Predicting Cost Deviation in Reconstruction Projects: Artificial Neural Networks versus Regression

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Abstract: This paper investigates the challenging environment of reconstruction projects and describes the development of a predictive model of cost deviation in such high-risk projects. Based on a survey of construction professionals, information was obtained on the reasons behind cost overruns and poor quality from 50 reconstruction projects. For each project, the specific techniques used for project control were reported along with the actual cost deviation from planned values. Two indicators of cost deviation are used in this study: cost overrun to the owner, and the cost of rework to the contractor. Based on the information obtained, 36 factors were identified as having direct impact on the cost performance of reconstruction projects. Two techniques were then used to develop models for predicting cost deviation: statistical analysis, and artificial neural networks (ANNs). While both models had similar accuracy, the ANN model is more sensitive to a larger number of variables. Overall, this study contributes to a better understanding of the reasons for cost deviation in reconstruction projects and provides a decision support tool to quantify that deviation.

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Introduction

The construction industry is one of the largest industries in North America and worldwide. In Canada investments in the construction industry amount to about 6% of the total investments in all industries (Statistics Canada 1998). In recent years, a larger portion of all construction work has been shifting from new to reconstruction projects. Lee (1996), for example, reported that during the last decade up to 50% of the total construction budget in the United States has been spent on a form of renovation, remodeling, or reutilization of existing buildings.

The uniqueness and increasing complexity of new construction projects make it very difficult to predict their time, cost, and quality of construction. This situation becomes even more complicated in the case of reconstruction projects due to various additional factors, including space constraints, safety regulations, and coordination requirements (Kritzek et al. 1996). While Statistics Canada (1998) groups the addition, renovation, or conversion of existing facilities under a broad category of "new construction projects," this study defines reconstruction projects as a distinct category that includes the modification, conversion, or phased complete replacement of an existing facility (McKim and Attalla 1998). Studying reconstruction projects in particular is important for the following three main reasons:

1. Large investments are being directed to reconstruction projects. In the United States, for example, the national average spending on reconstruction is approximately 25% of new construction spending (U.S. Census Bureau 1998).
2. Reconstruction projects are gaining increasing attention as owners, such as metropolitan governments, face huge problems with aging infrastructure projects that have large demographic, environmental, social, technological, and economic impacts (Sanvido and Riggs 1993; Attalla 1996).
3. As reported in a previous study (Attalla 1996; McKim et al. 2000), the performance of reconstruction projects is much lower than new construction. Comparing several new and reconstruction projects, the latter showed significantly higher time and cost overruns. Similar observations were also reported in Krug (1997) and Rasmussen (1997).

This paper attempts to identify the unique challenges facing reconstruction projects and their management requirements. It focuses on the identification of critical success factors for reconstruction projects and the development of a model to predict their cost overruns.

Cost Performance in Reconstruction Projects

Little usable information was found in the literature concerning reconstruction projects, particularly in operating facilities. Various research has reported interesting case studies. The $175 million reconstruction of Grand Central Terminal, for example, faced considerable problems with existing site conditions (Rasmussen 1997). The project had to proceed while keeping 500,000 pedestrians moving each day. One of the challenges that faced the project was the absence of accurate as-built drawings, which resulted in significant problems. Another case study focused on the reconstruction of a high-rise building in downtown New York City. The study, however, focused on the structural aspects only, without discussing the management process (Kaminetzky and Lavon 1996). It was mentioned, however, that a written plan for the construction sequence was very crucial to the success of this project.

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Documentation from the $400 million reconstruction of the Green Line in Chicago showed that making the facility nonoperational during reconstruction saved 50% of the schedule and 66% of the cost (Krug 1997). This gives an indication of the challenges that face reconstruction projects in operating facilities. Another example is the reconstruction of the Exchange Place Station in New York (Kerr et al. 1992); however, little was discussed about the management aspect of the project.

Kritzek et al. (1996) provided a detailed analysis of the reconstruction of an operating academic building. The study provided a comprehensive analysis of the problems faced and the lessons learned from the project, and also recommended the use of the critical path method (CPM) as an adequate schedule control technique. Various other success related factors were also discussed in a study concerning the full replacement of a high school in Toronto, Canada (Attalla et al. 1999). The project was a major undertaking and exhibited various difficulties in maintaining the operation of the old facility and the safety of 2,800 occupants.

