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A NEURAL NETWORK MODEL FOR PREDICTING THE TIME PERFORMANCE OF TRADITIONAL GENERAL CONTRACT (TGC) PROJECT

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Abstract: Several studies had shown that many project managers are facing difficulties in predicting the time performance of Traditional General Contract (TGC) projects because there are many factors that affect TGC project success. This study presents the development of a model that can be used to predict the time performance of TGC project. Through literature research, forty-four success factors affecting TGC project have been established. The degree of importance for these factors was determined through questionnaire survey. The outcome of the survey formed a basis for the development of the time performance prediction model using Artificial Neural Network technique. The best model was found to be a multi-layer back-propagation neural network consists of eight input nodes, five hidden nodes and three output nodes. The model was tested by using data from nine new projects. The results show that the mean error for this prediction model is relatively low. The developed model enables all parties involved in TGC projects to predict and ensure that their project is on time.

Keywords: *Artificial Neural Network, Project performance, Traditional General Contract*

1.0 Introduction

Construction projects are intricate, time-consuming undertakings. The total development of a project normally consists of several phases requiring a diverse range of specialized services. Traditionally, construction does not start until the architect-engineer has completed and finalized the design. This sequence is still predominant in the industry and is referred to as the Traditional General Contract (TGC) procedure (Richard *et al.*, 2000). It is possible to reduce the total construction time by starting the construction before completing the design of the entire project. Measurements of time performance provide management with invaluable feedback to guide daily decision-making. By regularly using such feedback, the management becomes more competent. On-time completion means that the job finished as it was scheduled.

Studies had shown that project managers always encounter difficulties to predict the performance of TGC project (Daniel, 2000; Richard *et al*., 2000). They need the skills to evaluate the factors that affect TGC project success. Under these circumstances, the study described in this paper tries to establish the factors affecting project performance and develop a model that can be used to predict the time performance of TGC projects.

2.0 Factors Affecting Project Performance

There are important factors affecting the outcome of construction projects irrespective of the contract conditions (Caren, 2006). Pinto and Slevin (1988) proposed ten factors including project mission, top management support, project schedule/plans, client consultation, personnel, technical tasks, client acceptance, monitoring and feedback, communication, and troubleshooting that are considered as critical for success at various stages (conceptual, planning, execution, and termination) of project life cycle. Jaselskis (1988) on the other hand used an objective measure of the management attributes in his study on project success. The key management factors identified from the study comprise those involving the project manager, his or her team, planning and control efforts, and some external factors.

In another study, Songer and Molenaar (1997) identified 15 characteristics of successful construction projects through literature review and unstructured interviews of academia and public sector agency representatives. They found that the top five important project characteristics were well-defined scope, shared understanding of scope, owner construction sophistication, adequate owner staffing, and established budget. Recent study by Albert *et al*. (2004) detailed out forty-four factors affecting the project performance. The factors, identified by them, found to be thorough and cover most of the factors identified by previous researchers. Table 1 shows the factors affecting project success that are categorized into attributes relating to the project characteristic, project procedures, project management actions, project participants, and external environment.

3.0 Methodology

The study was carried out in two distinct phases. Phase I involved identification of the degree of importance of the forty-four critical factors affecting TGC project performance that were identified from the review of past works. A self-administered questionnaire was designed to facilitate systematic data collection. Questionnaires were distributed to clients, consultants and contractors who had participated in TGC projects. In Phase II, a prediction model was developed using Artificial Neural Network (ANN) technique based on the results of the questionnaire survey. Multi-Layer Perception (MLP) had been chosen as the neural computational technique. In the model development, the important factors affecting project time performance that were identified through questionnaire

Table 1: Factors affecting project performance (Albert *et al.,* 2004)

Project Aspect	*Factors Related*
Project Characteristic	1. Type of project 2. Nature of project 3. Number of floors of the project 4. Complexity of project 5. Size of project
Project Procedures	1. Procurement method 2. Tendering method
Project Management Actions	1. Communication system 2. Control mechanism 3. Feedback capabilities 4. Planning effort 5. Developing an appropriate organization structure 6. Implementing an effective safety program 7. Implementing an effective quality assurance program 8. Control of subcontractors' work 9. Overall managerial actions
Project Participants	1. Client's experience means whether he is a sophisticated or specialized client. 2. Nature of client means whether he is privately or publicly funded. 3. Size of client's organization. 4. Client's emphasis on low construction cost. 5. Client's emphasis on high quality of construction. 6. Client's emphasis on quick construction. 7. Client's ability to brief. 8. Client's ability to make decision. 9. Client's ability to define roles. 10. Client's contribution to design. 11. Client's contribution to construction. 12. Project team leaders' experience. 13. Technical skill of the project team leaders. 14. Planning skill of the project team leaders. 15. Organizing skill of the project team leaders. 16. Coordinating skill of the project team leaders. 17. Motivating skill of the project team leaders. 18. Project team leaders' commitment to meet cost, time and quality. 19. Project team leaders' early and continued involvement in the project. 20. Project team leaders' adaptability to changes in the project plan. 21. Project team leaders' working relationship with others. 22. Support and provision of resources from project team leaders' parent company.
External environment	1. Economic environment 2. Social environment 3. Political environment 4. Physical environment 5. Industrial relations environment 6. Technology advanced

