607        80.000        10.551
     V95        -0.436        1.724        80.000       -34.909
     V96         0.121        1.621        80.000         9.703
     V97         0.073        2.596        80.000         5.875
     V98        -0.173        1.309        80.000       -13.871
     V99        -0.090        0.772        80.000        -7.205
    V100         0.152        1.028        80.000        12.141
    V101         0.317        1.945        80.000        25.351
    V102         0.720        2.895        80.000        57.620
    V103        -0.319        3.339        80.000       -25.496
    V104         0.312        1.626        80.000        24.978
    V105        -0.302        1.648        80.000       -24.136
    V106        -0.683        2.088        80.000       -54.627
    V107        -0.067        1.793        80.000        -5.397
    V108         0.081        1.639        80.000         6.510


 SAVE FILE CREATED.
 80 RECORDS WRITTEN TO SAVE FILE.

<a name="1"></a>

 PREDICTION STATISTICS
 =====================

            Minimum:   25839.816
            Maximum: 2131535.250
               Mean:  619974.629
 Standard Deviation:  386684.505
>USE 'C:\Mars run 5\train.SAV[spsswin]'
 VARIABLES IN RECT FILE ARE:
        V1       V2             V3             V4             V5
        V6       V7             V8             V9            V10
       V11      V12            V13            V14            V15
       V16      V17            V18            V19            V20
       V21      V22            V23            V24            V25
       V26      V27            V28            V29            V30
       V31      V32            V33            V34            V35
       V36      V37            V38            V39            V40
       V41      V42            V43            V44            V45
       V46      V47            V48            V49            V50
       V51      V52            V53            V54            V55
       V56      V57            V58            V59            V60
       V61      V62            V63            V64            V65
       V66      V67            V68            V69            V70
       V71      V72            V73            V74            V75
       V76      V77            V78            V79            V80
       V81      V82            V83            V84            V85
       V86      V87            V88            V89            V90
       V91      V92            V93            V94            V95
       V96      V97            V98            V99           V100
```

```
       V101     V102           V103           V104           V105
       V106     V107           V108           V109

 C:\Mars run 5\train.SAV[spsswin]: 517 RECORDS.

>KEEP
>CATEGORY
>LINEAR
>ADDITIVE
>REGRESSION = OLS
>MODEL V109
>KEEP V1, V2, V3, V4, V5, V6, V7, V8, V9, V10, V11, V12, V13, V14, V15,
>     V16, V17, V18, V19, V20, V21, V22, V23, V24, V25, V26, V27, V28,
>     V29, V30, V31, V32, V33, V34, V35, V36, V37, V38, V39, V40, V41,
>     V42, V43, V44, V45, V46, V47, V48, V49, V50, V51, V52, V53, V54,
>     V55, V56, V57, V58, V59, V60, V61, V62, V63, V64, V65, V66, V67,
>     V68, V69, V70, V71, V72, V73, V74, V75, V76, V77, V78, V79, V80,
>     V81, V82, V83, V84, V85, V86, V87, V88, V89, V90, V91, V92, V93,
>     V94, V95, V96, V97, V98, V99, V100, V101, V102, V103, V104, V105,
>     V106, V107, V108
>WEIGHT
>SELECT
>BOPTIONS SPEED = 1, PENALTY = 0.000000, BASIS = 100, INTERACTIONS = 50
>BOPTIONS MINSPAN = 0
>LIMIT DATASET = 0
>KNOT CROSS = 110
>STORE 'C:\Mars run 5\new.mdl'
>ESTIMATE/ALL

 MARS VERSION 2.0.0.20

 READING DATA, UP TO 8865 RECORDS.

