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Making decision toward overseas construction projects

An application based on adaptive neuro fuzzy system

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Abstract

Purpose – The purpose of this paper is to introduce a decision support aid for deciding an overseas construction project (OCP) using an adaptive neuro fuzzy inference system (ANFIS).

Design/methodology/approach – This study presents an ANFIS approach as a decision support aid for assessment of OCPs. The processing data were derived from 110 simulation cases of OCPs. In total, 21 international factors observed from a Delphi survey were determined as assessment variables to examine the cases. The experts were involved to evaluate and judge whether the company should Go or Not Go for an OCP, based on the different parameter scenarios given. To measure the performance of the ANFIS model, root mean square error (RMSE) and coefficient of correlation (R) were employed.

Findings – The result shows that optimum ANFIS model indicating RMSE and R scores adequately near between 0 and 1, respectively, was obtained from parameter set of network algorithm with two input membership functions, Gaussian type of membership function and hybrid optimization method. When the model tested to nine real OCPs data, the result indicates 88.89 percent accurate.

Research limitations/implications – The use of simulation cases as data set in development the model has several advantages. This technique can be replicated to generate other case scenarios which are not available publicly or limited in terms of quantity.

Originality/value – This study evidences that the developed ANFIS model can predict the decision satisfactorily. Therefore, it can help companies' management to make preliminary assessment of an OCP.

Keywords International construction, Simulation

Paper type Research paper

Introduction

Although internationalization is not a new issue in construction industry, starting an overseas construction project (OCP) is not as simple as beginning other types of industrial projects (Kim *et al.*, 2013). Undertaking the OCPs are one of the vulnerable activities to the global issues such as politic, economic, financial, socio-cultural and legal (Han and Diekmann, 2001; Gunhan and Arditi, 2005a, b). The projects are also distressed by varieties of risks in business, such as currency exchange, interest rate, inflation and credit (Zhi, 1995; Han *et al.*, 2004).

Meanwhile, the process of making a decision will gain a knotty and arduous problem when the process contains four properties, namely, multi-criteria, multi-decision makers,

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the degree of risk and uncertainty and incomplete information, imprecise data as well as vagueness (Singh and Tiong, 2005). Other than the four elements, subjectivity and objectivity of decision also shade decision makers in choosing options (Teale *et al.*, 2003). In international construction studies (ICS), researchers argue that a critical part when a company targeting a foreign market is how to make a better decision in connection with potential project selection (Ozorhon *et al.*, 2006; Kim *et al.*, 2013). It is a risky action if the decision-making process is merely based on the experiences and intuition.

In response to above facts, a number of multi-criteria decision making (MCDM) methods have been introduced in the context of ICS. For instance, Hastak and Shaked (2000) use analytical hierarchy process to assess latent risks affecting international construction market. Bu-Qammaz *et al.* (2009) employ analytical network process to rate the risk level associated with OCPs. Cross impact analysis was applied by Han and Diekmann (2001) to develop a risk-based go/no go decision making procedure by involving past knowledge and input of international experts. Some applications are; however, still lacking in terms of accuracy and subjectivity in judging the weighted score, rating the criteria and ranking the alternatives. They also overlooked the ill-defined and incomplete information following the process decision making.

In response to the lack of MCDM methods, researchers ascertain that fuzzy logic (FL) and artificial neural network (ANN) techniques enable to resolve the decision-making problems mentioned above. FL is a very adaptive and responsive method upon the nature of human thinking, reasoning, cognition and perception process when facing the subjectivity, vagueness and ambiguity (Sutrisna, 2004). It has been widely employed for making a decision, measuring productivity, cost and time performance, evaluation and assessment of risk. Conversely, according to Boussabaine (1996), ANN technique is believed more advanced in terms of its ability to self-learning, self-optimization, generalization of the solution, response to ill-defined data and complexity of the problem containing non-linear relationship. ANN offers an auspicious management method in several potential areas such as selection of alternative, estimation, classification and optimization tasks. Lam *et al.* (2001) proclaim that combination of FL and ANN is a perfect and powerful approach to many engineering problems. The integration of the two systems, NN and FS will bring advantages to existing ones.

Correspondingly, the realm of overseas construction operations requires expert knowledge, judgment and experience for their problem solutions. Both artificial intelligence methods can be applied extensively to support making the decision for overseas expansion of construction enterprises. Thus, this study aims to promote a model for OCPs (OCPs) decision making using an amalgamation form of FL and ANN, namely, Adaptive Neuro Fuzzy Inference System (ANFIS).

International factors in OCPs

Large size, escalating, fractured, regionally changeable, assorted, risky and very competitive are the market characteristics of the international construction (Li *et al.*, 2013). These typical properties are then perfectly nourished by some non-technical issues such as politics, social-culture, legal and economic financial (Gunhan and Arditi, 2005a, b). Such a complex combination of variables results in the creation of international construction projects strong contrast with those of domestic ones (Ling and Hoang, 2010). A complex environment in OCPs obviously impacts the enterprises' operation abroad. Thus, many studies have been undertaken to identify and analyze the affecting facets from various angles, mostly the risk dimensions, such as Hastak and Shaked (2000), Ling and Hoang (2010) and Pheng and Low (2013). The concerns of those studies are directed to help decision making in this business.

