International Journal of Technology (2017) 4: 761-772
ISSN 2086-9614

THE SUBCONTRACTOR SELECTION PRACTICE USING ANN-MULTILAYER

Fachrurrazi[1*], Saiful Husin[1], Munirwansyah[1], Husaini[2],

[1]*Department of Civil Engineering, Syiah Kuala University Jl. Teuku Nyak Arief, Darussalam, Kota Banda Aceh, Aceh 23111, Indonesia*
[2] *Department of Mechanical Engineering, Syiah Kuala University, Jl. Teuku Nyak Arief, Darussalam, Kota Banda Aceh, Aceh 23111, Indonesia*

(Received: May 2016 / Revised: March 2017 / Accepted: July 2017)

ABSTRACT

The practice of subcontracting selection emphasizes two important goals: the company's strategic goal to maximize profits by partnering with subcontractors and the project's operational goal for obtaining qualified subcontractors. Both goals are achieved by formulating the best multi-criteria weights. This is not easy to implement due to differences in subjectivity, viewpoint, and other consideration of assessors, but prioritizing the criterion weights can reduce these differences. This study presents an ANN (Artificial Neural Network) with the ability to generalize data. The purpose of the study is to develop an ANN model for subcontracting selection and to identify significant criteria related to the company's strategic goal. The initial training of the proposed ANN model utilized 40 subcontractor selection datasets containing data in the form of a subcontractor selection scheme consisting of 20 criteria and 5 major groups. Training of ANN model was successful with MSE learning at $1.37269e^{-7}$, MSE validation at 0.07985, and epoch 600 to 800. The quotation price is the significant criterion of the selection, and it has a great outcome for the contractor strategic goal. The interaction between the subcontractor selection practice and the ANN model shows that the ANN has an important role in the subcontractor selection practice.

Keywords: ANN model; Company goal; Multi-criteria; Multilayer architecture; Project goal; Subcontractor selection; Weight

1. INTRODUCTION

Procurement management in a project requires subcontractor selection. The procurement specialist, in turn, needs the support of advanced tools to speed up the right decision. This decision-making process in project management can take many directions, depending on the problem characteristics. The problems affecting subcontractor selection are quite complex and can be caused by a large number of criteria. The subcontractors, who are a part of the strategic decision, are often selected in any construction project implementation. Some researchers, such as Moselhi et al. (1992), have successfully applied Artificial Neural Network (ANN) to the case of subcontractor selection. The decisions based on the pattern of the weight criteria usually will vary and relate to the situation of the project, conditions, and the purpose of selecting the subcontractors (Azadnia et al., 2012). These changes must be accommodated without ruling out the experience on the decisions made by evaluator. The criterion weights determined in the subcontractor selection process should be adapted to the selection purpose, but the process for adapting the criterion weights is not easy because of variations in the subjectivity, viewpoints,

*Corresponding author's email: fachrurrazi@unsyiah.ac.id, Tel. +62-651-7552222, Fax. +62-651-7552222
Permalink/DOI: https://doi.org/10.14716/ijtech.v8i4.9490

and other considerations of assessors. One approach to minimize these variations is to use an ANN, a learning algorithm for generalization based on data input and output (Oliveira et al., 2015). The ANN has the ability to store information from the past and combine it with further experience, and it is updated more generally using the latest data (Oliveira et al., 2015).
The aim of the present study is to develop an ANN model for subcontractor selection and to identify the significant criteria that relate to the strategic goal of the main contractor. This aim is approached by developing the ANN architecture in five groups corresponding to five main criteria, with each group consisting of input layers that relate to a number of sub-criteria, as shown in Figure 2. This need is accommodated by determining the applicability of the ANN object by implementing ANN learning, which is meant to generalize data from any decisions made (Moselhi et al., 1992; Chiarazzo et al., 2014; Zhang et al., 2016) and could be visualized in the learning curve. This will improve the generalization of the criteria weights for the subcontractor selection. The performance improvement will provide continuous and simultaneous updating of the synaptic information of ANN for each process of the subcontractor selection. This goal will be achieved by conducting the initial training using 25 datasets of subcontractor selection (as shown in Table 1 in the appendix).

This paper presents a proposed development of the ANN model and its implementation for the case of subcontractor selection. Some of the sub-methods of ANN, the objects, and the attributes, have been referenced in several other studies. Nevertheless, this paper presents specificity for the architecture of ANN model, and the methods for supervised learning, which are placed on two levels. The characteristics of the architecture of the ANN model are tailored to the characteristics of subcontractor selection in the current case. A correlation test for validation is conducted to identify the potential criteria that most influence the decision based on expert judgment. This test is important for understanding the ANN model pattern that relates to the correlation of the strategic goal and the performance goal. One of research aim was to increase the knowledge of the ANN model by proposing an integrated interaction model between assessor assessment, expert judgment, and the ANN model. The interaction model is needed to provide an increase in the generating weights and acceleration of the subcontractor selection process. Testing the performance of the interaction model of ANN will be future research by other researchers in this field.

