Hybrid intelligent scenario generator for business strategic planning by using ANFIS

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A R T I C L E   I N F O

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A B S T R A C T

The aim of this study is to investigate a new method for generating scenarios in order to cope with the data shortage and linguistic expression of experts in scenario planning. The proposed hybrid intelligent scenario generator uses an Adaptive Neuro-Fuzzy Inference System (ANFIS) to deal with uncertain inputs. In this methodology, the strengths of expert systems, fuzzy logic and Artificial Neural Networks (ANNs) are joined to generate possible future scenarios. The proposed methodology includes four steps: step 1 defines the scope and internal and external variables and step 2 determines rules from experts. Then, step 3 prepares ANFIS system which is conducted by computer programming in Matlab environment. The last step is sensitivity analysis to study the effects of variation of inputs on outputs. The applicability of the proposed method has been tested against two different case studies.

1. Introduction

The purpose of strategic planning is to guide an organisation to achieve its desired goals of the long-term development under the variation of environment (Wang, 1999). Therefore, the future events play a key role in business strategic planning and managers need a mental model of the future to make better decisions. There are some differences among uncertainties pertaining to future occurrence probability. When there is the low level of uncertainties in environment, qualitative approaches such as probability distribution and forecasting techniques are very useful for managing the existing risk and uncertainty. In the high level of uncertainties, qualitative approaches such as scenario planning may be useful to employ (Alessandri, Ford, Lander, Leggio, & Taylor, 2004). Scenario planning is not aimed at obtaining a forecast but instead produces alternative images of the future which can avoid the pitfalls of more traditional methods (Goodwin & Wright, 2001; Postma & Lieb, 2005). Managers are able to have much better positioning with regard to unexpected events by using scenario planning methods. Scenario planning attempts to capture the richness and range of possibilities, and considers changes that decision makers would otherwise ignore (Schoemaker, 1995).

Scenario planning has been defined as “a process of positioning several informed, plausible and imaginative alternative future environment in which decisions about the future may be played out for the purpose of changing current thinking, improving decision making, enhancing human and organizational learning and improving performance” (Chermack & Lynham, 2002). Various scenario planning approaches from literature are classified into two major categories: qualitative and quantitative.

SRI (Ringland, 1998), Future Group (Chermack, Lynham, & Ruona, 2001), Global Business Network (Chermack et al., 2001), Schoemaker (Schoemaker, 1995), and DSLP (Royes & Royes, 2004) methodologies are all subjective, qualitative in nature and firmly process-oriented. This means that organisational learning process in these approaches is more important than the reliability of the content of the end product, which is the scenarios (Bradfield, Wrightb, Burta, Cairnsb, & Van Der Heijdena, 2005). These approaches are not based on past data but consider qualitative and subjective information of experts to construct scenarios. On the other hand, Godet's methodology (Godet, 2001, 2006; Godet & Roubelat, 1996) which has been known as a quantitative method is essentially outcome-oriented. A quantitative methodology develops scenarios for particular phenomenon and sets key variables for a specific subject. The experts' rules in quantitative methodologies are not based on past data but consider qualitative and subjective information of experts to construct scenarios. On the other hand, Godet's framework consider the conditional probability of each occurrence which is assumed for different sets of environmental and organisational variables. In all scenario planning methodologies, experts' role is critical for decision making, and uncertain data always are the basis for developing future scenarios.

Scenario planning deals with uncertain and ambiguous data and therefore, some researchers applied fuzzy logic and Artificial Neural Networks (ANNs) for better handling of the data shortage and also experts' linguistic expression. Khoo, Ho, and Choa (1994) developed a fuzzy management decision support system for scenario analysis using a hybrid technique: a combination of...
the fuzzy Delphi analysis and fuzzy reasoning technique. Wang (1999) proposed a method of fuzzy scenario analysis to forecast the possible development in a strategic planning. This method considered the uncertainties involved in strategic planning to determine the compatible and possible scenarios. Li, Ang, and Gay (1997) developed a scenario generation tool by using the theory of ANNs and truth value flow inference. ANNs were designed to forecast market share and market growth, and a fuzzy expert system model was developed to build a knowledge-base for defining a suitable marketing strategy. Royes and Royes (2004) developed a framework to indicate how the fuzzy set approach may contribute to the evaluation and exploration of scenarios for strategic planning. A hybrid methodology was developed which used three main modules: fuzzy sets, multicriteria analysis and case-based reasoning.