 RECORDS READ: 517
 RECORDS KEPT IN LEARNING SAMPLE: 517

<a name="2"></a>

 LEARNING SAMPLE STATISTICS
 ==========================

 VARIABLE         MEAN          SD           N          SUM
 ---------------------------------------------------------------
     V109   904530.576  938844.328     517.000  .467642E+09
       V1        0.076      14.188     517.000       39.346
       V2       -0.162      13.603     517.000      -83.545
       V3       -0.089      10.637     517.000      -45.964
       V4        0.106       8.639     517.000       54.933
       V5        0.053       6.905     517.000       27.425
       V6       -0.099       6.069     517.000      -50.959
       V7        0.181       4.065     517.000       93.770
       V8       -0.132       4.940     517.000      -68.021
       V9        0.015       5.049     517.000        7.977
      V10       -0.024       5.044     517.000      -12.400
      V11        0.007       5.018     517.000        3.637
      V12        0.039       4.971     517.000       20.007
      V13        0.027       4.958     517.000       13.970
```

V14	-0.086	4.728	517.000	-44.449
V15	-0.086	4.461	517.000	-44.307
V16	0.003	4.427	517.000	1.411
V17	0.096	4.317	517.000	49.764
V18	0.132	4.198	517.000	68.450
V19	-0.121	4.130	517.000	-62.586
V20	-0.093	3.986	517.000	-48.011
V21	-0.084	3.938	517.000	-43.218
V22	-0.047	2.888	517.000	-24.438
V23	0.177	2.580	517.000	91.643
V24	-0.202	3.297	517.000	-104.542
V25	0.020	3.646	517.000	10.219
V26	0.009	3.534	517.000	4.734
V27	-0.097	3.478	517.000	-50.382
V28	-0.005	3.343	517.000	-2.561
V29	-0.002	3.272	517.000	-0.809
V30	0.086	3.293	517.000	44.529
V31	-0.043	3.361	517.000	-22.152
V32	-0.114	3.028	517.000	-58.948
V33	-0.064	3.099	517.000	-32.842
V34	-0.041	3.167	517.000	-21.447
V35	0.074	2.952	517.000	38.390
V36	-0.052	3.010	517.000	-26.874
V37	0.066	2.371	517.000	33.938
V38	0.062	2.783	517.000	32.170
V39	0.012	2.840	517.000	6.125
V40	-0.018	3.059	517.000	-9.420
V41	0.003	3.037	517.000	1.630
V42	-0.041	2.993	517.000	-21.214
V43	0.015	2.967	517.000	7.535
V44	0.055	2.960	517.000	28.229
V45	0.021	2.775	517.000	10.949
V46	-0.042	2.649	517.000	-21.658
V47	-0.033	2.731	517.000	-17.011
V48	-0.064	2.501	517.000	-32.935
V49	-0.038	2.596	517.000	-19.550
V50	0.103	2.350	517.000	53.077
V51	-0.025	2.666	517.000	-12.746
V52	0.074	2.161	517.000	38.011
V53	0.029	2.655	517.000	14.844
V54	-0.071	2.398	517.000	-36.902
V55	-0.019	2.452	517.000	-10.034
V56	0.046	2.515	517.000	24.006
V57	-0.053	2.467	517.000	-27.599
V58	-0.010	2.380	517.000	-5.200
V59	-0.012	2.415	517.000	-5.977
V60	0.050	2.315	517.000	25.883
V61	0.001	2.351	517.000	0.542
V62	-0.092	1.719	517.000	-47.699
V63	-0.024	2.038	517.000	-12.213
V64	-0.026	2.255	517.000	-13.542
V65	-0.020	2.023	517.000	-10.555
V66	0.039	1.943	517.000	20.073
V67	0.030	2.181	517.000	15.552
V68	-0.110	1.958	517.000	-56.869
V69	-0.097	1.970	517.000	-50.395
V70	-0.032	1.991	517.000	-16.745

V71	-0.011	2.084	517.000	-5.575
V72	-0.067	1.858	517.000	-34.564
V73	0.156	1.102	517.000	80.613
V74	0.005	2.106	517.000	2.818
V75	-0.030	1.925	517.000	-15.498
V76	-0.010	1.938	517.000	-5.158
V77	0.078	1.950	517.000	40.205
V78	-0.018	1.789	517.000	-9.505
V79	-0.002	1.956	517.000	-1.187
V80	-0.035	1.924	517.000	-18.124
V81	0.032	1.405	517.000	16.327
V82	-0.038	1.777	517.000	-19.640