2. METHODOLOGY

The current subcontractor selection formally uses the Multi-Criteria Decision Analysis (MCDA) model, formulated using the Weighted Sum Model (WSM):

$$A_i^{WSM} = \sum_{j=1}^{n} w_j . a_{ij}, \ for\ i \in \{1, 2, 3, ..., n\}, and\ j \in \{1,2,3, ..., m\} \quad (1)$$

where A_i^{WSM} denotes the total score for each alternative-i; w_j is the relative weight of the importance level for each criterion-j; a_{ij} relates the performance value of alternative-i and criteria-j; i is the number of alternatives; j is the number of criteria; n is the maximum number of i alternatives, and m is the maximum number of j criteria. In this study, ANN is used to pattern the w_j by adjusting the weights, as shown in Figure 1. However, the weights could not formally describe the ANN pattern due to the black box.

2.1. Framework of the ANN Model

The ANN model uses a supervised learning mechanism, as shown in Figure 1, that is placed on the intermediate output (level 2) and on the final output (level 4) of the ANN architecture, as shown in Figure 2. The performance measurement of the ANN model is analyzed using MSE (Mean Square Error). The aim is to achieve a condition where the ANN outputs and targets are equal or the MSE learning is stable, as shown in Figure 3. The other sub-methods of the ANN refer to other research, such as ANN training, adjustment of the criterion weights, the activation function, the flow of information in a network, and reduction in error. The attributes are, respectively, supervised learning (Fachrurrazi et al., 2017a), the back propagation algorithm (Taghavifar et al., 2014; Zuna et al., 2016), sigmoid (Kusumoputro et al., 2016), feed forward (Euler-Rolle et al., 2016), and gradient descent (Kim et al., 2004).

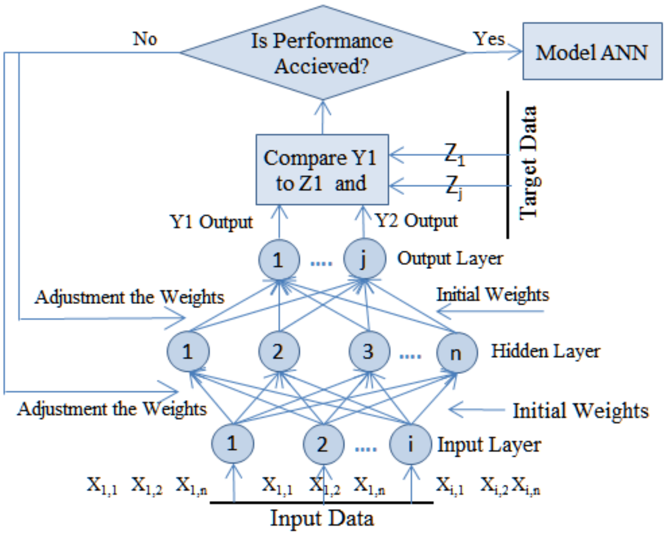

Figure 1 The supervised learning of ANN (Fachrurrazi et al., 2017a)

The architecture of the ANN has been built using a series of inputs, output layers, hidden layers, and number of nodes. The nodes are used as the processing signal by implementing the mathematical definition for a single node (Meruelo et al., 2016):

$$y = f(x) = f(\sum_i w_{ji} x_i + \theta_i) \quad (2)$$

where x and y are the i inputs and outputs, respectively, of the j^{th} node, w_{ji} is the weight for each input, θ_i is the bias, and $f(x)$ is referred to as the activation function. The activation functions $f(y)$ transfer the y output in the hidden layers process as a sigmoid function, in a mathematical function (Kusumoputro et al., 2016):

$$f(y) = \frac{1}{1+e^y} \quad (3)$$

2.2. Dataset

The data, totaling 40 sets used in this research, are from previous research by Fachrurrazi et al. (2017b). They consist of expert's judgment data, to be used as the target of ANN, and the director judgment of the main contractor. The dataset will be divided into two groups, consisting of 25 sets for ANN learning (as shown in Table 1 in the appendix) and 15 sets for ANN validation (as shown in Table 2 in the appendix). The splitting of the dataset between training and validation is based on the principle of independence of data, where 60% is used for training and 40% for validation of the model.

3. RESULTS

3.1. The Architecture of ANN Model

During the preparation stage of the ANN model, its objects, methods, attributes, and the architecture are the first considerations. Its characteristics are associated with the problem to be solved, as shown in Figure 2. This phase is conducted in the numerical experimental of ANN to find the effective model.