In an exploratory study by the Construction Industry Institute, critical success factors on retrofit projects were reported to include an experienced and cohesive project team, contract incentives, partnering arrangements, special procurement and preplanning strategies, and a high level of management support. The study was performed based on information gathered from 16 projects (Sanvido and Riggs 1991).

Preliminary Field Review

A preliminary field review was conducted through formal and informal discussions with construction professionals for the purpose of identifying reasons for change orders and poor performance in reconstruction projects. The field review also examined a compiled list of the factors that contribute to the success of reconstruction projects. The participants assigned a number from 1 to 5 to each factor to represent its significance.

The result of the field review confirmed the high relevance of 36 factors in seven categories, as shown in Table 1. These factors will serve as the independent variables in a predictive model of the cost overrun in reconstruction projects. In addition, the reasons for poor performance in reconstruction projects are summarized in Table 2.

Table 1. Results of Preliminary Field Review

Category	Factor	Source[a]
Cost	Budget baseline and budget allocations	L
	Work packages costing	L
	Cost breakdown structure (CBS)	L
	Cost variance (CV)	L
	Forecast analysis	L
	Unit prices	F
	Cash allowances	F
	Cash flow	F
Schedule	Work breakdown structure	L
	Bar charts	L
	Critical path method	L
	Incremental milestones	L
	Time variance	L
	Percent complete	L
	Coordination schedule	F
	Liquidated damages	F
	Change directive versus change notice	F
Quality	Quality standards and specifications (with input from O&M)	L
	Responsibilities of individuals toward quality	L
	Inspection and testing	L
	Independent inspection firms	F
	Inspection by operator/maintenance	F
	Inspection by end user	F
	Prequalification of contractors	F
Scope	As-built drawings	F
	Constructability review	F
	Design committees	F
Communication	Site meetings (biweekly with users' representatives)	L
	Electronic communication	L
	Implementation team	F
	Direct communication subteam	F
Safety	Joint health and safety committee	F
	Awareness sessions	F
	Emergency plan and procedures	F
Site	Site layout plan	L
	Relocation schedule	F

[a]L = literature review; F = field review.

Table 2. Reasons for Poor Performance in Reconstruction Projects

Item number	Description
1	Unforeseen existing site conditions
2	Scope change by owner
3	Design change (upgrade)
4	Schedule problems
5	Design coordination
6	Regulatory requirements
7	Poor performance by contractor

Questionnaire Survey

A questionnaire was developed to collect data from past reconstruction projects to be used in developing a predictive model of cost deviation. In the questionnaire, the 36 control factors of Table 1 were rearranged to follow the project life cycle: scope definition, tendering, schedule control, cost control, quality control, communication control, safety control, and project completion. Construction organizations, which are heavily involved in reconstruction projects, were selected and contacted in order to participate in this research. Personal contact was the major communication tool used to get organizations to participate in the study, and therefore almost a 100% return was achieved.

To encourage more participants in the survey, the questionnaire was designed to fit on one page. Each questionnaire collected data on a past reconstruction project in a structured interview format. The data included assessment of the 36 project control factors on a yes/no basis, as well as information on the actual performance of the project. Thirty-one organizations participated in this research, and the interviewees were mostly construction managers and project administrators. The questionnaire was divided into four main parts:

1. General project information: This section of the questionnaire gathered basic information about the project such as size, type of building, and type of reconstruction work (inte-

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rior renovations, structural modifications, addition/expansion, or phased replacement);

2. Preconstruction environment: This part of the questionnaire related to two aspects—planning and tendering;
3. During construction: This part started by asking the participant to assign a weight to the project manager's relative emphasis on controlling cost overruns and the quality of the project. This part also included detailed questions on the 36 factors that describe the level of schedule control, cost control, quality control, communication control, and safety control exercised in the project;
4. Actual cost performance: This part captured information about the actual outcome of the project. The required information included the total value of change orders and the cost of rework of repairs paid for by the contractor in addition to the original contract value. This information was used to calculate one quantifiable indicator of the cost performance of the project, the cost performance index (CPI).