V83	-0.014	1.836	517.000	-7.114
V84	0.012	1.904	517.000	6.334
V85	0.028	1.805	517.000	14.345
V86	-0.014	1.779	517.000	-7.205
V87	-0.006	1.861	517.000	-3.083
V88	0.018	1.675	517.000	9.495
V89	-0.057	1.655	517.000	-29.323
V90	0.082	1.532	517.000	42.635
V91	-0.067	1.583	517.000	-34.429
V92	-0.065	1.719	517.000	-33.852
V93	-0.003	1.688	517.000	-1.615
V94	-0.020	1.682	517.000	-10.550
V95	0.068	1.638	517.000	34.909
V96	-0.019	1.658	517.000	-9.703
V97	-0.011	1.425	517.000	-5.875
V98	0.027	1.651	517.000	13.871
V99	0.014	1.699	517.000	7.205
V100	-0.023	1.657	517.000	-12.141
V101	-0.049	1.512	517.000	-25.351
V102	-0.111	1.217	517.000	-57.620
V103	0.049	1.050	517.000	25.496
V104	-0.048	1.521	517.000	-24.978
V105	0.047	1.506	517.000	24.136
V106	0.106	1.384	517.000	54.627
V107	0.010	1.438	517.000	5.397
V108	-0.013	1.456	517.000	-6.510

Ordinal Response

	min	Q25	Q50	Q75	max
V109	11489.000	363925.000	576059.813	1022616.188	5910119.500

Ordinal Predictor Variables: 108

	min	Q25	Q50	Q75	max
V1	-12.629	-0.934	-0.904	-0.788	226.721
V2	-160.182	1.018	1.064	1.154	2.604
V3	-170.489	0.520	0.581	0.676	2.700
V4	-1.835	-0.962	-0.879	-0.292	137.680
V5	-1.241	-0.576	-0.500	-0.383	154.730
V6	-52.151	0.508	0.610	0.838	4.360
V7	-48.042	-0.376	-0.080	0.329	30.169
V8	-28.047	-1.437	-0.099	0.194	45.863
V9	-18.737	-1.015	-0.708	0.341	57.889

V10	-54.017	-0.236	-0.047	0.303	25.866
V11	-31.593	-0.668	-0.227	-0.006	36.890
V12	-45.189	-0.326	-0.184	0.099	54.147
V13	-21.711	-0.301	0.061	0.243	56.553
V14	-33.067	-0.093	1.227	1.675	8.297
V15	-25.782	-1.202	0.855	1.434	21.154
V16	-81.506	-0.174	0.211	0.653	15.558
V17	-17.495	-0.832	-0.585	0.392	35.997
V18	-19.100	-0.990	-0.688	0.082	33.895
V19	-48.288	-0.008	0.408	0.836	8.934
V20	-30.863	-0.368	0.425	0.814	19.921
V21	-87.483	-0.018	0.148	0.296	5.589
V22	-27.023	-0.160	0.432	0.648	13.930
V23	-12.602	-0.250	0.788	1.069	15.588
V24	-31.903	-0.316	-0.005	0.238	23.304
V25	-3.066	-0.515	-0.346	-0.016	76.745
V26	-20.835	-0.395	-0.165	0.768	19.717
V27	-35.702	-0.621	0.369	0.649	17.243
V28	-20.694	-0.191	0.156	0.488	20.756
V29	-28.265	-0.747	-0.127	0.937	12.581
V30	-24.230	-0.313	0.064	0.648	11.295
V31	-24.847	-0.578	0.133	0.498	21.149
V32	-19.564	-0.825	-0.077	0.216	10.971
V33	-23.735	-0.862	0.613	1.159	10.961
V34	-22.562	-0.079	0.237	0.832	14.676
V35	-13.759	-0.293	0.316	0.611	16.828
V36	-24.208	-0.499	0.272	0.473	15.365
V37	-17.857	-0.022	0.234	0.614	15.963
V38	-21.322	-0.183	0.109	0.332	15.101
V39	-11.014	-0.628	-0.322	0.115	26.440
V40	-12.314	-0.643	-0.188	0.530	15.949
V41	-8.346	-0.383	-0.096	0.168	33.637
V42	-21.351	-0.397	0.095	0.515	20.260
V43	-25.853	-0.446	-0.106	0.361	16.431
V44	-16.941	-0.713	-0.342	0.391	17.831
V45	-20.025	-0.144	0.078	0.286	18.939
V46	-24.144	-0.318	-0.085	0.236	9.213
V47	-15.681	-0.397	0.219	0.594	28.081
V48	-10.983	-0.771	-0.079	0.599	11.845
V49	-16.753	-0.299	0.028	0.323	10.913
V50	-7.261	-0.391	-0.135	0.130	22.921
V51	-30.167	-0.263	0.138	0.775	4.534
V52	-20.329	-0.200	0.024	0.394	8.856
V53	-1.236	-0.169	-0.039	0.032	59.804
V54	-10.179	-0.498	-0.076	0.204	11.212
V55	-12.980	-0.421	0.058	0.508	13.994
V56	-5.643	-0.348	0.013	0.252	40.000
V57	-28.058	-0.407	-0.038	0.585	6.868
V58	-16.066	-0.331	0.092	0.480	10.732
V59	-20.383	-0.345	0.075	0.341	12.215
V60	-17.787	-0.350	-.404420E-03	0.653	11.528
V61	-36.433	-0.357	0.041	0.278	23.715
