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A Contingency Cost Estimation System for Road Maintenance Contracts

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Abstract

Generally, a contingency cost is provided in a project to cover the change orders (CO) that may be generated in a project during the construction phase due to various reasons, such as unforeseen conditions, design errors, and scope changes. If the contingency cost could be accurately estimated during the contract's procurement phase, the CO cost could be properly managed during the construction phase. Traditionally, contingency costs are allocated around 10% to 15% of the project cost without considering any of the historical CO costs. In this study, a tool was developed to estimate the contingency cost of a road maintenance contract by using a mathematical model. The tool forecasts the contingency costs for each of the road maintenance activities included in the contract by using an artificial neural network model based on the historical CO data. The tool was validated using the CO cost data available from road maintenance contracts.

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Keywords: Contingency Cost; Road Maintenance Contracts; Artificial Neural Network; Change-Order;Unforeseen conditions.

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1. Introduction

Any project may require some additional time or cost to complete successfully. If any extra cost is added to the project, then the addition is known as cost contingency. Contingency costs are provided at the beginning of a project to deal with uncertainties during the construction phase. The method of providing additional costs may vary. For example, according to Lhee et al. [1], the Florida Department of Transportation used two approaches to compensate for uncertainty risks as well as funding required by additional work orders. Both approaches were in the form of contingency costs, one for the contingency amount as an item and another for contingency supplementary agreements. After conducting studies regarding contingency, Ford [2] and Marco et al. [3] claimed that management of the contingency budget is a very important issue for effective risk management of projects. Hence, if the contingency could be planned and managed well, it could cover the change orders (CO) and reduce problems with cost overruns.

The main purpose of contingency is to cover the unforeseen risk during the construction or maintenance period. Generally, the CO appears in a project during the construction phases. However, traditionally, the contingency is allocated around 10% to 15% of the project cost. Many papers indicated that this deterministic method of contingency allocation as some percentage of the project cost is not an accurate method. If a mathematical model could be developed to predict a contingency cost of the project, the CO could be managed more realistically during the construction or maintenance phase. Hence, in this study, a mathematical model is proposed to estimate contingency of a maintenance contract. Instead of adopting contingency percentages by using the traditional method, a tool developed in this study could assist the planner to design the contingency for a maintenance contract. A model using the artificial neural network (ANN) method was able to forecast the contingency cost of a maintenance project based on historical CO data.

The main objective of this study was to develop a contingency estimation tool for maintenance contracts in order to control cost overruns. If the overall contingency allocated for a project could cover the cost of changes that appears during the construction phase, no formal change order would be required. In this way, if the change orders could be prevented, unnecessary conflicts and delays would be avoided on construction projects.

2. Literature Review

Cost overruns are a very common problem in construction projects. That is why most of the projects normally have some contingency cost to cover them. In 1990, Yeo [4] conducted a study on the literature available regarding overruns in construction projects. According to his findings, the causes of the overruns were changes in the scope of work, problems in design, errors in the estimates, unforeseen cost inflation, poor project definition, problems in contract administration and policies, and new requirements for increased safety from government legislation. The author proposed a pseudo-probabilistic approach to prepare a project estimate to cover the overruns.

Smith et al. [5] stated that a wise decision concerning the amount of contingency used while bidding could have effects on whether one would win the contract. They interviewed 12 contractors about the contingency calculation method, and found that among these contractors, nobody was aware of any kind of estimation method for the contingency amount. Whenever, these contractors used contingency, they simply followed the traditional approach of adding some percentages to the project base cost as contingencies.

Chen and Hartman [6] studied multiple linear regression (MLR) and ANN methods for the prediction of contingency. The authors obtained their data from a large oil and gas company. They found that the ANN method predicted contingencies more accurately than the MLR method. After performing an extensive literature review, Moselhi et al. [7] mentioned that the ANN model had a powerful capability of recognizing data patterns and data prediction.

Sonmez et al. [8] proposed a regression model to predict contingencies required for international projects. The regression model was prepared based on data collected from Asia, Africa, Europe, and the Middle East from projects that Turkish contractors worked on. The regression model showed that contingencies had relationships with the country risk rating (CRR); the availability of materials in the host country; advanced payment amounts; and the project type, which was either a unit price or lump sum contract. According to the author, lower the value of CRR meant less risk in the country and the higher the value of CRR, the greater the level of risk in the country. The authors concluded that the contractors included a 5% extra contingency amount for a lump sum contract as compared to the unit price contract.