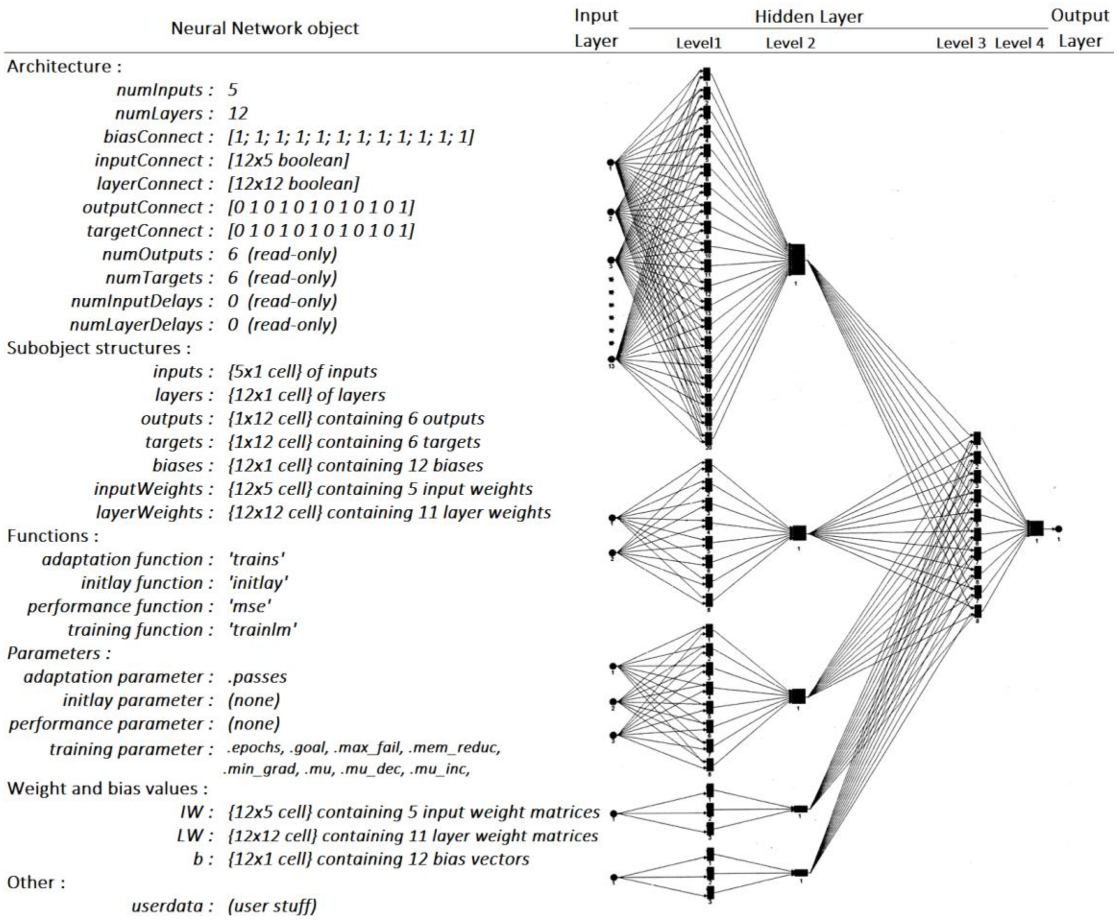

Figure 2 The ANN model architecture

The architecture of the ANN model is built based on the criteria hierarchy structure of actual subcontractor selection and object definition of the architecture using MATLAB. The objects of the ANN model consist of 5 groups of input layers (the numbers of input sizes in each group are successively 13, 2, 3, 1, and 1), 12 hidden layers, 12 bias connects, 5 middle output layers, 1 final output layer, 5 middle targets, and 1 final target. The sizes of the nodes in each hidden layer are 20, 8, 8, 3, 3, 1, 1, 1, 1, 1, 10, and 1, respectively. The details of objects, attributes, and architecture are shown in Figure 2.

3.2. Learning of the ANN Model

In the learning phase of the ANN model, the initial randomly generated values of weights are assigned to the ANN model (Nayak et al., 2016). The progress of the ANN learning can be followed by observing the learning curve in Figure 3. The learning showed a significant decrease in the initial until it reached the epochs of 600. After passing those epochs, the learning became stable. The epochs are iterated for both a forward pass and a backwards pass, for all the training examples. The ANN model is effective in patterning the subcontractor selection data with a minimal epoch achievement. Comparisons to other research about this learning include Creese et al. (1995) with the epochs of 15,000 to 50,000, Loyola et al. (2015) with the epochs of 200,000, Ko et al. (2007) with the epochs of 4000, and (Albino et al., 1998) with the epochs of 5000 to 50.000.

The learning performance of the ANN model is achieved at MSE of 1.37269E-07, as shown in Figure 3. This indicates that the learning of the proposed ANN model is achieved well. The learning performance is more accurate than that of Loyola et al. (2015) with MSE of 2.8e-07 or Ko et al. (2007) with RMSE 0.0082, but does still not achieve the result of Albino et al. (1998) with an MSE learning of 0.0 (zero).

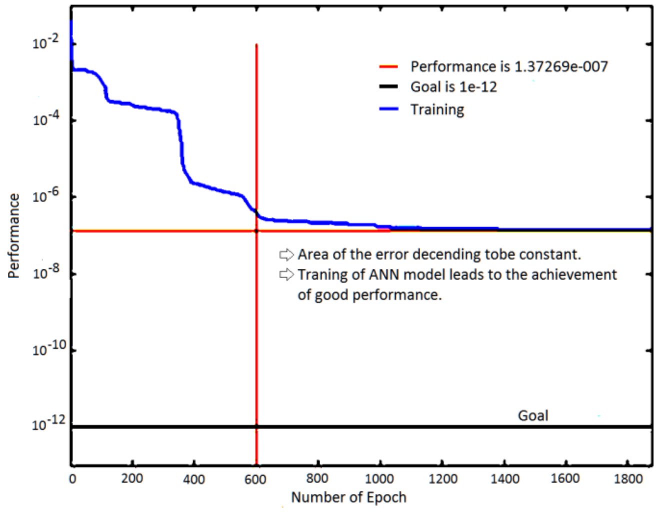

Figure 3 Learning curve of ANN

3.3. The Performance of the ANN Validation

The plotting of the output data, target data, and the error of ANN shows that outputs of the ANN model are also able to track the pattern of the target data, as shown in Figure 4. The ANN has therefore been able to act as a model application to solve the problems of multi-criteria for subcontractor selection.

