Evaluation of Quality Management Performance in Office of President using Modified Public Sector Management Quality Award (PMQA) Model

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Abstract

This paper presents the application of adaptive neuro-fuzzy inference systems (ANFIS), using Sugeno ANFIS to measure the quality management performance of Office of President (OOP). Attributes associated with Public Sector Management Quality Award (PMQA) criteria are considered as the input and output variables for the main-model and sub-models, respectively. The dependent variable is the quality management performance. Staffs in the Office of President provided data for this study. The result can be used to improve its quality as well as to achieve high performance organization.

Keywords: quality, adaptive neuro-fuzzy inference systems, Sugeno ANFIS
1. Introduction

Most educational projects are of unique and dynamic nature. The educational project has been continually criticized for not achieving the level of improvement in performance and productivity shown by other types of projects. The Office of President has been under considerable pressure to improve the efficiency of the educational process. Pressure is also increasing from clients who demand better outputs and outcomes in shorter duration. This has created a university need for reform to challenge the change for quality management in the Office of Present. New challenges require new approaches. A vision of change for quality management within the perspective of revaluing the Office of President 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 educational management, and sustainable development are the key issues affecting educational projects.

During the 1990s, the main emphasis of Thailand’s manufacturing industry was on implementing ISO 9000 standards. Although different TQM approaches and tools, such as just-in-time, total productive maintenance, have been applied since the 1980s [1], a number of foreign-owned companies within the electronics sector, and few Thai-owned groups, have successfully implemented TQM [2]. Considering TQM positioning, Thailand ranks in the middle of the developing countries of Southeast Asia. Its status in TQM is higher than Indonesia or Philippines, and lower than Malaysia or Taiwan [2].

For the implementation of TQM in Thailand, little empirical research has been rarely conducted in Thai manufacturing companies. The current situation of TQM implementation in Thai manufacturing companies is vague. As a result of the fact that the empirical studies in the area of TQM implementation are limited, it is difficult for Thai manufacturing companies to obtain sufficient information to support their TQM implementation process. Thus, Thai manufacturing companies are experiencing numerous difficulties, and even failures in implementing TQM. Many industries should take up the concept of total quality management (TQM) in order to improve their performance, especially for the construction industry. As Tyler and Frost [3] have pointed out, quality assurance (QA) has been taken seriously only recently in the UK construction industry, and even then only in the large contracting companies. For example, Bhattari [4] showed that none of the medium-sized construction companies had introduced QA systems.
One of the key emphases of a quality award is, for a company to achieve sustainable financial success. In the instance of MBNQA, the award winning firms reported a 44% higher stock-price return, 48% higher growth in operating income, and a 37% higher growth in sales than the control group of firms [5]. Organizations are using various criteria to help them during implementation efforts to evaluate themselves against criteria to determine how well their improvement efforts are progressing. Sets of criteria that the majority of organizations uses include Deming prize categories, Juran’s ten points, Crosby’s fourteen points, and the MBNQA criteria [6]. The present study will adopt a case from Thailand for examples. Accordingly, Public Sector Management Quality Award (PMQA) criteria will be adopted as the quality management performance evaluation criteria. The PMQA has a hierarchical structure. It has seven strategic criteria. Each strategic criterion has its associated sub-criteria. Currently, several studies have been done on development of the forecasting models which have focused on engineering performance, quality performance, innovation performance and sustainability performance. However, the appropriate indicators for the Office of President are rarely concerned. Therefore, the integration of quality management objectives and other objectives are not determined. Wang [7] 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 et, al. (2010) [8] proposed an adaptive neuro-fuzzy inference systems (ANFIS) to measure the innovation performance through knowledge management objective 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 on the quality management performance of the Office of President is not much concerned. The research focus is to investigate the factors affecting quality management performance in the Office of President. The main objective is to (1) determine the integration of PMQA criteria, (2) evaluate impacts of PMQA criteria on quality management performance (3) propose solutions for highway project manager to improve the project’s quality as well as to achieve high performance organization. A newly developed system is to automate and enhance the process of determining or measuring a reasonable quality performance for projects from the officers’ perspective. Projects developed by the Office of President have been used as data sources for this study.
2. Research Framework

