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Article

Using Artificial Neural Network for Selecting Type of Subcontractor Relationships in Construction Project

Pisal Nov[a] **and Vachara Peansupap**[b,*]

Department of Civil Engineering, Faculty of Engineering, Chulalongkorn University, Phayathai Rd., Wangmai, Pathumwan, Bangkok, 10330, Thailand
E-mail: [a]Pisal.No@student.chula.ac.th, [b]pvachara@chula.ac.th (Corresponding author)

Abstract. Previously, main contractors used to experience with wrong type selection of subcontractor relationships. This practice caused some controversies and hindered benefits for a long run business with the right subcontractor. This paper developed a model for determining a type of subcontractor relationships. The methodology was begun by identifying important factors of subcontractor relationship. Then 10 out of 22 factors were identified by using Mann-Whitney U test and Relative Importance Index analysis. Next, these factors were designed as questions by using a Likert scale. These questions were brought to ask main contractor for evaluating 93 subcontractors in type selection of subcontractor relationships. Last, Spearman's Rank Correlation Coefficient, Artificial Neural Network, and Sensitivity Analysis were applied to develop and test the model. As a result, Root Mean Squared Error (RMSE) result of training data had tolerance between 0.32 and 0.02 and varied in every time of training data about ±0.02. This result was steadily declined to a minimum of 0.02 and chosen as the best performance in training. In the testing data set, the result of RMSE had tolerance from 0.30 to 0.04. and steadily declined to a minimum of 0.04. Therefore, the model result provided higher accuracy in training and testing data.

Keywords: Main contractor, subcontractor, long-term relationship, short-term relationship, artificial neural network.

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1. Introduction

As main contractor is an important person who has to manage and coordinate many construction activities, the decision making for selecting the right subcontractor in relationship development is really essential. Akintoye, et al. [1] and Dainty, et al. [2] mentioned that a successful construction project is depended on main contractor who could address a capable subcontractor for becoming a long-term relationship partner. Moreover, if main contractor fails to understand this relationship issue, he or she does not gain more benefits for the organization [2]. Regarding the wrong selection of relationship with subcontractor, main contractor could have bad experience in construction activities including poor communication, coordination, commitment, and distrust, so it could shorten the construction business between main contractor and other parties [3]. Therefore, main contractor needs to have a good subcontractor as a partner in the future.

Possessing a good subcontractor is one of main contractor objectives to achieve in the competitive market. The main contractor usually selects subcontractor at different stages such as subcontractor selection, subcontractor performance, and subcontractor relationship. The meaning of subcontractor selection defined when main contractor evaluates subcontractor based on the prequalification factors [4]. Next, main contractor assesses the performance of subcontractor in the progress work which is based on the effectiveness of control and management. With good performance, main contractor will choose that subcontractor for the next project whereas a poor performance subcontractor will not select anymore [5]. After the relationship between main contractor and subcontractor is improved by time and cooperative work in many construction projects, main contractor is willing to determine a potential subcontractor for a long-term relationship [6]. Thus, it could ensure productivity in the future. Although, there are many benefits that are hindered by long-term relationship with the right subcontractor, the decision-making issue for selecting type of subcontractor relationships does not have much focused in the previous studies.

There are two types of subcontractor relationships namely a short-term relationship and a long-term relationship. The definition of short-term relationship explained when main contractor uses subcontractor in an essential occasion even subcontractor is lack of some factors such as distrust, lack of mutual understanding, and no commitment in the construction work [7]. In contrast, a long-term relationship was understood when main contractor commits or maintains this relationship with the subcontractor regularly in order to achieve the expected result as an outcome. Therefore, the meaning of each relationship was defined clearly by the objective and situation in construction work.

2. Problem Statement

Previous research studies still did not have any decision-making tool for evaluating subcontractor in relationship development because a little number study has focused on subcontractor relationship comparing to supplier, client or customer relationship. Patrick and Benson [8] studied long-term relationship development between main contractor and subcontractor in China and found some critical factors. Moreover, they found some majors barriers in this relationship such as inconsistent performance, lack of mutual trust, understanding and commitment. Then they also suggested some proactive strategies to solve in these problems such as regular meetings, incentive schemes, constant contracts, and well-structured documentation. Another researcher studied about main contractor and subcontractor relationship in project partnering and divided two types of relationships such as short-term relationship as project partnering and long-term relationship as strategic partnering. In addition, he pointed out some important factors in subcontractor relationship [8]. Winter and Preece [7] found that trust is an important factor by comparing the relationship marketing between main contractor and subcontractor in UK and German. Faisal, et al. [9] explored in business relationship of main contractor and subcontractor with other organizations like client or supplier and they found that the importance of developing long-term relationship with their partners could increase the financial performance and solve many barriers too. However, the relationship between main contractor and subcontractor is really significant to improve the productivity in the construction project, there is not any method to help main contractor for selecting subcontractor in relationship development. Thus, this research proposes a decision-making model for selecting type of subcontractor relationships. With the right decision, main contractor could work with a capable subcontractor who is able to sustain the construction business effectively.

Next, main contractor usually chooses a subcontractor for relationship development based on only personal preference and interest [5]. For example, the high position of main contractor company, who is a project manager or director, may use his or her power to designate subcontractor in the relationship development decision [9]. Thus, main contractor does not have a clear procedure for selecting type of subcontractor relationships. With the lack of systematic screening in this stage, it could cause a poor selection of the subcontractor relationship. Then main contractor has to work with subcontractor who is poor in work performance for a long time. Last, this practice hinders the benefits which could discover with a good subcontractor for the long-term relationship.

Since main contractor still does not have any model for selecting types of subcontractor relationships in decision making, a systematic model should be established to evaluate subcontractor in relationship selection whether it is considered a short-term or long-term relationship.

3. Literature Review

Previous research studies tried to help main contractor in decision making by using different factors using in selecting subcontractor relationship. Patrick and Benson [8] studied long-term relationship development between main contractor and subcontractor in China and found some critical factors such as trust, honesty, commitment, and communication. Moreover, next researcher who has studied about project partnering between main contractor and subcontractor relationship and also pointed out some important factors in subcontractor relationship such as trust, joint problem solving, commitment, continuous improvement, and cooperation [10]. In addition, there are some other factors that have been found in selecting subcontractor relationship as shown in Table 1.