Thal et al. [9] analyzed 203 construction projects of the U.S. Air Force, using a linear regression model to predict the contingency amount for a new project. According to the authors, the contingency amount was "a part of the budget intended to pay for changes initiated by either the client or the contractor after contract award" (p. 1181). They claimed that the regression model that they proposed in the study reduced the error in contingency estimations. The model had contingency funds required (CFR) as a dependent variable; other parameters – such as estimated/design cost at the awarding time, design duration, contract award month, type of work, and design life – were the independent parameters.

According to Barraza [10], the time contingency normally was calculated as a percentage of the total duration; then, the time contingency was allocated to each activity individually. The author defined the time contingency as the total time allowance (TTA), which was "the difference between projects planned duration (PPD) and project's target duration (PTD)…" (p. 260). The author proposed a stochastic method to allocate these PPDs and PTDs, where PPD always would be greater than PDT in order to have a positive total time allowance. Normally, time contingency is required to cover the problem of time overruns.

Baccarini and Love [11] studied 228 water infrastructure projects, and found that the mean contingency percentage allocated to the projects was 8.46%. However, they found that the total contingency cost required was 13.58%. The authors claimed that adding a deterministic percentage for contingencies to cover the cost growth, normally 10%, was not an accurate method.

This literature review section showed that either the regression analysis or the ANN method was appropriate to forecast the contingency cost of a project. This study selected the ANN method because it eliminates the requirement of knowing the best fit curves or equations suitable for the input dataset. ANN models are capable of generating the necessary weight adjustment factors for the input data, and can handle any kind of dataset that could have a best fit equation, such as linear, polynomial, logical, binomial, exponential, or logarithmic.

3. Methodology

In this study, a tool was developed to estimate the contingency cost for a maintenance contract based on historical records of CO for road maintenance activities in Kenya. In order to develop the tool, Visual C# and the R program were selected as the development platforms. For historical data, 614 road maintenance contracts were received from the Kenya Rural Road Authority (KeRRA) in Kenya. This data was used to validate the tool developed during this study. The steps required to develop the contingency estimation tool are given in Figure 1.

For the contingency estimation tool, a database system was designed, and all the contract data was imported to the database. Similarly, the necessary input and output interfaces were prepared. The contingency percentage was estimated based on such input parameters as work category, road surface type, road condition, accessibility, weather condition, location name, and the total activity cost.

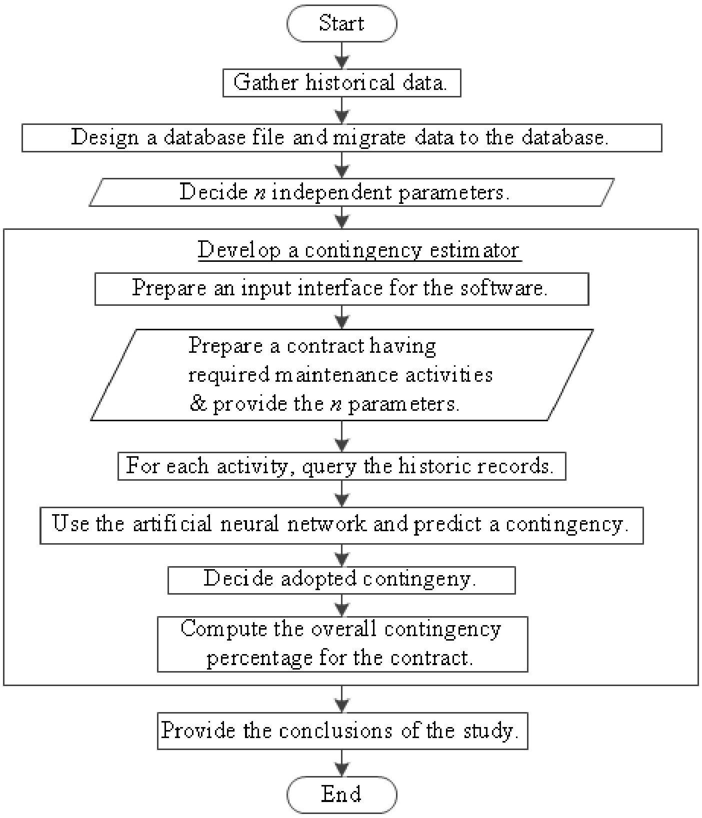

Figure 1: A flowchart to develop a contingency estimator for road maintenance contracts.