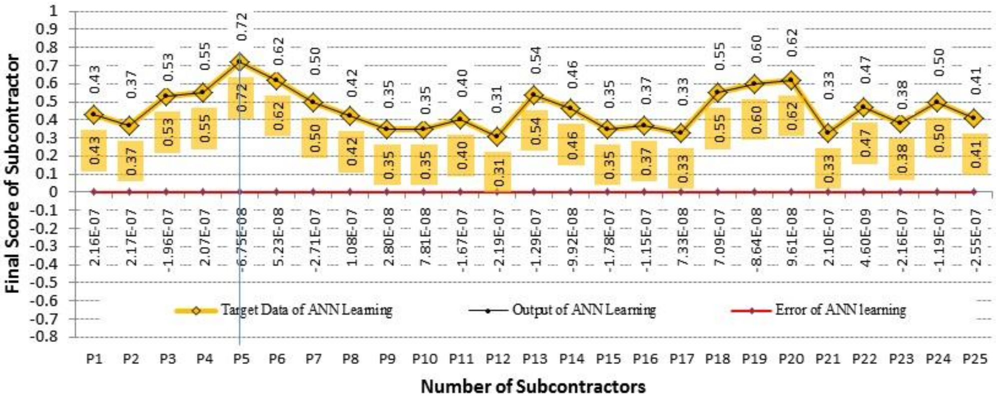

Figure 4 Output, target, and error of ANN learning

The error of the ANN model, analyzed using the MSE validation of 0.07985, is close to the validation results of Albino et al. (1998) with an MSE of 0.006 and of Ko et al. (2007), with an RMSE validation of 0.0141. This study shows three alternatives where the error exceeds 15%; namely, Q7, Q13, and Q14. However, on average, the overall error generated on the ANN model validation is still below 15%. This is possible because the data pattern of the alternative on learning of ANN differs from the data patterns Q7, Q13, and Q14. This difference will decrease with an increasing amount of data for learning ANN. This explains the adequacy of the data amount and meets all the situations/conditions in the subcontractor selection process; therefore, the ANN model can be made more accurate. However, the output pattern of the ANN model for the subcontractor selection shows a uniform shape toward the target output. Based on the validation results, we can conclude that the proposed ANN model is able to show the initial learning to adopt the knowledge of expert judgments, as shown in Figure 5. This agrees with the opinions of other researchers, who have determined a small bias for a generalized model using ANFIS (Adaptive Network-based Fuzzy Inference System) (Shahraiyni et al., 2015).

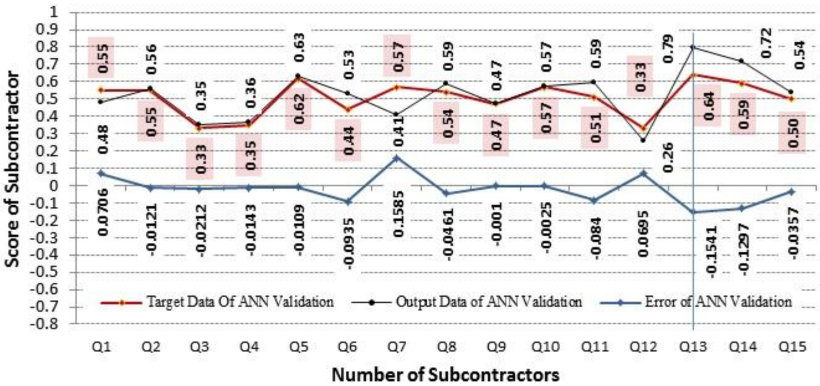

Figure 5 Output, target, error of ANN validation

4. DISCUSSION

4.1. Review the ANN Model for Subcontractor Selection

MSE validation results of the ANN model shows more than its MSE learning. It indicates that the ANN model still needs training to improve its accuracy. Further training processes will be carried out with a learning-by-doing mechanism, as shown in Figure 6. The advantage of these mechanisms, at least for the proposed ANN model, is that they will contribute to harmonize the strategic decisions by expert judgment and the performance appraisal by assessors. This will provide a decision for subcontractor selection that has a more general weight, or the pattern of the criteria weight of the previous assessors will also be considered for the formation of a new pattern of the criteria weight.

Both the indicators of MSE of learning and validation indicate that the ANN model is able to recognize the relationship pattern for both assessor's assessments and expert judgment, as previously reviewed. The correlation test indicates a strong positive between the ANN result and B1 criteria (quotation price) in both learning data (as shown in Table 3) and validation data (as shown in Table 4), at 0.82 and 0.74, respectively. The proximity value that exists between B1 (Quotation Price) and the output from ANN is explained by the R-square of the linear regression; i.e., 0.67 (0.82^2) and 0.55 (0.74^2), respectively. For learning, this means that 67% of B1 criteria can explain the expert judgment decisions, and 33% (100–67%) is explained by other criteria. For validation, this means that 55% of B1 criteria can explain the expert judgment decisions, and 45% (100–55%) is explained by other criteria.

The expert judgment decisions represent the strategic goal of the main contractor, one of which is to get more profit for the company. This strategic goal is directly related to the B1 criteria. Nevertheless, the final decision of the expert judgment does not release any other criteria to support the expert judgment decision. This is in line with Haksever et al. (1995) and Latham (1994), who illustrate that the use of price criteria as the sole basis for determining competent subcontractors will not guarantee the performance of the subcontractor. This is possibly because, in the practice of subcontractor selection, the cost parameter is one of the reasons the contractor has partnered with the subcontractor. It is also in line with Černá et al. (2016), who concluded that the crucial factors to the company for a services provider will be providing an optimal level of services at minimal cost. Elazouni et al. (2000) also asserted that subcontractors help contractors to overcome problems, including the need for special expertise, resource shortage, and financial limitations. This is a primary goal of the main contractor and will be achieved through the strategic decision.

