

Modeling the Cost of Political Risk in International Construction Projects

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■ Abstract

This paper describes a neural network model that can provide assistance in predicting the additional increase in project cost, due to political risk source variables affecting a construction project. The risk factors that affect a construction project are classified as “political source variables” and “project consequence variables.” These source variables are identified and represented in a neural network model. The paper explains how the developed political risk control model can be incorporated directly into a project cost estimation process. The paper concludes with a discussion of the capabilities and limitations of the proposed political risk estimation method, and how it will assist project managers in computing a realistic cost estimate for typical international construction projects under different political conditions.

Keywords: political risk; international projects; artificial neural networks; cost estimate

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Many cost and time overruns in international projects are mainly attributed to either unforeseen events or foreseen events for which risk has not been appropriately accommodated in the project budget. International construction firms operating in a foreign country face the challenge of identifying, analyzing, and evaluating various types of “political” risks that may affect their projects. *Political risk* is defined as a risk resulting from the actions of a government that will decrease the return of a planned foreign investment (Al-Bahar & Crandall, 1990). The cost of political risk can be a deciding factor for international firms for whether or not to enter into a bidding activity in a specific country. Further, an accurate budget update based on the changing project environment is necessary to obtain a realistic financial plan during the progress of the project. A systematic framework for identifying, evaluating, and quantitatively estimating the cost of political risk is essential for managing international construction projects.

In order to assess the impact of uncertainty and risk involved in a construction project, there are several traditional methods used that are based on subjective analytical examination. These techniques mainly rely on historical information and experience of the person/company involved (Bajaj, Oluwoye, & Lenard, 1997). If applicable historical data are inadequate or ab-

sent, then the subjective judgment of experts who have relevant knowledge and experience is traditionally used for risk assessment. For example, the common practice for construction risk cost estimating in international projects is to solicit an expert in the host country to evaluate the impact of risk based on history, culture, and policies of the host country. Based on this expert advice, a considerable contingency allowance to the overall estimate is added to the project cost. This contingency allocation approach is simplistic and based on a single estimator's perception of project risks, in which the estimator finds it difficult to justify or defend the judgment or to convincingly explain the perception about future risks. The determination of the right amount of the added contingency is implemented subjectively and without proper judgment or criteria externalization.

This paper introduces a representation-modeling tool for evaluating and quantifying political risks in international construction projects. An artificial neural network (ANN) methodology is proposed to represent the experience and knowledge of experts involved in risk assessment. ANN is a powerful artificial intelligence modeling method that facilitates the representation of human knowledge and expertise in fields where conventional algorithmic programming does not apply. ANN is used in this paper to develop a political risk-

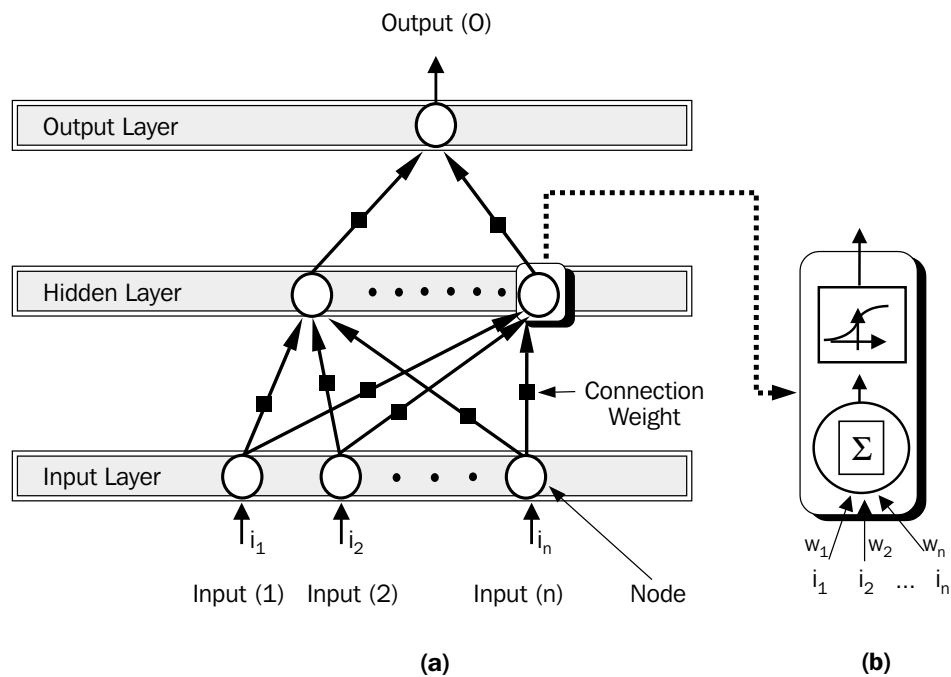


Figure 1. An ANN With Three Layers (a) and Activities at the Neural Network Node (b)

quantifying method and to aid the subjective political risk-assessment process of estimators.