The CPI represents a quantifiable and objective measure of cost performance. In the present study, the cost performance of a project is measured as a function of the cost overrun and the cost associated with the level of quality achieved. The cost of quality can be represented by the value of rework required from the contractor in order to achieve the required quality levels.

To develop the proposed CPI, questionnaire participants were asked to provide weighting factors for both cost overrun and cost of rework. The project CPI is then obtained by the following formula: CPI = cost of changes to owner + cost of quality to contractor

$$X \cdot \left[1 - \frac{\text{Change order cost}}{\text{Original contract value}}\right] \cdot 100$$
$$+ Y \cdot \left[1 - \frac{\text{Cost of rework}}{\text{Original contract value}}\right] \cdot 100$$

where X and Y are weighting factors for both indicators, with $X + Y = 1.0$. As such, the higher the CPI value, the less change order and rework cost, which accordingly indicates a better cost performance.

Data Analysis

Thirty-two organizations participated in the research and provided information on 50 projects, the total value of which was over $200 million. Some analysis was carried out on the data after collection. The purpose of the analysis was to confirm the sufficiency of the data for modeling purposes and to try to reduce the variables to a manageable number without loss of model accuracy. To facilitate the analysis, each independent variable was given a number from X1 to X36, and each case study project was given a number from P1 to P50. The values for the 36 input variables were specified as either 0 or 1, and the CPI was also calculated for each project case study.

With respect to examining the sufficiency of the data for modeling purposes, scatter plots were produced to draw a trend line between each independent variable and the calculated CPI in the various case studies. The scatter plots showed that all trend lines exhibit logical relationships, thus confirming the sufficiency of the data. For example, the scatter plot and the trend line for using critical-path method (CPM), showed an increase in the CPI (better performance), which is a logical trend.

With respect to reducing the number of variables, the data were analyzed using *Systat* commercial statistical analysis software. *Systat* produced the correlation coefficient (r), F-test, and *p-value* for every linear relationship between each variable and the CPI. Based on these tests, the variables that have a significant relationship with the CPI were considered for further analysis and model development. The criterion for selecting the variables for further analysis was that $r > 0.5$, as in other research in the literature (Ashley et al. 1987; Sanvido et al. 1992).

Table 3. Independent Variables Final List

Categories	Factors (independent variables)
Scope definition and planning	Type of reconstruction project
	As-built drawings
	Budget baseline and budget allocations
	Design committees
Tendering stage	Quality standards and specifications (with input from maintenance/operation)
	Prequalification of contractors
	Unit prices
	Cash allowances
Schedule	Coordination schedule.
	Bar charts
	Critical path method
	Incremental milestones
Cost	Cost variance (CV)
Quality	Independent inspection firms
Communication	Regular site meetings
	Rapid response mechanism
Safety	Joint health and safety committee
Project completion	Inspection by operator, maintenance, and end user

Based on the above criterion, only 17 factors were to be considered for further analysis and model development. The selected 17 factors include 3 at the planning and scope definition stage, 4 at the tendering stage, 4 for schedule control, 1 for cost control, 1 for quality control, 2 for communication control, 1 for safety control, and 1 at the project completion stage. This analysis confirms that the management and control of planning, tendering, and scheduling are a significant aspect of the cost performance of reconstruction projects. For the model to be sensitive to the different types of reconstruction projects, an eighteenth factor was added; the type of reconstruction (minor repair, structural modification, or complete phased replacement). Table 3 lists the final 18 factors used to develop the predictive models.

Statistical Predictive Model

Initial experimentation with a regression model that includes all 18 variables resulted in a model with poor performance, thus indicating that including all variables makes the model less sensitive to each of them. Accordingly, experiments to determine the best subset of data were made using stepwise regression to facilitate the development of a predictive model of cost deviation. The *Systat* software includes two different procedures for the development of stepwise models: forward selection and backward elimination. It also provides the user with the facility to add or remove criteria.

