ANN APPROACH TO DETERMINE COST CONTINGENCY IN INTERNATIONAL CONSTRUCTION PROJECTS

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Introduction

It is commonly acknowledged that carrying out international projects is much riskier than conducting domestic projects, because the international construction environment is highly affected by numerous complex conditions, which in turn create severe difficulties and risks. The success of construction companies carrying out projects in overseas markets is predominantly subject to the extent to which these risks are managed.

Construction companies usually include a reasonable contingency amount in their bids for such projects as a response strategy in order to shield themselves from possible failures and achieve an acceptable risk-return balance (Sonmez et al., 2007; Dikmen et al., 2007).

A bid price typically consists of direct costs (i.e. costs of equipment, material and labor directly involved in the physical construction of the permanent facility), indirect costs (i.e. costs that do not become a final part of the permanent facility but required for its orderly completion such as field administration, direct supervision, capital tools, insurance, taxes, etc.), and a bid mark-up (i.e., general overhead, profit and contingency in percentage) (Dikmen et al., 2007).

Contingency, which is also named as “risk mark-up”, is an amount of money allocated for possible uncertainties associated with a construction project in the bid prices (Lee and Chang, 2004).

In a competitive bidding environment, contractors should offer the lowest price in order to achieve competitive advantage against their competent rivals as winning the contract is predominantly determined by how low a contractor can bid relative to other bidders. In this context, pricing can be considered to be a part of a strategic plan of a contractor. Since the amount of contingency directly influences the bid price, determination of the right amount of contingency is vital in the bidding process.

While low amounts of contingency may result in significant losses in highly risky projects, high amounts of contingency may unnecessarily inflate bid prices in low risky projects and thereby cause contractors to lose the job due to their relatively high bids.

Contractors may determine contingency in various ways. However, most construction companies still tend to determine the amount of contingency based on their past experiences or intuitions. In this technique, expert estimators and project team members assign a level of contingency based on their experience and expertise considering the risk level of the project in question.

Although this method is criticized for being highly subjective, it is still very widely used because of its easiness and simplicity (Burroughs and Juntima, 2004). The main goal of this study is to develop an artificial neural network (ANN) model that will assist construction companies in estimating contingency that they will include in their bids for international projects in a more systematic, efficient, economical, fast and objective way.

Research Methodology

The methodology of this study mainly involves: (1) carrying out an extensive literature review on international construction in order to identify the factors that may affect construction companies' decisions on how much contingency they should include in their bids for international projects, (2) developing the general framework of a contingency estimation model, (3) designing a questionnaire based on the information gathered from literature review and delivering these questionnaires to construction experts and obtaining the actual data of 195 international construction projects, and (4) developing an artificial neural network (ANN) model, which will assist construction companies to estimate contingency more accurately, using collected data.

Identification of Risk Factors

Review of literature on international construction (e.g., Dikmen et al., 2007; Sonmez et al., 2007; Bu-Qammaz et al., 2009) revealed that 59 risk factors may bring about difficulties for construction companies and thereby affect their decision on how much contingency should be included in bid prices for international construction projects.

These risk factors are categorized into 6 major groups; 1) bidding stage-related factors, 2) construction stage-related factors, 3) finance-related factors, 4) country-related factors, 5) company-related factors, and 6) contract-related factors (Polat and Duzcan, 2011, Polat and Bingol, 2011). Six major risk groups and their constituent risk factors are presented in Table 1.

Framework of Contingency Estimation Model Artificial Neural Networks

In this study, project cost contingency amount (CC) is modeled as the function of the level of major risk groups in terms of risk magnitude (MR) (Polat and Bingol, 2011). The relation between CC and MR for each major risk group can be expressed as in Eq. (1):

$$CC = f\,(MR_A, MR_B, MR_C, MR_D, MR_E, MR_F), \qquad (1)$$

where CC is the project cost contingency amount as percentage of total contract value and MR_i is the magnitude of each major risk group. In this expression, the magnitude of major risk groups is defined as the average of the magnitudes of constituent risk factors (RM_{ji}) in each major risk group. The relation between MR_i and RM_{ji} can be mathematically expressed as in Eq. (2):

$$MR_i = \frac{1}{n}\sum_{j=1}^{n} RM_{ji}\ , \qquad (2)$$

where MR_i is the magnitude of each major risk group, RM_{ji} is the magnitude each risk factor in the major risk group i, and n is the number of risk factors in the major risk group i.

