

ANFIS multi criteria decision making for overseas construction projects: a methodology

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Abstract. A critical part when a company targeting a foreign market is how to make a better decision in connection with potential project selection. Since different attributes of information are often incomplete, imprecise and ill-defined in overseas projects selection, the process of decision making by relying on the experiences and intuition is a risky attitude. This paper aims to demonstrate a decision support method in deciding overseas construction projects (OCPs). An Adaptive Neuro-Fuzzy Inference System (ANFIS), the amalgamation of Neural Network and Fuzzy Theory, was used as decision support tool to decide to *go* or *not go* on OCPs. Root mean square error (RMSE) and coefficient of correlation (R) were employed to identify the ANFIS system indicating an optimum and efficient result. The optimum result was obtained from ANFIS network with two input membership functions, Gaussian membership function (*gaussmf*) and hybrid optimization method. The result shows that ANFIS may help the decision-making process for go/not go decision in OCPs.

1. Introduction

In the topic of internationalization of construction enterprises, the application of Multi-criteria Decision Making (MCDM) methods can be addressed to assess the capability of enterprises to operate outside their market origin and evaluate the potential projects to be considered for go or for bid [1]. In such decision, intuition and experience of decision makers in judging the capability of the firm may be more dominant. Several approaches such as Analytical Hierarchy Process [2], Cross Impact Analysis [3] and Analytical Network Process [4] have been adopted to solve the decision making problems in OCPs. Indeed, the intuition of decision makers plays important role in strategic decision making [5].

This study aims to demonstrate the integration of neuro-fuzzy system to support management decision in choosing OCPs. Adaptive Neuro-Fuzzy Inference System (ANFIS), a type of amalgamation of neural network (NN) and fuzzy logic (FL), was utilized to develop the decision model. NN can be used for dealing with a given problem if a set of data sample are available. Learning and computational abilities are the power of the NN [6]. Hence, a mathematical formulation and the previous knowledges are not necessary. The problem is that the solution deriving from the learning process in the networks cannot be interpreted because the character of the neural network seems a black box. On the other hand, the FL can be adopted to settle the problem if there is knowledge about the solution and the system can



be created by using the linguistic *if-then* rules. This system does not need training data and a mathematical model of the problem of interest [7]. The integration of the two systems will bring advantages to existing ones.

2. Concept 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 through implanting the Fuzzy Inference Rule (FIS) into the structure of adaptive networks [8]. The ANFIS model structure is constructed by both ANN and fuzzy logic which allow the model to work with uncertain and imprecise information [9]. It utilizes the NN training process to tune the membership function (MF) and the related parameter approaching the desired data sets [10]. Structurally, ANFIS consists of three devices namely, a rule base, a database, and a reasoning mechanism. The rule base constitutes fuzzy if-then rules following a linear function as described by Takagi and Sugeno [11].

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 the parameters determining the relation between input and output. ANFIS algorithm is composed of five layers as follows:

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

$$\begin{cases} \mu_i(x) \\ \mu_i(x) \end{cases} \quad (1)$$

Where $\mu_i(x)$ and $\mu_i(x)$ are membership functions of A and B fuzzy sets.

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 Equation 2.

$$\omega_i = \mu_i(x) \times \mu_i(x) \quad (2)$$

Layer 3: Every node N in this layer calculates the average ratio of previous outputs to produce a new output $\bar{\omega}$. It is obtained by Equation 3.

$$\bar{\omega} = \frac{\omega_i}{\sum \omega} \quad (3)$$

Layer 4: Square node in this layer produces an output $\bar{\omega}f_i$ based on Equation 4.

$$Y_i = \bar{\omega}f_i = \bar{\omega}(p_i x + q_i x + r_i) \quad (4)$$

Layer 5: This is an output layer in which the node calculates all outputs from Layer 4 by Equation 5.

$$Y = \sum_i \bar{\omega}f_i = \frac{\sum_i \omega f_i}{\sum_i \omega} \quad (5)$$

Learning process in a neural network aims to create a stable structure. In ANFIS, the learning process of network combines the least square estimate (LSE) and the gradient descent method. This hybrid learning procedure is composed of a forward step in which the input signal passes forward until Layer 4, where the output parameters are 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 [12]. 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 set.