The paper describes how an ANN system can be designed and developed so as to identify the cost deviations that occur, due to the political risk involved in a construction project, by observing the status of key factors that affect the project cost. With appropriate training on the ANN model, the project manager can incorporate the risk consequences into a bidding decision, and generate revised and updated risk estimates systematically and easily during the progress of the project. The model can be applied to a project at regular intervals to quantify the increase in budget cost. Once the increase in cost due to risk is identified, the baseline budget for the remainder of the project can be easily revised by a project manager, based on the change in risk perceptions.

Artificial Neural Networks

ANNs are a class of modeling tools composed of neurons or processing elements and connections that are organized in layers—an input layer, middle or hidden layer(s), and an output layer—as illustrated in Figure 1. The signals entering the input layer flow to the output layer through the middle layer(s), with the input signals detailing the problem to be solved and the output signals representing the network's solution to that problem. The connections among the neurons are associated with numerical values, called connection weights, that determine the influence of one neuron on another. The connection weights modify the output signal on each of the connec-

tion paths, making some connections stronger and other connections weaker. The neurons in the input layer receive their activation from the environment, while the activation levels of neurons in the middle and output layers are computed as a function of the activation levels of the neurons feeding into them. Typically, this involves the summation of all incoming signals (along with a bias associated with the middle layer neuron), followed by the application of a nonlinear function termed the *activation function* or *transfer function*.

During the training process, the connection weights are learned by the network, as training examples are presented repeatedly. The neural network modifies the weights between layers in successive iterations until the network is able to generate the desired output of the system to within a specified accuracy, or until the user-specified number of iterations has been performed. Knowledge is effectively learned and stored by the weights on the connections between the neurons. Once training has been completed, it is anticipated that the neural network will be able to generate the required output for example problems not considered during training. ANNs allow self-learning, self-organization, and parallel processing, and are well suited for problems involving matching of input patterns to a set of output patterns where deep reasoning is not required.

Figure 1(a) depicts a typical neural network representation of input, output, and hidden layers. Figure 1(b) shows the schematic of a single artificial neuron. For the current problem representation, the input layer consists of the status of construction risk environment

variables, while the output layer represents the expected variances in project cost. A good introduction to the general field of ANNs can be found in Lippmann (1987) and Caudill (1989). Neural networks are widely used in the field of project control and cost management. Al-Tabtabai, Kartam, Flood, & Alex (1997) proposed a neural network-based system in the area of project control, and Al-Tabtabai and Alex (1997; 1998) discussed using it to manage the construction cost during the progress of a project.

Political Risk in International Construction

The three targets of cost, time, and quality are subject to political risk and uncertainty in international construction projects. Contractors have to bear the majority of the risks pertinent to a project, as specified in the contract documents. In a highly competitive international market, marginal cost overruns can easily erase contractors' profits and may lead to major financial problems (Gorgan, 1995). Hence, project managers involved in international construction need to identify major political risk sources causing cost overruns in advance, to be

proactive in managing them. The major concern for the project manager, when project progress is affected by a risk situation, is to assess and select the most effective response to forecast the effect of political risk, and to apply mitigating strategies before actual project performance suffers.

If factors leading to a political risk can be identified in advance, then techniques for managing the risk can be an integral part of project design and implementation. To minimize the effects of political risk, a systematic approach to the management and assessment of project risks and uncertainties in the planning phase is required. International firms usually allocate contingency allowances in the budget to provide for unforeseen circumstances based on political and economic factors. The project baseline budget is modified, according to the magnitude of political risk expected for the project, in the form of a contingency added to budget cost. The provision of risk allocation should ensure that the budget set aside for project execution is realistic and sufficient to contain the unforeseen cost increases due to this risk. The cost effect of each significant risk factor should be analyzed to determine realistic cost estimates for projects. A realistic estimate that quantifies an appropriate allowance for all those risks and uncertainties is usually anticipated from experience and foresight (Perry, 1986).

A typical systematic approach to risk control should involve the identification of the risk sources, assessment of their effects on the current project, and selection of means to control them.

Risk identification is a difficult task, because it is often highly subjective, and there are no unerring procedures that may be used to identify construction risks other than relying heavily on the experience and insight of the key project personnel (Bajaj et al., 1997). Nevertheless, it is still possible to approach political risk in a systematic way. Risk involved in a project can be identified by subdividing a project into its major elements, and analyzing in detail the risk and uncertainty associated with each. Each work center can be treated as a risk center. The amount of contingency allowance to be allocated for each will be different. The reasoning used by the project manager, in predicting the expected political risk performance, requires an understanding of the characteristics of the project work and the environmental attributes surrounding the work that contribute to a particular performance.

