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PREDICTING THE PERFORMANCE OF TRADITIONAL GENERAL CONTRACT PROJECTS: A NEURAL NETWORK BASED APPROACH

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Abstract: Several studies had shown that many project managers are facing difficulties in predicting the performance of Traditional General Contract (TGC) projects. This is due to the fact that there are many factors that affect TGC project success. This paper presents the TGS project success factors that have been identified. In addition, a model to predict the performance of TGC project based on time is also described. Through literature research, a total of forty-four factors affecting TGC project success had 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 project performance prediction model. 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 showed that the mean error for this prediction model is relatively low. The model enables all parties involved in TGC projects to predict and ensure that their project performance is within the time constraints.

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

1. 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, field construction is not begun 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. It is possible to reduce the total construction time by starting the construction before completing the design of the entire project. Measurements of performance provide management with invaluable feedback to guide daily decision making and they become more competent. On-time completion means that the job finished as it was scheduled. However, time and budget measurements frequently come too late to guide daily management decision making.

Studies had shown that project managers always encounter difficulties to predict the performance of TGC project. 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 performance of TGC projects from the time aspect.

2. FACTORS AFFECTING PROJECT PERFORMANCE

Several empirical studies relevant to the identification of factors influencing project performance were reviewed. Pinto and Slevin (1988) proposed 10 factors including project mission, top management support, project schedule/plans, client consultation, personnel, technical tasks, client acceptance, monitoring and feedback, communication, and troubleshooting. All of them were 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. Songer and Molenaar (1997) 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 Albert et al. (2004) 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.

Table 1: Factors affecting project performance

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

3. METHODOLOGY

Forty-four potential factors affecting project performance were identified from the review of past works. In order to determine the most important factors affecting project performance, a self-administered questionnaire was developed to facilitate systematic data collection. Sixty sets of questionnaires had been distributed to clients, consultants and contractors who had participated in TGC projects. Based on the identified most important factors affecting project performance a prediction model was developed using Artificial Neural Network (ANN) technique where the Multi-Layer Perceptron (MLP) had been chosen as the neural computational technique. The data used in the model development were based on the input and output variables as given in Table 2 and collected through interviews with project managers.

Table 2: Variables for ANN prediction model

Var ref	Explanatory variables	Definition
INPUT		
$\mathbf{X_1}$	Complexity of project	Scale 1 – 5; 1 = Not Complex; 5= Highly Complex
$\mathbf{X_2}$	Control of subcontractors' work	Scale 1 – 5; 1 = Poor; 5 = Excellent
$\mathbf{X_3}$	Client's emphasis on quick construction	Scale 1 – 5; 1 = None; 5 = Very High
$\mathbf{X_4}$	Project team leaders' experience	Scale 1 – 5; 1 = No Experience; 5 = Highly Experience
$\mathbf{X_5}$	Technical skill of the project team leaders	Scale 1 – 5; 1 = Poor; 5 = Excellent
$\mathbf{X_6}$	Planning skill of the project team leaders	Scale 1 – 5; 1 = Poor; 5 = Excellent
$\mathbf{X_7}$	Coordinating skill of the project team leaders	Scale 1 – 5; 1 = Poor; 5 = Excellent
$\mathbf{X_8}$	Project team leaders' adaptability to changes in the project plan	Scale 1 – 5; 1 = Poor; 5 = Excellent
OUTPUT		
$\mathbf{Z_1}$	Ahead time	Project status value > 0
$\mathbf{Z_2}$	On time	Project status value = 0
$\mathbf{Z_3}$	Behind time	Project status value < 0

3.1 Training, Testing and Validation

Training is used to train the application while testing is used to measure the performance of a trained application. During training, neural techniques need to have some way of evaluating their own performance. Since they are learning to associate the inputs from the training with their outputs, evaluating the performance of the application on the training data may not produce the best results from the system. This is because if a network is left to train for too long, it will overtrain. This means that it will lose its ability to generalize. In order for the neural computing technique to monitor its performance in a more sensible fashion, another part of the data is set aside as a validation set.