survey became the input variables while project time performances were used as the output variables. The measurement scales for the input and output variables were determined from a series of interviews with project managers.

The input and output variables and its respective measurements are shown in Table 2. Sixty sets of TGC project data were used in the model development. The data were obtained through face-to-face interview with project managers.

Table 2: Variables for ANN model

Var ref	Explanatory variables	Definition
INPUT		
X_1	Complexity of project	Scale 1 – 5; 1 = Not Complex; 5= Highly Complex
X_2	Control of subcontractors' work	Scale 1 – 5; 1 = Poor; 5 = Excellent
X_3	Client's emphasis on quick construction	Scale 1 – 5; 1 = None; 5 = Very High
X_4	Project team leaders' experience	Scale 1 – 5; 1 = No Experience;5 = High Experience
X_5	Technical skill of the project team leader	Scale 1 – 5; 1 = Poor; 5 = Excellent
X_6	Planning skill of the project team leader	Scale 1 – 5; 1 = Poor; 5 = Excellent
X_7	Coordinating skill of the project team leaders	Scale 1 – 5; 1 = Poor; 5 = Excellent
X_8	Project team leaders' adaptability to changes in the project plan	Scale 1 – 5; 1 = Poor; 5 = Excellent
OUTPUT		
Z_1	Ahead time	1= Actual project time/planned time < 1.0
Z_2	On time	2= Actual project time/planned time = 1.0
Z_3	Behind time	3= Actual project time/planned time > 1.0

3.1 Training, Testing and Validation

A random selection of 75% of the data was used as a training data set for the neural network model while 10% used for validation and the remainder were used as a testing set in which the performance of the ANN was tested. Once the learning process had finished and the weights of the neural network had been calculated, the quality of the resulting model was checked based on the errors between the desired and the computed output values for the training data. The standard error measurement method that had been used in the model development was the Root Mean Square Error (RMSE), expressed by equation 1.

$$\sqrt{\sum_{p=1}^{r} \| b_p - Б_p \|^2 / r} \qquad (1)$$

where : $Б_p$ = Actual duration to accomplish the project;
b_p = Predicted duration to accomplish the project;
r = Total number of cases.

In the training process, a total number of seven models with different parameters had been used. This was aimed to evaluate the influence of the different parameters on the accuracy of the models. These different training parameters are summarized in Table 3.

The Neural Connection software version 2.1 was used to estimate the neural network models (SPSS Inc., 1999). Training was set to stop after 10,000 iterations or until convergence to a root mean square error (RMSE) of 0.001.

Table 3: Training parameters

Parameter	Description
Number of hidden layers	1, 2
Number of hidden nodes	3, 5, 7
Learning algorithm	Conjugate Gradient, Steepest Descent

4.0 Results

The initial stage of the questionnaire exercise resulted in the identification of the most important factors affecting project performance. They are the complexity of project, control of subcontractors' work, client's emphasis on quick construction, project team leaders' experience, technical skill of the project team leaders, planning skill of the project team leaders, coordinating skill of the project team leader, and project team leaders' adaptability to changes in the project plan. Figure 1 illustrates the architecture of ANN model developed based on the identified most important factors. The results of the network by using different training parameters are depicted in Table 4, 5 and 6.

(a) Number of hidden layers

The results of the networks with one and two hidden layers are shown in Table 4. The results indicate that model MLP2 with two hidden layers has higher training and testing errors compared to model MLP1 with one hidden layer.