Table 3 Correlation test of criteria to the ANN learning

A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A12	A12	A13	B1	B2	C1	C2	C3	D1	E1
0.03	0.57	-0.06	-0.07	0.07	-0.06	-0.23	-0.09	0.07	-0.34	0.10	-0.13	0.10	0.82	0.17	0.27	-0.04	0.32	-0.48	0.04

Table 4 Correlation test of criteria to the ANN validation

A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A12	A12	A13	B1	B2	C1	C2	C3	D1	E1
0.38	-0.26	0.34	-0.48	-0.29	0.23	0.24	0.12	-0.18	0.25	0.03	0.13	-0.17	0.74	0.48	-0.28	-0.12	0.38	0.27	-0.06

In the subcontractor selection practice, several criteria for the minimum requirements must be met by the subcontractor's performance, such as quality assurance criteria (A2). This is important, but the assessor assessment should be above the performance of the requirement, so the weight is not too significant. A difference in score from A2 is found in both alternatives of P5 (learning data of 0.9, as shown in Table 1) and Q13 (validation data of 0.3, as shown in Table 2). This difference of A2 (between learning and validation data) does not give significance to the final score of the expert judgment.

Some other criteria are not requirements, but they will get additional scoring from the assessor if they provide additional performance; one example is compression of schedule / D1. A difference in score from A2 is found in alternative P5 (in learning data of 0.0) and Q13 (in validation data of 0.2). Thus, the difference in score from A2 (between learning data and validation data) does not give significance to the final score of expert judgment (successfully, 0.72 and 0.64), Even the Q13 final score is smaller, which may be influenced by other larger criteria on alternative P5.

In the case of P4 and P13 alternatives, the B1 score of the assessor has the same value (0.5 and 0.5), and it is not in line with the final score of the expert judgment, which is the difference (0.53 and 0.46). This indicates that the expert judgment has a consideration for other criteria beyond the B1 criteria. Based on these conditions, we conclude that the decision of expert judgment is a strategic decision that is correlated with the quotation price (B1), and it does not neglect the importance of other criteria as decision support. This is the best practice for subcontractor selection, where the quotation price is part of the overall evaluation criteria that have significantly higher weight than other criteria. In this section, we conclude that the ANN model has been able to perform the initial learning to manage expert judgment decisions. Subsequent learning improvements will be made with the implementation of the ANN model in the subcontractor selection, as shown in Figure 6.

4.2. Implementation of the ANN Model for Subcontractor Selection

In the subcontractor selection practice, two things need to be achieved (Bailey, 2016): the company's strategic goal, which is maximized profits by the partnership, and the operational goal, which is to get a qualified subcontractor. Strategic goals are achieved through expert judgment decisions, while the operational goals are achieved through the performance measurement of the assessors. Both goals are implemented in the practice of subcontracting selection, as shown in Figure 6. This is in line with the opinion of Ko et al. (2017), who stated that the performance evaluation of the subcontractor by general contractors consists of two stages: primary and final scores. The interrelation between subcontractor performance and the strategic goal needs a connection using the ANN model. Finally, the ANN model will be able to substitute in full for the expert judgment or the directors in the decision-making of the subcontractor selection.

The role of the assessors to conduct the performance assessment will require the criteria and their weights. The performance criteria based on Fachrurrazi et al. (2017b), show that the weight criteria vary between each assessor, as indicated by the standard deviation of the criterion weights. This is in line with the subcontractor selection practice, where the main contractor usually gives a freedom to determine the criterion weight within a specified range to the assessor. Diversity in the weight criteria needs to be generated to achieve the ideal weights of all assessors, which will represent the entire process of the subcontractor selection. This is an important role for the ANN model for generating accuracy. The generalization capability of ANN, which will form the patterns of criterion weight in each evaluation process of the subcontractor, will improve the knowledge of ANN models. Furthermore, the general pattern of ANN models will improve the performance of the decision results. The interaction between the subcontractor selection process and the application of the ANN model (as shown in Figure 6) shows that the ANN model will have an important role in the subcontractor selection process.

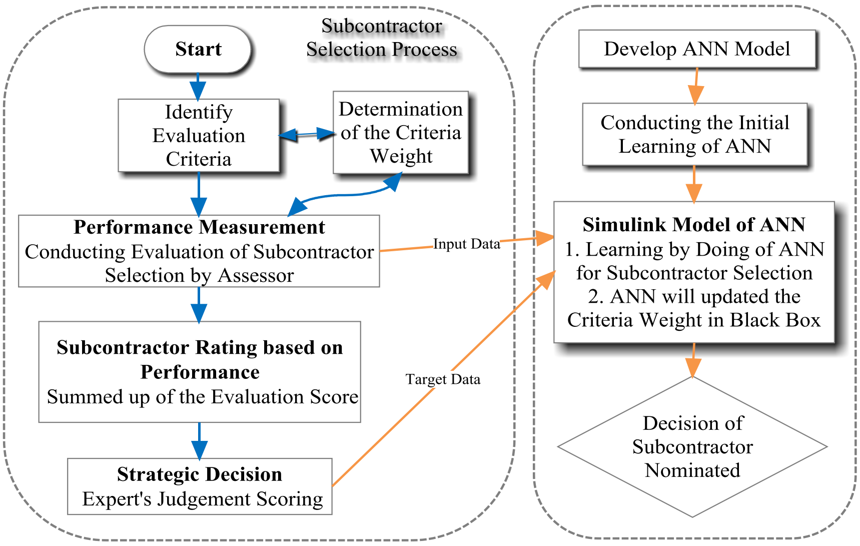

Figure 6 Interaction model of the subcontractor selection process and ANN Model

In the implementation phase, it will be interesting to change the ANN models into Simulink models (Salmi et al., 2012), as this is intended to enhance the excellent performance of the model as an application to continue the auto training in every real case. This implementation phase will provide decision of the subcontractor selection with better accuracy and more general weighting criteria (Oliveira et al., 2015).