Correspondingly, there exists overlapping areas in the discussion of international construction from decision-making point of view. For instance, a topic of entry mode choice, the selection of foreign market and overseas project could involve similar risk factors or international factors. So far, there has not been any consensus on such factors. Each researcher identifies and harnesses different international variables in their studies. For instance, Hastak and Shaked (2000) identified 73 risk attributes, while Han *et al.* (2008) and Bu-Qammaz *et al.* (2009) found 36 and 28 variables, respectively. Similarly, the scholars have also not yet reached an agreement on the categorization of the factors (Utama *et al.*, 2018).

Through an extensive literature review of relevant studies on decision making in OCPs, 131 variables were identified and tallied to view their frequency of occurrences. After scanning the variables list, 56 duplicates and related subjects were then integrated and transformed into 15 new names. Of 90 remaining, 59 variables having an appearance frequency of less than four were eliminated. Table I summarizes 31 international factors resulting of above arrangement.

Basic concept and applications of ANFIS

The basic concept of ANFIS is to create the stipulated input–output pairs through assembling a set of fuzzy IF-THEN rules with suitable membership functions (MFs) through implanting the fuzzy inference rule (FIS) into the structure of adaptive networks (Jang, 1993). The ANFIS model structure is constructed by both ANN and FL which allow the model to work with uncertain and imprecise information (Liu and Ling, 2003). It utilizes the NN training process to tune the membership function and the related parameter approaching the desired data sets (Wu *et al.*, 2009). Structurally, ANFIS consists of three devices, namely, a rule base, a database and a reasoning mechanism. FIS contains two rule bases following a linear function as described by Takagi and Sugeno (1985):

Rule 1: IF X_1 is A_1 and X_2 is A_1 THEN $Y_1 = p_1x_1+q_1x_2+r_1$,
Rule 2: IF X_1 is A_2 and X_2 is A_2 THEN $Y_2 = p_2x_1+q_2x_2+r_2$,

where X_1, X_2 and Y_1 and Y_2 are numerical inputs and outputs, respectively, A and B are numerical variables, and p, q and r are parameters determining the relation between input and output. ANFIS algorithm is composed of five layers.

Layer 1: this layer shows the number of numerical inputs belonging to the different fuzzy set. Every node i in this layer is represented by square node with the output function is as follows:

$$\begin{cases} O_i = \mu_{A_i}(x_1) \\ O_i = \mu_{B_i}(x_2) \end{cases}, \tag{1}$$

where is μ_{Ai} (x_1) and μ_{Bi} (x_2) are MFs for fuzzy sets of A and B.

Layer 2: in this layer, all incoming signals are multiplied to obtain an output, ω by which operator AND or OR are used, known as firing strength. The output is calculated by the following equation:

$$\omega_i = \mu_{A_i}(x_1) \times \mu_{B_i}(x_2). \tag{2}$$

Layer 3: every node N in this layer calculates the average ratio of previous outputs to produce a new output $\overline{\omega}$. This is obtained by the following equation:

$$\overline{\omega}_i = \frac{\omega_i}{\sum_i \omega_i}. \tag{3}$$

Layer 4: square node in this layer produces an output $\overline{\omega}_i\, f_i$ based on the following equation:

$$Y_i = \overline{\omega}_i f_i = \overline{\omega}_i(p_i x_1 + q_i x_2 + r_i). \tag{4}$$

Table I. Summary of international factors of OCPs decision making

Factors	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
1. Political stability and sensitiveness	X	X	X	X	X	X		X		X	X			X	X	X		X	X	X	X		X	X	X	X
2. Legal environment	X	X	X	X	X				X	X	X						X	X		X	X		X	X		X
3. Economic health and stability	X		X	X	X	X	X	X		X	X		X	X	X	X	X	X	X	X	X		X	X	X	X
4. Cultural, custom and language differences	X		X	X	X	X		X	X		X	X		X		X	X	X	X	X	X		X			
5. Easiness and attitude toward foreigner business and profit	X	X	X	X	X	X		X	X	X	X	X		X			X	X		X	X	X	X	X	X	X
6. Climate, weather and other natural condition	X		X	X					X	X												X				
7. Availability of basic infrastructure	X		X	X					X		X			X						X	X	X				X
8. Availability of local resources	X	X	X	X	X				X	X	X			X			X	X		X	X				X	X
9. Importance of market	X		X					X	X	X				X	X	X			X						X	
10. Hostilities with neighboring country or region	X	X									X												X		X	
11. Cost of conducting business					X		X		X								X									
12. Client's reputation			X	X				X			X							X		X		X				
13. Type of client								X								X			X	X					X	
14. The existence of strict quality requirement				X														X		X						X
15. Project location or distance from home country				X				X	X					X		X		X	X	X	X				X	
16. Adverse ground/site conditions	X			X																X		X				X
17. Project desirability to the host country		X	X						X														X		X	
18. Project scale/size			X	X				X								X		X	X	X		X	X		X	
19. Complexity of project			X	X				X								X		X	X	X		X	X		X	
20. Level of competition			X	X	X	X		X	X		X	X			X	X	X		X	X			X		X	
21. Type of project								X								X			X	X		X	X		X	
22. Types of contract	X		X					X								X			X			X		X		
23. Quality and clarity of contract condition	X			X				X	X	X	X		X			X		X	X	X		X		X		X
24. Contractual duration			X	X				X	X	X						X		X	X	X		X	X	X		
25. Strict safety requirement	X			X					X		X							X				X				
26. Strict environmental regulation														X				X			X					X
27. Relationship to stakeholders in host country	X	X	X	X	X	X			X					X	X		X	X		X	X		X	X	X	X
28. Current work load or need for work			X	X				X	X																	
29. Company's tract record and experience			X		X			X	X	X		X		X	X	X	X		X	X	X	X				
30. Familiarity with host country									X					X						X	X	X				X
31. Financial capability and support	X		X	X	X		X		X		X	X	X	X			X			X	X		X	X		