V62	-6.419	-0.781	-0.025	0.612	6.308
V63	-7.285	-1.142	-0.300	0.636	10.244
V64	-15.711	-0.727	-0.005	0.730	17.394
V65	-14.637	-0.440	0.070	0.663	8.764
V66	-11.887	-0.636	0.015	0.585	10.314

V67	-15.363	-0.361	-0.078	0.480	11.754
V68	-18.450	-0.319	0.054	0.387	9.835
V69	-14.839	-0.550	-0.129	0.406	17.008
V70	-7.322	-0.809	-0.188	0.493	9.047
V71	-15.153	-0.648	-0.041	0.476	15.615
V72	-12.631	-0.374	-0.073	0.274	14.142
V73	-6.644	-0.113	0.139	0.403	6.510
V74	-35.246	-0.020	-0.002	0.031	21.774
V75	-11.761	-0.486	0.105	0.654	10.466
V76	-6.546	-0.781	-0.356	0.399	11.535
V77	-5.349	-0.340	-0.015	0.328	38.629
V78	-6.438	-0.723	-0.225	0.503	17.513
V79	-26.793	-0.198	0.121	0.309	21.097
V80	-21.557	-0.316	0.042	0.422	5.023
V81	-7.174	-0.427	-0.048	0.296	7.094
V82	-13.802	-0.425	-0.021	0.417	7.024
V83	-5.534	-0.615	-0.080	0.422	14.123
V84	-19.825	-0.084	0.035	0.143	33.966
V85	-9.131	-0.476	-0.083	0.284	18.620
V86	-11.434	-0.350	0.037	0.280	7.562
V87	-8.795	-0.212	-0.003	0.137	24.107
V88	-7.691	-0.481	0.042	0.583	11.436
V89	-12.224	-0.565	-0.136	0.309	8.957
V90	-8.330	-0.220	0.038	0.384	8.747
V91	-10.883	-0.311	-0.002	0.332	8.270
V92	-14.548	-0.290	0.037	0.298	7.047
V93	-8.055	-0.312	-0.038	0.304	11.099
V94	-13.285	-0.413	0.033	0.266	13.317
V95	-8.868	-0.393	0.010	0.447	8.249
V96	-20.240	-0.233	0.019	0.226	12.234
V97	-10.801	-0.429	-0.013	0.334	6.831
V98	-8.415	-0.280	-0.003	0.376	7.489
V99	-17.396	-0.287	-0.021	0.192	17.179
V100	-15.907	-0.383	-0.017	0.264	12.866
V101	-12.058	-0.455	-0.047	0.460	6.920
V102	-5.629	-0.402	-0.042	0.298	6.655
V103	-4.796	-0.310	0.039	0.357	4.979
V104	-5.153	-0.514	-0.061	0.396	9.879
V105	-15.802	-0.295	0.051	0.370	5.342
V106	-4.190	-0.312	-0.010	0.333	9.164
V107	-7.665	-0.394	0.004	0.324	20.019
V108	-10.560	-0.394	0.012	0.497	5.927

110-fold cross validation used to estimate DF.

Estimated optimal DF(12) = 28.147 with (estimated) PSE = .255947E+12

Forward Stepwise Knot Placement
===============================

BasFn(s)	GCV	IndBsFns	EfPrms	Variable	Knot	Parent	BsF
0	.883137E+12	0.0	1.0				
2 1	.687286E+12	2.0	31.1	V3	0.549		
4 3	.636429E+12	4.0	61.3	V4	3.010		
6 5	.572628E+12	6.0	91.4	V37	0.114	V3	2
8 7	.538308E+12	8.0	121.6	V64	-2.442		
10 9	.539082E+12	10.0	151.7	V29	6.760	V4	4
12 11	.547945E+12	12.0	181.9	V11	-0.217	V3	1
14 13	.574054E+12	14.0	212.0	V44	-0.317	V29	10
16 15	.622541E+12	16.0	242.2	V70	1.956	V44	13
18 17	.687191E+12	18.0	272.3	V9	6.319		
20 19	.790569E+12	20.0	302.5	V53	0.261		
22 21	.914055E+12	22.0	332.6	V6	2.233	V53	20
24 23	.115711E+13	24.0	362.8	V35	-2.422	V6	22
26 25	.160751E+13	26.0	392.9	V81	1.449	V11	12
28 27	.246454E+13	28.0	423.1	V7	0.009	V9	18
29	.457462E+13	29.0	452.2	V1	-12.629	V6	22
31 30	.137901E+14	31.0	482.4	V42	0.166	V81	26
33 32	.715459E+15	33.0	512.5	V33	0.887	V53	20

Model 1 of 33

Estimated optimal model = response mean.
Model 2 of 33

Estimated optimal model = response mean.
Model 3 of 33

Estimated optimal model = response mean.
Model 4 of 33

Estimated optimal model = response mean.
Model 5 of 33

Estimated optimal model = response mean.
Model 6 of 33

Estimated optimal model = response mean.
Model 7 of 33

Estimated optimal model = response mean.
Model 8 of 33

Estimated optimal model = response mean.
Model 9 of 33

Estimated optimal model = response mean.
Model 10 of 33
Model 11 of 33
Model 12 of 33
Model 13 of 33