5. CONCLUSION

A proposed ANN model, where its architecture is prepared by following the hierarchy structure of decision criteria, has been successfully built for solving the problems of the selection of subcontractors. The proposed ANN model is effective in patterning the data of the subcontractor selection with minimal learning epochs of 600 to 800. The proposed ANN model is able to identify patterns in the data quickly. The performance of learning has been achieved in MSE-learning of $1.37269e^{-7}$ and MSE-validation of 0.07985. The findings show that the ANN model has good validity, even though it is still lacking when compared to its MSE learning. This indicates that the proposed ANN model needs increases in the raw dataset for training. This stage will be conducted in the implementation stage of the ANN model.

Our use of the ANN model has identified the Quotation Price criterion (B1) as a significant influence over the other criteria using the correlation method. This criterion (B1) is the critical criterion that will give the greatest opportunity in partnering for the subcontractor and for nomination in the selection.

The practice of selecting subcontractors in Indonesia, particularly in the reviewed case, has two important stages for conducting the subcontractor evaluation; namely: (1) a performance appraisal that relates to project needs and is conducted by assessors; and (2) a strategic assessment that relates to the needs of the main contractor firms and is conducted by expert judgment. The ANN role in the subcontractor selection process, which is to collaborate on the assessor assessments and the expert judgment decision, has also been described. The implementation phase of the ANN model is a crucial stage for generalizing the criterion weights to improve the performance of the subcontractor selection.

6. ACKNOWLEDGEMENT

The Authors appreciate to the parties in their contribution; we would like thank Director of PT. Waskita Karya and staff, and the CEM (Civil Engineering Management) Laboratory staff of Syiah Kuala University. Special thanks go to the reviewers for their great comments for improving this paper.

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APPENDIX

Table 1 Dataset of input and target for training of the ANN model (Fachrurrazi et al., 2017b)