Sources: (1) Hastak and Shaked (2000); (2) Al-Tabtabai and Alex (2000); (3) Han *et al.* (2008); (4) Han *et al.* (2007); (5) Gunhan and Arditi (2005a, b); (6) Chen (2008); (7) Kim *et al.* (2013); (8) Ozorhon *et al.*, 2006); (9) Kim *et al.* (2008); (10) Cheng *et al.* (2011); (11) Olcer and Akyol (2014); (12) Chen and Messner (2011); (13) Han *et al.* (2004); (14) Han and Diekmann (2001); (15) Li *et al.* (2013); (16) Dikmen and Birgonul (2004); (17) Tang *et al.* (2012); (18) Bu-Qammaz *et al.* (2009); (19) Dikmen *et al.* (2006); (20) Dikmen *et al.* (2007); (21) Han and Diekmann (2001); (22) Sonmez *et al.* (2007); (23) Pheng and Low (2013); (24) Ling and Hoang (2010); (25) Neo (1976); (26) Eybposh *et al.* (2011)

Layer 5: this is an output layer in which the node calculates all outputs from Layer 4 by the following equation:

$$Y = \sum_i \overline{\omega}_i f_i = \frac{\sum_i \omega_i f_i}{\sum_i \omega_i}. \tag{5}$$

Learning process in a neural network aims to create a stable structure. In ANFIS, the learning process of network combines the least squares estimate (LSE) and the gradient descent method. This hybrid learning procedure is composed a forward step in which the input signal passes forward until Layer 4, where the output parameters are then adjusted using the LSE of the error between the estimated output and the actual output. Then, on the backward step, the error rates propagate back through the system, and MFs in Layer 1 are updated by the gradient descent method (Opeyemi and Justice, 2012). The process of these forward and backward propagations is called as epoch. The hybrid learning algorithm trains the MF parameters to mimic the training data samples.

In the construction discipline, ANFIS algorithms have been adopted for different purposes of studies such as prediction, assessment and modeling. For instance, Ekici and Aksoy (2011) utilized ANFIS for predicting the needs of energy for building in preliminary design, while Marzouk and Amin (2013) used the method to predict the construction material prices. For the assessment or evaluation purposes, ANFIS has been employed by Ebrat and Ghodsi (2014) and Debnath *et al.* (2016) to assess risks in construction projects and occupational risks in construction sites, respectively. The use of ANFIS for modeling has been applied by Polat *et al.* (2014) who creating bid/no bid decision model and Latief *et al.* (2013) who developing a model for preliminary cost estimation.

Methodology

Determination of variables

The hierarchy structure of the model development for OCP decision making consists of four main steps; determination of variables, data collection, ANFIS operation and recommendation. The process begins with a determination of variables for OCP assessment. These variables were obtained from data analysis of a two-round Delphi survey. In the first round, the experts were asked to rank the importance level and to rate the frequency level of risk occurrence associated with the 31 international factors in OCPs as summarized in Table I. The results of the first round were then analyzed using mean score ranking to specify the relative ranking of the factors. The second round was conducted by sending the same questionnaire by attaching the analysis result of the first round.

One of the critical points in conducting Delphi study was to arrange the experts' panel. The number of panelists in previous studies was varying. However, an acceptable sufficient number of panelists should be fulfilled (Hsu and Sandford, 2007). In construction-related Delphi research, researchers advised a minimum sufficient number of panelists (Ameyaw, 2014). Thus, 11 panelists were identified using snowballing method to conduct the Delphi survey for this study.

From 11 panelists, three participants held the top level in their respective companies with industrial experience of more than 20 years. The rest of them were Heads of Department (two respondents), Heads of Division (three respondents), Head of Overseas Branch (one respondent) and two Project Managers. In general, all the experts were senior level personnel having rich industrial experience. Although their experiences in OCPs were relatively low, their position and industrial experience guaranteed the reliability of the feedbacks.

While analyzing the data obtained through the first- and the second round of Delphi survey, the internal consistency of data set was assessed. The Cronbach's α values for the importance of international factors and their frequency level of risk occurrence are obtained as 0.772 and 0.735, respectively. As these scores are marginally greater than 0.70, they represent a good internal consistency and reliability of the Delphi survey data. This implies that the adopted seven-point Likert scale is reliable.

One of the benefits of the Delphi method is that it can guide the panelist's opinions to reach a group consensus and reduce the bias at the same time given the unspecified nature of the process (Chan *et al.*, 2001). Kendall's *W* was used to assess the degree of consensus obtained in each round. The Kendall's *W* scores for the importance of international factors showed 0.481 and 0.571 for first and second round survey, respectively. The consensus among experts on the frequency level of risk occurrence was 0.751 and 0.873 in first and second round surveys. The relatively higher values of *W* scores indicate that optimum level of consensus was achieved in two rounds.