Since relationship factors are perceived when the subcontractor has been worked with main contractor as a partner, these factors still are not enough to support the decision making on the type selection of subcontractor relationship. Moreover, main contractor should examine the performance of subcontractor which will help them to understand the behavior of subcontractor in construction work. Moreover, subcontractor performance is one of important factors used by main contractors to select the optimal subcontractor for future work. There are many factors that have influenced this performance investigation. Wu [20] found some factors influencing subcontractor performance such as management ability, worksite condition, and subjective assessment. Then, the other 12 factors as shown in Table 2 by using a questionnaire survey for asking main contractor perspective in Taiwan [16]. Moreover, a dozen factors that main contractor has used for measuring the subcontractor's performance by interviewing such as workmanship, progress, health and safety, relationship and communication [17]. Last, Kang [5] proposed three main factors in subcontractor performance namely subcontractors' financial capability, experience and qualification, enterprise and project management knowledge of subcontractors. These factors were also divided into sub-factors.

Table 1. Factors for selecting the type of subcontractor relationships.

Factors	Hellard [11]	Hampson and Kwok [12]	Ramaseshan and Loo [13]	Black, et al. [14]	Cheng, et al. [15]	Chan, et al. [16]	Frodell [17]	Manu, et al. [18]	Pal, et al. [19]
Trust	√	√	√	√	√		√	√	
Commitment	√	√	√	√	√	√	√		
Communication	√	√	√	√	√	√			
Clear definition of responsibility						√			
Joint problem solving	√	√			√		√		√
Mutual objective	√								
Continuous improvement	√								√
Sharing culture						√			
Regular monitoring						√			
Coordination					√		√		
Management support					√				
Cooperation		√							
Clear understanding				√					
Flexibility to change				√					
Innovation									
Interdependence		√					√		

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Table 2. Evaluation factors of subcontractor performance [20].

No	List of factors
1	Construction technique
2	Time control
3	Material wastage
4	Cooperativeness
5	Collaboration with other subcontractors
6	Service after work completion
7	Safety and protection
8	Tool usage habit
9	Workspace cleanliness
10	Management ability
11	Financial status
12	Subcontractor personality

Regarding relationship and performance factors, a framework of relationship development with subcontractor was developed by dividing the factors into two main parts which are subcontractor characteristic and subcontractor performance. The subcontractor characteristic consists of 10 sub-factors such as trust, honesty, commitment, experience, flexibility to change, clear understanding, resources, financial status, profit base, knowledge. Another part is subcontractor performance which is classified into two sections including subcontractor ability and subcontractor work performance. Each section is classified into sub-factors. Subcontractor ability consists of innovation, communication, coordination, joint problem solving, cooperation, monitoring. Subcontractor work performance is related to time control in planning, safety training for employees, work quality, safety control system, wastage disposal control, and employee skill training. These factors are used to design a questionnaire for conducting an interview with main contractor. The following framework is showed in Fig. 1.

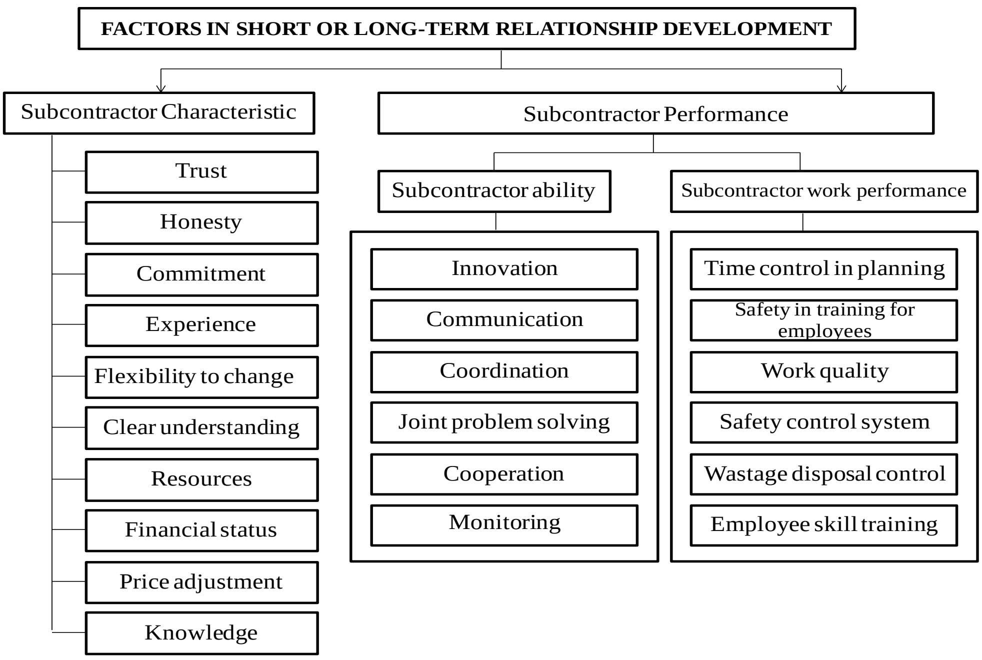

Fig. 1. A framework for selecting short or long-term relationship with the subcontractor.

4. Methodology

The methodology of this study was classified into two stages. First, the study identified the important factors of subcontractor relationship. The data collection focused on building construction project and respondents were main contractors who were project managers and directors. The questionnaire was designed by using a Likert scale and 35 respondents were asked to rate the score in twenty-two factors of subcontractor relationship. Table 3 shows percentages of participants in the first stage. The data analysis used the Mann-Whitney U test and relative importance index (RII). Next, the study used the result of important factors in subcontractor relationship to develop a model for selecting type of subcontractor relationships. The important factors were designed as a questionnaire using a Likert scale. 93 participants, who were project managers and directors of Cambodia construction companies, were asked to rate their own subcontractors in type selection of subcontractor relationship. Table 4 shows percentages of participants in the second stage. Then the data was analyzed by using spearman's rank correlation coefficient, artificial neural network and sensitivity analysis. In this study, Qnet 2000 was software for supporting the ANN analysis. Last, the data collection process took place from November until January 2012 and the detail information of model development was illustrated in the next section.

