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# DEVELOPMENT OF A TWO-STEP NEURAL NETWORK-BASED MODEL TO PREDICT CONSTRUCTION COST CONTINGENCY

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**SUMMARY:** *An owner's cost contingency is one of the most important cost elements within a base estimate to account for unpredictable risks and changes in the delivery of construction projects. The accurate estimation of an optimal contingency is critical for the financial success of a project and for ensuring the optimal use of an owner's funds. Existing methods for estimating contingency are deficient in that the answers they generate are often far from optimal causing problems such as depletion of budgets, disputes, and reduction in work quality. This study proposes a two-step neural network-based method for estimating the optimal contingency for an owner's funding of transportation construction projects that has the objective of achieving solutions that are closer to the optimum than existing tools. The two-step method is a development of a one-step neural network approach that has been found to perform better than the approach currently adopted by the Florida Department of Transportation (FDOT). The two-step ANN-based prediction model is shown to generate estimates of contingency that are closer to the optimum than the one-step ANN-based approach. As a consequence, the two-step approach has the potential to improve an owner's budgetary decisions, reducing the risk of either underutilizing or over committing funds.*

**KEYWORDS:** *Artificial neural networks; Construction cost contingency; Form of contingency; One-step ANN-based model; Two-step ANN-based model.*

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## 1. INTRODUCTION

Construction projects intrinsically involve many uncertainties and risks throughout all phases from start-up to completion. Construction participants including owners, contractors, and designers have added cost contingency in order to cover intangible costs from unpredictable changes that are made to a project basis after the release of a base estimate. In practice, contingency accounts for stochastic factors that affect the cost of construction, possible change orders, and errors in the original estimate. Contingency is directly related to the accuracy of a base estimate since it is one of the cost elements within an estimate prepared before the commencement of a project. Therefore, the accurate prediction of contingency and its adequacy is closely related to the financial success of projects. Contingency may have a tremendous impact on project outcome for project participants (Dey et al. 1994; Baccarini 2004). From an owner's perspective, a contingency that is too large can result in poor cost management, uneconomic completion of a project, and a lack of available funds for other organizational activities. On the other hand, a contingency that is too low can give rise to inadequate funding for executing a project, an unrealistic financial environment, and unsatisfactory performance outcomes.

### 1.1 Existing approaches

The most widely used method of determining contingency in the architecture, engineering and construction (AEC) industry is the traditional fixed percentage method which is a subjective one based on gut feeling and intuition by estimators or project managers. It attempts to quantify risks associated with a project based on past experiences with similar types of projects for the purpose of ensuring that the project budget is sufficient to include any cost incurred by unforeseen circumstances.

Modern estimating textbooks usually represent contingency as a fixed percentage of the estimated contract amount using this method. The percentage reported is generally around 5-10 % of the contract amount (Smith and Bohn 1999). However, according to Karlsen and Lereim (2005), this method has several weaknesses: (1) it is overly simplistic and heavily dependent on estimators' faiths in their own past experiences; (2) the percentage is broadly estimated and not appropriate for a specific project; and (3) there is a tendency to double count risks. In order to complement these disadvantages, several methods for estimating an optimal contingency have been proposed and studied (Gunhan and Arditi 2007). Mak and Picken (2000) proposed a methodology termed "Estimating using Risk Analysis (ERA)" implemented by the Hong Kong Government in order to substantiate contingency by identifying uncertainties and estimating their financial implications. Oberlender and Trost (2001) developed the Estimate Score Program (ESP) to predict contingency and to assess the accuracy of cost estimates by statistical methods such as factor analysis and multivariate regression to analyze historical cost data (Trost and Oberlender 2003). Touran (2003) proposed a probabilistic contingency prediction model that considers the expected number of change orders and their average cost, assuming that the change orders can be represented by a Poisson distribution and that the change orders are represented by independent random variables. Thal et al. (2010) developed a multivariate linear regression model to predict contingency amounts for Air Force construction projects.

Recently, interest has been shown in using artificial neural networks (ANNs) for predicting contingency. ANNs are empirically derived estimators trained using a comprehensive set of examples of the problem at hand and their corresponding target solutions. The expected main advantage of ANNs over the linear regression models is that they facilitate the development of complicated non-linear functions to map between the predictor variables and the corresponding target solution. Moselhi et al. (1993) developed a decision-support system that helps contractors prepare competitive bids for building construction projects in order to estimate an optimum contingency percentage in future bid situations using the popular feedforward network trained using the error back-propagation (BP) method. Chen and Hartman (2000) also developed an ANN-based model to predict the total contingency amount at the front-end stage of project development using BP and general regression neural network (GRNN) methods. Lhee et al. (2012) proposed an ANN approach to predict the owner's contingency for transportation construction projects using a three-layer feedforward BP network. Lhee et al. (2012) also developed an easy-to-use contingency prediction tool for several ANN model types on FDOT (Florida Department of Transportation) construction projects after passing the validation process. At the development phase of models, after identifying possible input factors that affect the owner's contingency, transportation construction projects were divided into several categories such as project work type (asphalt resurfacing, asphalt paving, bridge work, combination of asphalt paving and bridge work, and others), delivery method type (design-bid-build and design-build), contract agreement type (unit price and lump sum), bid award type (lowest bidding and cost plus time bidding), geographical location (urban and rural area), and letting type (central office letting and district office letting). The contingency amount and rate as a form of output parameter were used in ANN models where a one-step ANN method was adopted to directly predict the most appropriate contingency. The studies found that the model predicting contingency amount outperformed that predicting contingency rate (Lhee et al. 2012).