The results of the survey were then analyzed to find the significance index of each factor using the following equation:

$$\mathrm{IF}_{\mathrm{SI}} = \frac{\sum_{m=1}^{n} \sqrt{\mathrm{IF}_{\mathrm{IR}} \times \mathrm{IF}_{\mathrm{RO}}}}{n},$$

where IFSI is significance index of the international factors, IFIR is the importance rate assessment of the international factors, IFRO is the risk occurrence assessment of the international factors, and *n* is the number of respondents. The indices determine which essential factors significantly influence the decision makers in evaluating an OCP and are further used to design an evaluation form. Of 31 OCP factors, 21 variables have a significant index of 4.0 and above. Borrowing idea from previous research, these variables were then grouped into five criteria: project (X1), contract (X2), client (X3), host country (X4) and business (X5).

OCP evaluation form

After determining the variables, an evaluation form of OCP, as illustrated in Figure 1, was designed as an instrument to build cases database. Each variable was given a unique parameter measurer. Tree types of parameters were considered, ordinal, categorical and numeric as measurement scale. The ordinal parameter belongs to the criteria such as project scale/size, the complexity of the project, client reputation, while the categorical scale matches with the attributes like types of contract, types of client and contract duration. Project's scale for instance, has four parameter scales (small-medium-large-mega), showing the project is categorized under small, medium, large or mega project. How experts or contractors consider the scale of project, it depends on each individual preference on the project such as duration, budget, and social impact. Such approach was employed in many neural network studies in "construction management" such as Lam *et al.* (2001), Wanaous *et al.* (2003), Dikmen and Birgonul (2004), and Ebrat and Ghodsi (2014). Numeric scales were applied to the five criteria ranging from 1 to 9 in which 1 represents the lowest and 9 is the highest. These scales indicate a score of each criterion obtained from judgment of the experts based on their experience and intuition. The last categorical attribute is expert decision assigning either "Go" or "Not Go" based on the highlighted parameters of attributes and scores of the main criteria.

Prior to the evaluation, the form was discussed with three experts, two from industry and one from university to seek suggestions regarding clarity and conformity of parameters. One important suggestion arose when the experts argued that the information of several attributes, such as level of competition and adverse site condition, tend to be unavailable or unknown, even though a market research was carried out. This unavailable information can be found in a country with lacking governmental organization system and just freed from

EVALUATION FORM OF OPC
Project code: ....

	Criteria and Attributes	Parameter				
$X_{1.1}$	Project scale/size	Small	Medium	Large	Mega	
$X_{1.2}$	Complexity of project	Low	Medium	High		
$X_{1.3}$	Type of project	Never done before	Few experience	Many experience		
$X_{1.4}$	Level of competition	Low	Medium	High	UI	
$X_{1.5}$	Project location or distance from home country	Near	Medium	Far		
$X_{1.6}$	Adverse site condition	Low	Medium	High	UI	
	Project score (X_1)	(lowest) 1–2–3–4–5–6–7–8–9 (highest)				
$X_{2.1}$	Types of contract	Local standard	Combination	International std	UI	
$X_{2.2}$	Quality and clarity of contract condition	Low	Medium	High	UI	
$X_{2.3}$	Contractual duration	Short	Medium	Long	UI	
	Contract score (X_2)	(lowest) 1–2–3–4–5–6–7–8–9 (highest)				
$X_{3.1}$	Type of client	Host gov.	Host private	Home private	Home gov.	
$X_{3.2}$	Client's reputation	Poor	Medium	Good	Excellence	UI
	Client score (X_3)	(lowest) 1–2–3–4–5–6–7–8–9 (highest)				
$X_{4.1}$	Political stability and sensitiveness	Poor	Medium	Good	Excellence	UI
$X_{4.2}$	Legal environment	Poor	Medium	Good	Excellence	UI
$X_{4.3}$	Economic health and stability	Poor	Medium	Good	Excellence	UI
$X_{4.4}$	Cultural, custom and language differences	Low	Medium	High		
$X_{4.5}$	Easiness and attitude toward foreign business	Poor	Medium	Good	Excellence	UI
	Host country score (X_4)	(lowest) 1–2–3–4–5–6–7–8–9 (highest)				
$X_{5.1}$	Availability of local resources	Poor	Medium	Good	Excellence	UI
$X_{5.2}$	Cost of conducting business	Low	Medium	High	Very high	UI
$X_{5.3}$	Importance of market	Low	Medium	High		
$X_{5.4}$	Familiarity with host country	Low	Medium	High		
$X_{5.5}$	Familiarity capability and support	Poor	Medium	Good	Excellence	
	Business score (X_5)	(lowest) 1–2–3–4–5–6–7–8–9 (highest)				
	Decision (Y)	GO	NOT GO			

Note: UI, unidentified

Figure 1.
OCP evaluation form

political conflict. To counter the unknown information, a scale "unidentified" was given for attributes, such as level of competition and adverse site condition.

The evaluation form was utilized to assess historical data from previous and targeted projects overseas. Unfortunately, to find such data was not a gentle work as neither the government agencies nor private institutions in Indonesia archived the OCPs undertaken by Indonesian firms. Moreover, collecting the data from experienced companies one by one was unsuccessful. Only nine projects were successfully collected through this afford. Regardless of insufficient number of data, the researcher faced a lack of access in collecting the data. Besides, most of the real data contained preferred scenarios to present an ideal environment in making decision, whereas other possible scenarios never occured. Thus, those problems gave a robust reason to generate and to use simulation cases as a data set.