Forward stepping begins with no variables in the equation, enters the most significant variable at the first step, and continues adding and deleting variables until none can significantly improve the fit. Backward stepping, on the other hand, begins with all

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Table 4. Statistical Models

Variable	Coefficient	T-statistics	Partial F
Model A1: backward-stepping[a]			
Constant	75.691	83.163	0.000
As-built	7.371	3.587	0.000
Unit prices	2.012	1.981	0.021
CPM	3.981	3.836	0.001
Prequalifications of contractors	3.771	3.021	0.019
Inspection by O&M/end-users	5.601	3.713	0.010
Model A2: forward-stepping[b]			
Constant	75.001	85.896	0.000
As-built	6.992	4.362	0.000
Unit prices	4.967	4.106	0.000
Joint health and safety committee	5.421	3.879	0.001
Inspection by O&M/end-users	3.325	2.321	0.029

[a] F-ratio$=81.638$; P value$=0.00$; adjusted squared multiple $R=0.897$.
[b] F-ratio$=98.371$; P value$=0.00$; adjusted squared multiple $R=0.784$.

candidate variables, then removes the least significant variable at the first step and continues until no insignificant variables remain. Data splitting was cited as one of the available and acceptable means for model validation (Montgomery 1990). Nine cases (20% of available data) were selected randomly and set aside for validation purposes, and 41 case studies were used for model building. Using *Systat*, two models were developed, as shown in Table 4.

Based on the results in Table 4, the backward-stepping technique (model A1) was slightly more accurate in predicting the cost performance of reconstruction projects, with a higher adjusted squared multiple R. As reported in the literature, backward stepping is preferable to forward selection because it has the advantage of looking at all the available variables in the early stages of the model development process.

The underlying formula of model A1 is $\text{CPI}=75.691 + 7.371\,(\text{as-built}) + 2.012\,(\text{unit prices}) + 3.981\,(\text{CPM}) + 3.771\,(\text{prequalification of contractors}) + 5.601\,(\text{inspection by O \& M end-users})$ where each of the five variables can have a 0 (unused) or 1 (used) value. The model's adjusted squared multiple $R=0.897$, indicating that the model is able to explain 89.7% of the variability in the data. This value is considered an excellent indicator of the model's expected performance. Tolerance is also an indicator of muticollinearity which inflates the variance of the least squares estimators and possibly any predictions made.

All the variables in model A1 have >0.1 tolerance, indicating that muticollinearity does not exist among the predictor variables. It is noted that the model is a function of the five variables used in its formula and ignores the other variables, including the type of reconstruction involved.

As an example, the model is used in a potential reconstruction project with the following characteristics: the facility has good as-built drawings available (1); unit prices are included in the tender submission (1); CPM will not be used (0); prequalification of contractors will take place (1); and inspection by operators/maintenance will not take place (0). The predicted CPI will be obtained as follows: $\text{CPI}=75.691+7.371*1+2.012*3.981*0+3.771*1+5.601*0=88.845$.

This result means that this project is expected to have a poor performance equal to 100 less 88.845, which equals 11.115% poor performance; 11.115% is considered an expected value for a cost overrun in this project.

Table 5. Validation for Model A1

Project	Predicted CPI	Actual CPI	Error(Y)
1	76.356	77.532	−1.176
2	81.798	87.612	−5.814
3	94.035	89.77	4.265
4	77.987	78.830	−0.843
5	93.791	88.651	5.14
6	87.630	88.937	−1.307
7	75.619	75.212	0.407
8	92.823	92.978	−0.155
9	91.997	95.026	−3.029
—	—	r	0.9031

Validation

The nine case studies excluded during model development were used for validation purposes. The model was used to produce nine predicted values for the CPI of the nine projects. Afterwards, a correlation was performed between the predicted and the actual CPI for the nine projects. The resulting correlation coefficient was $r=0.9031$, indicating that the developed model A1 has excellent predictive capabilities, as shown in Table 5.

Artificial Neural Network Model

In addition to the brainlike structure of artificial neural networks (ANNs), their major advantage is their ability to be trained on previous situations. Training is required to continuously adjust the connection weights until they reach values that allow the ANN to predict outputs that are very close to the actual outputs while being able to generalize well on new cases (Hegazy et al. 1994).