5. Important Factors Identification for Selecting the Type of Subcontractor Relationships

In the first stage, the data were analyzed by using Mann-Whitney U test and relative importance index (RII). The Mann-Whitney U test is a non-parametric test. This test is used to compare two sample means that come from the same population and used to test whether two sample means are equal or not. The Mann-Whitney U test is usually used when the data is ordinal scale like a Likert scale. In this study, the Mann-Whitney U test was applied to see the level of different answers between project managers and directors on twenty-two factors of subcontractor relationship. The null hypothesis of this analysis is written down as "H_0=There is no significant difference between the project managers and directors on each factor of subcontractor relationship. Moreover, the alternative hypothesis is "H_1=There is a significant difference between the project managers and directors on each factor of subcontractor relationship". After analysis, if Z value is less than -1.96, or greater than 1.96, it will reject the null hypothesis. Moreover, when a normal approximation which is given by Asymp Sig (2-tailed), is smaller than 0.05, it will also reject the null hypothesis. Equation 1 shows the Mann-Whitney U test.

$$U = n_1 n_2 - \frac{n_2(n_2+1)}{2} - \sum_{i=n_1+1}^{n_2} R_i \qquad (1)$$

where:
U is Mann-Whitney U test
N_1 is sample size one
N_2 is sample size two
R_i is the rank of the sample size

Next, the relative importance index (RII) primarily determines the importance level of factors by ranking number. The score was rated on each factor from 1 to 5. 1 referred to the lowest level of important whereas 5 represented the highest level of important. Then, the answer scores applied with Eq. (2) of the relative importance index. The results rank each factor based on the value of relative important index. Last, the important factors of subcontractor relationship are determined when value of relative important index is equal and greater than (⩾) the mean index value.

$$RII = \frac{\sum_{i=1}^{5} W_i X_i}{\sum_{i=1}^{5} X_i} (1 \le RII \le 5) \qquad (2)$$

where:
W_i is the score given to each factor
X_i is the percentage of respondents scoring
i is the order number of respondents.

Table 3. Percentages of participants in the first stage of the study.

Position of main contractor	Frequency	Percentage	Cumulative percentage
Project manager	22	62.86	62.86
Director	13	37.14	100.00
Total	35	100.00	

Table 4. Percentages of participants in the second stage of the study.

Position of main contractor	Frequency	Percentage	Cumulative percentage
Project manager	31	33.33	33.33
Director	62	66.67	100.00
Total	93	100.00	

6. Model Development by Using Artificial Neural Network (ANN)

In the second stage, the data were analyzed by using Spearman Rank Correlation Coefficient, Artificial Neural Network (ANN) and Sensitivity Analysis. First, to test the correlation of important factor in subcontractor relationship, Spearman's rank correlation coefficient is a non-parametric measure of statistical dependence between two variables. Spearman r value varies between +1 and -1, where +1 shows a perfect positive correlation or "agreement", while -1 value indicates a perfect negative correlation or "disagreement". A value close to zero indicates no correlation. The formula for the spearman rank correlation coefficient is given by Eq. (3). As a result, the higher value of r shows a strong agreement between the two sets of rankings.

$$r = 1 - \frac{6\sum d_i^2}{n(n^2 - 1)} \tag{3}$$

where:

r is spearman rank correlation coefficient

di represents the difference in ranking between project managers and directors

n is the number of rank pairs.

Next, Artificial neural network was developed by McCulloch and Pitts in 1943 [21]. This method tried to follow the process of the nervous system in the brain's networks. Moreover, it was a mathematical method that could use to simulate information processing as the human brain and able to deal with the complicated problem in the research field [22]. Cybenko [23], Hornik, et al. [24] mentioned that ANN could be a universal function approximator because it could automatically approximate to the desired degree of accuracy in the data calculation. ANN method is able to reduce the level of error and maximize the accuracy of the training and testing data. In addition, it does not need to concern about the assumptions in the model. Therefore, this network was a popular method that could perform a wide range of complex tasks, especially in decision-making issue.

6.1. Training Sample and Test Sample

Training and test sample was required to build an ANN model. The training sample was used to develop the ANN model whereas the testing sample was used for checking the predictive accuracy of the model. Besides training and testing samples, validating sample was required to improve the accuracy of the model [25]. However, if the data set was small, it used as one testing data set for both testing and validating purposes. The division of the data into the training and testing data sets was an important issue to consider in developing ANN. There was no clear solution to specify the number of training and testing samples. Previous studies suggested some rule of 90% vs. 10%, 80% vs. 20% or 70% vs. 30%...etc. Nam and Schaefer [26] studied the effect of different training sample size and found that when the training sample size is increased, the ANN result performs better and better. Granger [27] mentioned at least 20 percent of samples should keep for testing for non-linear models. Chang, et al. [28] divided training, testing and validating samples into 85%, 10%, and 5%. Moreover, based on Qnet program, the minimum requirement of testing data set is around 10%. Therefore, our sample is around 93, it was divided into 79, 9 and 5 for training, testing and validating samples respectively.

6.2. The Architecture of a Neural Network

To develop a decision model for selecting the type of subcontractor relationships by using ANN, 10 important factors of the subcontractor relationship were selected for the input node and two types of subcontractor relationships were placed in the output node. The computation process was based on the feed-forward method. Figure 2 shows the feed-forward topology of the model.

The elements of the model architecture were summarized such as:

- One input layer had 10 variables or10 input nodes
- One hidden layer had 10 variables or 10 hidden nodes
- One output layer had 1 variable or 1 output node
- 110 of connected arcs between input and hidden nodes and between hidden and the output node.
- The transfer function between hidden and output nodes was sigmoid function.
- The training algorithm was applied by using a back-propagation algorithm.
- The transformation of input data was calculated by the linear transformation formula.
- Data normalization was used between 0 and 1 to represent the long-term and short-term relationships.
- The number of training, testing and validating data set was divided into 79, 9 and 5 samples respectively.
- The performance of accuracy measurement was used by the root mean square error (RMSE).