As mentioned earlier, the objectives of this study are; first, to determine the integration of PMQA criteria. The PMQA has seven strategic criteria. Each strategic criterion has its associated sub-criteria. This study used the PMQA criteria as a guideline for developing a model. Figure 1 presents 31 sub-criteria and the integration among sub-criteria or sub-attributes associated with each criterion or attribute in a proposed model. In addition, the integration among attributes was considered. The second objective is to measure impact of PMQA criteria on the quality management performance of the Office of President. In order to realize this objective, a research framework is developed. The framework is a simple linear model of the relationship between the independent and dependent variables. Attributes associated with PMQA criteria are considered as the independent and dependent variables for the main-model and sub-models, respectively. For the main-models, the independent variables consists of six blocks including 1) leadership (LD), 2) strategy planning (SP), 3) customer and stakeholder (CS), 4) information technology (IT), 5) human resource (HR), and 6) process management (PM). The dependent variable is the quality management performance considered from the combination of six variables including 1) prestige measurement, 2) unique competitive ability gaining performance, 3) customer satisfaction, 4) information management performance, 5) human resource development performance, and 6) process management performance. In total, there are 31 sub-criteria as shown in Fig.1.

For the sub-models, the independent variables associated with each of these six blocks are determined separately. For example, the leadership model has five independent variables including 1) operational value and ideals restructure, 2) organizational quality improving mission, 3) top managers’ leading style, 4) quality culture construction and, 5) increasing of social contribution. Dependent variable is Prestige measurement. Sub-attributes associated with each block are shown in Fig 2.

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 [9]. 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 [10]; 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.
**Fig 1** Criteria and sub-criteria of Public Sector Management Quality Award (PMQA) model
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 [11]. 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) [10].

3.2. Input/output Indicators

The first step in the modeling process based on an ANFIS involves the identification of the input and output variables. 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. For example if a two input (x, y)
and one output (f) fuzzy inference system is considered, then for a first-order Sugeno fuzzy model, a typical rule set with two fuzzy IF/THEN rules can be expressed as

Rule 1: If \( x \) is \( A_1 \) and \( y \) is \( B_1 \), then \( m_1 = x_1 + y_1 + z_1 \)

Rule 2: If \( x \) is \( A_2 \) and \( y \) is \( B_2 \), then \( m_2 = x_2 + y_2 + z_2 \)

where \( x_1, x_2, y_1, y_2, z_1 \) and \( z_2 \) are linear parameters, and \( A_1, A_2, B_1 \) and \( B_2 \) are nonlinear parameters.

The ANFIS structure includes five layers as shown in Fig 3. 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. The input, output and node functions of each layer, is discussed in the subsequent sections. Each of these layers consists of a number of nodes connected through direct links. Each node represents a process unit, and the links between nodes specify the causal relationship between the connected nodes. Some parts of the nodes are adaptive while others are fixed. Adaptive nodes are denoted by using square box while the circular nodes denote fixed nodes. Each adaptive node has a set of parameters that performs a particular function (node function) on the incoming signal. The learning rules specify the parameters of adaptive nodes that need to be changed to minimize a prescribed error measure. However, the change in values of the parameters results in change in the shape of membership functions associated with the fuzzy inference system.
Layer 1 is the fuzzy layer, in which m and n are the input of nodes A1, B1 and A2, B2 respectively. A1, A2, B1 and B2 are the linguistic labels used in the fuzzy theory for dividing the membership functions. The membership relationship between the output and input functions of this layer can thus be expressed as:

\[ O_{i,j} = \mu_{A_i}(m) \quad (i = 1, 2) \]  
\[ O_{i,j} = \mu_{B_j}(n) \quad (j = 1, 2) \]

where, \( O_{i,j} \) denotes the output functions and \( \mu_{A_i} \) and \( \mu_{B_j} \) denote the membership functions.

