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Evaluation of Innovation Performance in Construction with ANFIS

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Abstract. This study aims to measure the innovation performance of consulting companies in Thailand construction industry. Input variables include factors associated with quality objectives, engineering objectives, innovation objectives and technical information resource Adaptive neuro-fuzzy inference systems (ANFIS) is used to develop an evaluation model by applying Sugeno ANFIS. The decision makers can use the fuzzy neural network approach to adjust the resource allocation to meet the company's objectives.

Keywords: innovation, quality, adaptive neuro-fuzzy inference systems, Sugeno ANFIS

1. Introduction

Construction projects are of unique and dynamic nature. The construction industry has been continually criticized for not achieving the level of improvement in performance and productivity shown by other industrial sectors. The industry has been under considerable pressure to improve the efficiency of the construction process. Pressure is also increasing from clients who demand better products in shorter duration and using fewer resources. This has created a national need for reform to challenge the change for innovation in construction. New challenges require new approaches. A vision of change for innovation within the perspective of revaluing the construction industry is very necessary to develop a culture of continuous improvement. The global competitiveness, organizational culture and change, usage of IT, performance measures and benchmarking for continuous improvement, best practices for constructability, and sustainable development are the key issues affecting construction industry in Thailand.

Currently, several studies have been done on development of the forecasting models which have focused on engineering performance, quality performance, and sustainability performance. However, innovation performance and the appropriate indicators of long-term technology investment into consideration are rarely concerned. Therefore, the integration of innovation objectives and other objectives are seldomly determined, especially in the construction industry. Wang and Chien (2006) [1] elaborated an innovation performance forecasting model wing an adaptive neural network (ANN), it still existed some problems, such as choosing the influence indicators, solving the linguistic character of sources, explaining the training procedure of outcome, describing how to simulate the rules for prediction, and finding robust forecasting techniques. To overcome these drawbacks, Chien, Wang and Lin (2010) [2] proposed an adaptive neuro-fuzzy inference systems (ANFIS) to measure the innovation performance through technical information resource and innovation objective. However, many scholars have suggested that both total quality management (TQM) and organizational learning can individually and effectively promote innovation. The study on the measurement of impact of TQM and organizational learning on the innovation performance is not much concerned. The research focus is to investigate the factors affecting innovation in Thailand construction industry. The main objective is to (1) determine the integration of TQM regarding quality objectives, engineering objectives, innovation objectives and technical information resource (2) evaluate impacts of quality objectives, engineering objectives, innovation objectives and technical information resource on

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innovation performance (3) propose solutions for decision makers to adjust the resource allocation to meet their innovation objectives.

2. Research Framework

As mentioned earlier, the objectives of this study were, first, to examine the integration of TQM regarding quality objectives, engineering objectives, innovation objectives and technical information resource, and second, to investigate the impact of the integration on innovation performance. In order to realize this objective, as articulated in three research questions above, a research framework was developed. The framework is a simple linear model of the relationship between the independent and dependent variables. Organizational practices as the independent variable consists of four blocks. The first block of organizational practices is labeled as engineering performance, and comprises nine sets of practices: construction cost with strict quality requirements, changes in owner's policy(s), construction cost increase due to deficiencies in defining owner's requirements, design deficiencies due to changes in owner's requirements, design deficiencies due to owner reducing project duration, design deficiencies due to owner reducing project cost with strict quality requirements, contractor selection is based mainly on cost criterion, changes in owner's requirements, unclear information during an early stage of a project. TQM practices as the second block comprise of six variables: leadership, strategy and planning, customer focus, information and analysis, people management, and process management. Innovation objectives as the third block consist of eleven variables: improvement of production flexibility, improvement of product, extending product, opening up new product, fulfillment of regulation & standards, replacement of product, reduction of labor cost, reduction of raw material consumption, reduction of energy consumption, reduction of environmental damage, and government support. The forth block is the technical information resources including thirteen variables: source within company, other companies within group, competitors, clients or customers, consultancy companies, supplier of equipment, materials, universities or other education institutes, government non-profit organizations, patent disclosers, professional conferences, meetings, journals, computer-based information networks, fairs, exhibitions, and strategic allies.