Risk evaluation of construction projects requires the analysis of various construction processes in order to account for the involved and perceived risk associated with these processes. It can be observed that the cognitive process of the project manager leads to a conceptual representation of the circumstances surrounding a project performance at a given time, in order to forecast the expected risk effects. This representation includes

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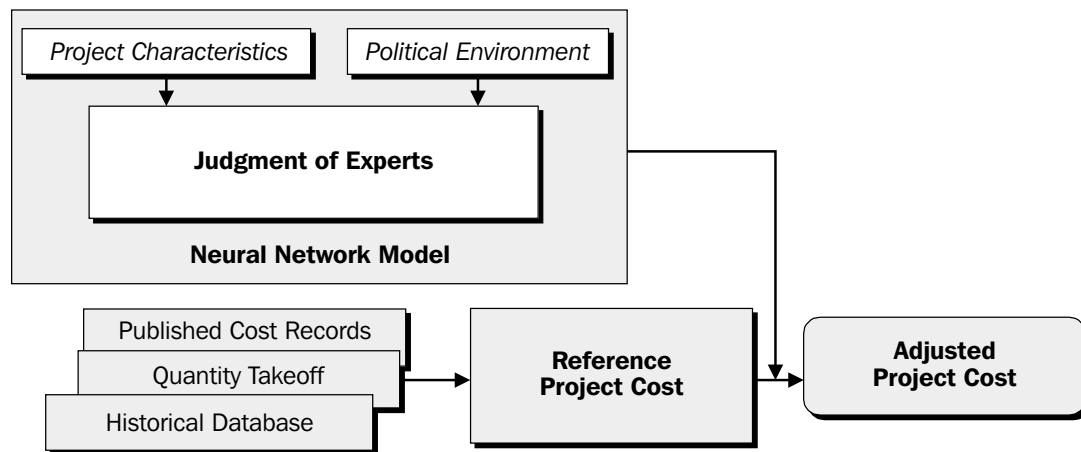


Figure 2. Proposed Risk Estimation Process

functional relationships among various factors causing risk and the cost performance of the project. Any prediction on the effect of political risk requires a clear understanding of the key political risk variables that impact the performance of the project.

Risk does not completely follow historical data; rather it also depends on environmental factors. Most projects contain a number of reasonably standard and recognizable political risk situations (Bajaj et al., 1997). In such situations, the judgment of the project manager plays an important role in forecasting political risk, rather than basing the estimate on historical frequencies.

Once the political risk variables that affect the cost are identified and the cost's status is determined, an expert in political risk can make intuitive judgments about the expected influence of these variables on the risk parameters, based on analogy and without the necessity of deep reasoning. A project manager uses her expert knowledge, gained through education and experience in the construction environment, to identify the magnitude of variation in cost from the reference project cost. This knowledge includes technical skills; economic, political, and financial knowledge; and social, communication, and legal skills, as well as political knowledge. A systematic pattern of these judgments can be coded and represented in a neural network. The list of political risk source variables will act as the input variables for the network, while the expected variance rating due to the perceived risk, represented in a suitable form, will be the corresponding output variables.

Different work elements of a project can be evaluated using a trained neural network to identify the variations in cost from the planned values. The trained neural network mimics the decision process of the expert whose judgment is employed for training. Outputs from such systems can be used to update the risk statistics and to generate revised estimates at various execu-

tion stages of the project. The concept of the proposed risk assessment system is represented in Figure 2.

Neural Networks for Political Risk Prediction

Identification of Environmental Factors. The environmental risk factors affecting a project have been well categorized by Ashley and Bonner (1987); they divide the political risk factors into political source and project consequence variables. These in turn affect the four different elements of cash flow—labor cost, material cost, overhead cost, and revenue. The major political source variables that affect any international construction project are as follows:

- *Firm's relationship to the government.* This variable represents the firm's relationship to the government, agencies, unions, groups, and so on. Good relationships with the members of the government will protect the interests of the firm and provide information and support.
- *Firm's relationship to the power groups* (labor unions, business associations, environmental protection groups, radical groups, etc.). This factor is increasingly found in most of the developed and developing countries. Labor strikes initiated by labor unions and termination of construction operations for environmental reasons by environmental groups are a few examples of the impact of this factor.
- *Involvement of local business interests.* Considerable political risk can be avoided by involving a high level of participation by host country nationals (e.g., using local suppliers or local subcontractors or having an efficient local partner).
- *Impact of regional and external factors.* Regional risk factors include terrorism, crime rate, and vandalism, which can affect the business on a daily basis. External risk factors include armed or political conflicts between

Political Source Variables

- Firms Relationship to Government
- Firms Relationship to Power Groups
- Involvement of Local Business Interest
- Impact of Regional and External Factors
- Nationalist Attitude Toward the Firm
- Project Desirability to the Host Country

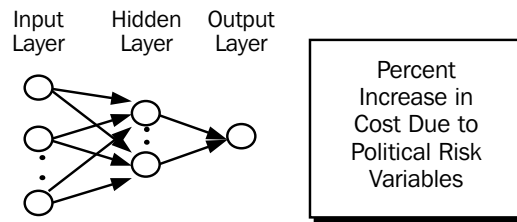


Figure 3. Input and Output Vectors of the Neural Networks

a country and its neighbors, as well as other sociopolitical disorders.