Build up data set

Having the difficulties to collect the real data, in fact, there are four sources of data that can be used in training the network (Dikmen and Birgonul, 2004). They may be derived from previous works, simulation results, hypothesis results and a set of data prepared by domain experts. In different disciplines such as marketing (e.g. Zhang and Qi, 2005), education (e.g. Iraji *et al.*, 2012), water engineering (e.g. Sudheer and Mathur, 2010) and manufacturing (e.g. Kurnaz *et al.*, 2010), the use of simulation data for neuro fuzzy operation is a common approach.

Several benefits of using simulation data set were pointed out by Lopez-Rojas and Axelsson (2012) as follows: a freedom to select attributes contributing to the complexity of the structure of data, simplifying the preparation of data and extraction from the real sources, possibility of tuning different scenarios tailored to meet various conditions which are not available in real data sets, possibility of setting the quantity of data for different trial setup, availability of data set representing realistic scenarios and providing data set for reproducing experiment by other researchers. Therefore, for proper analysis in this research, a set of simulation data (case profiles) reflecting the real cases and the future scenarios of OCPs were used.

Based on the benefits above, a set of simulation case scenarios was provided. The initial OCP form was then rectified by adding objectives of research, instructions, assumptions and explanations of each attribute and parameter. These additional features are crucial as the cases are supplied by investigator (in this case by authors). These assumptions and information are needed to avoid ambiguities and to simplify the decision-making process. The OCP evaluation forms were prepared by randomly highlighting the parameter of each attribute. Based on the highlighted parameters, the scores of the five criteria along with the decision attribute are determined by the experts.

In total, 15 experts including 11 Delphi panelists and other four experts identified using snowballing method were involved to evaluate the simulated data. Each expert was asked to evaluate ten different case scenarios. Of 150 cases sent to the experts, 110 cases were sent back by 11 experts. Other four experts failed to complete evaluation with unrevealed personal reasons. Thus, there were a total of 110 cases used further in this research. The grades given by the experts on each criterion were then recorded and normalized using the following equation:

$$x' = \frac{x - \min.}{\max. - \min.}, \tag{6}$$

where x' is normalized score, x is initial score, min. and max. are the smallest and the largest score. This equation casts the initial scores in one unified range (from 0 to 1). The different range between input value and output value needs the data to be normalized. According to Khalil and Muhammad-Ali (2013), there are two reasons why the data normalized. First, it abolishes the influence of one factor over another and second, it converges weight faster than with un-normalized data. On the output side, the categorical scales on decision (Y) should be transformed into crisp number in which the program can recognize the input attribute. Linguistic variables of output were coded in a binary digit representing 1 for Go and 0 for Not Go. However, Lam *et al.* (2001) advice that the use of 1 and 0 approach in imitative based learning algorithms results in very slow learning speed. They suggest assigning 0.95 and 0.05 instead of 1 and 0 to avoid expected slow convergence.

Application of ANFIS and validation

ANFIS system needs a set of pair input–output data. Of 110 generated case scenarios, 70 percent of them were randomly selected for training data and the rest was considered as checking (20 percent) and testing data (10 percent). The nine real cases were used for validation of the model. Training and testing were performed through trial and error experiment on ANFIS environment (learning method, the number of input membership function, error tolerance and epochs) to obtain an optimum model. The experiment iterations were conducted by modifying the environment with different settings by which the setting with the minimum error is selected. The training data set was used for generating an initial ANFIS model, whereas the testing and checking data sets were set for validation and generalization of the model respectively. A computer software, MATLAB from Mathwork Inc. was utilized to help generate the ANFIS network.

To validate and verify the applicability and performance of a FNN, two methods, convergence and generalization proposed by Refenes (1995) were adapted. Convergence views the learning mechanism implemented for training data. It indicates the optimum performance of the model and the accuracy. The common indicators to measure the performance are root mean square error (RMSE) and mean absolute percentage error. Regarding its efficiency, the model is indicated by the correlation coefficient (R) and coefficient of determination (R^2). In this research, RMSE and R were employed. The ideal characteristics of the model have RMSE score of 0 and R closed to 1 or 100 percent. The equation of RMSE and R are as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}(A_i - F_i)^2}, \tag{7}$$

$$R = \frac{\sum_{i=1}^{N}\left(A_i - \overline{A}\right)\left(F_i - \overline{F}\right)}{\sqrt{\sum_{i=1}^{N}\left(A_i - \overline{A}\right)^2 \times \sum_{i=1}^{N}\left(F_1 - \overline{F}\right)^2}}, \tag{8}$$

where A_{i}, F_{i} and N are actual scores, calculated score produced by model and number of data respectively.

On the other hand, generalization indicates the ability of the network model to pattern recognition when the test samples are tested (Refenes, 1995). In total, 10 percent of cases were provided to check the applicability and performance of the model. Again, RMSE and R of data checking were captured. The model was then verified with nine real data to view the correctness of result of the model.

Results and discussions

Prior to generate initial ANFIS structure, the involved parameters in generating initial FIS rule are set in ANFIS tool box. To generate an initial ANFIS structure, following parameters were tuned: the number of MF, the type of MF, type of optimization, in this case grid partition, type of training, in this case hybrid, error tolerance and number of epoch. The hybrid type combines the LSE and the gradient descent method. The hybrid learning algorithm trains the MF parameters to mimic the training data samples. Error tolerance is functionated to determine a stopping criterion of training related to the size of error. Since the performance of training error is unsure, the error tolerance was kept in default form (0). Different numbers of epochs were applied in studies related construction such as Ebrat and Ghodsi (2014) and Polat *et al.* (2014) who set 500 and 100 epochs, respectively. In contrast, Guneri *et al.* (2011) set only 40 epochs in their study.