Table 4: Training and testing results based on number of hidden layers

Model	Hidden Layer	Training		Testing	
		RMSE	MAPE	RMSE	MAPE
MLP1	1	0.4043	7.2677	0.0232	0.7747
MLP2	2	0.4042	7.4244	0.0297	0.9916

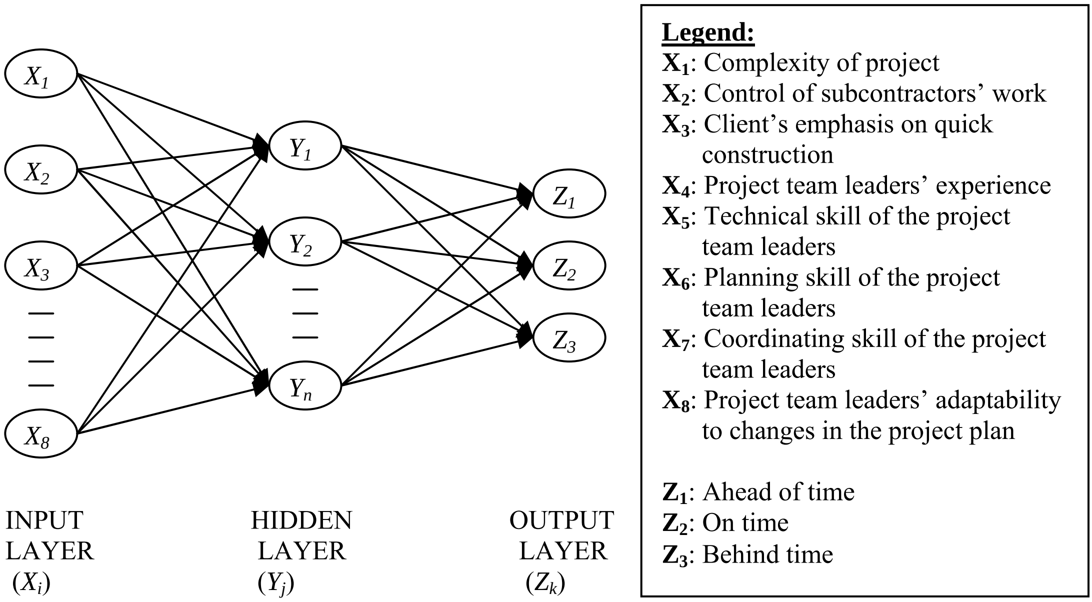


Figure 1: ANN architecture of the time performance prediction model

(b) Number of hidden nodes

The results of the networks with three, five and seven hidden nodes are shown in Table 5. The results indicate that the optimum number of nodes in the hidden layer is 5. Model MLP4 has a training error of 0.1217 while training errors of models MLP3 and MLP5 are 0.2038 and 0.1218 respectively.

Table 5: Training and testing results based on number of hidden nodes

Model	Hidden Nodes	Training		Testing	
		RMSE	MAPE	RMSE	MAPE
MLP3	3	0.2038	3.1515	0.0040	0.1126
MLP4	5	0.1217	1.1574	0.0020	0.0386
MLP5	7	0.1218	1.1737	0.0222	0.3660

(c) Learning algorithm

The results from Table 6 show that different learning algorithm have different effect on the accuracy of the developed models. Model MLP6 with conjugate gradient learning algorithm had higher training and testing errors as compared to the one with steepest descent learning algorithm.

Table 6: Training and testing results based on learning algorithm

Model	Learning algorithm	Training		Testing	
		RMSE	MAPE	RMSE	MAPE
MLP6	Conjugate Gradient	0.1217	1.1574	0.0020	0.0386
MLP7	Steepest Descent	0.1217	1.1452	0.0015	0.0283

Figure 2 depicts the comparison of the actual and predicted values of time performance for the nine performance prediction test projects. The predicted values are the time performance values generated from the best network.