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, it is important to check the quality of the resulting model. In the case of supervised learning, a measure of the quality can be given in terms of 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 project performance model development is Root Mean Square Error (RMSE) Method, expressed by Equation, which can be defined as:

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

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

The Neural Connection software version 1.0 (SPSS, 1995) was used to estimate the neural network models. The training data sets was used to map the input variable pattern to the target output pattern and minimize the error by adjusting the weights of the network links in an iterative process. Training was set to stop after 10,000 iterations or until convergence to a root mean square error (RMSE) of 0.001.

4. RESULTS

The initial stage of the questionnaire exercise resulted in the identification of the most important factors affecting project performance, which 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. Figure 1 illustrates the architecture of ANN model developed based on the identified most important factors.

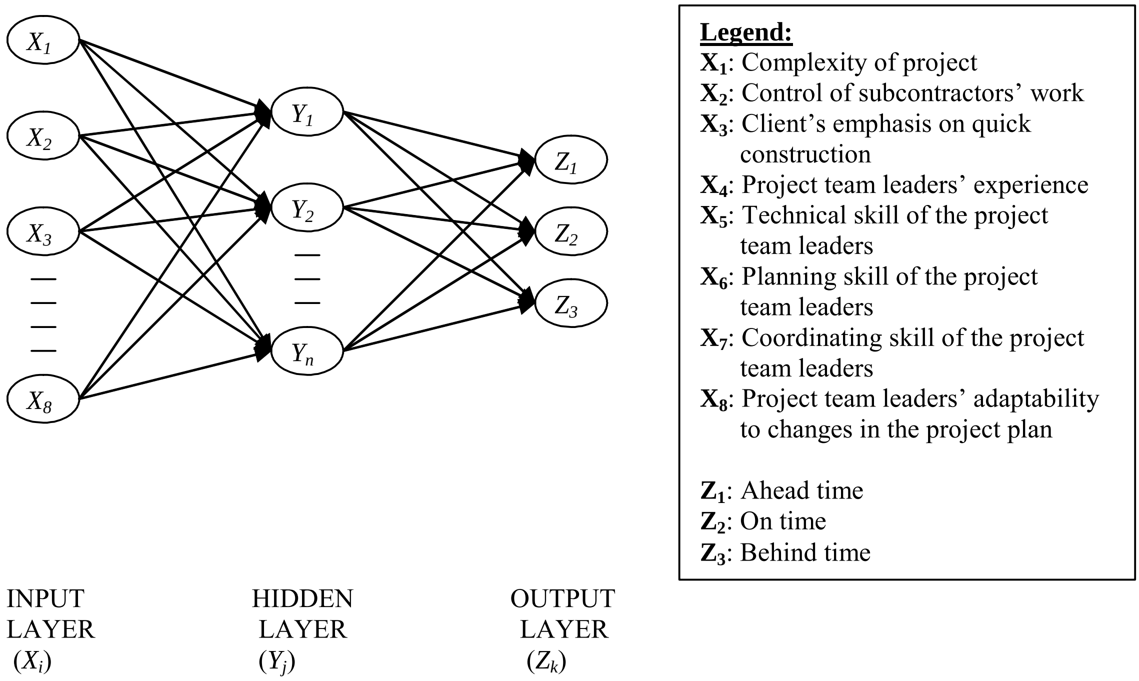


Figure 1. ANN architecture of project performance prediction model

In the training process a total number of seven models had been developed based on different parameters. This is aimed to evaluate the influence of these different parameters on the accuracy of the ANN prediction model. These different training parameters are summarized in Table 3. The results of the networks by using different training parameters are depicted in Table 4, 5 and 6.

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

(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

(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 shows 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 depicted the comparison of the actual and predicted values of time performance for the nine performance prediction test project. The predicted values are the time performance values generated from the best network.