This paper presents a new hybrid methodology to combine the advantages of fuzzy logic and ANNs. Other methodologies use only one method, fuzzy logic or ANNs, for dealing with the data shortage and experts’ linguistic expression. Li’s method is the only methodology developing a hybrid intelligent system based on fuzzy logic and ANNs but the major difference of this method with the proposed methodology is related to the proposal using ANNs. In Li’s framework, ANNs are utilized for forecasting market share and growth, while the suggested methodology applies ANNs as a tool to learn from experts and make decisions. The main goals of this new hybrid intelligent architecture will be:

- To improve the ability of managers to deal with uncertainty.
- To present intelligent advice on business strategic planning.
- To keep and use the experts’ knowledge.

To attain these objectives, the proposed framework applies an Adaptive Neuro-Fuzzy Inference System (ANFIS) which is suggested by Jang (1993) to better deal with an ill-defined and uncertain system. It can serve as a basis for constructing a set of fuzzy if-then rules with appropriate membership functions to generate the stipulated input–output pairs (Jang, Sun, & Mizutani, 1997). ANFIS architecture is designed to tune fuzzy system parameters based on input/output pairs of data. The fuzzy inference process is implemented as a generalised ANN, which is then tuned by gradient descent techniques (Fuller, 2000). Antecedent parameters of fuzzy rules are also tuned as well as consequent parameters. ANFIS provides a method for the fuzzy modelling procedure to learn information about a dataset, in order to compute the membership function parameters allowing the associated fuzzy inference system to track the given input/output data (Huang, Chen, & Huang, 2007). ANFIS is used in many areas such as forecasting (Aznarte et al., 2007), classifying (Ozturk, Arslan, & Hardalac, 2008; Sengur, 2008), controlling (EiElmas, Ustun, & Sayan, 2008), recognition (Avci & Avci, 2007; Avci, Hanbay, & Varol, 2007) and diagnosing (Güler & Übeyli, 2004; Polat & Gunes, 2007; Übeyli, 2008). The goal of this research is to develop an intelligent scenario generator based on ANFIS to eliminate the weaknesses of previous methodologies. The theory of ANNs will be used to enable learning and correcting from experts. Furthermore, fuzzy logic theory will be applied to deal with reasoning and using linguistic information acquired from experts.

In Section 2, the details of ANFIS methodology for generating scenarios have been described. Two case studies are introduced in Section 3. The findings of case studies will be discussed in Section 4. In final section, the result of this research will be explained.

2. ANFIS Methodology for generating scenarios

This section is related to design of a new intelligent methodology for generating scenarios including four steps as follows:

Step 1: Defining the scope and internal and external variables.

The first step tries to define the problem and also the boundary of the system under examination. Identifying variables, relationship between variables and defining key variables are other main objectives of this step. This research recommends Godet’s method (2001) in defining the key variables.

Step 2: Determining rules from experts.

In this step, the knowledge of expert should be gathered and summarised in the form of if–then rules.

Step 3: Preparing ANFIS system.

The ANFIS architecture contains a 6-layer forward pass ANNs as shown in Fig. 1. The output and input of each layer has been presented as following:

\[ y_k^i = \text{output of neuron } i \text{ in layer } k; \quad x_k^i = \text{input of neuron } i \text{ in layer } k. \]

Layer 1 is the input layer whose neurons transmit external crisp signals directly to the next layer as follows:

\[ y_1^i = x_1^i. \]  

Layer 2 is the fuzzification layer. Neurons receive a crisp input and identify the degree of neurons’ fuzzy sets. Based on Jang’s

![Fig. 1. Adaptive neuro-fuzzy inference system (ANFIS).](image-url)
model, the membership function of fuzzification neurons is a bell activation function which is specified as follows (Jang et al., 1997; Negnevitsky, 2002):

\[
y_i^3 = \frac{1}{1 + \left(\frac{x^3 - a}{b} \right)^2},
\]

(2)

\(a, b, \text{ and } c\) are parameters that control, respectively, the centre, width and slope of the bell activation function of neuron \(i\).

Layer 3 is the fuzzy rule layer. The inputs of fuzzy rule neuron come from the fuzzification neuron. For example, neuron \(R1\) receives inputs from neurons \(A1\) and \(B1\). The conjunction of the rule antecedents is evaluated by the fuzzy operation intersection and implemented by the product operator (Negnevitsky, 2002).

\[
y^3 = \prod_{j=1}^{k} x^{3}_{ji} = \mu_i.
\]

(3)

\(x^3_{ji}\) are the inputs and \(y^3_i\) is the output of the rule neuron \(i\) in layer 3. \(\mu_i\) represents the firing strength or the truth value of rule \(i\) (Jang et al., 1997).