```
 Model 14 of 33
 Model 15 of 33
 Model 16 of 33
 Model 17 of 33
 Model 18 of 33
 Model 19 of 33
 Model 20 of 33
 Model 21 of 33
 Model 22 of 33
 Model 23 of 33
 Model 24 of 33
 Model 25 of 33
 Model 26 of 33
 Model 27 of 33
 Model 28 of 33
 Model 29 of 33
 Model 30 of 33
 Model 31 of 33
 Model 32 of 33
 Model 33 of 33

 Piecewise Linear GCV = .680085E+12, #efprms = 16.500
<a name="4"></a>


 Final Model (After Backward Stepwise Elimination)
 =================================================

 Basis Fun  Coefficient     Variable       Parent    Knot
 -------------------------------------------------------------------
        0   347729.313
        1  2160884.750       V3                        0.549
        4  -161361.938       V4                        3.010
        6   143573.984      V37            V3          0.114
        8   296869.188      V64                       -2.442
       10    18109.969      V29            V4          6.760
       14     9289.705      V44           V29         -0.317
       15     7624.673      V70           V44          1.956
       22  -231047.984       V6           V53          2.233
       23    39573.816      V35            V6         -2.422
       25  1140948.375      V81           V11          1.449
       26   269260.594      V81           V11          1.449
       28    40768.789       V7            V9          0.009
       29    27609.438       V1            V6        -12.629
       31   345902.313      V42           V81          0.166

 Piecewise Linear GCV = .297086E+12, #efprms = 218.000
<a name="5"></a>
```

ANOVA Decomposition on 14 Basis Functions
===

fun	std. dev.	-gcv	#bsfns	#efprms	variable	
1	350663.785	.487162E+12	1	15.500	V3	
2	154971.292	.300681E+12	1	15.500	V4	
3	281409.506	.471261E+12	1	15.500	V64	
4	185200.917	.357699E+12	1	15.500	V3	V37
5	233343.526	.352454E+12	1	15.500	V4	V29
6	411541.499	.333012E+12	1	15.500	V6	V53
7	212509.000	.381636E+12	1	15.500	V7	V9
8	229570.837	.401336E+12	1	15.500	V4 V44	V29
9	213678.595	.326722E+12	1	15.500	V6 V53	V35
10	305532.581	.453069E+12	2	31.000	V3 V81	V11
11	618639.215	.447758E+12	1	15.500	V1 V53	V6
12	187427.133	.361304E+12	1	15.500	V4 V44	V29 V70
13	118457.863	.302994E+12	1	15.500	V3 V42	V11 V81

Piecewise Cubic Fit on 14 Basis Functions, GCV = .741091E+12

Relative Variable Importance
============================

	Variable	Importance	-gcv
3	V3	100.000	.695862E+12
6	V6	86.178	.593242E+12
53	V53	86.178	.593242E+12
64	V64	66.089	.471261E+12
11	V11	64.982	.465477E+12
81	V81	64.982	.465477E+12
29	V29	62.524	.452978E+12
1	V1	61.468	.447758E+12
44	V44	58.919	.435521E+12
4	V4	54.515	.415598E+12
7	V7	46.046	.381636E+12
9	V9	46.046	.381636E+12
70	V70	40.129	.361304E+12
37	V37	38.987	.357699E+12
35	V35	27.261	.326722E+12
42	V42	12.172	.302995E+12
2	V2	0.000	.297086E+12
5	V5	0.000	.297086E+12
8	V8	0.000	.297086E+12
10	V10	0.000	.297086E+12
12	V12	0.000	.297086E+12
13	V13	0.000	.297086E+12

14	V14	0.000	.297086E+12
15	V15	0.000	.297086E+12
16	V16	0.000	.297086E+12
17	V17	0.000	.297086E+12
18	V18	0.000	.297086E+12
19	V19	0.000	.297086E+12
20	V20	0.000	.297086E+12
21	V21	0.000	.297086E+12
22	V22	0.000	.297086E+12
23	V23	0.000	.297086E+12
24	V24	0.000	.297086E+12
25	V25	0.000	.297086E+12
26	V26	0.000	.297086E+12
27	V27	0.000	.297086E+12
28	V28	0.000	.297086E+12
30	V30	0.000	.297086E+12
31	V31	0.000	.297086E+12
32	V32	0.000	.297086E+12
33	V33	0.000	.297086E+12
34	V34	0.000	.297086E+12
36	V36	0.000	.297086E+12
38	V38	0.000	.297086E+12
39	V39	0.000	.297086E+12
40	V40	0.000	.297086E+12
41	V41	0.000	.297086E+12
43	V43	0.000	.297086E+12
45	V45	0.000	.297086E+12
46	V46	0.000	.297086E+12
47	V47	0.000	.297086E+12
48	V48	0.000	.297086E+12
49	V49	0.000	.297086E+12
50	V50	0.000	.297086E+12
51	V51	0.000	.297086E+12
52	V52	0.000	.297086E+12
54	V54	0.000	.297086E+12
55	V55	0.000	.297086E+12
56	V56	0.000	.297086E+12
57	V57	0.000	.297086E+12
58	V58	0.000	.297086E+12
59	V59	0.000	.297086E+12
60	V60	0.000	.297086E+12
61	V61	0.000	.297086E+12
62	V62	0.000	.297086E+12
63	V63	0.000	.297086E+12
65	V65	0.000	.297086E+12
66	V66	0.000	.297086E+12
67	V67	0.000	.297086E+12
68	V68	0.000	.297086E+12
69	V69	0.000	.297086E+12
71	V71	0.000	.297086E+12
72	V72	0.000	.297086E+12
73	V73	0.000	.297086E+12
74	V74	0.000	.297086E+12
75	V75	0.000	.297086E+12
76	V76	0.000	.297086E+12
77	V77	0.000	.297086E+12
78	V78	0.000	.297086E+12