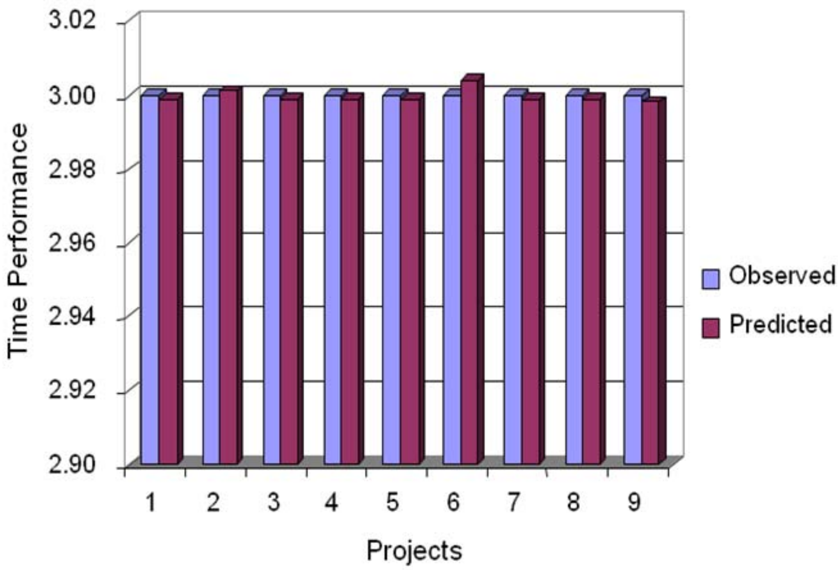


Figure 2: Time performance - observed vs. predicted for the ANN model

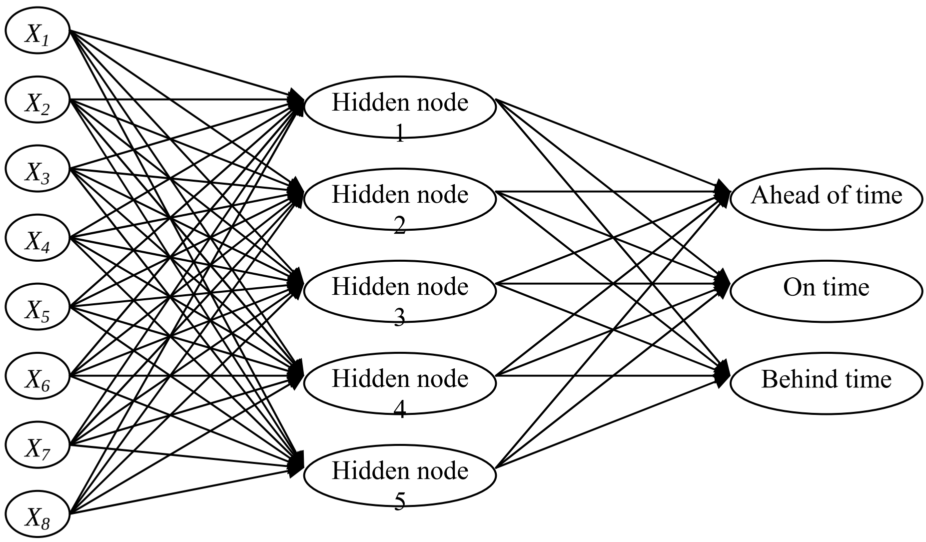
5.0 Discussion

Throughout the experimentation process, the model with two layers did not result in good prediction accuracy. However, the model with one hidden layer produces a satisfactory result. This had matched with the results produced by other researchers that demonstrated no improvement could be achieved with more than one hidden layer (Boussabaine *et al.*, 1999; Cheung *et al.,* 2000; and Ogunlana *et al.*, 2001).

Apart from this, it is also very important to determine the proper number of hidden nodes for developing the model. Three models using 3, 5 and 7 nodes had been developed respectively. The model with 5 hidden nodes presented the best performance. If the hidden nodes are continuously increased, there will be no further improvement beyond that point. This is because too many nodes in the middle layer would lead to too many connections occurred. Hence, this will produce a network that memorizes the input data and lack of generalizing capability.

Learning algorithm had also significant impacts on the accuracy of the developed models. However, the impact is not as significant as the one cause by varying the hidden layers or nodes. In this research, the best model consists of 1 hidden layer, 5 hidden nodes and using steepest descent learning algorithm. The architecture of this model is depicted in Figure 3. The training and testing error for the best model is only 0.1217 and 0.0015 respectively.

The neural network approach to predict project performance in this study does not require a prior assumption of the functional relationship. Besides, the model is also able to generate satisfactory solutions with incomplete and previously unseen data, which is definitely beneficial in the construction environment where decision is often expected without complete information. The model had helped to organize the interdisciplinary knowledge about the construction project performance from the aspect of time accuracy.



Legend:

X_1: Complexity of project **X_2**: Control of subcontractors' work **X_3**: Client's emphasis on quick construction **X_4**: Project team leaders' experience	**X_5**: Technical skill of the project team leaders **X_6**: Planning skill of the project team leaders **X_7**: Coordinating skill of the project team leaders **X_8**: Project team leaders' adaptability to changes in the project plan

Figure 3: Architecture of the best ANN prediction model

To provide simple access to the developed ANN model, an interface was developed to facilitate data input and automate performance prediction. The interface was developed on Microsoft Excel using its macro programming tools (refer to Figure 4). The project data input screen is shown in Figure 5 and the predicted performance screen is depicted in Figure 6.