The number of training epochs in this research were set at 100 meaning the process of training will stop whenever the epoch reaches the maximum number (100 in this case) or the training error achieves the setting error tolerance. A large epoch numbers in training process may result overfitting, otherwise, it impacts on the ability of network to map a pattern. The illustration of training error plots of training and checking data set can be seen in Figure 2.

Figure 2 shows FIS process of training and checking data by two number of MFs with eight types of MFs. The crosses (top line) indicate the error plots of the checking data, and the asteriks (bottom line) are the error plots of the training data. Of eight types of MFs, two types of them which are *dsigmf* and *psigmf* produced a similar pattern of training errors against epochs. Training error stop generating a new error value before 20 epochs when

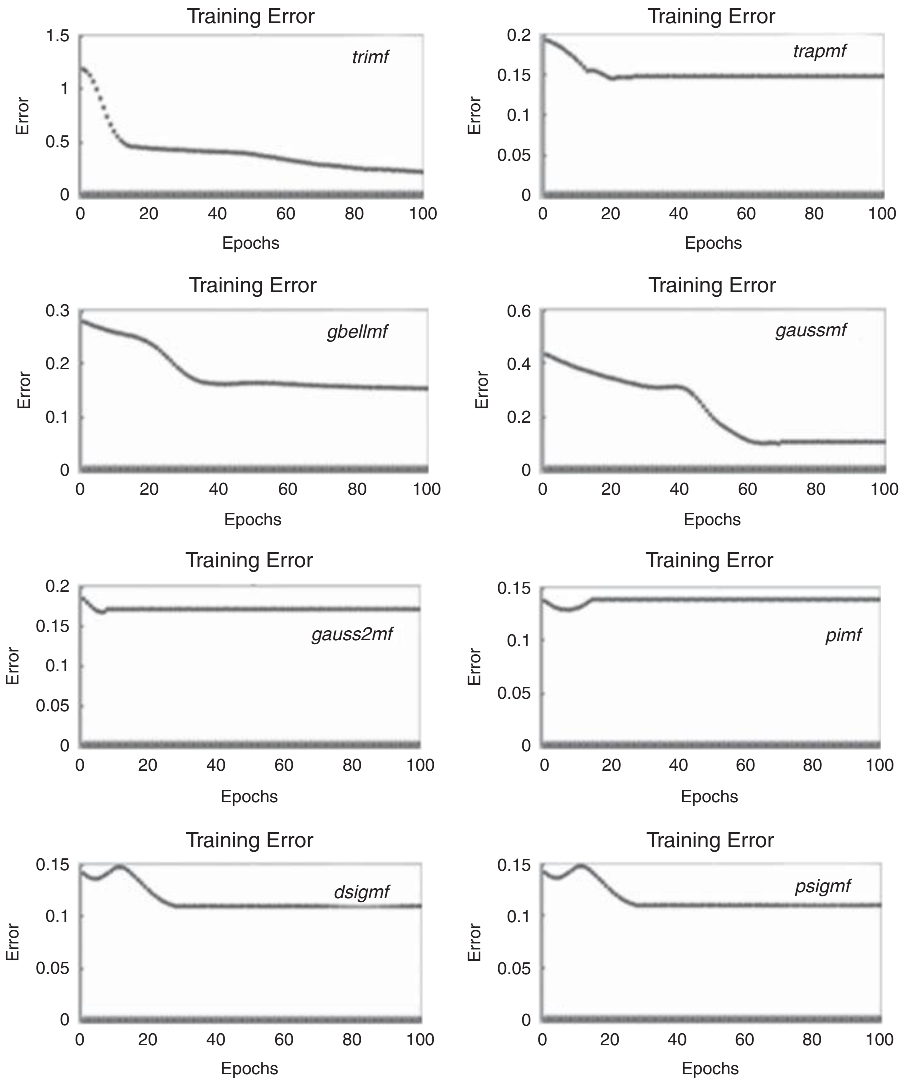

Figure 2.
Plot of training and checking data set for two number MFs

tuning MF with *gauss2mf* and *pimf*. Other setting of MF types stoped the training process after 20 epochs. At glance, there are six figure indicate the overfitting, showing the trends increase at several epochs, but they are unnoticeable.

Each train-FIS process basically creates an ANFIS model, which is a trained system. To obtain the optimum ANFIS model, which is indicated by the training minimum error, the number and type of input MFs were tuned arbitrarily. The training error is the variance between the output value of training data set and the output of the FIS for the same input value of training data set. The training error records the RMSE of the training and checking data set at each epoch. To find the RSME of each data set, the trained systems were then tested against training, testing and checking data set. Each result of different parameter settings was recorded and tabulated as presented in Table II.

Overall, the RMSE of each data for various number and types of MFs show very small value (almost zero). Generally, these values can be said that the network works well under all parameters. The minimum training errors of training data for two and three number MFs of input were obtained from *gaussmf* (5.31×10^{-6}) and *trapmf* (1.44×10^{-7}), respectively. The average training error for testing data of both parameters were 0.130 and 0.227, and for checking data are 0.075 and 0.323. Based on the results, the ANFIS model for Go/Not Go decision on OCP is developed using the parameters as follows; two input MFs, Gaussian (*gaussmf*) type membership function and hybrid optimization method.