■ *Nationalistic attitudes toward the firm.* The degree of acceptance that the firm can expect from entities within the host country is reflected in this factor. Examples include anti-foreign sentiment and difficulties due to origin, religion, and perceptions.

■ *Project desirability to the host country.* This variable refers to the relative importance of the project to both the government and local power groups. A desirable project may benefit from "political smoothening" and elimination of barriers.

The list of selected political risk factors represents the majority of typical project risks. These variables lead to project consequence variables that affect the cash flow and profitability of a project. The variables that influence the estimation of expected political risk for international construction operation are selected as the input variables for the neural network model shown in Figure 3.

Risk Judgment. For proper analysis of risk, it is important to create multiple scenarios of the future. Scenarios (case profiles) with random values for each of the input variables were used for judgment collection in our research. For illustrative purposes, five project managers with more than 20 years of international construction contracting and management experience were selected, and their judgments on 50 case profiles were collected. Each case represents a unique situation of a project. Experts provided their responses for the input variables using seven labels, as shown in Figure 4. A rating in the form of a percentage change in cost from the baseline cost forms the output vector for the neural network model. For Figure 4, a slightly risky situation is assumed to cause a 10% increase in cost, while a very risky situation imposes a 60% increase in cost. Potential users can modify these ranges according to the nature of the project and the host country in which the project is implemented.

The input variables used in the models are inherently continuous in nature, and, hence, any of an infinite number of values could be input. However, there was a need to select some scale to which a user of the system could relate. The neural network is an empirically derived model, as opposed to a theoretically de-

rived model. A quantification of each input variable (into one of seven values) is not difficult for an expert in the field. For example, Attribute 1 (Firm's Relationship to Government) can have a range value between 1 (Very Good) to 7 (Very Poor). When an attribute is labeled as "very good," it refers to the best favorable condition that an expert can think of regarding that attribute, while an attribute labeled as "very poor" refers to the maximum worst condition that an expert can think of regarding that attribute. Once the experts identify these extremes from their experience and skill, they can then easily quantify other intermediate scale values between these extremes. Such experts make such judgments on a day-to-day basis when evaluating the performance of a project, albeit in a less formal manner. The choice of words to express each level for a variable (where appropriate) facilitates this task by using terms that are familiar to the expert.

The experts analyzed the state of inputs describing the case profile, and exercised their judgments on the expected change of cost due to political risk for the described project. The judgments of each expert on these case profiles were further given as feedback to each of the other participants for modification and revision of judgments. The revised judgments were averaged to reach a smoothed output value for each of the case profiles. These hypothetical case profiles with the extracted output values were coded to generate a set of training data.

The total number of possible cases is effectively infinite since the input variables are inherently continuous. The fact that the authors chose to limit the actual values of each input to a finite set does not alter this point. As far as the neural network is concerned, it is fitting a continuous function to the training data. The number of training points that are needed to develop an accurate continuous function model depends on other factors, most notably: the complexity of the solution surface being modeled (i.e., how many hills and valleys it contains), the stochastic content of the data (i.e., one needs enough training points to prevent bias due to random fluctuations), and the number of input variables (though not the number of values considered for each variable where they are inherently continuous). The capability of neural networks to generalize on limited quantities of training data combined with

Case # _____

Rating → Factors ↓	1.00	2.00	3.00	4.00	5.00	6.00	7.00
Cue: 1 Firm's Relationship to Government	Very Good	Good	Slightly Good	Normal/Neutral	Slightly Poor	Poor	Very Poor
Cue: 2 Firm's Relationship to Power Groups	Very Good	Good	Slightly Good	Normal/Neutral	Slightly Poor	Poor	Very Poor
Cue: 3 Involvement of Local Business Interests	Very High	High	Slightly High	Normal	Slightly Low	Low	Very Low
Cue: 4 Impact of Regional and External Factors	Highly Favorable	Favorable	Slightly Favorable	Normal	Slightly Unfavorable	Unfavorable	Highly Unfavorable
Cue: 5 Nationalist Attitude Toward Firm	Very Friendly	Friendly	Slightly Friendly	Neutral	Slightly Hostile	Hostile	Very Hostile
Cue: 6 Desirability of Government Toward the Project	Highly Desirable	Desirable	Slightly Desirable	Neutral	Slightly Undesirable	Undesirable	Highly Undesirable

How risky is the above situation? (Please circle the digit.)