Figure 4: Interface for ANN project performance prediction model

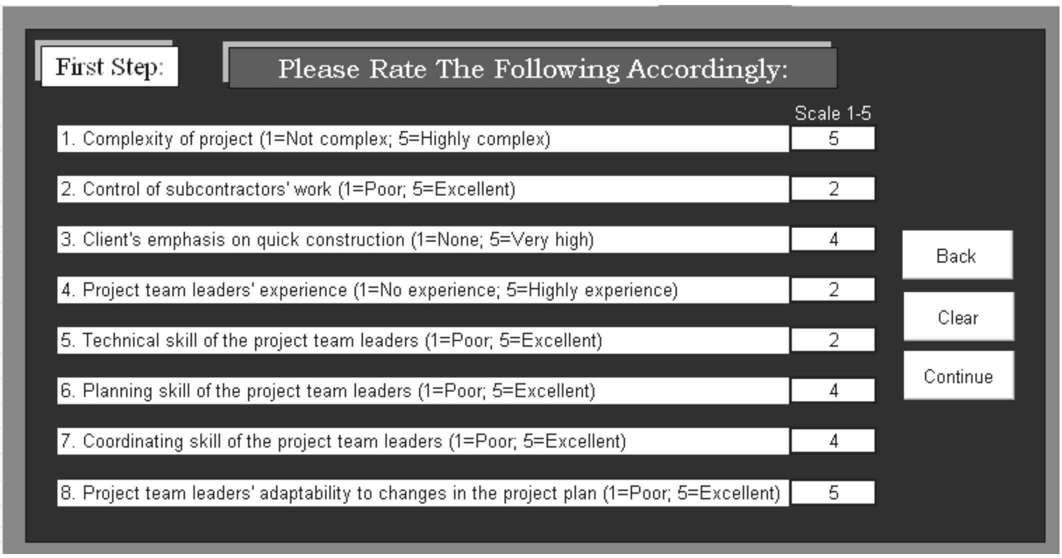


Figure 5: Project data input screen

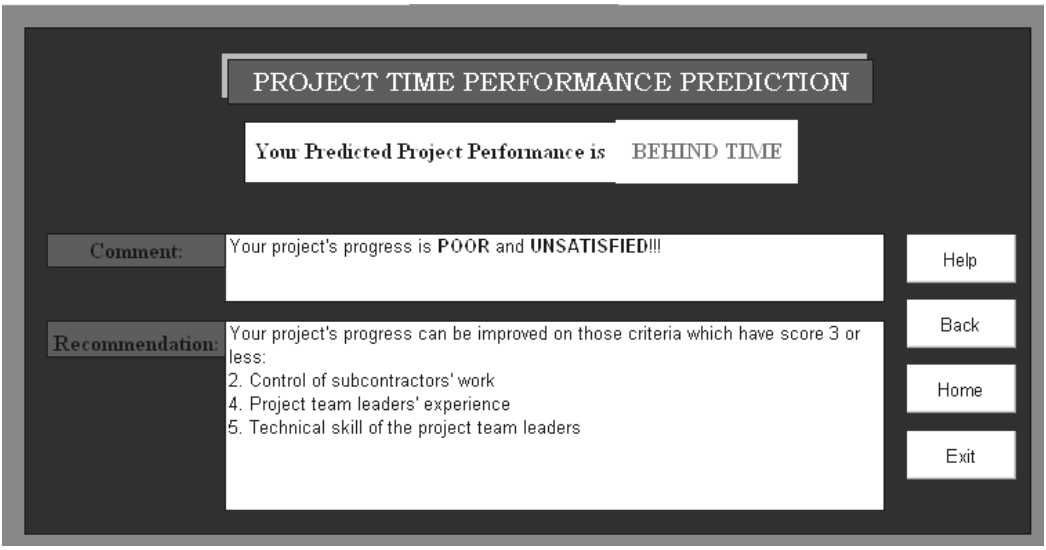


Figure 6: Predicted project performance screen

6.0 Conclusions

Forty-four factors that affect TGC project success had been established in the literature. The degree of importance for these factors had been determined through questionnaire survey done in this study. Eight out of forty-four factors that affecting project performance were found to be the most important factors from the viewpoint of project managers and contractors in the Malaysia construction industry. These factors are complexity of project, control of subcontractors' work, client's emphasis on quick construction, project team leaders' experience, technical skill of the project team leaders, planning skill of the project team leaders, coordinating skill of the project team leader and project team leaders' adaptability to changes in the project plan. A model to predict construction project performance based on time has been developed based on the outcome of the survey and Artificial Neural Network (ANN) technique. The best time performance prediction model was the multilayer back-propagation neural network, which consisted of eight input nodes, five hidden nodes and three output nodes.

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