Of the trained system, the ANFIS rule which is the ANFIS model for Go/Not Go decision making in OCP was obtained, as depicted in Figure 3. This IF-THEN rule displays the all records of FIS and enables management to make a quick choice of OCP by subtitute the input scores based on an analysis of a particular project. This rule shows an score output (1.26) for five input pairs (project, contract, owner, host country and market) with given score average of 0.5. Changes made on score of each input (circle on Figure 3) will generate a new output value. The decision makers can further determine a threshold output score in deciding Go or Not Go for OCPs under evaluation which is 0.5 for this study.

Model validation

The developed ANFIS model must be validated to view its effectiveness. "Model validation is the process by which the input vectors from input/output data sets on which the FIS was not trained, are presented to the trained FIS model, to see how well the FIS model predicts the corresponding data set output values" (Matworks Inc., 2015). As explained earlier, the model effectiveness was measured using two methods, convergence and generalization as suggested by Refenes (1995) as applied by Wanaous *et al.* (2003).

Two statistical methods, RMSE and R were adopted to observe the convergence and generalization capability of the model. Convergence verifies the learning mechanism

		Average training error (RMSE)					
		2 MFs of input			3 MFs of input		
No.	Type of MF	Train	Test	Check	Train	Test	Check
1	Trimf	1.14×10^{-5}	0.304	0.215	2.97×10^{-7}	0.277	0.295
2	Trapmf	6.52×10^{-6}	0.256	0.148	1.44×10^{-7}	0.227	0.323
3	Gbellmf	5.71×10^{-6}	0.347	0.153	3.17×10^{-7}	0.119	0.160
4	Gaussmf	5.31×10^{-6}	*0.130*	*0.075*	1.90×10^{-7}	0.220	0.287
5	Gauss2mf	7.89×10^{-6}	0.305	0.172	1.33×10^{-7}	0.203	0.396
6	Pimf	5.82×10^{-6}	0.290	0.139	1.23×10^{-7}	0.208	0.405
7	Psigmf	4.30×10^{-6}	0.277	0.109	1.66×10^{-7}	0.196	0.370
8	Dsignmf	4.30×10^{-6}	0.277	0.109	1.66×10^{-7}	0.196	0.370

Table II. Result of Test-FIS of training, testing and checking data

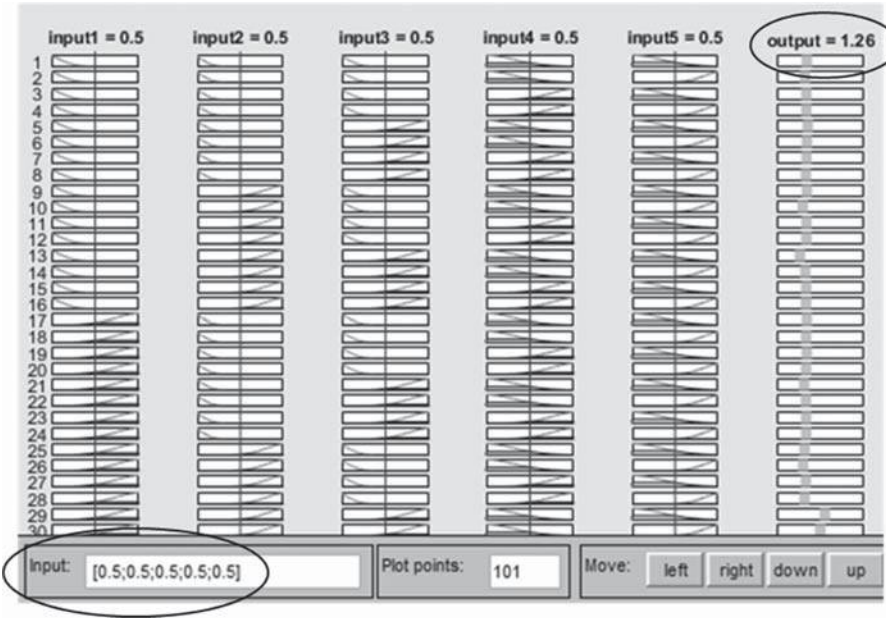

Figure 3.
ANFIS rule of Go/Not Go decision model

implemented for training data. As shown in Table II, Gauss MFs with two input MFs and hybrid learning method generated very small prediction errors (RMSE $=$ 0.130) for 22 cases of testing data and (RMSE $=$ 0.075) for 11 cases of checking data. These results verify the performance of modeling capability for the given cases.

The R between testing/checking data output and output result of trained ANFIS signifies the efficiency of the model. The closer the score of R to 1, the better the model fitness is obtained (Ebrat and Ghodsi, 2014). To calculate R value, first, the desired (A) and predicted outputs (F) were collected. Using ANFIS rule, the input scores of 22 testing and 11 checking data were set, while the generated outputs (F) were then recorded and tabulated. The score of R for testing and checking data set was then calculated using Equation (8). The calculations present the correlation between desired simulated test data set and predicted ANFIS model and between desired simulated checking data set and computed ANFIS model. R scores show 0.995 and 0.976 for testing and checking data, respectively, indicating a strong correlation as explained that the closeness of R scores to 1 is an indication of the fitness of the designed ANFIS model. Of both RMSE and R values, can be summarized that the performance of designed ANFIS model for Go/Not Go decision making in OCPs was found to be satisfactory.