Although ANNs have proven successful for solving complex nonlinear problems, they are black-box devices providing no explanation of the output results, are not able to extrapolate beyond the scope of examples used for training, and often require a large and comprehensive set of training patterns in order to achieve good learning. Flood and Issa (2010) systematized a rigorous procedure for the development and implementation of empirical modeling methodologies such as ANNs to ensure the validity and value of the end product. They emphasized the establishment of application objectives of a model as the first step in development, addressing such issues as the selection of output variables, the decision on the form of the output (i.e. static or dynamic), and the focus of the study (i.e. on internal structures of the model or generated output values). Flood and Kartam (1994b) also noted that testing various formats of input and output variables is often the only means for determining which format is the most effective for an ANN model. In other words, the experiment about the selection of an appropriate form of contingency as output (dependent) variable and about the transformation of an inferior output variable for improving the performance of an ANN model, which is the focus of this study, is an extremely important task in optimizing the performance of an ANN estimator. Accordingly, this paper proposes the development of a two-step ANN-based model in order to achieve an accurate prediction of the owner's contingency on transportation construction projects. The performance of the two-step ANN-based model was compared with that of a one-step ANN-based model to determine its validity and relative performance in the prediction of contingency.

## 1.2 Artificial Neural Network (ANN) Methodology

Artificial Neural Networks (ANNs) have proven successful in solving a wide range of poorly-defined non-linear problems encountered in civil engineering (Flood and Kartam, 1994b), and from the extensive literature it is apparent they are one of the most versatile empirical modeling methods currently available (Flood 2008). They are suitable for solving complex cognitive problems from the adaptability of their structures such as hidden layers and the nonlinear activation function (Chao and Skibniewski 1994). Partly inspired by biological neural systems, ANNs gain analogy-based problem solving abilities by learning from many input patterns and their related output patterns. Since the late 1980s, applications of ANNs have been made for various problems in civil engineering including process optimization, construction simulation, cost estimation, as well as problems involving pattern classification and selection (Flood and Kartam 1994a). For example, Adeli and Wu (1998) used a regularization network to estimate highway construction costs. Sinha and McKim (2000) applied the ANN based methodology for predicting the level of organizational effectiveness in a construction firm. Flood et al. (2004) developed an approach for simulating the time-wise thermal behavior of buildings using the Radial Gaussian Incremental Network (RGIN) method. An ANN model to predict the escalation of highway construction costs over time was proposed by Wilmot and Mei (2005). Yan et al. (2008) used a two-layered back-propagation neural network to classify strain-based vehicles crossing over a bridge deck system. Alex et al. (2010) suggested an ANN model to estimate the costs of water and sewer installation services for residential facilities in the City of Edmonton, Canada. Shehab et al. (2010) showed that the ANN approach provided better accuracy over regression analysis in development of cost estimating models for utility rehabilitation projects. Arafa and Alqedra (2011) developed an efficient model to estimate the cost of building construction projects at an early phase in the project using ANNs. In summary, ANNs are a powerful artificial intelligence based approach that offer a convenient and accurate solution to a wide range of complex nonlinear computation problems encountered in civil engineering.

## 2. ANN DEVELOPMENT AND IMPLEMENTATION

This study proposes and evaluates a two-step ANN-based model to improve the estimation of contingency, whereby an ANN is used to generate values of an intermediate output variable which are then post-processed to provide the optimal value for an owner's contingency. This study focuses on transportation construction projects. The procedure shown in Figure 1 is followed in developing the ANN-based estimator.

Step 1 represents the first step in developing and applying neural networks and involves determining the specific output variable to be used by the ANN, in this case for quantifying contingency. Either the contingency amount or rate can be considered as the output variable from the neural networks (Lhee et al. 2012). Moselhi et al. (1993) estimated an optimal contingency rate on the decision-