```
   79      V79           0.000  .297086E+12
   80      V80           0.000  .297086E+12
   82      V82           0.000  .297086E+12
   83      V83           0.000  .297086E+12
   84      V84           0.000  .297086E+12
   85      V85           0.000  .297086E+12
   86      V86           0.000  .297086E+12
   87      V87           0.000  .297086E+12
   88      V88           0.000  .297086E+12
   89      V89           0.000  .297086E+12
   90      V90           0.000  .297086E+12
   91      V91           0.000  .297086E+12
   92      V92           0.000  .297086E+12
   93      V93           0.000  .297086E+12
   94      V94           0.000  .297086E+12
   95      V95           0.000  .297086E+12
   96      V96           0.000  .297086E+12
   97      V97           0.000  .297086E+12
   98      V98           0.000  .297086E+12
   99      V99           0.000  .297086E+12
  100     V100           0.000  .297086E+12
  101     V101           0.000  .297086E+12
  102     V102           0.000  .297086E+12
  103     V103           0.000  .297086E+12
  104     V104           0.000  .297086E+12
  105     V105           0.000  .297086E+12
  106     V106           0.000  .297086E+12
  107     V107           0.000  .297086E+12
  108     V108           0.000  .297086E+12
<a name="7"></a>


 ORDINARY LEAST SQUARES RESULTS
 ==============================

 N: 517.000                                R-SQUARED: 0.887
 MEAN DEP VAR: 904530.575              ADJ R-SQUARED: 0.884
                  UNCENTERED R-SQUARED = R-0 SQUARED: 0.941

    PARAMETER USE "C:\Mars run 5\valid.SAV[spsswin]"         ESTIMATE
S.E.      T-RATIO  P-VALUE
 ----------------------------------------------------------------------
---
 Constant           |   347729.178    66068.471    5.263  .210208E-06
 Basis Function 1   |  2160884.984   106882.971   20.217  .999201E-15
 Basis Function 4   |  -161361.956    20811.565   -7.753  .501821E-13
 Basis Function 6   |   143574.000    11119.712   12.912  .999201E-15
 Basis Function 8   |   296869.243    15248.899   19.468  .999201E-15
 Basis Function 10  |    18109.977     1445.771   12.526  .999201E-15
 Basis Function 14  |     9289.707      589.553   15.757  .999201E-15
 Basis Function 15  |     7624.673      578.941   13.170  .999201E-15
 Basis Function 22  |  -231048.352    21042.807  -10.980  .999201E-15
 Basis Function 23  |    39573.856     3793.985   10.431  .999201E-15
 Basis Function 25  |  1140948.654   123827.760    9.214  .999201E-15
 Basis Function 26  |   269260.645    14297.806   18.832  .999201E-15
 Basis Function 28  |    40768.813     2803.589   14.542  .999201E-15
 Basis Function 29  |    27609.461     1508.298   18.305  .999201E-15
```

```
 Basis Function 31  |   345902.298    43089.400    8.028  .710543E-14
 ----------------------------------------------------------------------
---
 F-STATISTIC =  281.594               S.E. OF REGRESSION =  319901.078
     P-VALUE =  .999201E-15     RESIDUAL SUM OF SQUARES =  .513730E+14
   [MDF,NDF] = [ 14, 502 ]     REGRESSION SUM OF SQUARES =  .403444E+15
 ----------------------------------------------------------------------
---

 The Following Graphics Are Piecewise Linear


 PURE ORDINAL CONTRIBUTION:
    CURVE 1: V64 , max = 0.39391E+07
              ------------------------------------------------------
  3939078.250 |**                          |                       |
              | **                         |                       |
  3446693.469 |  ***                       |                       |
              |    **                      |                       |
  2954308.688 |     ***                    |                       |
              |       **                   |                       |
  2461923.906 |        ***                 |                       |
              |          **                |                       |
  1969539.125 |           ***              |                       |
              |             **             |                       |
  1477154.344 |              **            |                       |
              |                **          |                       |
   984769.563 |                 **         |                       |
              |                   **       |                       |
   492384.781 |                    **      |                       |
              |                     ***    |                       |
        0.000 |                       *****************************|
              ----------------------------- ------------------------
           -15.711           |           0.842        |
17.394
                         -7.434                    9.118
   srf     1:  x(    7), x(    9).  max =     0.96142E+07

 1 curves and 1 surfaces.