At the beginning of the prediction, this tool queries the historical data on CO in the database for the selected activity. Then, this tool prepares an ANN model for the data prediction. The neural network is prepared by the R program, and this data is used to train the neural network model. For that activity, the contingency is predicted. This process is repeated for each of the activities, and the contingency required for the contract is computed based on the cost weightage of the activities.

The tool that was developed during this study considered the following steps, given below, to predict the contingency of a contract.

1. Provide the contract name and number.
2. Select the region name and the road that has to be assigned to the maintenance contract.
3. Choose the work category, whether it is routine maintenance, periodic maintenance, or spot improvement & rehabilitation work.
4. Provide weather data.
5. Provide information regarding site accessibility.
6. Select activities (*n* activities) to be included in the contract.
7. Provide the desired quantities, *Q* units, for each activity.
8. Provide the unit price, \$ *P* per unit, to do each activity.
9. Determine the total cost of the contract using Equation 1:

$$\text{Total Cost } (TC) = \sum_{i=0}^{n} (P_i * Q_i) \quad (1)$$

10. Recommend a contingency by using the ANN method for each of the road activities, based on the historical data.
11. Provide the adjusted contingency percentage, C %, for each of the activities.
12. Finally, compute the overall contract contingency based on the cost weightage value of each activity, as given by Equation 2.

$$\text{Overall contingency \%} = \sum_{i=0}^{n} \left(C_{\mathrm{i}} * \frac{(P_i * Q_i)}{TC} \right) \quad (2)$$

For the ANN model, the input parameters and an output will be as shown in Figure 2. The input parameters are the work category, site accessibility, weather condition, road surface type, road condition, location name, and the activity bid amount. This ANN model will be able to predict the CO percentage as a contingency for the activity. The ANN model prepared for this study is a three-layer model having an input layer, a hidden layer, and an output layer. Two biased inputs are provided in the model, one for the hidden layer and one for the output layer.

In order to use the ANN method for contingency prediction, the supervised training process was considered rather than an unsupervised training process normally used for pattern recognition. Supervised training is a process in which the ANN model receives input for training purposes along with the respective output data. This training process adjusts the weightage value while reducing errors by using a resilient back-propagation method. The resilient back propagation method is very similar to the back propagation method; the only difference that is this method uses different learning rates at different training stages; however, the back propagation method uses only one learning rate to adjust the error during the training process. Once the training process is completed, then contingency prediction could accomplished by providing the seven independent input variables in order to obtain the contingency as the dependent output variable.

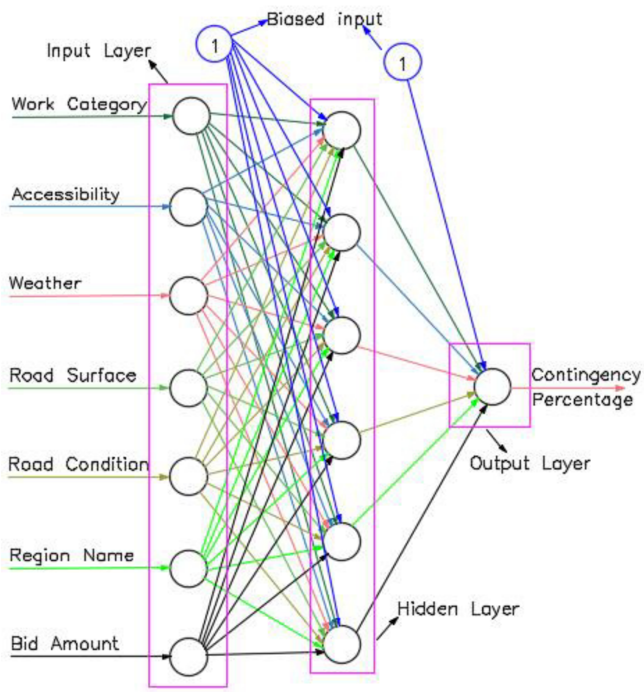

Figure 2: A sample artificial neural network (ANN) used for contingency predictions.