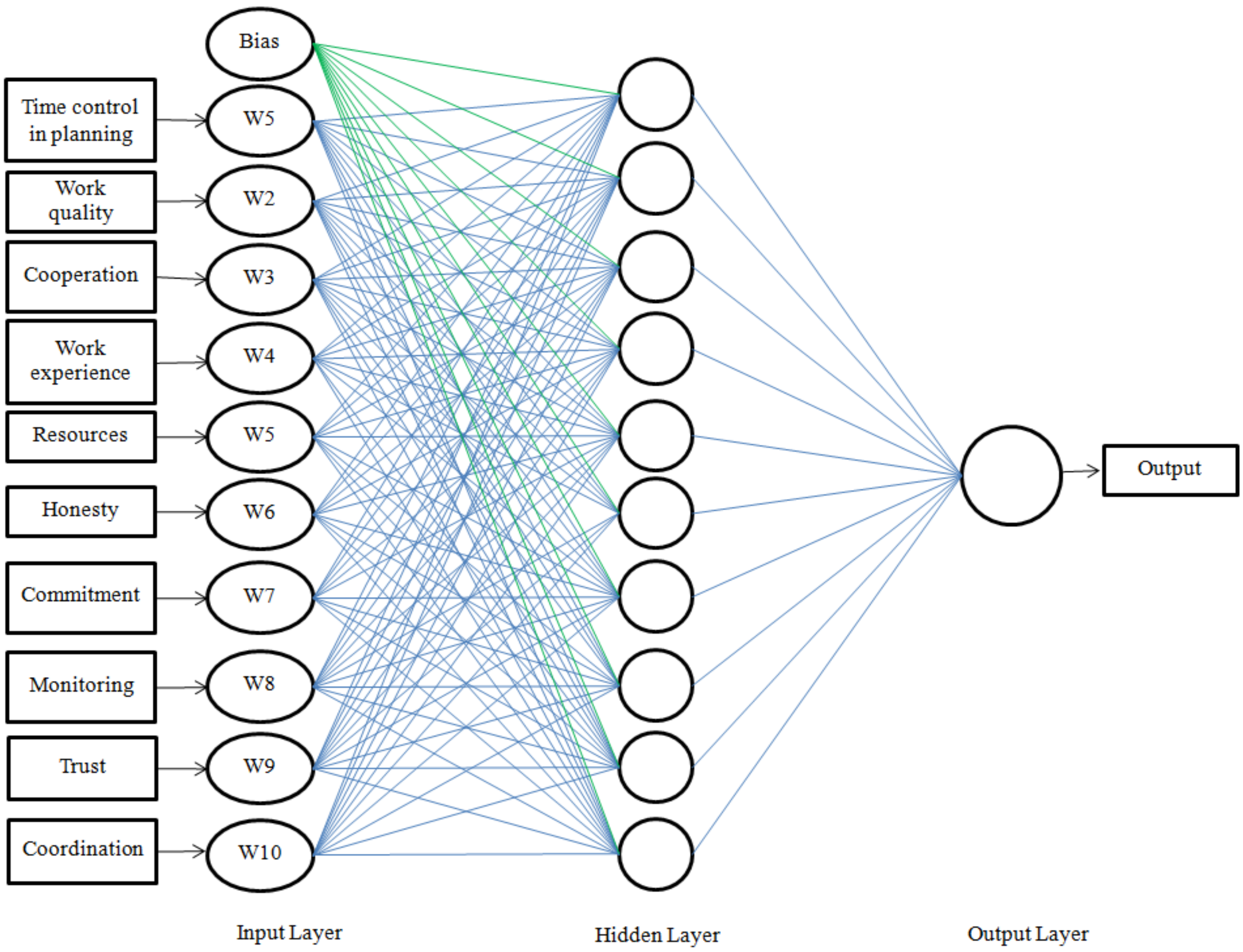

Fig. 2. The feed-forward topology of the model.

6.3. Training Control Option of Qnet

To apply the ANN, the model was developed by using Qnet 2000 and some key options were needed to set for obtaining a good result in the training data. First, the learning rate coefficient was used to calculate the node size by adjusting the weight in the training period. The higher learning rate coefficient could provide a faster learning speed. But it led to instability and divergence. The smaller value of this coefficient can improve the numerical convergence. When the coefficient was ranged from 0.001 to 0.1, it gave a good process of training data without the risk of divergence [23]. Next, the momentum factor of Qnet's training algorithms was ranged from 0.8 to 0.9. This was no rule to select the iteration numbers and they were increased by the complexity of problem. Last, the remained options were followed by the default of program. Finally, our model was summarized in the training control option and shown in Table 5.

The predictive accuracy, which was based on the error value between predicted and actual value, was evaluated by training and testing set. Root mean squared error (RMSE) was the most popular method that uses to determine the error in the classification. This method was applied when the actual outputs are continuous and the output targets are binary variables [24]. The RMSE formula was given in Eq. (4).

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(X_{pre} - X_{obs})^2}{n}} \quad (4)$$

where X_{pre} was a predicted value
X_{obs} was an observed value for ith observation
n was the number of observations

6.4. Sensitivity Analysis

Third, to determine the influencing factor of subcontractor relationship in the current practice from the main contractor evaluation, sensitivity analysis is an efficient tool. It is used to apply in a trained feed-forward neural network for automatically identifying all input parameters that influence on the output. This method an optimal method used to provide the contribution percentage of input to the model outputs [29]. Moreover, in artificial neural network, the sensitivity method could be determined the contribution percentage of each input by the result of input node interrogator option in the software Qnet 2000. This option is used to determine the sensitivity by repeating the training patterns process again and again with each input and computing the result of the network's output. In addition, we should remember the interpretation of this sensitivity result has assumed that the value of input is independent. Therefore, the result of influencing factor of subcontractor relationship is determined by sensitivity approach in neural network.

Table 5. Summary of the training control.

Network Definition		Training Controls	
Network Layers:	3	Max. Iterations:	20000
Input Nodes:	10	Learn control start:	10001
Output Nodes:	1	Learn Rate:	0.001
Hidden Nodes:	10	Learn Rate Max:	0.1
Transfer Functions:	Sigmoid	Learn Rate Min:	0.001
Connections:	110	Momentum:	0.8
Training Patterns:	79		
Test Patterns:	9		

7. Results and Discussion

7.1. Important Factors Identification for Selecting the Type of Subcontractor Relationships

After data collection in the first stage of this study, the Mann-Whitney U test was applied to test the level of different answers between project managers and directors on twenty-two factors of subcontractor relationship. Due to the result of Mann-Whitney U test, the twenty-two factors of subcontractor relationship have the Z value between -1.96 and 1.96. Moreover, Asymp Sig (2-tailed) values of all factors were bigger than 0.05. Thus, it will not reject the null hypothesis. The answers of project managers and directors on each factor of subcontractor relationship were not different and could use to support identifying the important factors of subcontractor relationship. Table 6 shows the result of Mann-Whitney U test with twenty-two factors of subcontractor relationship.

Before a model was developed in the decision making, the important factors of the subcontractor relationship were determined by using relative importance index (RII). As a result, ten out of twenty-two factors are passed the average value of relative important index (0.802). These ten important factors were shown in Table 7 and consisted of time control in planning, work quality, cooperation, experience, resources, honesty, commitment, monitoring, trust, and coordination. Moreover, the rest of other factors were less considered by main contractor for developing subcontractor relationship. Therefore, to develop an effective model, this research used these 10 important factors for developing a decision-making model by using artificial neural network.