	No Risk	Slightly Risky	Risky			Very Risky	
Label	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Increase in Cost	0%	10%	20%	30%	40%	50%	60%

Figure 4. A Typical Case Profile Used for Expert Judgment

the randomness in the training set will alleviate any chance of bias due to the limited number of training cases.

Neural Network Design. In this research, a continuous function-mapping network design has been adopted, since the values of the output variable (percent increase in cost due to risk) and the input variables are continuous. Continuous mapping functions can represent both continuous and discrete data, whereas discrete mapping functions are limited in their ability to represent continuous data. However, certain discrete sets of values (attribute labels) were used to provide meaningful anchors for the scale values in order to ease the judgment process of experts during knowledge acquisition.

Back Propagation Algorithm. The back propagation algorithm is the most widely used training technique for continuous function mapping. This algorithm has been shown to be theoretically sound (Rumelhart, Hinton, & Williams, 1986), performs well in modeling nonlinear functions, and is simple to code. Back propagation algorithm training develops the input to output mapping by minimizing a sum squared error cost func-

tion measured over a set of training examples. The mean squared error (MSE) is expressed as:

$$MSE = \sum \frac{(D - A)^2}{n}$$

where "A" is the actual output generated by the neural network, "D" is the desired output value, and "n" is the number of training examples.

The transfer function computes the activation level of a neuron from the sum of input values. The function adopted for the current problem was a sigmoidal curve, given by:

$$\text{Transfer Function } (x) = \frac{1}{1 + e^{-x}}$$

where "x" is the sum of the inputs to the neuron. The sigmoidal function generates output values between 0 and 1.

Learning Rate Coefficient. Another important network design variable is the learning rate coefficient (η) that represents the degree by which the weights are changed when two neurons are excited. Each time a pattern is presented to the network, during learning the weights leading to a neuron are modified slightly in the direction required to produce a smaller error at the outputs the

next time that the same pattern is presented. The amount of weight modification is proportional to the learning rate. The value of η ranges between 0.0 and 1.0, where a value closer to 1 indicates significant modification in weight, while a value close to 0 indicates little modification. A small learning rate of 0.15 was arbitrarily chosen for the current problem, since larger learning rates often have been found to lead to oscillations in weight changes resulting in a never-ending learning process.

Momentum Coefficient. One way to allow faster learning without oscillations is to make the weight change, in part, a function of the previous weight change. A momentum coefficient represents this portion of the weight change. In this study, a coefficient of 0.7 was found to perform well.

Hidden Layers. The number of hidden layer(s) and the number of hidden neurons in the hidden layers provide the power of internal representation in capturing the nonlinear relationship between the input and output vectors. Hence, a larger number of hidden layers and hidden neurons provides the potential for developing a more effective network. However, the addition of more hidden neurons increases the number of undetermined parameters (weights and biases) associated with the network. A large number of training examples is then needed to solve these parameters and to get a good approximation of the problem domain. When too few training examples are provided, the network will try to memorize, resulting in poor generalization. Carpenter and Hoffman (1995) determined that to provide a good approximation over the problem domain, one should have overdetermined approximations; that is, the number of training pairs should be greater than the number of undetermined parameters. Undetermined parameters in neural network approximations are the weights and biases associated with the network. To capture and represent the features within a set of data, there usually should be one to two hidden layers. One hidden layer with 14 hidden neurons constitutes the current network arrangement.

Neural Network Training. The generated input-output data pairs (50 cases) were each divided into a training set and a test set. The test set was derived from the data set by selecting 10–20% of data pairs randomly. NEUROSHHELL, a commercially available neural network development software from Ward System Group Inc., was employed to train and develop the neural network model. Six input neurons and one output neuron with 14 hidden neurons constitute the neural network arrangement for the political risk module.

The training of a neural network is stopped when the error falls below a user-specified level, or when the user-defined number of training iterations has been reached. In this case, 20,000 iterations were planned for the final training process, as this was found adequate in a series of test runs. Network development was performed on an IBM-compatible machine (100MHz, 16MB RAM). Training took 30 minutes, and the least-

average error of the network, which was accumulated over all the training sample cases, reached 0.0000054. The neural network approach discussed in this paper (to develop a political risk system) is illustrated in Figure 5.

Table 1 provides the comparison between the actual output and the neural network-generated output for the testing set. The MSE for the neural network model when applied to the test cases was found to be 0.3902, and the percentage of average operational error for the test cases was found to be only 7.016%. These statistics show the ability of the network to predict the political risk judgment values with moderate to high precision. Figure 6 plots the expert judgment (solid line) and the predicted values by the neural network (thin line) for the complete data set of the political source decision variables.