3. Methodology

The hierarchy structure of the model development for OCP selection is illustrated in Figure 1. It consists of four main steps; determination of attributes, data collection, ANFIS operation, and recommendation. The process begins with a determination of criteria for OCP assessment. These criteria were obtained from data analysis of Delphi survey. Based on the criteria, an evaluation form of OCP was designed as an instrument to build cases database.

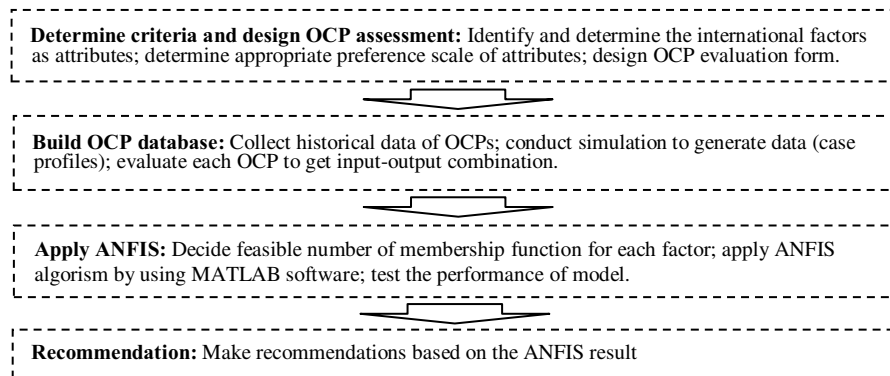


Figure 1. Hierarchical structure of model development

Two methods, convergence and generalization proposed by Refenes [13] were adapted to validate and verify the applicability and performance of the model. Convergence views the learning mechanism implemented for training data. It indicates the optimum performance of the model and the accuracy. The indicator to measure the performance is Root Mean Square Error (RMSE). Regarding its efficiency, the model is indicated by the correlation coefficient (R) formulated as:

$$R = \frac{\sum_{i=1}^N (A_i - \bar{A})(F_i - \bar{F})}{\sqrt{\sum_{i=1}^N (A_i - \bar{A})^2 \times \sum_{i=1}^N (F_i - \bar{F})^2}} \quad (6)$$

Where A_i , F_i and N are actual scores, calculated score produced by model and number of data respectively. The ideal characteristics of the model have RMSE score of 0 and R closed to 1 or 100%.

4. ANFIS based ‘Go/Not go’ decision model

ANFIS system needs a set of input-output pair data. In preparation of such data, the OCP cases were then tabulated in a table presenting five input attributes (project, contract, owner, host country and business) and one output (Go/Not Go). The grades given by the experts were then normalized using equation $x' = \frac{x - \min}{\max - \min}$ where x' is normalized score, x is initial score, and \min and \max are the smallest and the largest scores. This equation casts the initial scores in one unified range [0 to 1]. The different ranges between input value and output value need the data to be normalized.

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. [14] advice that the use of 1 and 0 approach in imitative based learning algorithms result in very slow learning speed. They suggest assigning 0.95 and 0.05 instead of 1 and 0 to avoid expected slow convergence. The cases are then divided into training (70%), testing (20%) and checking (10%) data sets. The training data set is used for generating an initial ANFIS model, whereas the testing and checking data sets are used for validation and generalization of the model respectively.

Before starting the fuzzy inference system (FIS) training, an initial FIS model structure needs to be specified by choosing *grid partition* that generates a single-output Sugeno-type FIS by using grid partitioning on the data. While generating FIS, the number of membership functions (MFs) at INPUT, were set for [2 2 2 2 2] which indicate that each input has two MFs (Low – High), whereas their type of MFs were set at “trimf” indicating triangular MF, and at OUTPUT, “linear” was chosen as the type of MF. The ANFIS editor provides eight types of MFs. This setting creates an ANFIS model structure in which to obtain the optimum ANFIS model indicated by the training minimum error, the number and type of input MFs are tuned arbitrarily.

Given the above parameters, the system was trained with *hybrid* learning algorithm. Another set parameter in ANFIS editor is *Error tolerance*, which determines a stopping criterion of training related to the size of error. 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 RMSE of the training and checking data sets at each epoch.