3. Neuro-Fuzzy Model

The neuro-fuzzy system attempts to model the uncertainty in the factor assessments, accounting for their qualitative nature. A combination of classic stochastic simulations and fuzzy logic operations on the ANN inputs as a supplement to artificial neural network is employed. Artificial Neural Networks (ANN) has the capability of self-learning, while fuzzy logic inference system (FLIS) is capable of dealing with fuzzy language information and simulating judgment and decision making of the human brain. It is currently the research focus to combine ANN with FLIS to produce fuzzy network system. ANFIS is an example of such a readily available system, which uses ANN to accomplish fuzzification, fuzzy inference and defuzzification of a fuzzy system. ANFIS utilizes ANN's learning mechanisms to draw rules from input and output data pairs. The system possesses not only the function of adaptive learning but also the function of fuzzy information describing and processing, and judgment and decision making. ANFIS is different from ANN in that ANN uses the connection weights to describe a system while ANFIS uses fuzzy language rules from fuzzy inference to describe a system.

The ANFIS approach adopts Gaussian functions (or other membership functions) for fuzzy sets, linear functions for the rule outputs, and Sugeno's inference mechanism [3]. The parameters of the network are the mean and standard deviation of the membership functions (antecedent parameters) and the coefficients of the output linear functions as well (consequent parameters). The ANFIS learning algorithm is then used to obtain these parameters. This learning algorithm is a hybrid algorithm consisting of the gradient descent and the least-squares estimate. Using this hybrid algorithm, the rule parameters are recursively updated until an acceptable level of error is reached. Each iteration includes two passes, forward and backward. In the forward pass, the antecedent parameters are fixed and the consequent parameters are obtained using the linear least-squares estimation. In the backward pass, the consequent parameters are fixed and the error signals propagate backward as well as the antecedent parameters are updated by the gradient descent method. Based on the original ANFIS study [4]; the learning mechanisms should not be applied to determine membership functions in the Sugeno ANFIS, since they convey linguistic and subjective descriptions of possibly ill-defined concepts. Hence, the choice of membership function should depend on the specific types of data.

3.1. ANFIS Architecture

The acronym ANFIS derives its name from adaptive neuro-fuzzy inference system. The ANFIS has five layers. The first layer calculates the degree of membership of all inputs. The second layer calculators examine the fitness of each rule. The third layer calculators determine the normalized value of the fitness. The fourth layer calculates the output of each rule. The fifth layer produces the output of the fuzzy system. In this network, both the characteristic parameters and the conclusion parameters are included. During the training process, ANFIS dynamically adjusts these parameters. As a result, the network can accurately describe the mapping between the input and output data [5]. An ANFIS architecture is equivalent to a two-input first-order Sugeno fuzzy model with nine rules, where each input is assumed to have three associated membership functions (MFs) [4].

3.2. Input/output Indicators

The input/output indicators are the input/output vectors of the ANFIS. Generally, the decision makers adopt the input vector, along with output vector, to train the ANFIS and subsequently to obtain the weights. Eleven innovation objectives and thirteen innovation information resources are used as input variables; simultaneously, eight innovation performance measurements are used as output variables. These input variables were used in the measurement of the innovation performance by Wang and Chien (2006) [1]. Together, these variables were proposed by the OECD's 'Oslo Manual' [6] as standardized measurements. This study consider impact of quality performance and engineering performance, thus attributes associated with the quality performance and engineering performance become the input variables. Input/output variables are presented in Table 1.