Artificial neural network is a parallel distributed processing system that is widely used for solving complex problems, whose solutions are difficult to define and do not follow linear patterns. A neural network consists of an input layer, an output layer, and one or more hidden layers. All these layers are connected by neurons. Each neuron is a processing element that receives one or more inputs and generates an output signal using a transfer function (activation function). The transfer function may be either linear or nonlinear. The most commonly used transfer function is the sigmoid function. The goal of a transfer function is to prevent the output value being too large.

Table 1. Risk Hierarchy (Polat and Bingol, 2011)

Major Risks and Constituent Risk Factors	
MR$_A$ Bidding stage-related risks	
RM$_{1A}$ Design complexity	RM$_{6A}$ Inexperience of personnel working in the bidding department
RM$_{2A}$ Incompatibilities between design documents and specifications	RM$_{7A}$ Inadequate market investigations
RM$_{3A}$ Inadequate site investigations	RM$_{8A}$ Unrealistic budget allocation for mobilization and overhead costs
RM$_{4A}$ Insufficient time for bid preparation	RM$_{9A}$ Unfamiliarity with the specifications and standards prevailing in the host country
RM$_{5A}$ Vagueness of the project scope	RM$_{10A}$ Lack of site visits
MR$_B$ Construction stage-related risks	
RM$_{1B}$ Difficulties in procuring resources that comply with the project requirements in the host country	RM$_{6B}$ Unfamiliarity with the construction technique used in the project in question
RM$_{2B}$ Unavailability of qualified subcontractors and suppliers in the host country	RM$_{7B}$ Tight schedule
RM$_{3B}$ Technical and technological complexities	RM$_{8B}$ Insufficiency of necessary resources owned by the contractor
RM$_{4B}$ Poor performance of subcontractors	RM$_{9B}$ Inexperience of the company in obtaining the required construction permits in the host country
RM$_{5B}$ Adverse weather conditions	RM$_{10B}$ Poor planning
MR$_C$ Finance-related risks	
RM$_{1C}$ Difficulties in taking credits	RM$_{4C}$ Delay in payments
RM$_{2C}$ High inflation rate in the host country	RM$_{5C}$ High fluctuations in exchange rates
RM$_{3C}$ Low % of advance payment	RM$_{6C}$ Unfamiliarity with the tax system in the host country
MR$_D$ Country-related risks	
RM$_{1D}$ Bribery	RM$_{8D}$ Bureaucratic difficulties
RM$_{2D}$ Unavailability of qualified workforce in the host country	RM$_{9D}$ Security problems (e.g., theft, public disorders, etc.)
RM$_{3D}$ High wages of qualified workforce in the host country	RM$_{10D}$ Instability of economical conditions in the host country transfers
RM$_{4D}$ Poor productivity of laborers in the host country	RM$_{11D}$ Frequent changes in regulations and laws
RM$_{5D}$ Poor attitude towards the project	RM$_{12D}$ Difficulties in obtaining visa for the employees
RM$_{6D}$ Poor attitude of the host country	RM$_{13D}$ Inadequate banking system and difficulties in money
RM$_{7D}$ Difficulties in transporting materials and equipments to the host country	RM$_{14D}$ High commissions for construction permits
MR$_E$ Company-related risks	
RM$_{1E}$ Difficulties in keeping records	RM$_{4E}$ Poor health and safety conditions
RM$_{2E}$ Poor managerial capabilities	RM$_{5E}$ Poor productivity due to high turnover of the employees
RM$_{3E}$ Poor motivation of the employees	
MR$_F$ Contract-related risks	
RM$_{1F}$ Poor contract conditions that do not comply with international standards	RM$_{8F}$ Vagueness of contract conditions regarding the situations for which penalties will apply
RM$_{2F}$ Unclear contract conditions regarding the rights and responsibilities of the parties	RM$_{9F}$ Inadequate definition of force majors
RM$_{3F}$ Unsatisfactory contract conditions regarding delays in designs	RM$_{10F}$ Unsatisfactory contract conditions regarding the dispute resolution method
RM$_{4F}$ Strict contract conditions regarding delays and cost overruns resulting from design and site conditions	RM$_{11F}$ High % of retention money
RM$_{5F}$ Unsatisfactory contract conditions regarding escalations	RM$_{12F}$ High penalties
RM$_{6F}$ Unsatisfactory contract conditions regarding claims due to design changes and additional works	RM$_{13F}$ Long guarantee period
RM$_{7F}$ Unsatisfactory contract conditions regarding fluctuations in exchange rates	RM$_{14F}$ Vagueness of contract conditions regarding claims due to delays in payment