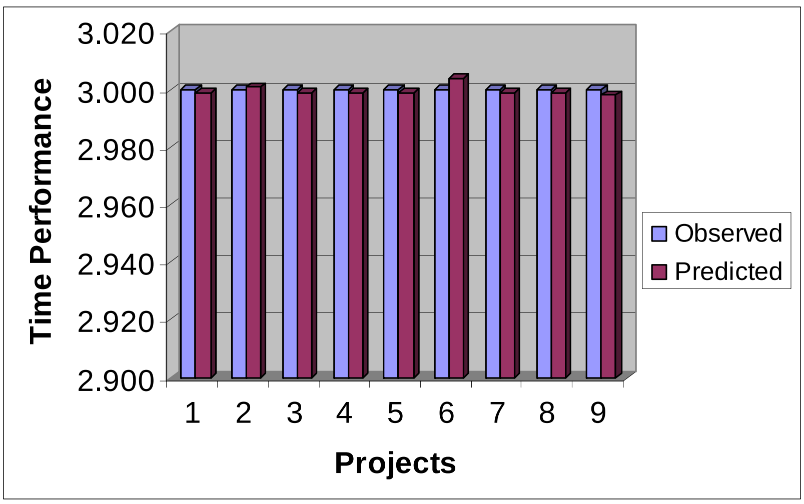


Figure 2. Time performance - observed vs. predicted for the ANN model

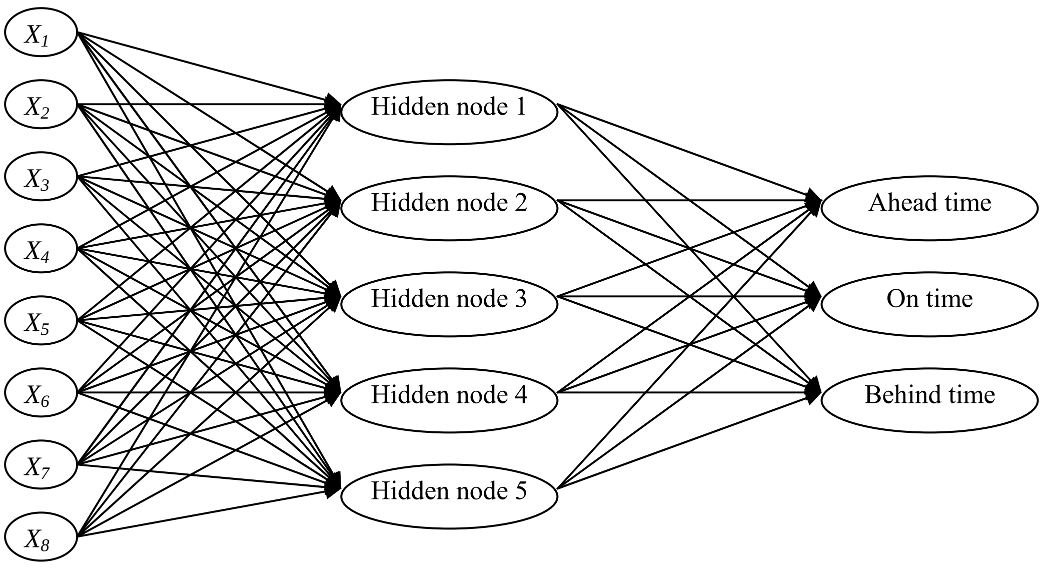
5. DISCUSSION

Table 4, 5 and 6 give the results of ANN prediction model by using different training parameters. 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 very important also to determine the proper number of hidden nodes for developing the model. Three models which 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 due to the fact that too many nodes in the middle layer would lead to too many connections occurred. Hence this will produce a network which 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 is 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_5**: Technical skill of the project team leaders
X_2: Control of subcontractors' work	**X_6**: Planning skill of the project team leaders
X_3: Client's emphasis on quick construction	**X_7**: Coordinating skill of the project team leaders
X_4: Project team leaders' experience	**X_8**: Project team leaders' adaptability to changes in the project plan

Figure 3. Neural network architecture of project performance 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 5.