3.3. Training ANFIS and Obtaining the Innovation Performance of Project

For proving the applicability of the model and illustration, the proposed model was applied in ten of the consulting companies in Thailand. The first step to apply the model was to construct the decision team. The decision team included top and middle managers: strategic planning manager, financial manager, engineering manager, quality control and insurance manager and process manager. For training the ANFIS, some experiences about the system behaviour are necessary. For this aim, a questionnaire was designed including different combinations of criteria. The decision team was asked to give a score to them if possible at all, based on their knowledge about the system. But where the number of antecedents (criteria) is large, it is not practical to ask the decision team. Thus, they were asked to consider the input variables as shown in Table 1for being the assessment criteria for their company. Then, they rated the potential projects with respect to each criterion in the range of [0, 10]. From 44 attributes generated by the proposed approach, the decision makers derived 44 completed questions, as much as possible for decision team to answer. We used 50 of them for training the ANFIS and the rest (30) for checking and validation of the model. For rule generation, we used subtractive clustering where the range of influence, squash factor, acceptance ratio, and rejection ratio were set at 0.5, 1.25, 0.5 and 0.15, respectively during the process of subtractive clustering. The trained FIS includes 28 rules (clusters) as present in Fig 1. Because by using subtractive clustering, input space was categorized into 28 clusters. Each input has 28 Gaussian curve built-in membership functions. Fig 2 shows the surface of ANFIS after training. The training error of the ANFIS was 0.013 after 100 epochs. The rate of projects with respect to criteria and the output of ANFIS (innovation performance level of projects) have been shown in Table 2. By increasing the number of epochs, we could have reached the less training error, but the over-fitting would occur (incremental trend of checking error).

4. Concluding Remarks

A major objective of this paper was to propose an ANFIS model to predict the innovation performance for Thailand's construction industry. The findings confirm factors associated with quality objectives, engineering objectives, innovation objectives and technical information resource are the four input dimensions, while innovation performance is the output variable for the proposed model. To face the challenge in the competitive environment, construction industries are training to innovative activities, in order to sustain their competitiveness. Since it is an important lesson for decision makers aiming to perform the suitable strategies and resources allocation, the findings present a model of how innovation performance was predicted through quality objectives, engineering objectives, innovation objectives and technical information resource In addition, the results reveal that the ANFIS model improves innovation performance forecasting by using fuzzy rules to generate the adaptive neuro-fuzzy network, as well as a rotation method of training and testing data selection which is designed to enhance the reliability of the sampling process before constructing the training and testing model. Moreover, our find points to that model based on the neuro-fuzzy network can achieve better results than the neural network or statistical techniques. Finally, the ANFIS model can explain the training procedure of outcome and how to simulate the rules for prediction. Meanwhile, it also offers more accuracy on prediction. For the evaluated project, the factors of Leadership, Product innovation,, Source within company, and Computer-based information networks were found to be the key issues that the company need to confront environment if the company want to sustain a distinctive competency.

Table 1: input/output indicators

Input variable				Output variable
Engineering performance criteria for private project	Quality performance criteria	Innovation objective	Technical information resource	Innovation performance
1. Reduction of construction cost with strict quality requirements 2. Changes in owner's policy(s) 3. Construction cost increase due to deficiencies in defining owner's requirements 4. Design deficiencies due to changes in owner's requirements 5. Design deficiencies due to owner reducing project duration 6. Design deficiencies due to owner reducing project cost with strict quality requirements 7. Contractor selection is based mainly on cost criterion 8. Changes in owner's requirements 9. Unclear information during an early stage of a project	1. Leadership (lead) 2. Strategic planning (plan) 3. Customer focus (cust) 4. Information & analysis (info) 5. People management (peop) 6. Process management (proc) 7. Technology management (tech) 8. Research & development (r&d) 9. Product quality (qual) 10. Product innovation (pdin) 11. Process innovation (pcin)	1. Improve production flexibility 2. Improve product 3. Extend product 4. Open up new markets 5. Fulfill regulation & standards 6. Replace products 7. Reduce labor costs 8. Reduce raw material consumption 9. Reduce energy consumption 10. Reduce environmental damage 11. Government support	1. Source within company 2. Other companies within group 3. Competitors 4. Clients or customers 5. Consultancy companies 6. Supplier of equipment, materials 7. Universities or other education institutes 8. Government non-profit organizations 9. Patent disclosers 10. Professional conferences, meetings, journals 11. Computer-based information networks 12. Fairs, exhibitions 13. Strategic allies	1. Number of incrementally innovative products introduced in the last three years (INCRPROD) 2. Number of radically innovative products introduced in the last three years (RADIPROD) 3. Number of new innovative construction processes introduced in the last three years (INNOPRON) 4. Number of innovative construction processes introduced in the last three years (INNOPROI) 5. Percentage of current sales due to incrementally innovative products introduced in the last three years (SALEINCR) 6. Percentage of current sales due to radical innovative products introduced in the last three years (SALERADI) 7. The number of R&D employees in the last three years over current total number of employees (RDEMPLYE) 8. Number of patents acquired in the last three years (PATENTS)