Artificial Neural Networks

An artificial neural network begins by establishing connections between the neurons in the input and output layers, finding linear relationships between the inputs and output(s), and assigning weight values to those connections. After those connections are established and weighted, neurons are added to the hidden layer(s) so that nonlinear relationships can be found. Input values in the first layer (i.e., input layer) are multiplied by the weights and passed to the neurons in the hidden layer, which activates the neurons in the hidden layer. Neurons in the hidden layer produce outputs calculating the sum of weighted input values passed to them and pass those calculated values to the neurons in the output layer in the same fashion. Finally, neurons in the output layer produce the desired result(s) (predictions or outputs). An artificial neural network is trained to achieve the desired result(s).

The process of training typically involves the application of input and corresponding output vectors, which are referred as training examples. When a set of training examples is presented to a neural network, the result(s) that the network produces are repeatedly compared with the actual result(s) and the interconnection weights between layers are adjusted slightly in the direction of the correct result(s). The aim is to minimize the differences between the actual and predicted values (i.e., errors) so that the neural network learns the implicit knowledge, expertise, or rules implied by these training examples. Different algorithms have been proposed to minimize the error function, in other words to train a neural network. Among these algorithms, back-propagation (BP) algorithm is the most common one, which can be categorized under supervised learning techniques. In a BP neural network, the weights and biases are adjusted by error-derivative (delta) vectors backpropagated through the network in order to obtain the final desired output. The gradient descent method is used to adjust the network's weights and biases to minimize the output error. When training is completed, the neural network becomes capable of providing solutions to new situations and ready to provide the desired output(s) for given input(s). The superiority of a neural network is to detect by themselves the relationships that link inputs to output(s) and thereby learn to generalize past examples (e.g., Wang and Elhag, 2007; Jin and Zhang, 2011).

Questionnaire Design and Data Collection

Having identified the factors that may affect construction companies' decisions on how much contingency they should include in their bids for international projects and developed the general framework of the contingency estimation model, a questionnaire survey consisting of 60 questions was designed. The questionnaire comprised two main sections. The first section included 59 questions, which were meant to explore the magnitude of risk factors presented in Table 1 by ratings such as *Very Low, Low, Medium, High* and *Very High*. The second section included only one question that inquired about the contingency amount in percentage of contract value included in the bid price proposed for the project in question. Questionnaires were submitted to the randomly selected 100 Turkish contractors, which are registered to Turkish Contractors Association (TCA) and predominantly carry out projects in international construction markets. Out of these 100 contractors, 85 returned 195 duly completed questionnaires that include data collected from 195 construction projects that had been carried out in foreign countries. The contact persons were experienced civil engineers, who have at least 20 years of experience in the construction industry, working as estimators in the respondent companies. In this study, data obtained from the projects that had been performed under lump sum contracts were taken into account.

ANN-based Contingency Estimation Model

Performance Evaluation Criteria

Several criteria have been identified in the literature to evaluate the performance of a model. In this study, mean absolute percentage error (MAPE), the root mean square error

(RMSE), and correlation coefficient (R) were used to measure the performance of the developed ANN-based contingency estimation model. They are defined as follows:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{a_i - p_i}{a_i}\right| \times 100, \quad (3)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(a_i - p_i)^2}\ , \quad (4)$$

$$R = \frac{\sum_{i=1}^{n}(a_i - a) \times (p_i - p)}{\sqrt{\sum_{i=1}^{n}(a_i - a)^2 \times (p_i - p)^2}}, \quad (5)$$

where n is the number of all examples in the data set to which the net is applied, a_i is the actual values, p_i is the predictions, a is the average of the actual values, and p is the average of the predicted values. It is desired that the developed model has low MAPE and RMSE and high R.

Model Development and Results

In this research, the Neural Network Toolbox in MATLAB was used to develop the contingency estimation model. The training parameters are all set as the default values of the Neural Network Toolbox in MATLAB, namely Epoch = 1,000, mu = 0.001 and minimum gradient = 1E-10. The feed-forward back propagation network, Levenberg-Marquardt (TRAINLM) training function, gradient-descent-with-momentum (LEARNGDM) adaptation learning function, mean squared error (MSE) performance function and tangent sigmoid (TANSIG) transfer function were selected. In this study, the BP artificial neural network (BP-ANN) with one single hidden layer was designed as the universal approximation theorem indicates that a neural network with a single hidden layer can theoretically relate any given set of inputs to a set of outputs to an arbitrary degree of accuracy (Wang and Elhag, 2007). In order to determine the number of neurons in the hidden layer, a trial and error method was performed. Table 2 shows the performance of three layer BP-ANN model with varying number of neurons in the hidden layer.