The ANN type most suited for developing predictive models such as the one at hand is feed-forward networks trained using a back-propagation algorithm that uses a gradient-descent approach for adjusting the ANN weights. During training, a neural network is exposed to the training data thousands of times (called cycles or epochs). After each cycle, the errors between the predicted and the actual outputs are propagated backward to adjust the weights in a manner that is mathematically guaranteed to converge (Rumelhort et al. 1986).

The model design phase includes two main tasks: (1) problem analysis, and (2) problem structuring. Problem analysis is the identification of the independent factors that fully describe the

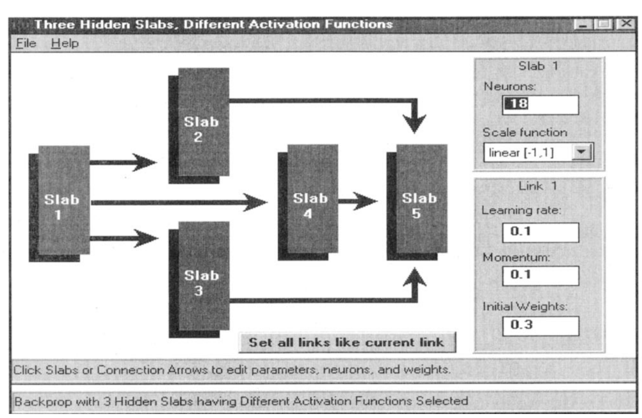

Fig. 1. Architecture of best artificial neural network

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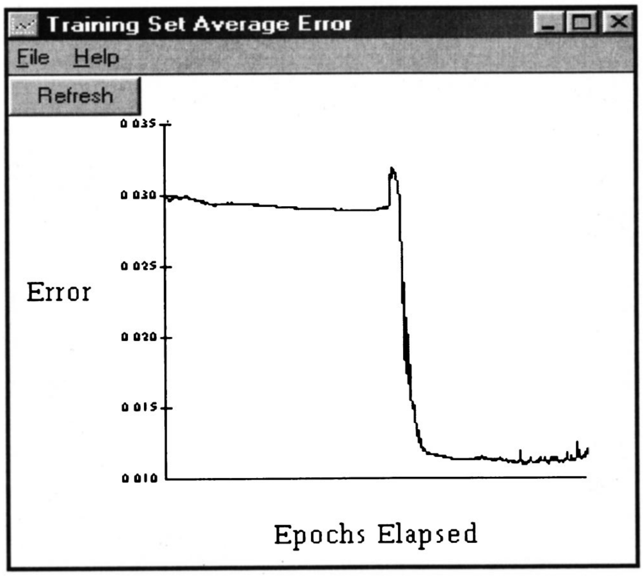

Fig. 2. Training set average error

problem; problem structuring, on the other hand, entails the arrangement and representation of the independent factors and the response variables. In the present application, the same 18 variables defined earlier will be used in ANN development.

To develop the ANN model, *Neuro Shell 2* software was chosen for its ease of use, speed of training, and host of neural network architectures, including back-propagation with flexible user selection of training parameters. The user has the ability to specify the learning rate, momentum, activation functions, and initial weight range. *Neuro Shell 2* also has multiple criteria for stopping the training, in addition to different methods for handling missing data and viewing the weight values during training.

The quality of ANN training is dependent on the quantity of training data and on how the data are presented to the network. Therefore, several data-representation experiments with various network architectures were performed during training in order to arrive at the best-trained net. In these experiments, network parameters such as the number of hidden layers, hidden nodes, network connections, and transfer functions were tested and the best result was documented. The selected architecture, which was proven to produce the best predictive net, is shown in Fig. 1, which depicts a back propagation network with five layers or slabs: one input layer, one output layer, and three hidden layers. It also shows that slab 1 contains 18 neurons, which are the model's 18 factors being analyzed in the input layer. Furthermore, Fig. 1 shows the training characteristics of this net, which are a learning rate of 0.1, a momentum of 0.1, and an initial weight of 0.3.