Also, each node in Layer 2 multiplies the incoming signals from the various inputs. In layer 2, each node is a representation of one rule and the inputs are degrees of membership functions which are multiplied through a T-norm operator to determine the degree of fulfillment of wi of the rule. Hence each node output is the firing strength of the rule.

\[ O_{2,i} = w_i = \mu_{A_i}(m)\mu_{B_j}(n) \quad (i = 1, 2) \]

where, \( O_{2,i} \) denotes the output of layer 2.
Further, all the nodes in third layer are fixed nodes and for every $i^{th}$ node, the ratio of the $i$th rule's firing strength in inference layer to the sum of all the rules' firing strengths is calculated as

$$O_{3,i} = \bar{w}_i = \frac{w_i}{\sum_{i=1}^{2} w_i} \quad (i = 1, 2)$$

(4)

The output, $O_{3,i}$ of this layer is called the normalized firing strength.

Furthermore, the fourth layer is the de-fuzzy layer whose nodes are adaptive. The output equation for this layer becomes $w(x_i m + y_in + z_i)$, where $x_i$, $y_i$, and $z_i$ represent the linear parameters or so called consequent parameters of the node. The de-fuzzy relationship between the input and output of this layer can thus be defined as:

$$O_{4,i} = \bar{w}_{ij} = \bar{w}_i (x_i m + y_in + z_i) \quad (i = 1, 2)$$

(5)

where, $O_{4,i}$ denotes the output of layer 4.

The final output in the layer 5 computes the summation of all incoming signals. Thus there is just one node in this layer with a simple summing function, defines as:

$$O_{5,i} = \sum \bar{w}_i f_i = \sum \frac{w_i f_i}{\sum_{i=1}^{2} w_i} \quad (i = 1, 2)$$

(6)

where, $O_{5,i}$ denotes the output of layer 5.

For the main-model, input variables include 1) leadership (LD), 2) strategy planning (SP), 3) customer and stakeholder (CS), 4) information technology (IT), 5) human resource (HR), and 6) process management (PM). The output variable is the quality management performance. There are six sub-models associated with the input variables of the main-model. Table 1 shows the input/output variables of the sub-models. This study considers factors having the impact on quality management performance, thus attributes associated with the quality management performance become the input variables.

3.3. Training ANFIS

For proving the applicability of the model and illustration, the proposed model was applied in thirty of the research projects in Thailand. The first step to apply the model was to construct the decision team. The decision team included officers in Office of President. For training the ANFIS, some experiences about the system behavior 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. Then, they rated the educational projects with respect to each criterion. The input parameters are represented on the unit universe [0,10] with triangular or trapezoidal membership functions describing the linguistic variables such as the operation performance, for example: "low", "medium" or "high" (Fig. 4). The system was built in the Matlab Fuzzy Toolbox and Simulink environment. A Matlab programme was generated and compiled. The pre-processed input/output matrix which contained all the necessary representative features, was used to train the fuzzy inference system. Fig 5 show membership functions describing the linguistic variables such as the Operational values and ideals restructure (C1), for example: "low", "medium" or "high" after training the network. Fig 6 shows the structure of the ANFIS; a Sugeno fuzzy inference system was used in this investigation. Based on the collected data, 50 data sets were used to train the ANFIS and the rest (41) for checking and validation of the model. For the first sub-model (Leadership) for 5 attributes generated by the proposed approach, the decision makers derived 6 completed questions, as much as possible for decision team to answer. Subtractive clustering was used for rule generation, 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 14 rules (clusters). Because by using subtractive clustering, input space was categorized into 14 clusters. Each input has 14 Gaussian curve built-in membership functions. Fig 6 shows the surface of ANFIS after training. The training error of the ANFIS was 0.8074 after 30 epochs as shown in Fig 7. The trained fuzzy inference system includes 14 rules (clusters) as present in Fig 8.