The sample model, shown in Figure 2, has an input layer with seven neurons, a hidden layer with six neurons, and an output layer with a neuron. Based on a thumb rule, the number of neurons (nodes) in the hidden layer should 1) be less than the twice the size of the number of input neurons or 2) in between the number of neurons in the input layer and the number of neurons in the output layer [12]. In this study, the number of neurons in the hidden layer was determined as given by Equation 3.

$$N = (m + b + o) * 2/3 \tag{3}$$

where,

N = the number of neurons in hidden layers
m = the number of neurons in the input layer
b = the number neurons as biased inputs
o = the number of neurons in output layers

The accuracy of the model depends upon the data available to train the ANN model. For the execution of the ANN model, the R program was used, supported by a Comprehensive R Archive Network (CRAN) repository. This repository provides the necessary routines to be executed in the R-program. For this study the 'USA (CA 2)' CRAN mirror was used to obtain the necessary packages. The 'neuralnet' package was loaded into the R library for the required neural network functions. The tool developed for this study linked the R program, loaded the necessary packages into the R library, and made a prediction by means of the ANN model.

This tool executed the R commands iteratively to predict the required contingency for each activity in the contract. Hence, the tool was able to provide a dynamic process as well as automation for the contingency estimations because this tool prepares a separate neural network model for each activity and uses each to predict the contingency. Finally, based on these predictions, this tool provided a contingency estimate for a contract.

4. Software Development

For this tool development, all the interfaces required were designed with the Microsoft Visual Studio Professional 2012 environment (version 11.0.50727.1 RTMREL © 2012 Microsoft Corporation). All of the required methods were coded in the Visual C# platform. For the data storage and retrieval process, a database was designed using the Microsoft Access program. The database was designed in such a way that all historical CO data for the contracts, as well as for the new contract prepared, were stored in the same file. All activities that were packaged under the contract were saved in the same database so that these records could be queried anytime whenever required. In this way, this database system helps to store and retrieve historical data as well as newly saved data on maintenance contracts. The primary key set for each table, and the relationships between the tables, kept the association between them. These keys and relationships between the tables organized the data properly and provided a way to query data systematically.

In this study, the predictor parameters adopted for the contingency prediction were the road condition, road surface type, weather condition, site accessibility, work category, region name, and contract award cost. Based on the value of these parameters, the ANN method, as described in the methodology section, was used to determine the contingency for the activity. However, if the historical data was not available at all for a road maintenance activity, the tool simply returned a zero value instead of a predicted value. Iteratively, all the activities were assigned respective contingencies by using the ANN method. For flexibility, an adjusted contingency could be provided for each activity. Finally, based on the cost weightage of each road maintenance activity, this tool computed the overall contingency required for the contract.

The tool developed in this study appears as shown in Figure 3. The contingency estimator only had one interface by which to enter all necessary input data, such as contract details, as well as a list of the maintenance activities packaged under the contract. This contingency estimator tool used the RDotNet tool, a dynamic linked library (DLL) that is available free online, to connect the R-program, which also is free software. Then, the R program provided the required ANN methods. In this way, this contingency estimator was able to execute all methods required to predict the contingency cost for a road maintenance contract.