Each Train-FIS process basically creates an ANFIS model which is a trained system. As stated above, the average training error records the RMSE, and to find the RMSE of each data set, the trained systems were then tested against training, testing and checking data set. Test-FIS in ANFIS editor is used to test the data set. The average train errors shown for each option constitute the RMSE for the given data as tabulated in Table 1.

Table 1. Result of Test-FIS of training, testing and checking data

No	Type of MF	Average training error (RMSE)					
		2 MFs of input			3 MFs of input		
		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

Overall, the RMSE of each data for various numbers and types of MFs show very small value (close to 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 errors for testing the data of both parameters were 0.130 and 0.227, and for checking the data were 0.075 and 0.323. Based on the results, the ANFIS model for GO/Not Go decision on OCP was developed using three parameters: two input membership functions, Gaussian membership function (*gaussmf*), 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 illustrated in Figure 2. This IF-THEN rule displays the all records of FIS and enables management to make a quick choice of OCP by substituting the input scores based on an analysis of a particular project. Changes made on score of each input generate a new output value. Thus, the decision makers can further determine a threshold output score in deciding Go or Not Go for OCPs under evaluation.

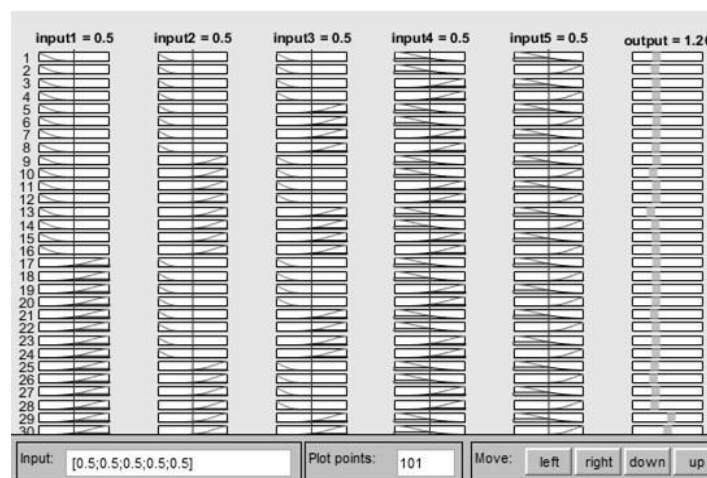


Figure 2. ANFIS rule of Go/Not go decision model

The correlation coefficient (R) between testing/checking data output and output result of trained ANFIS signifies the efficiency of the model. To calculate R value, first, the desired and predicted outputs were collected. Using ANFIS rule (Figure 2), the input scores of 22 testing and 11 checking data were set, while the generated outputs were then recorded. The score of R for testing and checking data set was then calculated using the given equation. The results are 0.995 and 0.976 showing a strong correlation and 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. Nine real cases of OCPs performed by Indonesian firms were used for this purpose. Before assessing the decision of the projects using ANFIS model for Go/Not Go decision making, the input data was normalized. Each normalized project data was then entered into trained system in which the ANFIS rule (Figure 2) processes the data and generates an output score. With nine real-life cases of OCPs executed by Indonesian large contractors, the ANFIS model could predict the desirable decision with 11.11% 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.

5. Conclusion

This paper demonstrates the ability of ANFIS for supporting the decision-making in OCPs selection. The developed model using this approach gives several advantages combining fuzzy reasoning (e.g. ability in handling uncertainty regarding imperfect information) and neural network (i.e. ability in learning and generalizing from a set of prior knowledges). The developed model was based on the simulation cases of OCPs which evaluates the Indonesian contractors. The evaluation results may be different from other contractors, so the model may also diver.

The use of simulation cases and small number of data sets are the limitation of this study. However, there exist several advantages of using simulation cases, such as a freedom to select attributes contributing to the complexity of the structure of data, and the possibility of tuning different scenarios tailored to meet various conditions which are not available in real data sets. In future, the use of an appropriate numbers of real data sets is encouraged. A cross-validation method, comparing results with other approaches, such as statistical techniques and case based reasoning, can be carried out to view the accuracy of each tool.

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