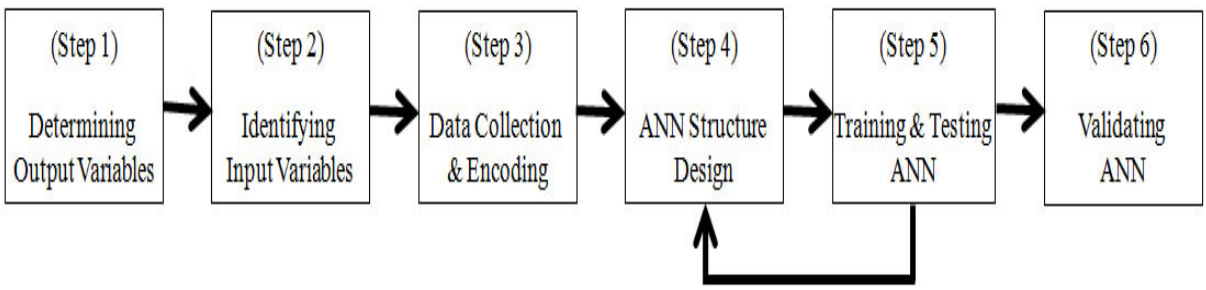


*FIG. 1: Steps for applying artificial neural networks*

support system to help contractors preparing competitive bids for building construction projects. Chen and Hartman (2000) predicted a total contingency amount at the front-end stage of project development. Lhee et al. (2012) found that the single step ANN model predicting contingency amount performed more accurately than that predicting contingency rate. Mak and Picken (2000) determined that contingency can be compared with the total value of contractual variations to assess the accuracy of contingency. Baccarini (2004) found that the accuracy of a contingency can be measured by comparing the initial contract amount against the actual final contract amount. From these findings, the desired (optimal) contingency in this study is defined as the cost item which can compensate for all unforeseen work orders and related risks during the delivery of transportation construction projects and it is equivalent to the accurate cost item in the estimate for an on budget (not over-budget or under-budget) project. The desired contingency amount can be calculated from the difference between the adjusted original contract amount and the final contract amount as shown in Figure 2. The desired contingency rate is obtained by dividing the desired contingency amount by the adjusted original contract amount (i.e. project amount). In this study, the adjusted original contract amount represents the original contract amount minus the initial contingency amount.

The second phase (Step 2) in developing the ANN-based estimator is to identify the input variables critical to determining an optimal value for contingency. The *Major Project Program Cost Estimating Guidance* prepared by the FHWA (Federal Highway Administration) suggested that several factors including design-build contracts, number of concurrent contracts, contractor proposed construction changes, construction time, transportation management plan for work zones, environmental impacts, and differing site conditions may have an impact on the contingency item (FHWA 2007). Popescu et al. (2003) also noted that the magnitude of contingency depends on the type of contract agreement, type of construction work, and project location.

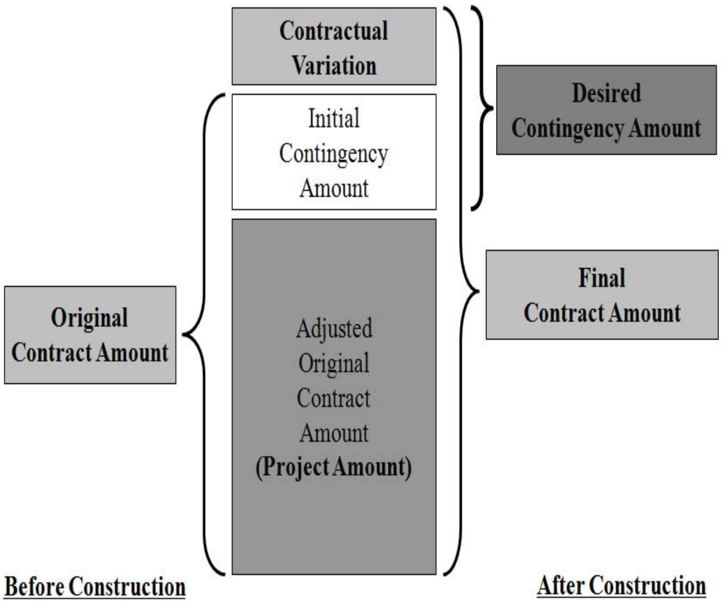


*FIG. 2: Calculation for the desired contingency amount and rate*

Based on these recommendations, three categories of potential input variables on contingency for transportation construction projects were identified as shown in Figure 3. However, the inclusion of unordered categorical input variables (such as "Project Work Type" and "Project Delivery Method Type") in an ANN is usually problematic because it introduces discontinuities in the mappings from inputs to outputs that are inherently difficult for most ANNs to learn (Flood and Issa 2010). Unordered categorical variables as such are best handled by developing a separate ANN for each category. Further pruning of the input variables to be considered was necessary due to gaps in the available database. As a result, four numerical input variables were selected for inclusion at the input layer of the ANN, these were: the Number of Bidders, Project Letting Year, Project Duration, and Project Amount.