Multi-Criteria of The Decision		Alternative (Number of Subcontractors)																								
		P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16	P17	P18	P19	P20	P21	P22	P23	P24	P25
A. Subcontractor Credibility																										
1. Company profile																										
a. Management Capabilities																										
• Quality system																										
- ISO certification, similar	**A1**	0.60	1.00	0.80	0.50	0.60	0.60	0.60	0.90	0.60	0.60	0.50	1.00	0.00	1.00	0.50	0.50	0.20	1.00	0.80	0.90	0.50	0.50	0.80	0.65	1.00
- Quality assurance	**A2**	0.30	0.50	0.60	1.00	0.90	0.50	0.65	0.50	0.50	0.40	0.50	0.30	0.90	0.00	0.00	0.50	0.30	1.00	0.60	1.00	0.60	0.50	0.60	0.90	1.00
- Company profile	**A3**	0.20	1.00	0.60	1.00	0.40	0.40	0.80	0.55	0.50	0.70	0.60	0.50	0.60	0.50	0.50	0.80	0.50	1.00	0.20	1.00	0.70	1.00	0.80	0.65	1.00
• Financial Stability																										
- Balance Sheet	**A4**	0.80	0.60	0.30	0.90	0.60	0.60	0.55	0.60	0.60	0.30	0.55	0.65	0.10	0.10	0.60	0.90	0.50	1.00	0.20	0.50	0.25	0.20	0.80	0.80	1.00
- Bank guarantee	**A5**	0.80	0.90	0.30	1.00	0.50	0.70	0.65	0.20	0.80	0.30	0.30	0.70	0.90	0.50	0.20	1.00	0.30	1.00	0.30	0.60	0.90	0.85	0.25	0.90	1.00
b. Technology capability																										
• Facilities	**A6**	0.80	0.70	0.50	0.60	0.80	0.30	0.60	0.80	0.50	0.20	0.70	0.85	0.90	0.60	0.70	0.50	0.80	0.75	0.10	0.80	0.65	0.45	0.45	0.60	0.50
• Transport	**A7**	0.80	0.60	0.60	0.70	0.50	0.10	0.80	0.20	0.40	0.50	0.60	0.20	0.50	0.30	0.80	1.00	0.60	0.65	0.70	0.30	0.90	0.55	0.80	0.60	0.60
• Equipment	**A8**	0.80	0.70	0.60	0.80	0.50	0.10	0.50	0.80	0.40	0.50	1.00	0.40	0.70	0.50	0.10	1.00	0.30	0.50	0.90	0.30	0.80	0.90	0.60	0.45	0.70
2. Contract Trustworthy																										
a. Project Experience	**A9**	0.60	1.00	0.50	0.90	0.30	0.90	0.25	0.30	0.60	0.30	0.50	0.30	0.80	0.50	0.50	0.30	0.40	0.90	0.30	0.50	0.60	0.65	0.85	0.60	1.00
b. Project achievement	**A10**	0.40	1.00	0.90	0.20	0.30	0.30	0.65	0.70	0.30	0.50	1.00	0.80	0.70	0.60	0.80	0.50	0.50	0.80	0.30	0.40	0.40	0.80	0.50	0.30	1.00
c. Type, amount of insurance	**A11**	0.90	0.60	0.90	0.30	0.50	0.80	0.50	0.60	0.50	0.40	1.00	1.00	0.90	0.70	0.30	1.00	0.20	1.00	0.90	0.90	0.90	0.35	0.60	0.50	1.00
d. Registered in associations	**A12**	1.00	0.20	0.90	0.50	0.50	0.60	0.40	0.50	0.50	0.20	0.50	1.00	0.80	0.50	0.10	1.00	0.90	1.00	0.10	0.30	0.80	0.60	0.45	0.80	0.90
e. Company legitimate	**A13**	0.50	0.90	1.00	0.50	0.80	1.00	0.60	0.20	0.50	0.80	0.40	1.00	0.50	0.40	0.80	0.80	0.50	1.00	0.80	0.20	0.40	0.85	0.30	0.60	1.00
B. Quotation																										
1. Quotation Price	**B1**	0.35	0.25	0.50	0.60	0.80	0.70	0.65	0.40	0.30	0.10	0.15	0.05	0.60	0.50	0.25	0.30	0.40	0.60	0.70	0.30	0.20	0.50	0.30	0.40	0.20
2 Methods of Payment	**B2**	0.00	0.25	0.20	0.30	0.80	0.40	0.10	0.50	1.00	1.00	1.00	0.20	0.50	0.00	0.00	0.30	0.00	0.50	0.60	0.40	0.20	0.20	0.20	0.40	0.40
C. Technical Capabilities																										
1. Expertise of personnel	**C1**	0.80	0.10	0.50	0.30	0.90	1.00	0.10	0.20	0.70	0.80	0.90	0.30	0.90	0.80	0.50	0.60	0.30	0.20	0.80	0.90	1.00	0.50	0.60	0.80	0.60
2. Specializes in working methods	**C2**	0.50	0.60	0.40	0.10	0.55	0.80	0.35	0.65	0.45	0.20	0.30	0.80	0.70	0.55	0.60	0.40	0.50	0.80	0.30	0.20	0.60	0.70	0.50	0.95	0.40
3. Material specification	**C3**	0.70	0.60	0.90	0.90	0.90	0.90	0.90	0.80	0.60	0.90	0.70	0.90	0.60	0.80	0.70	0.50	0.60	0.90	0.80	0.50	0.70	0.90	0.60	0.70	0.80
D. Execution Time																										
1. Compression of schedule	**D1**	0.20	0.30	0.40	0.10	0.00	0.20	0.60	0.30	0.10	0.20	0.50	0.60	0.50	0.40	0.60	0.50	0.40	0.30	0.10	0.15	0.25	0.35	0.60	0.45	0.55
E. Type of Project References																										
1. Number of similar work	**E1**	0.80	0.60	0.90	0.80	0.70	0.30	0.10	0.20	0.50	0.55	0.45	0.65	0.00	0.35	0.60	0.10	0.00	0.00	0.40	0.30	0.20	0.20	0.30	0.50	0.60
Data for Target																										
A. Subcontractor Credibility		0.69	0.76	0.64	0.67	0.57	0.53	0.59	0.55	0.54	0.43	0.62	0.71	0.58	0.52	0.48	0.76	0.44	0.90	0.50	0.66	0.65	0.58	0.62	0.65	0.89
B. Quotation		0.29	0.25	0.45	0.55	0.80	0.65	0.56	0.42	0.42	0.25	0.29	0.08	0.58	0.42	0.21	0.30	0.33	0.58	0.68	0.73	0.20	0.45	0.28	0.40	0.23
C. Technical Capabilities		0.67	0.43	0.60	0.43	0.78	0.90	0.45	0.55	0.58	0.63	0.63	0.67	0.73	0.72	0.60	0.50	0.47	0.63	0.63	0.53	0.77	0.70	0.75	0.82	0.60
D. Execution Time		0.20	0.30	0.40	0.10	0.00	0.20	0.60	0.30	0.10	0.20	0.50	0.60	0.50	0.40	0.60	0.50	0.40	0.30	0.10	0.15	0.25	0.35	0.60	0.45	0.55
E. Type of Project References		0.80	0.60	0.90	0.80	0.70	0.30	0.10	0.20	0.50	0.55	0.45	0.65	0.00	0.35	0.60	0.10	0.00	0.00	0.40	0.30	0.20	0.20	0.30	0.50	0.60
Final Score of The Expert Judgment		0.43	0.37	0.53	0.55	0.72	0.62	0.50	0.42	0.35	0.35	0.40	0.31	0.54	0.46	0.35	0.37	0.33	0.55	0.60	0.62	0.33	0.47	0.38	0.50	0.41
Output of ANN Learning		0.43	0.37	0.53	0.55	0.72	0.62	0.50	0.42	0.35	0.35	0.40	0.31	0.54	0.46	0.35	0.37	0.33	0.55	0.60	0.62	0.33	0.47	0.38	0.50	0.41

Table 2 Dataset of input and target for validation of the ANN model (Fachrurrazi et al., 2017b)