7.2. Artificial Neural Network Analysis Result

Prior to developing the model, the Spearman Rank Correlation Coefficient (r) was applied to test the correlation between each factor of the subcontractor relationship. As a result, the correlation coefficient values of all factors were bigger than 0.05 or 0.01. Thus, each factor has positive and negative correlations. Table 8 shows the correlation result of 10 important factors in subcontractor relationship. Therefore, it also seems likely to show an agreement between each factor of subcontractor relationship. Next, these factors could be used to develop the model for selecting the type of subcontractor relationship in the next step.

Next, the RMSE result of training data had a tolerance between 0.32 and 0.02 and varied in every time of training data about ± 0.02. So the result of RMSE was steadily declined to a minimum of 0.02. Next, the result of RMSE in test data had tolerance from 0.30 to 0.04. It meant that the result of RMSE is steadily declined to a minimum of 0.04. When the minimum value of RMSE was used as a criterion for determining the best-trained network, the tolerance result was around 0.02 and would be chosen as the best performance in training. Figures 3 and 4 show the number of iterations against RMSE for both training and testing data sets.

Next, the correlation coefficient assessed how well the network predictions trend with the targets for the cases outside the training and test set. The range of correlation coefficient was between -1 and 1. From the result of Figs. 5 and 6, the correlation coefficient value of training and testing data were 0.998 and 0.982 respectively. Thus, it meant that our network is a high correlation between the target and output data.

On the other hand, the RMSE of the training and test data could use to understand overtraining behavior. When the testing data set error was increased, the training data set error was continually descended. Thus, overtraining has occurred. From Figs. 3 and 4, the RMSE curve of training and testing data set was decreased at the same time. Then, the model development was not overtraining and did not impact the predictive capabilities of the model being developed.

From the result of this model, the graph was plotted between network outputs and target values and shown in Fig. 7. The vertical line referred to the network output whereas the horizontal line indicated the training target. Moreover, when the point closely fell to the red optimal agreement line (or called the equality line), the model had a good result of the overall agreement. Next, in Fig. 8, another graph was plotted between the targets/outputs and the pattern sequence. The vertical line indicated the targets or outputs whereas the horizontal line was pattern sequence. Three curves told about the closely agreement namely the training set targets, the training outputs, and the test outputs. In conclusion, both results of Figs. 7 and 8 provided a close agreement between the target and output results.

Table 6. Results of Mann-Whitney U test with twenty-two factors of the subcontractor relationship.

	Trust	Honesty	Commitment	Experience	Flexibility to change	Clear understanding
Mann-Whitney U	111.500	137.000	119.000	141.000	101.000	128.000
Wilcoxon W	364.500	228.000	372.000	232.000	354.000	219.000
Z	-1.166	-.259	-1.034	-.074	-1.804	-.645
Asymp. Sig. (2-tailed)	.244	.796	.301	.941	.071	.519
Exact Sig. [2*(1-tailed Sig.)]	.287	.853	.428	.960	.159	.625

	Innovation	Communica-tion	Coordination	Joint problem solving	Cooperation
Mann-Whitney U	121.500	129.500	119.500	110.500	131.000
Wilcoxon W	374.500	382.500	372.500	363.500	384.000
Z	-.958	-.627	-.933	-1.245	-.482
Asymp. Sig. (2-tailed)	.338	.530	.351	.213	.629
Exact Sig. [2*(1-tailed Sig.)]	.468	.649	.428	.271	.699

	Monitoring	Time control in planning	Safety training for employees	Work quality	Safety control system
Mann-Whitney U	119.000	135.500	137.000	111.000	115.500
Wilcoxon W	210.000	388.500	228.000	364.000	368.500
Z	-1.119	-.293	-.217	-1.244	-1.057
Asymp. Sig. (2-tailed)	.263	.769	.829	.214	.291
Exact Sig. [2*(1-tailed Sig.)]	.428	.801	.853	.287	.353

	Wastage disposal control	Employee skill training	Financial status	Profit base	Resources	Knowledge
Mann-Whitney U	125.000	126.500	107.000	138.500	131.000	137.000
Wilcoxon W	378.000	379.500	198.000	229.500	222.000	228.000
Z	-.684	-.689	-1.337	-.175	-.478	-.237
Asymp. Sig. (2-tailed)	.494	.491	.181	.861	.632	.812
Exact Sig. [2*(1-tailed Sig.)]	.555	.578	.229	.880	.699	.853

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Table 7. Result of important factors in the subcontractor relationship.

Criteria	RII	Rank
Time control in planning	0.903	1
Work quality	0.891	2
Cooperation	0.851	3
Experience	0.834	4
Resources	0.829	5
Honesty	0.823	6
Commitment	0.823	7
Monitoring	0.823	8
Trust	0.811	9
Coordination	0.806	10
Clear understanding	0.800	11
Joint problem solving	0.794	12
Innovation	0.789	13
Communication	0.789	14
Profit base	0.789	15
Flexibility to change	0.783	16
Safety training for employees	0.783	17
Employee skill training	0.783	18
Safety control system	0.754	19
Knowledge	0.743	20
Wastage disposal control	0.731	21
Financial Status	0.714	22
Average value	0.802	

Table 8. Correlation result of 10 important factors in the subcontractor relationship.