Table 2. Performance of a Three-Layer BP-ANN Model with Varying Number of Neurons in the Hidden Layer

Criterion	Number of neurons in the hidden layer								
	2	3	4	5	6	7	8	9	10
MAPE (%)	9.55	9.19	9.13	10.20	9.31	9.06	8.52	8.46	8.33
RMSE	0.90	0.88	0.87	1.03	0.90	0.88	0.85	0.84	0.83
R	0.94	0.94	0.95	0.92	0.94	0.94	0.95	0.95	0.96

It is observed that the performance of BP-ANN shows variation as the number of neurons in the hidden layer changes. Since too many neurons in the hidden layer may bring about over-fitting but lack of generalization problems, insufficient number of neurons in the hidden layer results in poor learning. In this study, a BP-ANN model with 4 neurons in the hidden layer seems to be appropriate. As seen in Table 2, the root mean square error (RMSE) for the BP-ANN model with 4 neurons in the hidden layer was found 0.87. This indicates that, for instance, when an estimator determines the contingency amount as 10% of the contract value based on his or her past experience or intuition, the ANN model gives a forecast of 9.13% or 10.87%. Given the subjective nature of the judgments by the respondent estimators, it can be concluded that the developed ANN-based contingency estimation model is valid and robust and has captured the significant components of the underlying nonlinear and complex relationships between the risk factors and the contingency amount included in bid prices for international projects. The architecture of three-layer BP-ANN for cost contingency estimation model is shown in Figure 1.

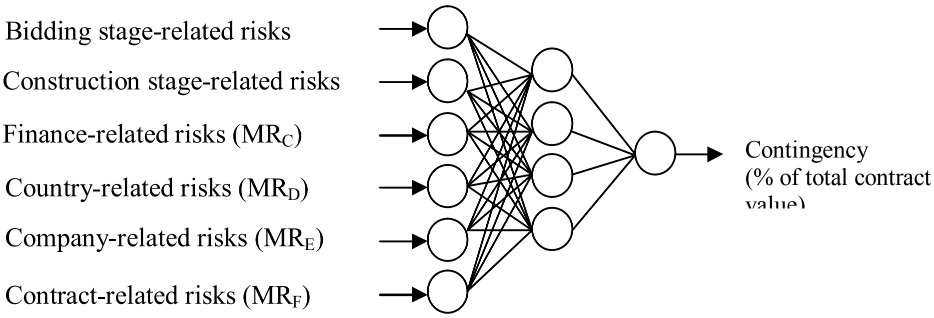

Figure 1. BP-ANN Architecture for Contingency Estimation

Conclusions

In this paper, an ANN-based contingency estimation model, which enables construction companies to assess the risk level of the projects in a more systematic and objective way and thereby allows them to estimate cost contingency amounts more accurately, was presented. Training and test data were obtained from 195 international construction projects that had been completed by 85 large-scaled Turkish contractors carrying out projects in international markets. Several statistical indicators were used to measure the performance of the developed model. The results indicate that the proposed model is satisfactory, valid, and has captured the significant components of the underlying nonlinear and complex relationships between the risk factors and the contingency amount included in bid prices for international projects. Although the proposed model makes the process of bid contingency estimation easy, fast, objective, and accurate, it has some limitations. In future studies, more than 59 risk factors may be incorporated into the model and the artificial neural network may be trained and tested with more cases, and the results of that study can be compared with the findings of this study.

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Abstract

Construction companies try to expand into international markets to create new job opportunities. Since international construction environment is highly subject to several complex conditions, carrying out international projects is much riskier than conducting domestic projects. In this risky business environment, contractors usually include a reasonable contingency amount as an allowance for potential risks in their bid prices to shield themselves from the outcomes of possible failures. In this context, determination of the right amount of contingency is critical. In this study, an ANN-based contingency estimation model, which can assist construction companies to estimate contingency more systematically and accurately, is presented.

Keywords: international construction, risk management, cost contingency, quantitative technique, artificial neural networks