Multi-Criteria of The Decision		Data for Validation														
		Alternative (Number of Subcontractors)														
		Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13	Q14	Q15
(1)	(2)	(3)														
A. Subcontractor Credibility																
1. Company profile																
a. Management Capabilities																
• Quality system																
- ISO certification, similar	**A1**	1.00	1.00	0.00	0.80	0.80	0.90	0.80	0.50	0.20	0.60	0.50	0.10	0.50	0.90	0.40
- Quality assurance	**A2**	1.00	1.00	1.00	0.60	1.00	0.50	0.50	0.10	0.30	0.30	0.80	0.60	0.30	0.40	0.50
- Company profile	**A3**	0.60	0.70	0.30	1.00	0.50	0.80	0.20	0.50	0.20	0.80	0.60	0.20	0.50	0.80	0.80
• Financial Stability																
- Balance Sheet	**A4**	0.70	0.50	0.80	0.70	0.85	0.50	0.20	0.50	0.80	0.25	0.50	0.80	0.20	0.50	0.60
- Bank guarantee	**A5**	1.00	1.00	1.00	0.50	0.40	0.80	0.80	0.70	0.60	0.80	0.90	0.40	0.30	0.30	0.80
b. Technology capability																
• Facilities	**A6**	0.20	0.50	0.60	0.50	1.00	0.90	0.60	0.40	0.60	0.50	0.30	0.30	0.40	0.80	0.50
• Transport	**A7**	1.00	1.00	0.30	1.00	0.50	0.45	0.50	0.90	0.70	0.35	0.40	0.20	0.80	0.60	0.50
• Equipment	**A8**	0.75	0.50	0.30	0.60	0.50	0.70	0.90	0.70	0.20	0.80	0.20	0.50	0.90	0.30	0.50
2. Contract Trustworthy																
a. Project Experience	**A9**	1.00	0.50	0.70	1.00	0.40	0.35	1.00	0.80	0.60	0.75	0.10	0.60	1.00	0.50	0.70
b. Project achievement	**A10**	0.50	0.10	0.40	0.20	0.50	0.15	1.00	0.50	0.40	0.50	0.50	0.20	0.50	0.70	0.50
c. Type, amount of insurance	**A11**	0.50	1.00	0.60	1.00	1.00	0.50	1.00	0.30	0.50	1.00	0.60	0.70	0.90	0.60	0.60
d. Registered in associations	**A12**	1.00	1.00	0.30	1.00	0.80	0.20	1.00	0.70	0.60	0.75	0.80	0.20	0.40	0.80	0.60
e. Company legitimate	**A13**	0.70	1.00	0.50	1.00	0.60	0.50	1.00	0.20	0.50	0.80	0.40	0.50	0.60	0.60	0.30
B. Quotation																
1. Quotation Price	**B1**	0.55	0.60	0.20	0.10	0.60	0.35	0.65	0.55	0.40	0.60	0.50	0.20	0.70	0.55	0.60
2 Methods of Payment	**B2**	0.00	0.00	0.00	0.20	0.55	0.60	0.40	0.55	0.30	0.25	0.80	0.70	0.90	1.00	0.00
C. Technical Capabilities																
1. Expertise of personnel	**C1**	0.90	0.80	0.50	0.60	0.40	0.50	0.65	0.45	0.85	0.70	0.60	0.55	0.35	0.60	0.50
2. Specializes in working methods	**C2**	0.50	0.60	0.90	0.60	0.80	0.10	0.50	0.30	0.80	0.70	0.30	0.60	0.50	0.80	0.50
3. Material specification	**C3**	0.80	0.90	0.60	0.80	0.70	0.50	0.60	0.90	0.60	0.70	0.80	0.50	0.60	0.90	0.80
D. Execution Time																
1. Compression of schedule	**D1**	0.10	0.20	0.25	0.30	0.30	0.30	0.10	0.20	0.25	0.45	0.15	0.15	0.20	0.35	0.25
E. The Type of Project References																
1. Number of similar work	**E1**	0.80	0.50	0.60	0.90	0.80	0.70	0.30	0.65	0.65	0.60	0.35	0.30	0.60	0.20	0.40
Data for Target																
A. Subcontractor Credibility		0.77	0.79	0.61	0.76	0.71	0.61	0.71	0.53	0.49	0.62	0.52	0.40	0.55	0.62	0.56
B. Quotation		0.46	0.50	0.17	0.12	0.59	0.39	0.61	0.55	0.38	0.54	0.55	0.23	0.73	0.63	0.50
C. Technical Capabilities		0.73	0.77	0.67	0.67	0.63	0.37	0.65	0.55	0.75	0.70	0.57	0.55	0.48	0.77	0.60
D. Execution Time		0.10	0.20	0.25	0.30	0.30	0.30	0.10	0.20	0.25	0.45	0.15	0.15	0.20	0.35	0.25
E. Type of Project References		0.80	0.50	0.60	0.90	0.80	0.70	0.30	0.65	0.65	0.60	0.35	0.30	0.60	0.20	0.40
Final Score of The Expert Judgment		0.55	0.55	0.33	0.35	0.62	0.44	0.57	0.54	0.47	0.57	0.51	0.33	0.64	0.59	0.50
Output of ANN Learning		0.4794	0.5621	0.3512	0.3643	0.6309	0.5335	0.4115	0.5861	0.471	0.5725	0.594	0.2605	0.7941	0.7197	0.5357