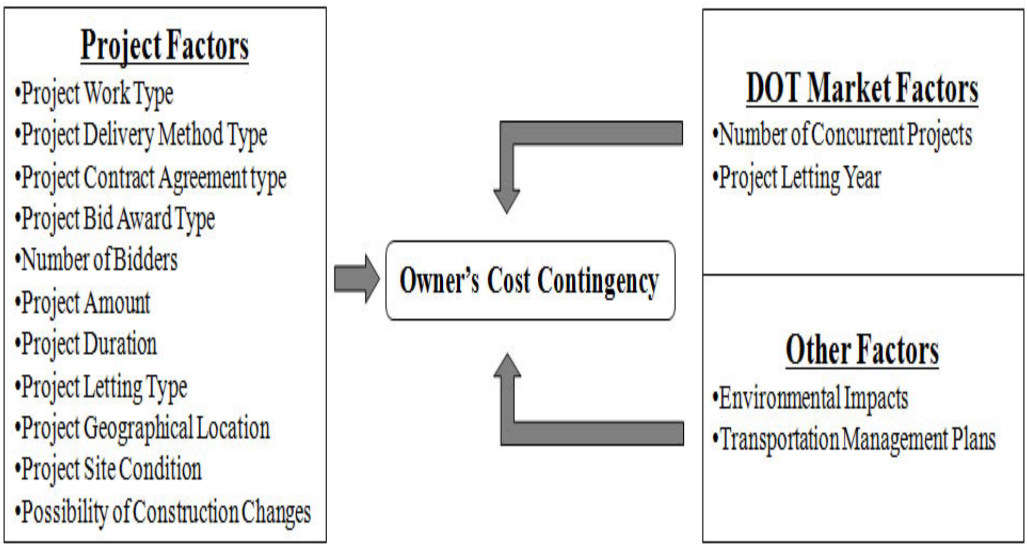


*FIG. 3: Potential input variable on contingency*

Data were collected from 495 FDOT (Florida Department of Transportation) projects which were completed from 2004 to 2006 for developing the ANN estimator. Contingency-related data were retrieved from FDOT Quarterly Time and Cost reports and bidding tabulation documents. Data were randomly divided into three groups: a training dataset of 315 projects, a testing dataset of 88 projects, and a validation dataset of 92 projects, providing an approximate 60% to 20% to 20% split of the data. All project data were selected to fall within DBB (Design-Bid-Build) as project delivery method type and LB (Lowest Bid) method as bid award type in order to minimize the potential impacts of categorical input variables on the owner's cost contingency.

As an implementation tool for neural networks, the NeuroShell Predictor software developed by the Ward System Group, Inc. (2012) was adopted for this study. As shown in Figure 4, the basic structure of the ANN is a three-layer feedforward back-propagation network consisting of one input, one hidden, and one output layer, and uses the sigmoid activation function at each neuron. This is the most commonly used architecture for civil engineering applications due to its simplicity. The input layer comprises four neurons, one for each input variable, while the output layer has just one neuron representing the ANN's estimate of the optimal contingency for the specific project described at the input layer. The number of hidden neurons included in the ANN will affect its performance at estimating an optimal contingency, and so the NeuroShell Predictor software was allowed to search automatically for this number as part of the ANN development process.

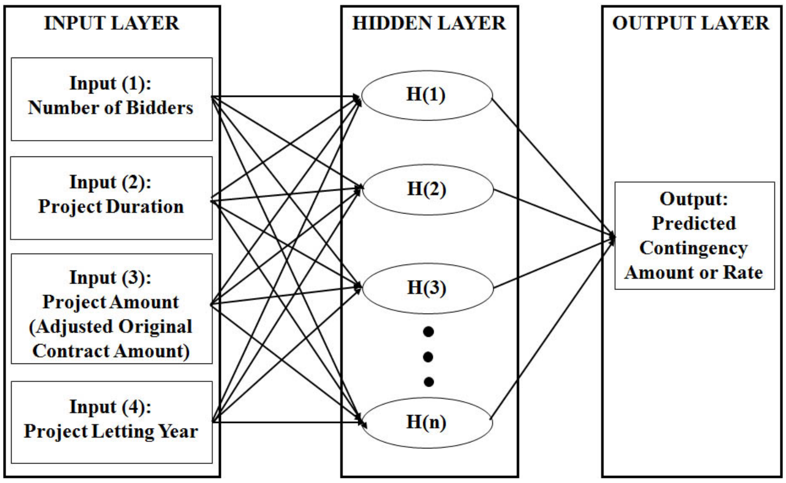


*FIG. 4: Basic structure of artificial neural network*

The NeuroShell Predictor software provides the following net statistics as parameters for evaluating the performance of an ANN-based prediction model. In this study, the target output values mean the desired contingencies calculated by the difference between adjusted original contract amounts and final contract amounts as shown in Figure 2 and the predicted output values are estimated through the ANN model as shown in Figure 4. By comparing the two output values (i.e. desired contingencies vs. predicted contingencies) within the software or by manual calculations, the values of the net statistics are calculated and determined as follows:

1. Average Error: for a given set of patterns, the sum over all patterns of the absolute differences between the target output values and those estimated by the ANN, divided by the number of patterns.
2. MSE (Mean Squared Error): for a given set of patterns, the sum of the squares of the differences between the target output values and those estimated by the ANN, divided by the number of patterns.
3. Correlation: the Pearson's correlation coefficient between the target output values and those estimated by the ANN.