Neural Network Implementation. The next step following the model development is to incorporate it in existing estimation systems. A preliminary observation of several project sites indicated that a typical computing facility consists of a Windows-based PC, which uses powerful and inexpensive estimating systems (e.g., Precision Estimator), along with spreadsheets. These systems allow the user to customize various operations conveniently. Recently, popular software houses have begun to provide at least one programming language support to its software systems. This allows the user to create powerful macros that automate various sequences of actions within the software systems.

Most Windows-based systems allow the transfer of data between compatible systems using dynamic data exchange, object linking and embedding, clipboard transfer, open database connectivity, etc., along with the import and export of data files in predefined formats. Given these capabilities, it is possible to incorporate the developed models in most of the conventional estimation and cost management systems.

The following general steps can be adopted to integrate the models with popular spreadsheet packages used in the construction industry. The steps required are embed: the trained networks in any spreadsheet file (most neural network development tools can represent the learned network as a dynamic link library that can be inserted to any Windows-based spreadsheet), import the cost data file to the spreadsheet file, input the current values of risk variables in the spreadsheet, activate the networks to predict the percentage increase in project cost based on the input variables, and modify the initial cost estimates with the percentage increase in cost suggested by the neural network.

A more advanced user interface can be developed using interface-programming languages. Queries regarding the environmental factors required by the model can be prompted using created dialogue boxes, and the user entries about the status of these factors can then be used by the model to generate the risk-adjusted cost. The neural network can be automatically applied

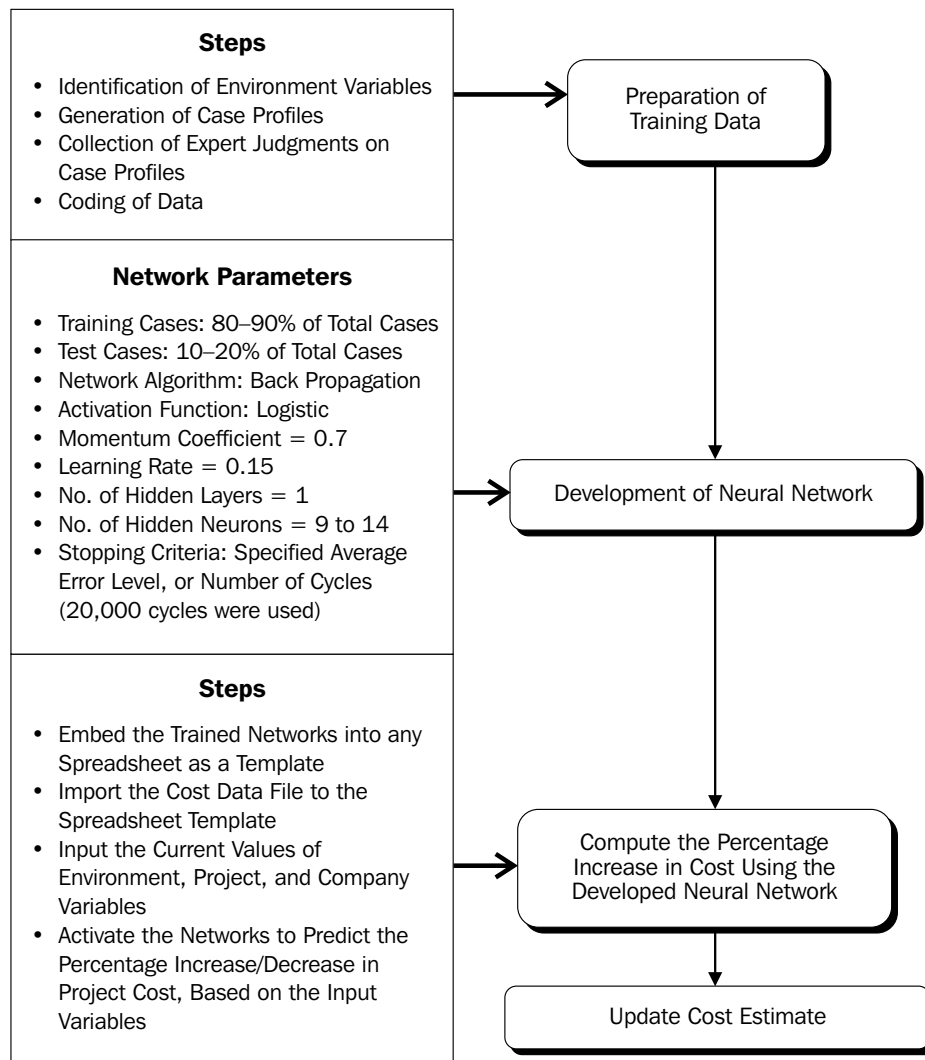


Figure 5. Development Procedures of the Neural Network-Based Risk Assessment System

to the remaining work packages, or those in progress, and the resulting changes will be reflected in the total cost by estimating the tasks based on these predictions. The set of instructions required to implement this function can be automated using a macro, which can be attached to a toolbar button in a spreadsheet application.