Table 1 Input/output variables of sub-models

| Sub-model                  | Input variable                                      | Output variable                   |
|----------------------------|-----------------------------------------------------|-----------------------------------|
| Leadership (LD)            | Operational values and ideals restructure (C1)      | Prestige measurement             |
|                            | Organizational quality improving mission (C2)       |                                    |
|                            | Top managers’ leading style (C3)                    |                                    |
|                            | quality culture construction (C4)                   |                                    |
|                            | The increasing of social contribution (C5)          |                                    |
| Strategy planning (SP)     | Organization of operation strategy planning (C6)    | Unique competitive ability        |
|                            | Operation structure adjustment (C7)                 | gaining performance               |
|                            | The quality improvement of strategy (C8)            |                                    |
| Customer and stakeholder   | Market operation strategy development (C9)          | Customer satisfaction             |
|                            | Business relation management (C10)                  |                                    |
| Category                | Examples                                                                 |
|-------------------------|--------------------------------------------------------------------------|
| Customer relationship management (C11) | Information technology (IT) process redefinition of R&D and innovation (C12) |
|                         | Input of R&D and innovation (C13)                                        |
|                         | Evaluation of R&D and innovation results (C14)                           |
|                         | Construction technology information receiving channel (C15)             |
|                         | Internet applications (C16)                                              |
|                         | Construction technology information utilization (C17)                   |
| Human resource (HR)     | Human resource planning (C18)                                            |
|                         | Human resource development (C19)                                         |
|                         | Human resources utilization (C20)                                        |
|                         | Employee relationship management (C21)                                   |
|                         | Knowledge management (C22)                                               |
| Process management (PM) | Manufacturing process management (C23)                                   |
|                         | Supportive activity planning (C24)                                       |
|                         | Cross-unit (Department) Management (C25)                                 |
| Result based management (RM) | Customer satisfaction (C26)                                               |
|                         | Human resource development performance (C27)                             |
|                         | Information management performance (C28)                                 |
|                         | Process management performance (C29)                                     |
|                         | Unique competitive ability gaining performance (C30)                    |
|                         | Prestige measurement (C31)                                               |

**Fig 4.** Membership functions of the leadership sub-model (before Training)

**Fig 5.** Membership functions of the operation performance (after Training)

Fig 9 depicts a three dimensional plot that represents the organizational quality improving mission (in2) and increasing of social contribution (in5) to prestige measurement (out1). The assumption is that the collected data are representative of the features of the data that the
trained FIS is intended to model. However, the accuracy of the model is affected by the inherently insufficient and training data which cannot cope with every feature of the data that should be presented to the trained model.

**Fig 6.** Network of leadership performance by the ANFIS

**Fig 7.** Training error of the ANFIS

**Fig 8.** Trained main ANFIS surface of supply chain performance

**Fig 9.** Trained main ANFIS surface: quality management performance

### 4. Concluding Remarks

A major objective of this paper was to propose an ANFIS model to predict the quality management performance for educational projects in the Office of President. The findings confirm factors associated with the PMQA criteria are the six input dimensions, while quality management performance is the output variable for the proposed model. To face the challenge in the dynamic environment, officers should understand the quality activities so as to sustain their competitiveness.
This paper examines a method named Adaptive Neuro-Fuzzy Inference System (ANFIS) as a tool to capture expert judgements on how the quality management performance can be assessed. Educational projects are used to demonstrate the models developed regarding the PMQA criteria. For example, five independent variables associated with the leadership performance are modeled using the proposed model. The value of leadership performance can then be calculated. From this study it can be recommended that the ANFIS can be used as tool to assess the quality management performance. However, each project is unique. The forecasted values are depended on a combination of expertise and the actual situation of a particular educational project being considered. The developed model can provide the value used as a guideline for assessing the quality management performance.

5. References

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