## 2.1 One-step ANN-based Prediction Model vs. Two-step ANN-based Prediction Model

Lhee et al. (2012) undertook an experiment on the prediction of the owner's contingency on transportation construction projects using the one-step ANN approach implemented within the NeuroShell Classifier (Ward Systems 2012) software and found that the contingency rate is not a better output than the contingency amount for the ANN model in terms of predicting contingency. The desired contingency amount and rate are defined as cost items to cover all unforeseen change orders and related risks in the delivery of the projects. That finding was determined from the performance of the one-step ANN-based model in which both the predicted contingency amount was directly retrieved from the network inputting numerical values of four variables in the neural network software as shown in Figure 5(a). In an attempt to improve the performance of the single step model that predicts contingency amount, a two-step model was considered that first predicts the contingency rate and then modifies this by the *adjusted original contract amount* to obtain the contingency amount (see Fig. 5(b)). The two-step ANN-based model was implemented and then compared with the one-step ANN-based model. Initially the NeuroShell Predictor (Ward Systems 2012) software produced the predicted contingency rate in the same way as the one-step ANN-based model. Next the newly predicted contingency amount as output value is calculated from the predicted contingency rate multiplied by the adjusted original contract amount. Finally, the net statistics such as average error, MSE, and correlation in the two-step ANN-based model are calculated and are compared with those in the one-step ANN-based model to predict the contingency amount.

## 2.2 Comparison of the Performances of the ANN-based Prediction Models

This study considers two neural network-based approaches to predict the owner's contingency on transportation construction projects. The first ANN model predicts the contingency amount directly at its output. The second predicts the contingency rate which is then multiplied by the adjusted original contract amount to get the contingency amount. Table 1 shows the performances of the two neural network-based approaches for both the training and testing datasets.

As seen in Table 1, both the one-step and two-step ANN-based models demonstrated good learning for the training dataset based on the high correlation values of 0.827 and 0.863, respectively. However, the two-step model demonstrated better performance than the one-step model in terms of all error metrics for the two datasets. The performance in terms of average error was improved by 27% on the training dataset and by 32% on the testing dataset. The performance in terms of MSE were improved by 4% on the training dataset and by 30% on the testing dataset. Finally, the correlation for the two-step model was slightly higher than that of the one-step model for both the training and testing datasets.

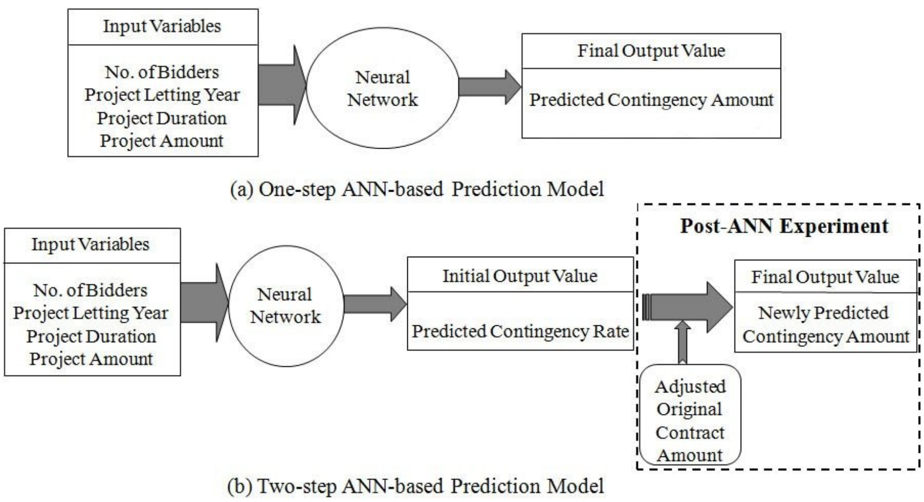


*FIG. 5: One-step ANN-based model vs. Two-step ANN-based model*

Figure 6 shows a plot of the desired versus predicted contingency amounts for the two ANN-based models for the training dataset. If the networks had learned all training patterns perfectly, then all points would fall on the 45° line shown.

*Table 1: Performances of Two ANN-based Modeling Approaches to Predicting the Contingency Amount for both the Training and Testing Datasets*

| Dataset | Net statistics | One-step ANN-based model | Two-step ANN-based model |
|---|---|---|---|
| Training dataset | Average Error ($) | 275290.0 | 200293.6 |
| | MSE ($) | 4.20E+11 | 4.04E+11 |
| | Correlation | 0.827 | 0.863 |
| Testing dataset | Average Error ($) | 281241.8 | 192100.5 |
| | MSE ($) | 3.93E+11 | 2.76E+11 |
| | Correlation | 0.550 | 0.561 |