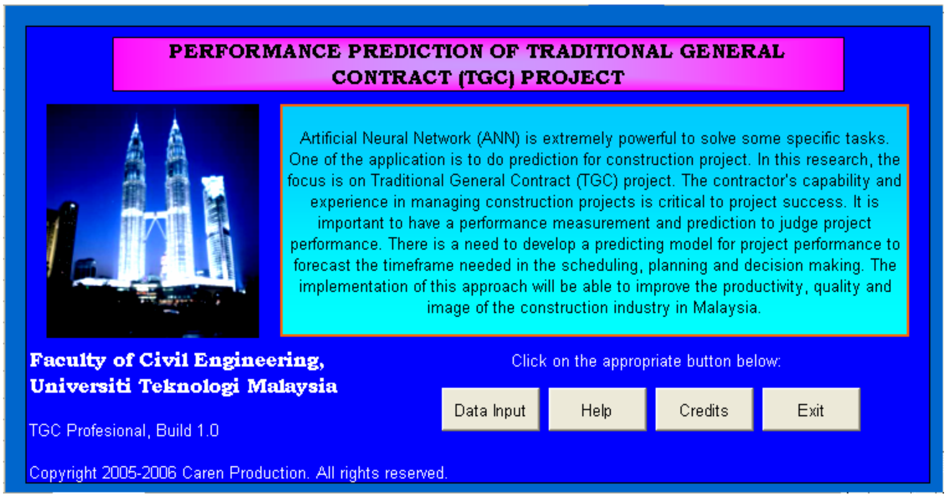


Figure 4. Interface for ANN project performance prediction model

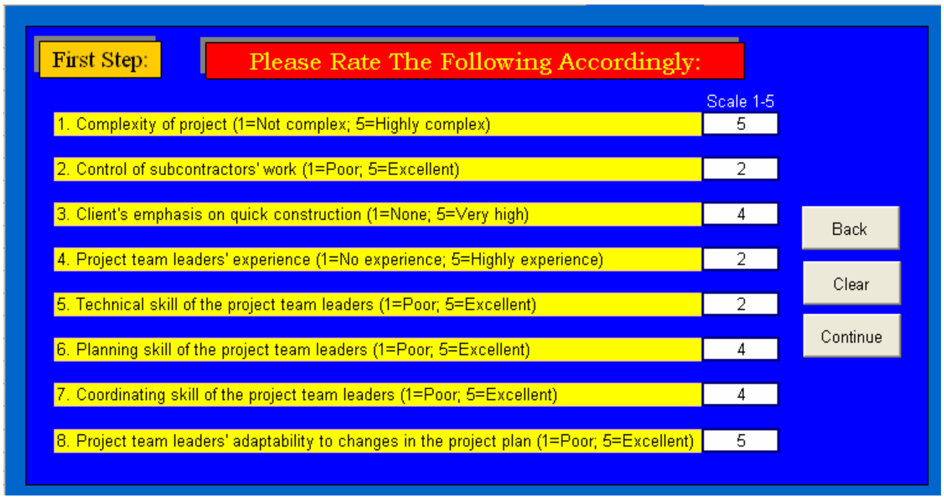


Figure 5. Project data input screen

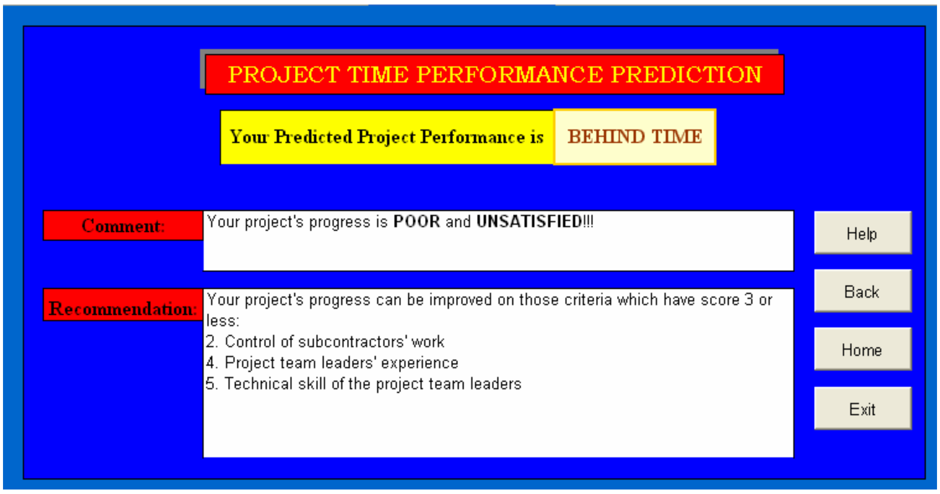


Figure 6. Predicted project performance screen

6. CONCLUSIONS

Through literature research, a total of forty-four factors that affect TGC project success had been established. The degree of importance for these factors had been determined through questionnaire survey. 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. The outcome of the survey formed a basis for the model development. Artificial neural network (ANN) technique is used to construct the models to predict construction project performance based on time. The best performance model was the multilayer back-propagation neural network model, which consisted of eight input nodes, five hidden nodes and three output nodes.

7. REFERENCES

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