Correlations

			Time control in planning	Work quality	Cooperation	Experience	Resources	Honesty	Monitoring	Trust	Commitment	Coordination
Spearman's rho	Time control in planning	Correlation Coefficient	1.000	.082	-.090	-.091	.177	.306	.314	-.074	.079	.469**
		Sig. (2-tailed)	.	.639	.607	.602	.310	.074	.066	.673	.652	.004
		N	35	35	35	35	35	35	35	35	35	35
	Work quality	Correlation Coefficient	.082	1.000	.188	.194	.027	.226	-.401*	.190	.007	-.175
		Sig. (2-tailed)	.639	.	.280	.265	.879	.191	.017	.273	.967	.313
		N	35	35	35	35	35	35	35	35	35	35
	Cooperation	Correlation Coefficient	-.090	.188	1.000	.312	.236	.199	-.049	-.388*	.036	-.115
		Sig. (2-tailed)	.607	.280	.	.068	.173	.253	.781	.021	.836	.511
		N	35	35	35	35	35	35	35	35	35	35
	Experience	Correlation Coefficient	-.091	.194	.312	1.000	-.272	.082	-.063	-.015	-.345*	-.250
		Sig. (2-tailed)	.602	.265	.068	.	.114	.639	.717	.934	.042	.147
		N	35	35	35	35	35	35	35	35	35	35
	Resources	Correlation Coefficient	.177	.027	.236	-.272	1.000	.059	.337*	-.424*	.224	.122
		Sig. (2-tailed)	.310	.879	.173	.114	.	.734	.048	.011	.195	.484
		N	35	35	35	35	35	35	35	35	35	35
	Honesty	Correlation Coefficient	.306	.226	.199	.082	.059	1.000	.315	.196	.066	.096
		Sig. (2-tailed)	.074	.191	.253	.639	.734	.	.065	.258	.706	.582
		N	35	35	35	35	35	35	35	35	35	35
	Monitoring	Correlation Coefficient	.314	-.401*	-.049	-.063	.337*	.315	1.000	-.097	.158	.382*
		Sig. (2-tailed)	.066	.017	.781	.717	.048	.065	.	.581	.365	.024
		N	35	35	35	35	35	35	35	35	35	35
	Trust	Correlation Coefficient	-.074	.190	-.388*	-.015	-.424*	.196	-.097	1.000	.135	.009
		Sig. (2-tailed)	.673	.273	.021	.934	.011	.258	.581	.	.438	.960
		N	35	35	35	35	35	35	35	35	35	35
	Commitment	Correlation Coefficient	.079	.007	.036	-.345*	.224	.066	.158	.135	1.000	.451**
		Sig. (2-tailed)	.652	.967	.836	.042	.195	.706	.365	.438	.	.007
		N	35	35	35	35	35	35	35	35	35	35
	Coordination	Correlation Coefficient	.469**	-.175	-.115	-.250	.122	.096	.382*	.009	.451**	1.000
		Sig. (2-tailed)	.004	.313	.511	.147	.484	.582	.024	.960	.007	.
		N	35	35	35	35	35	35	35	35	35	35

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

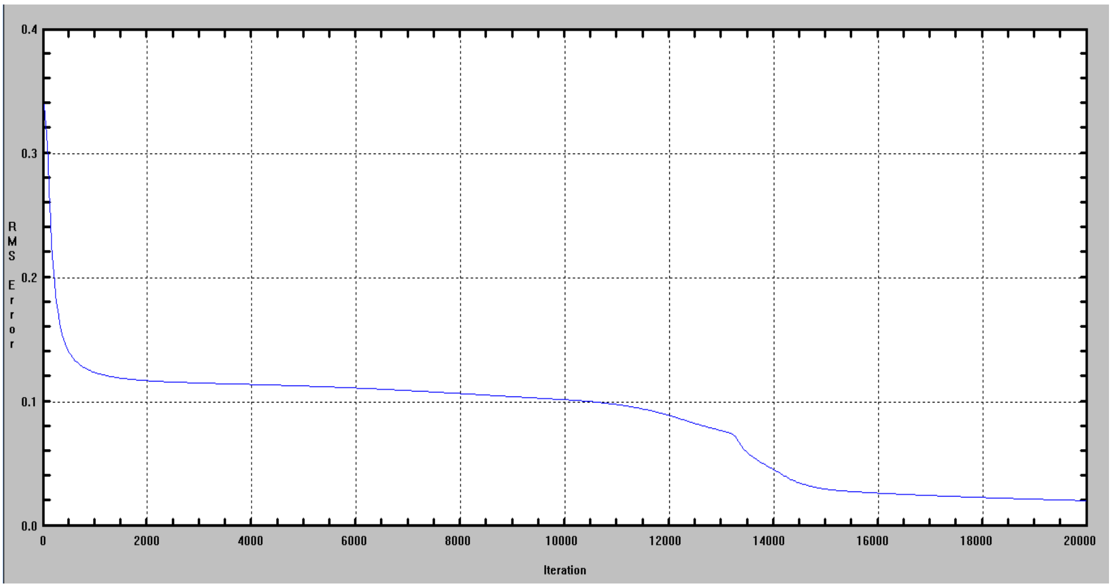

Fig. 3. Iteration numbers and RMSE for the training data set.

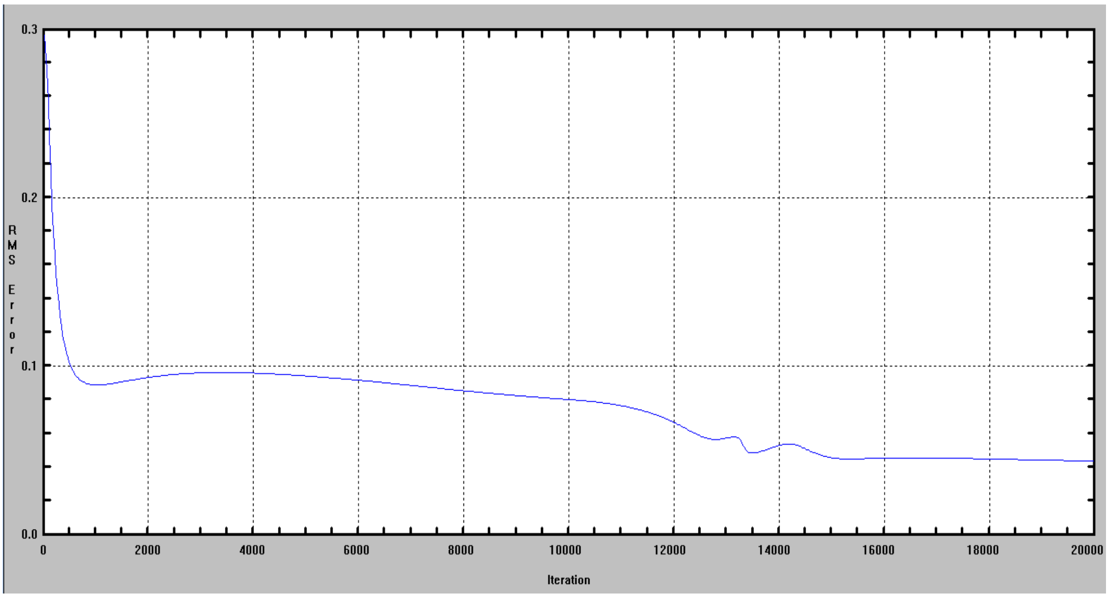

Fig. 4. Iteration numbers and RMSE for the testing data set.