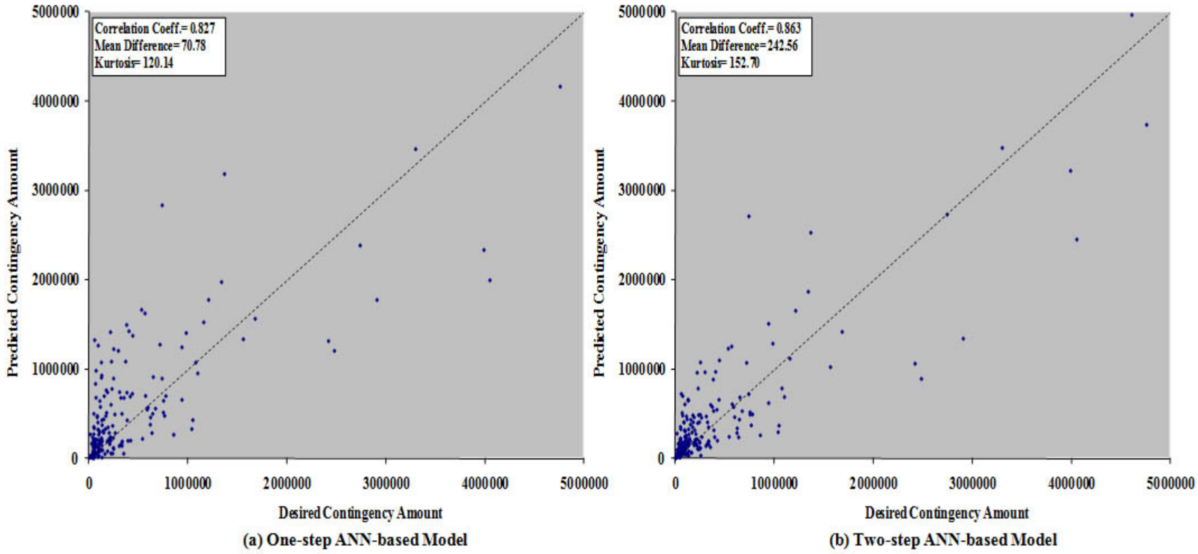


*FIG. 6: Correlation between desired and predicted contingency amounts for the training dataset*

Figure 7 plots the desired versus predicted contingency amounts for the two models for the testing dataset. In this case, if the two models were perfect predictors then all points in Figure 7 would fall on the 45° line shown. In order to know whether the two models on the testing dataset under-predicted or over-predicted the contingency amount, mean differences between the desired contingency amounts and predicted contingency amounts were checked. For the testing dataset, the one-step model tended to predict higher contingencies than desired with a mean value of $79,269. The two-step model also tended to predict higher contingencies than desired, but this time with a 13% lower mean value of $68,640.

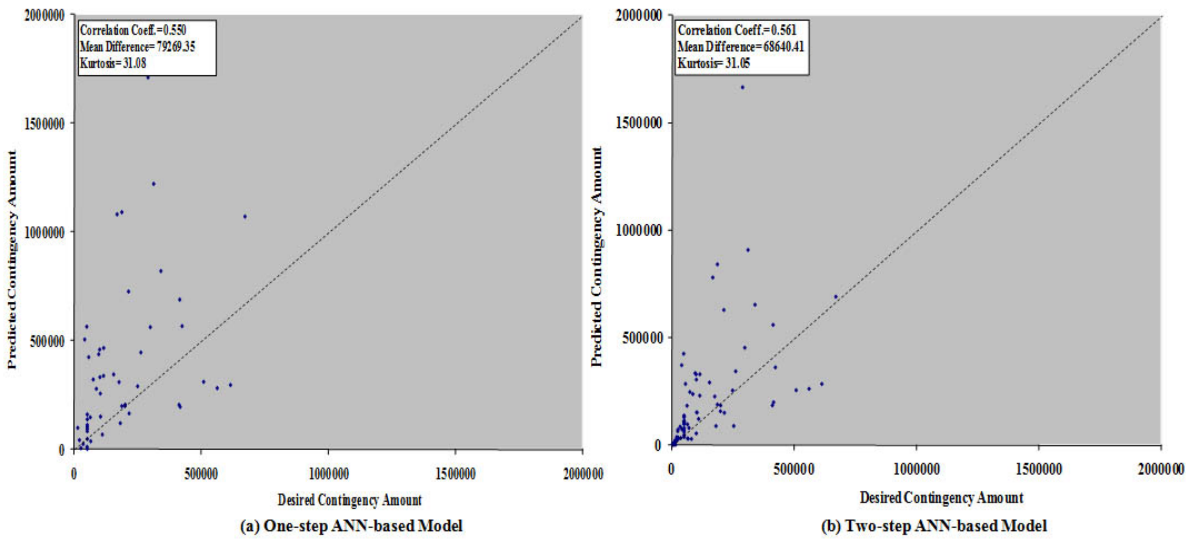


*FIG. 7: Correlation between desired and predicted contingency amounts for the testing dataset*

The kurtosis was also checked as a statistical measure used to describe the distribution of absolute differences between predicted and desired contingency amounts about the mean. A high kurtosis indicates that errors tend to have a distinct peak near the mean, decline rather rapidly, and have heavy tails, while a low kurtosis indicates that datasets tend to have a flat top near the mean rather than a sharp peak. In other words, kurtosis indicates whether the mean error is composed of many small errors or a few large errors. From the positive values of kurtosis ($\text{kurtosis}_{(\text{one-step})}$=31.08, $\text{kurtosis}_{(\text{two-step})}$=31.05), it was found that the distribution of the absolute differences on the two ANN-based models for the testing dataset is a shape with a distinct peak near the mean and heavy tails.