<a name="8"></a>


 Basis Functions
 ===============

 BF1 = max(0, V3 - 0.549);
 BF2 = max(0, 0.549 - V3 );
 BF4 = max(0, 3.010 - V4 );
 BF6 = max(0, 0.114 - V37 ) * BF2;
 BF8 = max(0, - 2.442 - V64 );
 BF10 = max(0, 6.760 - V29 ) * BF4;
 BF12 = max(0, - 0.217 - V11 ) * BF1;
 BF13 = max(0, V44 + 0.317) * BF10;
 BF14 = max(0, - 0.317 - V44 ) * BF10;
 BF15 = max(0, V70 - 1.956) * BF13;
 BF18 = max(0, 6.319 - V9 );
```

```
 BF20 = max(0, 0.261 - V53 );
 BF22 = max(0, 2.233 - V6 ) * BF20;
 BF23 = max(0, V35 + 2.422) * BF22;
 BF25 = max(0, V81 - 1.449) * BF12;
 BF26 = max(0, 1.449 - V81 ) * BF12;
 BF28 = max(0, 0.009 - V7 ) * BF18;
 BF29 = max(0, V1 + 12.629) * BF22;
 BF31 = max(0, 0.166 - V42 ) * BF26;

 Y = 347729.313 + 2160884.750 * BF1 - 161361.938 * BF4
               + 143573.984 * BF6 + 296869.188 * BF8 + 18109.969 *
BF10
               + 9289.705 * BF14 + 7624.673 * BF15 - 231047.984 * BF22
               + 39573.816 * BF23 + 1140948.375 * BF25
               + 269260.594 * BF26 + 40768.789 * BF28
               + 27609.438 * BF29 + 345902.313 * BF31;

 model V109 = BF1 BF4 BF6 BF8 BF10 BF14 BF15 BF22 BF23 BF25 BF26 BF28
BF29
             BF31;


 Current model information saved to binary file: C:\Mars run 5\new.mdl
>STORE/CURRENT "C:\Mars run 5\train.mdl"

 Current model information saved to binary file: C:\Mars run
5\train.mdl
>
 VARIABLES IN RECT FILE ARE:
        V1       V2             V3             V4             V5
        V6       V7             V8             V9            V10
       V11      V12            V13            V14            V15
       V16      V17            V18            V19            V20
       V21      V22            V23            V24            V25
       V26      V27            V28            V29            V30
       V31      V32            V33            V34            V35
       V36      V37            V38            V39            V40
       V41      V42            V43            V44            V45
       V46      V47            V48            V49            V50
       V51      V52            V53            V54            V55
       V56      V57            V58            V59            V60
       V61      V62            V63            V64            V65
       V66      V67            V68            V69            V70
       V71      V72            V73            V74            V75
       V76      V77            V78            V79            V80
       V81      V82            V83            V84            V85
       V86      V87            V88            V89            V90
       V91      V92            V93            V94            V95
       V96      V97            V98            V99           V100
      V101     V102           V103           V104           V105
      V106     V107           V108

 C:\Mars run 5\valid.SAV[spsswin]: 80 RECORDS.