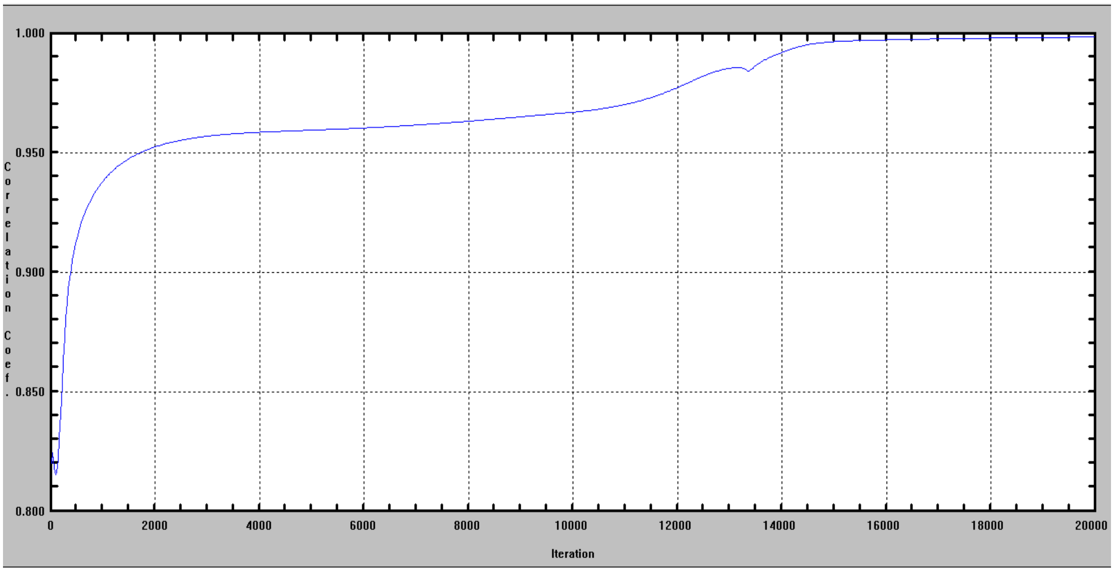

Fig. 5. Iteration numbers and correlation coefficient for the training data set.

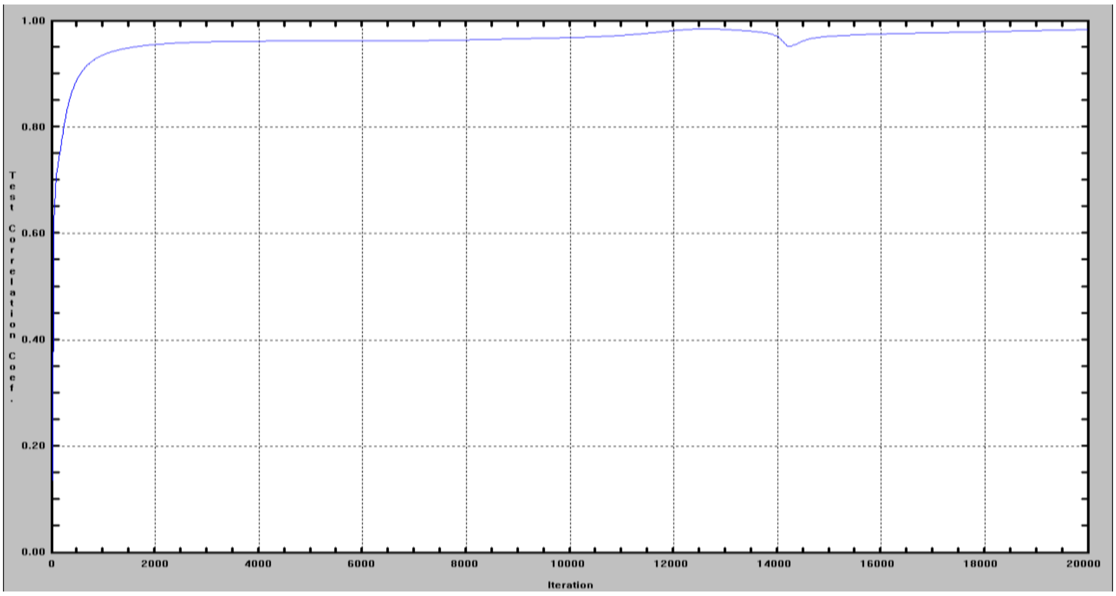

Fig. 6. Iteration numbers and correlation coefficient for the testing data set.

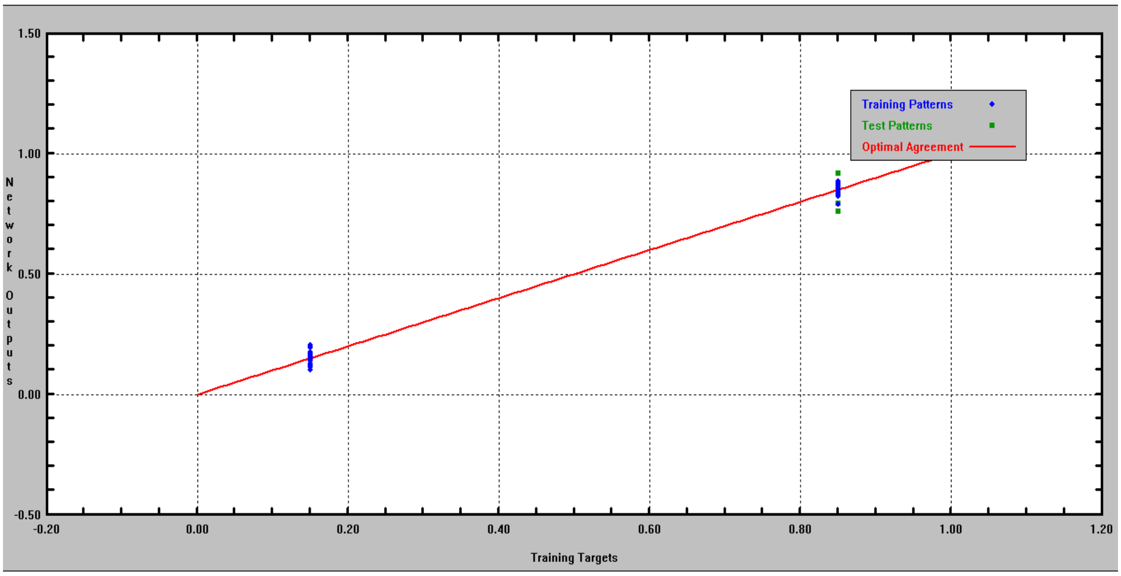

Fig. 7. Comparisons of targets vs. outputs.