In order to provide a final assessment of the performance of both ANN-based approaches at predicting the contingency amount and show the validity of the two-step prediction model, it was decided to re-evaluate the performance of the models using a 3$^{rd}$ dataset (the validation set). As shown in Table 2, of the two approaches the two-step ANN-based model had the superior performance, reducing the average error by 22% and the MSE by 23% for the validation dataset. In addition, the value of correlation on the two-step ANN-based model was slightly higher than that on the one-step ANN-based model. Figure 8 shows scatter graphs between the desired contingency amounts and the predicted contingency amounts of the two prediction models for the validation dataset. The scatter graphs for the two models on the validation dataset have similar distribution forms as the correlation and kurtosis values were found to be similar. Both the one-step and two-step models were positively biased in that they predicted higher contingencies than desired (the mean differences between desired contingency amounts and predicted contingency amounts was $73,868 for the one-step model and $59,690 for the two-step model). However, the two-step model reduced the mean difference by 19%. Based on positive values of the kurtosis ($\text{kurtosis}_{(\text{one-step})}$=14.81, $\text{kurtosis}_{(\text{two-step})}$=21.98), the distribution of the absolute differences on the two prediction models on the validation dataset have a relatively peaked shape around the mean absolute differences.

In order to reconfirm the improvement of performance from the two-step ANN-based model over the one-step model in predicting the contingency amount, a statistical analysis of the error rates was performed. Error rates in both prediction models on the validation dataset were calculated using Eq. (1).

$$\text{Error Rate (\%)} = \left|\frac{\text{Actual Output Value} - \text{Predicted Output Value}}{\text{Actual Output Value}}\right| \times 100 \qquad (1)$$

*Table 2: Performances of Two ANN-based Models on the Validation Dataset*

| Net statistics | One-step ANN-based model | Two-step ANN-based model |
|---|---|---|
| Average Error ($) | 242759.8 | 189596.7 |
| MSE ($) | 1.94E+11 | 1.50E+11 |
| Correlation | 0.518 | 0.524 |

Table 3 shows the mean and standard deviation of the error rates of the two models for the validation dataset. For the mean of the error rates, the two-step ANN-based model provided nearly a 100% improvement over the one-step ANN-based model. In the case of the standard deviation of the error rates, the two-step model provided about a 230% improvement over the one-step model. The two-step model provided more accurate and reliable predictions of contingency amounts than the one-step model.

*Table 3: Statistical Analysis of ANN-based Models for the Validation Dataset*

| Prediction Model | Mean(Error Rates) | Standard deviation(Error Rates) |
|---|---|---|
| One-step ANN-based model | 3.13 | 6.24 |
| Two-step ANN-based model | 1.57 | 1.89 |

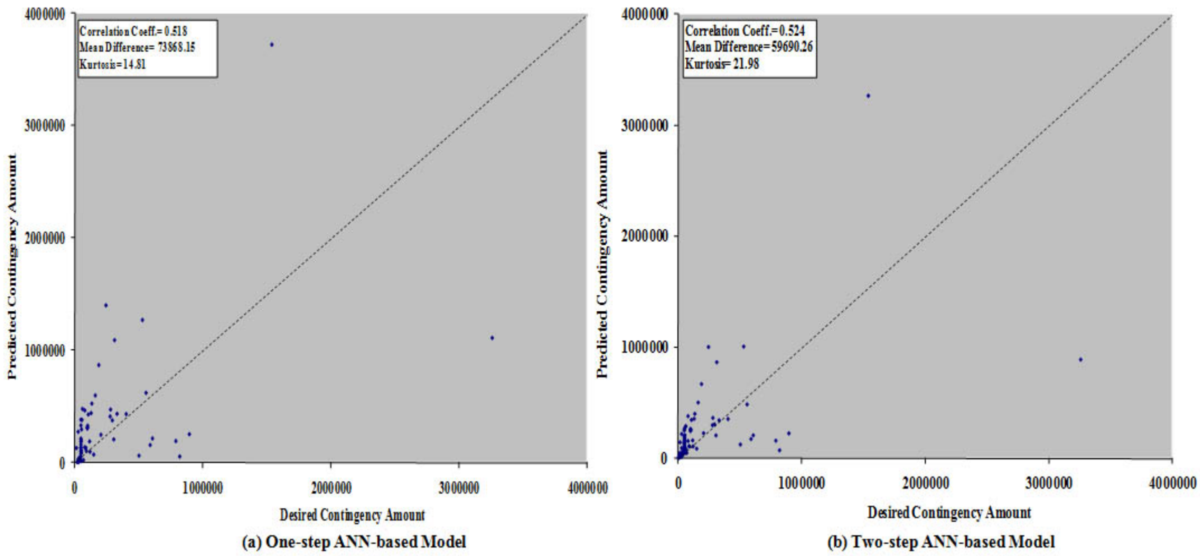


*FIG. 8: Correlation between desired and predicted contingency amounts for the validation dataset*

## 2.2 Analysis of the Generalized Performance of the Two-step ANN-based Prediction Model

Analysis of the generalized performance of the two-step ANN-based prediction model was next made to see if it performed satisfactorily and consistently across the entire problem domain. This task can be done visually by plotting testing errors against each input variable. Figure 9 shows the distribution of the testing errors against each of the four input variables in the model for the full scope of the problem. For the input variables “number of bidders” and “project letting year”, the model appeared to be performing relatively consistently across all values. However, for the input variables “project duration” and “project amount”, the performance of the model tended to degrade for higher values of these variables. This corresponds with a reduction in the density of training patterns in these regions of the problem. A reasonable future experiment, therefore, would be to increase the density of training patterns that have higher values of "project duration" and "project amount."