Discussion

The high-risk nature of construction projects has led to many cost overruns in the history of construction. Therefore, contractors should use a systematic approach to managing risk. Uncertainty inherent in these elements and its impact on results can be characterized by applying a neural network and incorporating it directly in the risk quantification decision process. The management of cost risks begins with a systematic political risk evaluation and appropriate allocation of contingency. The contractors often require the calculation of a risk

premium to transfer their risk to an insurance agency, subcontractors, owners and/or joint venture partners. Risk needs to be quantified in all these situations.

Risk analysis consists of three distinct stages: the identification of risk elements (categorizing foreseeable risk), the quantification of risk consequences (measuring monetary losses and gains resulting from risk events), and risk control (reducing or removing the exposure of a given risk by substituting proven technology for experimental technology) (Park, 1979). People need assistance in making accurate judgments about risk-associated consequences. Risk assessment requires experience and expert knowledge. A single estimator's experience may be limited. Hence, a collective expertise needs to be applied to calculate the risk-adjusted cost of a project.

ANNs offer a potentially powerful tool for estimating risk parameters from current project conditions. The prime reason for the selection of an ANN paradigm from other available artificial intelligence tools is its

Case Profile #	Desired Output (a)	Neural Network Output (b)
8	4.0000	5.2834
18	3.0000	3.6001
24	6.0000	5.3586
28	5.0000	5.4446
30	5.0000	4.4824
32	6.0000	5.8848
37	6.0000	5.8532
39	6.0000	5.5499

Mean Square Error = 0.3902

$$\text{Average Operational Error} = \frac{1}{n} \sum \left[\frac{b-a}{a} * 100 \right] = 7.0\%$$

Table 1. Comparison of Neural Network-Generated Output Versus Desired Output (Expert Judgment) on Unseen Cases

ability to learn and adapt a solution to a problem from experience. The major advantages of adopting ANNs for the quantification of risk-associated consequences are due to its ability to model the complex nonlinear mapping required in the decision-making process, fault-tolerance capability in smoothing out the noise in the data collected for training, and ability to generalize on incomplete information.

However, there are several factors that need to be addressed during the development of the system.

- The accuracy of the political risk evaluation models mainly depends on the soundness of the underlying expert decisions. In other words, the quality of the generated predictions by the neural network models depends on the legitimacy of judgments used for training.
- The training cases generated from the judgment of experts are not free of bias because of the intuitive and subjective nature of the judgment process of individuals.
- Any political risk variables that have a bearing on the cost performance, if omitted during the knowledge representation stage, will alter the predictions.

The provision of cognitive feedback of judgments among the experts allows to a great extent a reduction in the bias in judgments. In addition, the ability of neural networks to operate with noisy and incomplete data suggests that the earlier-mentioned limitations can be overcome to some degree. This ability can be enhanced by choosing high-quality, well-experienced professionals in the local construction industry as domain experts for knowledge representation. Increasing the number of training cases with a wide representation of various possible situations will enable the network to generalize and learn the problem more accurately.

Training cases can also be obtained from actual projects. In this case, the environmental variables and the risk effects of these variables on the work package will be

known and can be related to each of the risk domains. Careful observation of the project environment in a host country at regular intervals is necessary to generate such training cases. Thus, a more realistic representation can be obtained for training. The network modules can be further trained to represent any unique and peculiar characteristics of a specific country. New data can be appended to the training set for subsequent revision of the network knowledge.

Concluding Remarks

Misunderstanding the political risk involved in a construction project can jeopardize the project success. Estimating contingency amount by guesswork without proper judgment aid, when added to the capital cost estimate, can affect the outcome of the project's economic analysis. A contractor with a good risk understanding of his project can feel more secure with his project. Inability of management to fully anticipate conditions that affect cost leads to overruns. Monitoring those factors that have been identified as surrogates for the difference between original bid cost and final cost will help control the cost of projects.