The generalization ability of the ANFIS model is then examined further. This examination aims to verify the accuracy and correctness of the model when measuring real cases. This course of action measures the ability of the model in recognizing patterns beyond the learning samples (Wanaous *et al.*, 2003). Nine real cases of OCPs performed by Indonesian firms were used for this purpose. The evaluation of the five input variables was obtained from the experts who also involved in the projects. Though all projects were actually carried out, by observing the genuine environment during the execution of the projects, the experts were invoked to reassess and judge whether the projects are potentially feasible to be grabbed.

Before assessing the decision of the projects using ANFIS model for Go/Not Go decision making, the input data have to be normalized. Equation (6) was utilized to normalize the input data. Each normalized project data was then entered into trained system in which the ANFIS rule processes the data and generates a new output score.

With nine real-life cases of OCPs executed by Indonesian large contractors, the ANFIS model was able to predict the desirable decision with 11.11 percent fault. The result of real cases suggests a very good generalization ability of the proposed ANFIS model for Go/Not Go decision making in OCPs. Table III compares the decision made by experts between ANFIS model on nine real OCP cases.

Conclusion

The opening era in global trade has reinforced the business entity in which the local firms can expand their marketplaces outside their domestic market. Dealing with the complexity of problems in OCPs is a big challenge for decision making that either contractor should Go or should Not Go. In this paper, a new approach of supporting decision making based on the ANFIS algorithm in OCPs was demonstrated to resolve the problem. This neuro fuzzy technique resulted in a Go/Not to Go model with a good accuracy, above 88 percent of nine real cases of OCPs.

The development of the model began with determining the international factors in examining an OCP and creating a set of simulation cases representing OCPs' scenery. An evaluation form was designed to generate input–output scenario data set for ANFIS application. The optimum ANFIS model was achieved by trying all possible settings and comparing the error scores of each setting. The best setting of model was attained using a combination of parameter setting, e.g., number of membership function (two inputs), type of membership function (Gaussian or *gaussmf*) and optimization method (hybrid). Two measurers, RMSE and coefficient of correlation (*R*), also indicated that the model was found to be satisfactory.

Thoroughly, it should be noted that the aim of simulation cases is not merely to generate data set in the view of real world. Otherwise, it supplies an alternative scenario to enrich the environment of data set, so the experts can make decision in various circumstances. The expert's judgements on each case play a vital role in determining the decision model. This research has promoted and demonstrated a model for OCP decision making which a potential ability of neuro fuzzy integration in ANFIS was used. By determining the important key for international factors in OCPs and designing the OCP evaluation form, this study presents another method for making decision with multiple criteria in the context of international construction study.

Numerous efforts have been devoted to minimize the errors and the fallacy in this research. However, this research is limited by the lack of record of the OCPs which have been undertaken by Indonesian contractors, while there were difficulties to collect such information from primary sources. To solve this problem, the simulation cases reflecting the OCPs' environment were created as a historical databank. Consequently, the generated data might be nor representative or biased information. Thus, the model may or may not be genuine due to the involvedness of unknown variables.

Finally, this research used the ANFIS algorithm to develop the decision model. This system fully depends on the given historical data to generate an ANFIS based Go/Not Go model. In fact, different data enter to the system will produce different models. This system also needs a sufficient number of data in order to maximize its learning mechanism, so the produced model enables to accurately predict a new case. In consequence, the decision makers are restricted to incorporate a new factor or an attribute. In order to accommodate the new factor or attribute, the decision makers have to prepare a new database containing the new factor and redevelop a new model.

As indicated in research limitation, this study recommends using the real-life cases for improving the accuracy of the model and to produce the definitive evidences. Lastly, a cross-validation method, comparing results with other equal decision-making tools, such as general feedforward neural network can be carried out to view the accuracy and compare the performance of each tool.

Table III.
Data of OCPs for model generalization

OCP	Experts' judgement on real cases of OCPs					Expert judgement	ANFIS analysis							
	Project (X1)	Contract (X2)	Owner (X3)	Host country (X4)	Business (X5)		X1	X2	X3	X4	X5	Output score	Predicted decision	Note
A	8	7	4	7	3	Go	0.88	0.75	0.38	0.75	0.25	0.80	Go	Correct
B	6	7	8	6	6	Go	0.63	0.75	0.88	0.63	0.63	1.07	Go	Correct
C	7	3	5	7	6	Not Go	0.75	0.25	0.50	0.75	0.63	0.09	Not Go	Correct
D	4	4	6	6	7	Not Go	0.38	0.38	0.63	0.63	0.75	0.54	Go	Incorrect
E	8	6	6	5	5	Go	0.88	0.63	0.63	0.50	0.50	1.15	Go	Correct
F	6	8	4	5	5	Go	0.63	0.88	0.38	0.50	0.50	0.85	Go	Correct
G	6	7	6	8	4	Go	0.63	0.75	0.63	0.88	0.38	1.06	Go	Correct
H	8	7	7	7	5	Go	0.88	0.75	0.75	0.75	0.50	0.90	Go	Correct
I	7	8	7	5	7	Go	0.75	0.88	0.75	0.50	0.75	1.08	Go	Correct

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