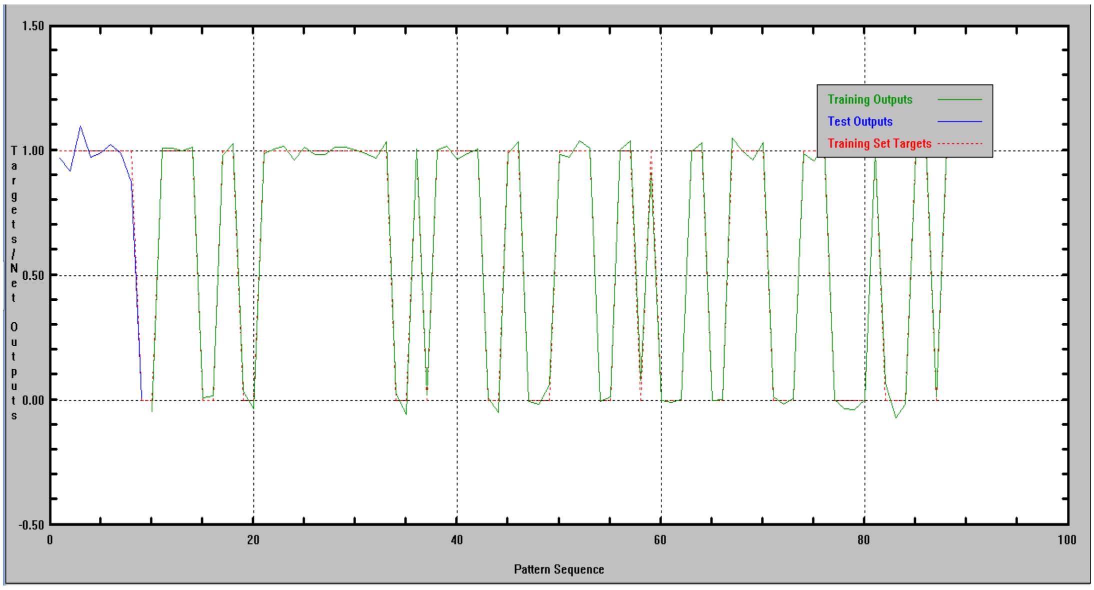

Fig. 8. Comparisons of targets/ outputs vs pattern sequence.

7.3. Validation Result

Last, some samples data were used in verification purpose and these data were not used in the training and testing process. Shanker and Hu [30] found that the cut off value of two groups' classification in the neural network was 0.5. By applying this cut off value in our research, if the output value was larger than 0.5, it was long-term relationship. Moreover, if the output was equal or less than 0.5, it was short-term relationship. Regarding the result of Table 9, the wrong answer of 5 verification data sets was only one because this subcontractor was evaluated by medium score for most of the factors in subcontractor relationship. However, the model was still higher accuracy. In conclusion, ANN was a significant method that could accurately produce the model for selecting type of subcontractor relationships.

7.4. Result of Sensitivity Analysis

By using the input node interrogator, the inputs influenced the output that could be understood by the contribution percentages. As a result, trust, cooperation, work quality, time control in planning and monitoring were the top five variables that have a higher percentage among the other. Table 10 shows the contribution percentages of factors in subcontractor relationship. Therefore, these factors could influence the selection type of subcontractor relationships.

8. Conclusion

The previous practice of main contractor used only the personal judgment for selecting subcontractor in relationship development. With the mismatched result of the relationship among subcontractors, main contractor might have the controversies with subcontractor and could hinder a long-term benefit. This research aimed to develop a model for selecting type of subcontractor relationships between main contractor and subcontractor. The research methodology used a survey questionnaire to collect data from each main contractor. There are two main stages of this study. First, the respondents were asked to identify the important factors of subcontractor relationship. The relative important index was used to analyze and could identify 10 out of 22 factors as the important factors of subcontractor relationship. Next, these 10 factors were used to evaluate their own subcontractors for selecting type of subcontractor relationships. Then the model was developed by using the Artificial Neural Network (ANN). As a result of training and testing data sets, the error level of training and testing data sets was 0.02 and 0.04 respectively. It meant that the accuracy of training and testing results are 98% and 96%. Moreover, based on the result of ANN, the study found that five main factors of subcontractor relationship have higher influence on selecting type of subcontractor relationships including trust, cooperation, work quality, time control in planning and monitoring. Last, this research would be useful for main contractor decision making when they would like to select type of subcontractor relationships. The future study should focus on the result that this model development is applied with a real case study.

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Table 9. Comparisons of targets vs outputs of validation samples.

Number of samples	Target	Output	Result
1	1.00000	0.92950	Correct
2	0.00000	0.26418	Correct
3	0.00000	0.01593	Correct
4	0.00000	0.54390	Wrong
5	1.00000	1.00827	Correct

Table 10. Contribution percentages of input to output.

Output Node	Input Node	Node Name	Percent Contribution
1	1	Work quality	11.17
1	2	Time control in planning	9.13
1	3	Experience	4.7
1	4	Cooperation	23.17
1	5	Honesty	2.23
1	6	Commitment	4.71
1	7	Resources	5.25
1	8	Coordination	2.79
1	9	Monitoring	7.83
1	10	Trust	29.03

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Pisal Nov was born in October 27, 1987 in Phnom Penh, Cambodia. He received Bachelor Degree from two Universities. One university, he graduated Bachelor Degree of Civil Engineering at Norton University in 2010. Another one, he graduated Bachelor Degree of Professional Communication (PC) in English at Institute of Foreign Languages (IFL) in 2010. In 2011 and 2013, he was awarded by ASEAN country scholarship to continue the M.S. and Ph.D. Degree in field of Construction Engineering and Management, Chulalongkorn University, Thailand.

Since 2019, he has been a lecturer with Civil Engineering Department, Paragon International University. His research interests include construction project planning, construction contract and construction technology like builing information modeling (BIM).

Dr. Pisal Nov is a member of Engineering Board Cambodia.

Vachara Peansupap received the B.S. in Civil Engineering from King Mongkut's Institute of Technology Ladkrabang, Thailand in 1994. In 1997, he graduated Master Degree in Construction Engineering and Management from Chulalongkorn University, Thailand. In 2005, he received the Ph.D. Degree in Built Environment from RMIT University, Australia.

Since 1998, he has been an Assistant Professor with the Civil Engineering Department, Chulalongkorn University, Thailand. His research interests include construction innovation, knowledge management, construction automation, building information modeling (BIM), lean construction, quality management.

Assist.Prof.Dr. Vachara Peansupap is a member of Council of Engineers.