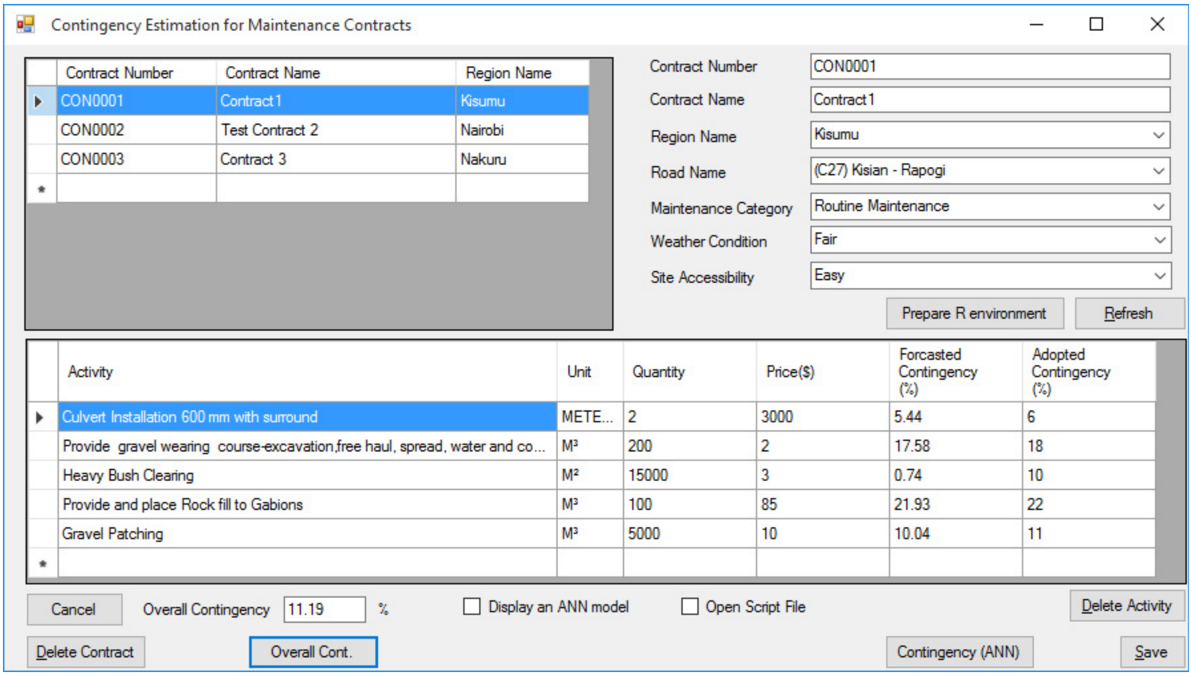

Figure 3: The Contingency Estimation tool.

In the screen given by Figure 3, all the necessary parameters are provided. Some fields are to be typed, and some fields are entered using the drop box options provided by the system. For example, such data as the maintenance category, weather conditions, site accessibility, region name, and road names are entered by using the dropdown options. The maintenance category should be selected from the list of items, such as ‘Routine maintenance,’ ‘Periodic maintenance,’ ‘Structures,’ and ‘Rehabilitation & spot improvement.’ Weather conditions could be any one among ‘Favorable,’ ‘Good,’ ‘Fair,’ ‘Bad,’ or ‘Worst.’ Site accessibility could be any one among ‘Easy,’ ‘Difficult,’ ‘Very difficult,’ or ‘Not accessible.’ Similarly, all required road maintenance activities are listed in a table by a list provided by the dropdown options.

If a maintenance activity is not in the dropdown list, that activity will not have the historic change-order information. To setup new activities, first, the database has to be prepared by importing the historic change-order information for that activity. Then, the activity will appear in the dropdown list automatically. Once the required maintenance activities are listed in the activity table, the work quantities and unit price for each activity should be provided. Having all the required information, the button ‘Prepare R environment,’ should be executed, because this command prompts for CRAN selection; then, ‘USA (CA 2)’ CRAN is selected to load the ‘neuralnet’ package.

A sample calculation presented in Figure 3 was based on the 614 maintenance contract data. The overall contingency was computed based on the cost weightage of each maintenance activity for the contract. The R program helps to forecast the contingency required for each maintenance activity based on the historical CO data. For flexibility in the contingency estimation, this tool allows users to provide adopted contingency value. Before computing the overall contingency of the contract, the adopted contingency value should be provided from the last column of the activity table. Then, the button ‘Overall Cont.’ calculated the contingency required for the contract. This tool is capable of displaying the ANN model prepared by the R program during the prediction process.

5. Conclusion

Much of the literature mentioned that the traditional approach of allocating the determined percentage for contingency cost of a project, such as 10% or 15%, is not an accurate method. To address this issue, a tool was developed in this study to estimate the contingency cost for a road maintenance contract. The prediction of contingency was based on historical records of change orders for road maintenance activities in Kenya. For each maintenance activity in a contract, a contingency was estimated based on the change-order data. In addition, this tool has an option to provide an adjusted contingency value. According to the cost weightage value of each maintenance activity, the overall contingency value for the project could be determined.

As this tool computes the contingency based on the cost weightage of the maintenance activities and on an historical record of the change orders, the contingency calculated for a contract was more scientific than by simply adopting the traditional approach. If this predicted contingency actually does cover future change orders, then the risk of having a conflict between contracting parties and cost growth problems could be prevented.

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