>RETRIEVE "C:\Mars run 5\new.mdl"
>SAVE "C:\Mars run 5\new.XLS[xls7]"
>APPLY
```

Dependent variable: V109 not found on your dataset.

READING DATA, UP TO 8865 RECORDS.

RECORDS READ: 80
RECORDS KEPT IN LEARNING SAMPLE: 80

LEARNING SAMPLE STATISTICS
==========================

VARIABLE	MEAN	SD	N	SUM
V1	-0.492	1.075	80.000	-39.346
V2	1.044	0.083	80.000	83.545
V3	0.575	0.066	80.000	45.965
V4	-0.687	0.739	80.000	-54.934
V5	-0.343	0.372	80.000	-27.426
V6	0.637	0.740	80.000	50.960
V7	-1.172	8.719	80.000	-93.770
V8	0.850	4.730	80.000	68.022
V9	-0.100	2.609	80.000	-7.977
V10	0.155	1.254	80.000	12.400
V11	-0.045	1.534	80.000	-3.637
V12	-0.250	1.145	80.000	-20.007
V13	-0.175	1.072	80.000	-13.970
V14	0.556	2.133	80.000	44.449
V15	0.554	1.934	80.000	44.307
V16	-0.018	1.065	80.000	-1.411
V17	-0.622	0.955	80.000	-49.764
V18	-0.856	0.961	80.000	-68.450
V19	0.782	0.982	80.000	62.586
V20	0.600	1.746	80.000	48.011
V21	0.540	1.178	80.000	43.218
V22	0.305	6.669	80.000	24.439
V23	-1.146	7.093	80.000	-91.643
V24	1.307	4.450	80.000	104.542
V25	-0.128	1.223	80.000	-10.220
V26	-0.059	2.091	80.000	-4.734
V27	0.630	1.529	80.000	50.382
V28	0.032	2.907	80.000	2.560
V29	0.010	2.828	80.000	0.809
V30	-0.557	2.309	80.000	-44.530
V31	0.277	1.290	80.000	22.152
V32	0.737	3.610	80.000	58.949
V33	0.411	2.985	80.000	32.842
V34	0.268	2.090	80.000	21.447
V35	-0.480	3.304	80.000	-38.390
V36	0.336	2.625	80.000	26.874
V37	-0.424	5.360	80.000	-33.939
V38	-0.402	3.635	80.000	-32.171
V39	-0.077	3.272	80.000	-6.125
V40	0.118	1.369	80.000	9.420
V41	-0.020	0.762	80.000	-1.630
V42	0.265	0.821	80.000	21.214

V43	-0.094	0.965	80.000	-7.535
V44	-0.353	0.959	80.000	-28.229
V45	-0.137	2.200	80.000	-10.949
V46	0.271	2.663	80.000	21.658
V47	0.213	1.809	80.000	17.011
V48	0.412	3.011	80.000	32.935
V49	0.244	2.403	80.000	19.550
V50	-0.663	3.492	80.000	-53.077
V51	0.159	1.194	80.000	12.747
V52	-0.475	4.053	80.000	-38.012
V53	-0.186	0.447	80.000	-14.844
V54	0.461	2.731	80.000	36.902
V55	0.125	2.072	80.000	10.033
V56	-0.300	1.127	80.000	-24.007
V57	0.345	1.262	80.000	27.599
V58	0.065	1.670	80.000	5.200
V59	0.075	1.131	80.000	5.976
V60	-0.324	1.552	80.000	-25.884
V61	-0.007	0.825	80.000	-0.542
V62	0.596	4.070	80.000	47.699
V63	0.153	2.960	80.000	12.213
V64	0.169	1.370	80.000	13.542
V65	0.132	2.693	80.000	10.555
V66	-0.251	2.957	80.000	-20.073
V67	-0.194	1.441	80.000	-15.551
V68	0.711	2.623	80.000	56.869
V69	0.630	2.492	80.000	50.395
V70	0.209	2.323	80.000	16.745
V71	0.070	1.494	80.000	5.575
V72	0.432	2.672	80.000	34.564
V73	-1.008	4.502	80.000	-80.613
V74	-0.035	0.100	80.000	-2.818
V75	0.194	2.042	80.000	15.498
V76	0.064	1.833	80.000	5.158
V77	-0.503	1.452	80.000	-40.206
V78	0.119	2.409	80.000	9.505
V79	0.015	1.080	80.000	1.187
V80	0.227	1.254	80.000	18.124
V81	-0.204	3.544	80.000	-16.327
V82	0.245	1.972	80.000	19.639
V83	0.089	1.468	80.000	7.113
V84	-0.079	0.382	80.000	-6.334
V85	-0.179	1.521	80.000	-14.345
V86	0.090	1.710	80.000	7.204
V87	0.039	0.760	80.000	3.083
V88	-0.119	2.128	80.000	-9.495
V89	0.367	2.121	80.000	29.323
V90	-0.533	2.573	80.000	-42.635
V91	0.430	2.314	80.000	34.429
V92	0.423	1.474	80.000	33.852
V93	0.020	1.613	80.000	1.615
V94	0.132	1.607	80.000	10.551
V95	-0.436	1.724	80.000	-34.909
V96	0.121	1.621	80.000	9.703
V97	0.073	2.596	80.000	5.875
V98	-0.173	1.309	80.000	-13.871
V99	-0.090	0.772	80.000	-7.205

```
    V100            0.152         1.028        80.000        12.141
    V101            0.317         1.945        80.000        25.351
    V102            0.720         2.895        80.000        57.620
    V103           -0.319         3.339        80.000       -25.496
    V104            0.312         1.626        80.000        24.978
    V105           -0.302         1.648        80.000       -24.136
    V106           -0.683         2.088        80.000       -54.627
    V107           -0.067         1.793        80.000        -5.397
    V108            0.081         1.639        80.000         6.510

SAVE FILE CREATED.
80 RECORDS WRITTEN TO SAVE FILE.
```



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PREDICTION STATISTICS
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           Minimum:   25839.816
           Maximum: 2131535.250
              Mean:  619974.629
Standard Deviation:  386684.505
>
```

VITA

Roshan Pawar received a B.E. in Construction Engineering from M. H. Saboo Siddik College of Engineering, University of Mumbai in 2002. He worked as a Site Engineer before enrolling for a M.S. degree in Civil Engineering with emphasis in Construction Engineering and Management at Texas A&M University in 2005. He can be reached at his parents' address at:

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