Table 6. Neural Network Result

Characteristic	Values
R^2	0.8501
r^2	0.8563
Mean square error	10.9210
Mean absolute error	2.2310
Minimum absolute error	0.0390
Maximum absolute error	6.2410
Correlation coefficient r	0.9132

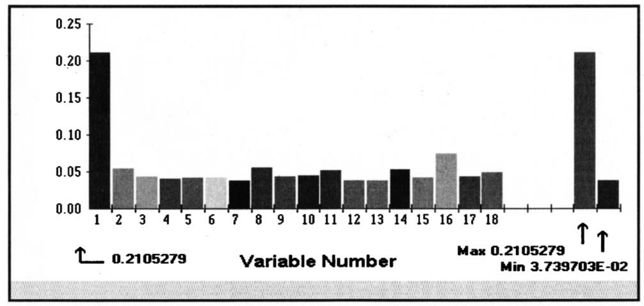

Fig. 3. Relative contribution of input variables

To overcome the overfitting problem associated with neural network training, a training set of 41 cases was used in addition to a test set of the remaining 9 cases. The selected cases for both training and testing sets were the same as those used in the regression model. One feature of *Neuro Shell 2* was used to allow model development and validation to occur at the same time. The test set extract feature was used, and the training was set to save the network when the errors on the test set are minimal to improve its generalization. During training, the mean square error between the actual and predicted values for CPI overall patterns is plotted, as shown in Fig. 2, in which the error was reduced to a stable level at which no further improvement was achievable.

Table 6 summarizes the model characteristics and its achieved result, an R^2 value 0.8501. Also, the correlation coefficient between the predicted and the actual CPI was 0.9132. These results show that the developed ANN with its 18 input variables possesses a high predictive performance.

After training, the postprocessing feature of *Neuro Shell 2* indicated the relative contributions of all factors in the model are equally significant (Fig. 3), with variable one (type of project) being more significant than the others. Once the network was trained and a satisfactory error level achieved, it is possible to apply the model to any new project to estimate its CPI value.

Decision-Support Tool

To provide simple access to the developed ANN, a spreadsheet interface was developed to facilitate data input and automate per-

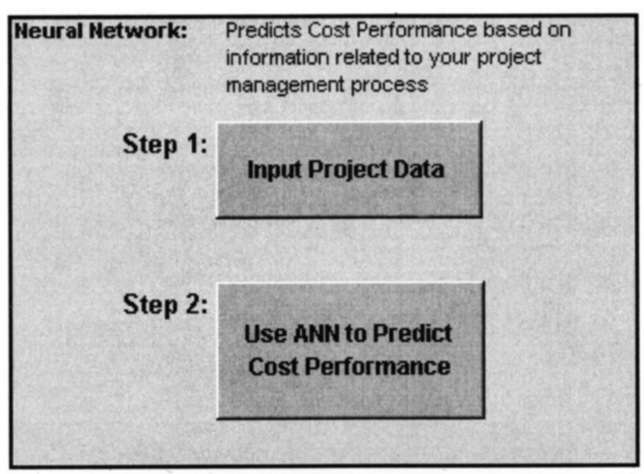

Fig. 4. Decision support system

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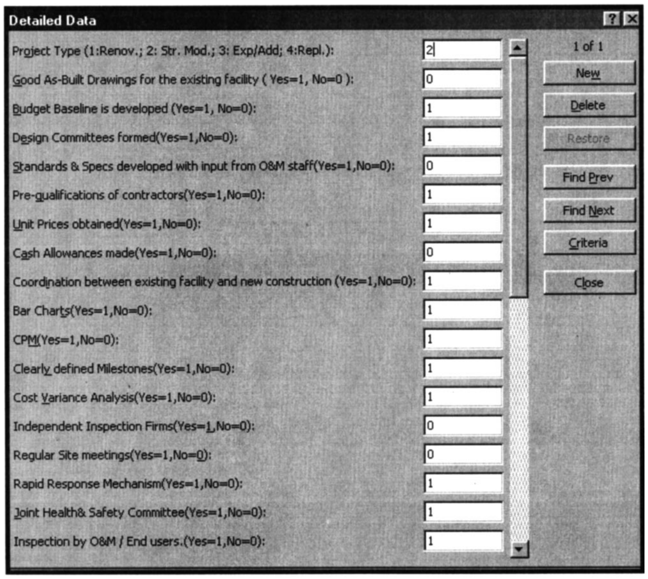