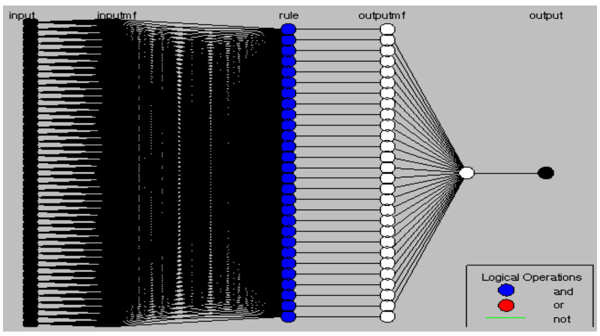

Fig1: Network of innovation performance by the ANFIS

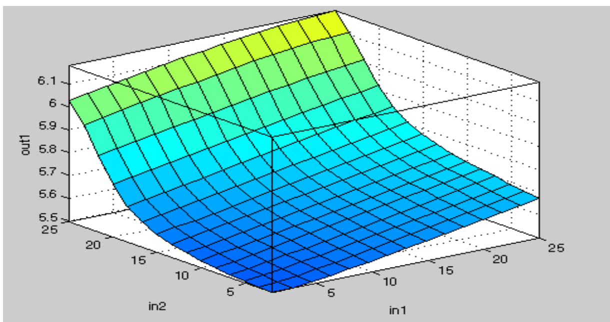

Fig. 2: Trained main ANFIS surface

Table 2: Inputs (rates of a case study project) and output of ANFIS

Input variable/input value	Output variable/output value

Engineering performance criteria for private project		Quality performance criteria		Innovation objective		Technical information resource		Innovation performance	
1. Reduction of construction cost with strict quality requirements	0.8	1. Leadership (lead)	3.2	1. Improve production flexibility	1.8	1. Source within company	4	1. Number of incrementally innovative products introduced in the last three years (INCRPROD)	20
2. Changes in owner's policy(s)	0.4	2. Strategic planning (plan)	1.8	2. Improve product	0.2	2. Other companies within group	1.8	2. Number of radically innovative products introduced in the last three years (RADIPROD)	
3. Construction cost increase due to deficiencies in defining owner's requirements	1.2	3. Customer focus (cust)	0.2	3. Extend product	0.8	3. Competitors	2.4	3. Number of new innovative construction processes introduced in the last three years (INNOPRON)	
4. Design deficiencies due to changes in owner's requirements	0.6	4. Information & analysis (info)	0.2	4. Open up new markets	1.2	4. Clients or customers	1.2	4. Number of innovative construction processes introduced in the last three years (INNOPROI)	
5. Design deficiencies due to owner reducing project duration	1.8	5. People management (peop)	0.8	5. Fulfill regulation & standards	1.8	5. Consultancy companies	1.8	5. Percentage of current sales due to incrementally innovative products introduced in the last three years (SALEINCR)	
6. Design deficiencies due to owner reducing project cost with strict quality requirements	0.2	6. Process management (proc)	1.8	6. Replace products	0.8	6. Supplier of equipment, materials	1.2	6. Percentage of current sales due to radical innovative products introduced in the last three years (SALERADI)	
7. Contractor selection is based mainly on cost criterion	0.8	7. Technology management (tech)	0.8	7. Reduce labor costs	1.2	7. Universities or other education institutes	2.4	7. The number of R&D employees in the last three years over current total number of employees (RDEMPLYE)	
8. Changes in owner's requirements	0.4	8. Research & development (r&d)	1.8	8. Reduce raw material consumption	1.2	8. Government non-profit organizations	2.4	8. Number of patents acquired in the last three years (PATENTS)	
9. Unclear information during an early stage of a project	1.8	9. Product quality (qual)	0.8	9. Reduce energy consumption	1.2	9. Patent disclosers	1.2		
		10. Product innovation (pdin)	3.2	10. Reduce environmental damage	4	10. Professional conferences, meetings, journals	1.2		
		11. Process innovation (pcin)	0.2	11. Government support	1.8	11. Computer-based information networks	5		
						12. Fairs, exhibitions	1.2		
						13. Strategic allies	0.2		

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