An artificial neural network has been developed to quantify the cost consequences of political risk associated with construction projects. The paper has demonstrated the potential for applying neural networks to quantify construction risk. Neural networks are well suited to decision-making in analogy-based problems using the intuition and experience of experts. ANNs can embody more knowledge derived from the judgment process of a group of experts, and can represent the functionally independent and meaningful chunks of expert insight. This results from their ability to learn and generalize from experience. Research has shown

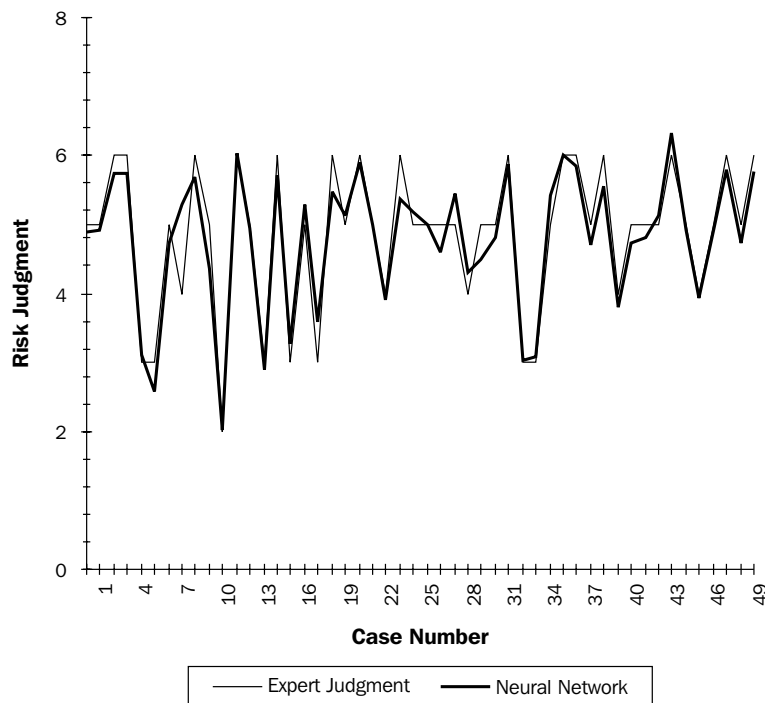


Figure 6. Comparison of Actual (Expert) Decision Versus Neural Network-Generated Decision

that neural networks are suitable for modeling complex relations between construction risk conditions and performance of the project, as reflected in the performance of various work packages.

As shown, it is best to break down the political risk domain into easily manageable modules with individual but systematic neural network representation, and then integrate these using an interface to provide the final solutions. The division of the political risk problem domain into different risk models reduced the complexity of a network and facilitated the knowledge-gathering process. The results obtained from the models were compared with the recommendations provided by the experts. The comparison showed the neural network solutions to be accurate. The test cases were limited in the illustration; however, a larger number of test cases would provide greater confidence in these results. The developed neural network-based political risk model can be integrated into spreadsheets used for cost estimation. Such integration facilitates the practical use of the proposed approach by consulting engineers performing supervision and by construction managers responsible for project risk management and control functions.

References

Al-Bahar, J., & Crandall, K. (1990). Systematic risk management approach for construction project. *Journal of Construction Engineering and Management*, ASCE, 116 (3), 533–547.

Al-Tabtabai, H., Kartam, N., Flood, I., & Alex, A.P. (1997). Construction project control using artificial neural networks. *AI EDAM: Artificial Intelligence for Engineering Design, Analysis and Manufacturing*, 11 (1), 45–57.

Al-Tabtabai, H., & Alex, A.P. (1997). Prediction of cost performance in construction projects using artificial neural networks. *Kuwait Journal of Science and Engineering*, 24 (2), 227–240.

Al-Tabtabai, H., & Alex, A.P. (1998). Preliminary cost estimation of highway construction projects using neural networks. *Cost Engineering*, 41 (3).

Ashley, D.D., & Bonner, J.J. (1987). Political risk in international construction. *Journal of Construction Engineering and Management*, 113 (3), 447–467.

Bajaj, D., Oluwoye, J., & Lenard, D. (1997). An analysis of contractor's approaches to risk identification in New South Wales, Australia. *Construction Management and Economics*, 15, 363–369.

Carpenter, W.C., & Hoffman, M.E. (1995, March). Training back prop neural networks. *AI Expert*, 30–33.

Caudill, M. (1989, Feb.). Neural networks primer. *AI Expert*, 61–67.

Gorgan, T. (1995). Special report: Forecast '95. *Engineering News Rec.*, 234 (4), 43–46.

Lippmann, R.P. (1987, April). An introduction to computing with neural nets. *IEEE ASSP Magazine*, 4–22.

Park, W. (1979). *Construction bidding for profit* (pp. 168–177). New York: John Wiley & Sons.

Perry J.H. (1986). Risk management—An approach for project managers. *International Journal of Project Management*, 211–216.

Rumelhart, D.E., Hinton, G.E., & Williams, R.J. (1986). Learning internal representation by error propagation. In D.E. Rumelhart, J.L. McClelland, & the PDP Research Group (Eds.), *Parallel Distributed Processing* (pp. 318–362). Cambridge, MA: MIT Press.

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