Fig. 5. Project data input screen

formance prediction. The interface was developed on *Microsoft Excel* using its macro programming tools. One of the useful features of the *Neuro Shell 2* Software is the ability to create Run Time versions of its trained nets that can be called from *Microsoft Excel* to automatically produce the required predictions. Using this feature, a decision support system was developed.

To use the system, two simple steps are to be followed: project data entry, and applying the ANN. The user interface for the decision support tool is shown in Fig. 4. The project data input button activates the project data input screen, as shown in Fig. 5. It presents the 18 variables and the user's assessment of each variable. After data input, the user closes the input screen and activates the ANN from the main screen to initiate the prediction. The predicted performance screen will appear, as shown in Fig. 6.

The project manager can experiment with different scenarios for expected values of the variables to determine the impact of using various project management techniques. This experimentation can take place by manipulating the answers in the project data input screen and monitoring the changes in the predicted CPI values in the predicted performance screen.

Comparison between Neural Network and Regression Models

Table 7 compares the two types of models developed in this study. The comparison was based on three characteristics: coefficient of determination R^2, coefficient of correlation r, and the number of variables; R^2 explains the overall utility of the model or its ability to explain the variation of the data, and (r) is the correlation coefficient between the predicted and the actual CPI.

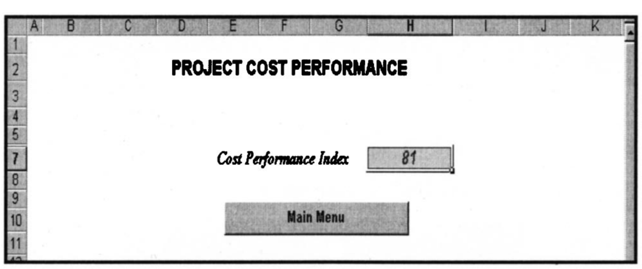

Fig. 6. Predicted performance screen

Table 7. Comparison between Models

Comparison factor	Model: Artificial neural network	Model: Regression
R^2	0.8501	0.8970
r	0.9132	0.9031
Number of variables	18.0000	5.0000

Both the regression and the neural network models produced relatively close results for both R^2 and r. The difference, however, is that the ANN model was able to develop these results while using the 18 variables, while the regression model used only 5 variables. The ANN sensitivity to all variables in predicting the outcome of a future project may be advantageous; it would give the user of the model a larger opportunity to investigate different project control techniques.

Conclusion

This paper investigated the risky environment of reconstruction projects and identified the factors that impact their cost performance. A questionnaire survey was then developed and used in a structured interview format to obtain information related to the actual cost performance in different case studies.

A single quantifiable measure, the cost performance index (CPI), was developed to measure the cost performance of the surveyed projects and was considered the dependent variable in model development. A preliminary statistical analysis was performed on the collected project data, and accordingly 18 significant variables were identified.

Two models were developed to predict the cost performance of reconstruction projects. One model was developed using statistical regression analysis and one model was developed using artificial neural networks (ANNs). Forty-one cases were used for model development, while the remaining nine cases were used for model validation and testing. Both models produced a high correlation between the predicted CPI values and the actual values. One essential benefit of the model based on ANNs is its use of larger number of variables, and as such the model becomes more diverse. ANNs have proven useful and suitable for dealing with such a complex problem and developing user-friendly predictive models. They are able to detect any patterns found in the data and provide larger opportunity to investigate different options and project control techniques.

While both statistical analysis and neural networks worked well for the application at hand, neural networks can be an alternative modeling technique for problems that may include a higher degree of uncertainty in the data and when statistical analysis may not be practical.

A decision support system was developed to facilitate use of the neural network models. The spreadsheet works as a decision support tool that automates the prediction of the CPI for reconstruction projects as a function of the set of control tools specified by the user.

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