## 3. CONCLUSION

Previous ANN models for predicting the contingency item on construction projects have used the one-step method, where the estimated value is generated at the output layer of the neural network. In order to check the possibility of improving the prediction ability and minimizing the prediction error in the allocation of contingency, this paper proposes a two-step ANN-based approach. The model was developed by manipulating an intermediate form of contingency (i.e. contingency rate) as the output variable of the neural network to predict the owner's contingency on transportation construction projects. The validity and value of this model was shown through the comparison of the performances with the one-step ANN-based model. In the two-step prediction model, the output value was represented as the new contingency amount manually calculated from the predicted contingency rate directly obtained through the NeuroShell Predictor software as a post-ANN computation. Based on the net statistics such as average error, MSE, and correlation values and the statistical analysis about error rates, the predictive performance of the two-step model was shown to be better than that of the one-step model. Thus, accurate predictions of contingency using the newly proposed model can help project owners such as departments of transportation (DOTs) better manage contingency requirements on financing their projects by allowing a more effective usage of available project funds.

In conclusion, ANNs are powerful empirical modeling techniques that provide fast and convenient solutions to complex nonlinear problems. However, the success of an ANN implementation depends not only on the quality of the data used for training, the type and structure of the neural network adopted, and the method of training, but also on the method of

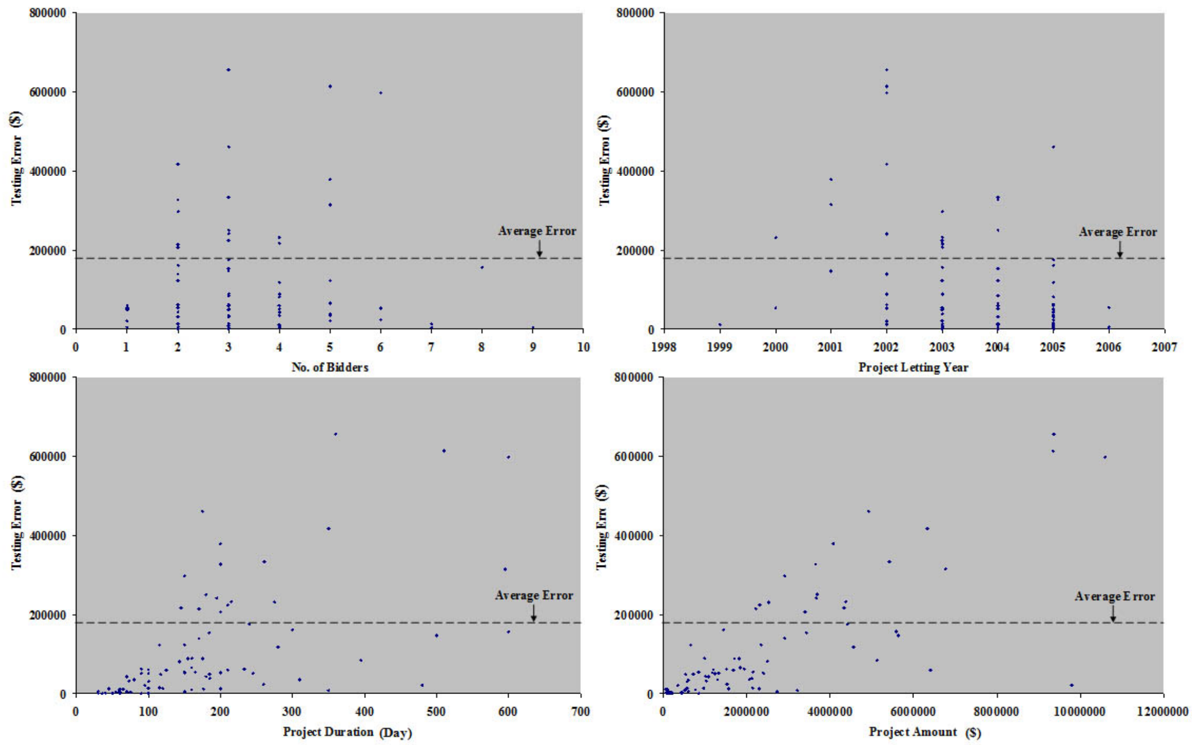


*FIG. 9: Evaluating testing error across the problem domain for two-step ANN-based model*

representing and interpreting the input and output data. In other words, designs and strategies on the development step of ANNs including the determination of an appropriate form for output variables and the identification of potential input variables can have a significant impact on the performance of the resultant networks. Therefore, ANN model developers should invest sufficient time and effort into determining an appropriate design and coding for the input and output variables.

Further work should consider defining more practically the scope of the problem domain (to encompass all problems likely to be encountered in application), pre-treatment of outliers and increasing the density of the training patterns in low density regions of the problem domain, the use of different neural network structures and training algorithm.

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