Layer 4 is the normalisation layer. Neurons receive inputs from the fuzzy rule neuron and normalised firing strength of a given rule. The output of neuron \(i\) in layer 4 is determined as,

\[
y^4_i = \frac{x^4_d}{\sum_{j=1}^{n} x^4_{ji}} = \frac{\mu_i}{\sum_{j=1}^{n} \mu_j} = \tilde{\mu}_i.
\]

(4)

Layer 5 is the defuzzification layer whose neurons are in this layer is connected to the respective normalisation neurons, and also receives initial inputs (Negnevitsky, 2002).

\[
y^5 = x^5 \ast f_i = \mu_i \ast f_i.
\]

(5)

Layer 6 is a summation neuron which calculates the sum of all defuzzification neurons as follows:

\[
y = \sum_{i=1}^{n} y^5 = \sum_{i=1}^{n} \mu_i \ast f_i.
\]

(6)

In the ANFIS training algorithm, each epoch is composed of a forward and a backward pass (Negnevitsky, 2002). In the forward pass, outputs are based on the layer by layer calculation and rule consequent parameters are determined by the least-squares estimators. Linear equations can be formed in terms of the consequent parameters for training data as:

\[
\begin{align*}
x_y(1) &= \tilde{\mu}_1 f_1(1) + \tilde{\mu}_2 f_2(1) + \cdots + \tilde{\mu}_n f_n(1), \\
x_y(2) &= \tilde{\mu}_1 f_1(2) + \tilde{\mu}_2 f_2(2) + \cdots + \tilde{\mu}_n f_n(2), \\
x_y(P) &= \tilde{\mu}_1 f_1(P) + \tilde{\mu}_2 f_2(P) + \cdots + \tilde{\mu}_n f_n(P),
\end{align*}
\]

(7)

where \(P, n\) are the number of input–output training sets and neurons in the rule layer, respectively. In matrix notation, \(y_d\) can be shown as:

\[
y_d = A K,
\]

(8)

where \(y_d\) is a \(P \times 1\) vector of desired output,

\[
y_d = \begin{bmatrix} y_d(1) \\ y_d(2) \\ \vdots \\ y_d(P) \end{bmatrix}.
\]

(9)

\(A\) is a \(P \times n \times (1 + m)\) matrix where \(m\) is the number of input variables:

\[
\begin{bmatrix}
\tilde{\mu}_1(1) & \tilde{\mu}_1(1) x_1(1) & \cdots & \tilde{\mu}_1(1) x_m(1) & \cdots & \tilde{\mu}_1(1) x_1(1) & \cdots & \tilde{\mu}_1(1) x_m(1) \\
\tilde{\mu}_2(1) & \tilde{\mu}_2(1) x_1(2) & \cdots & \tilde{\mu}_2(1) x_m(2) & \cdots & \tilde{\mu}_2(1) x_1(2) & \cdots & \tilde{\mu}_2(1) x_m(2) \\
& \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\
\tilde{\mu}_1(P) & \tilde{\mu}_1(P) x_1(P) & \cdots & \tilde{\mu}_1(P) x_m(P) & \cdots & \tilde{\mu}_1(P) x_1(P) & \cdots & \tilde{\mu}_1(P) x_m(P)
\end{bmatrix}
\]

(10)

and \(K\) is an \(n \times (m + 1) \times 1\) vector of unknown consequent parameters,

\[
k = [k_{10} \ k_{11} \ k_{12} \ \cdots \ k_{1m} \ \cdots \ k_{n0} \ k_{n1} \ k_{n2} \ \cdots \ k_{nm}].
\]

(11)

In the forward pass, a least square estimate of \(k, K'\), minimises the squared error \(|Ak - y_d|^2\) which is done by using the pseudo inverse technique (Negnevitsky, 2002):

\[
K' = (A^T A)^{-1} A^T y_d,
\]

(12)

\[
y = A \times K'.
\]

(13)

where \(A^T\) is the transpose of \(A\), and \((A^T A)^{-1} A^T\) is the pseudo inverse of \(A\) if \(A^T A\) is nonsingular. The error vector can be computed by the actual network output vector \(y\).

\[
e = y_d - y.
\]

(14)

The backward pass applies the back-propagation algorithm. For instance, a correction of parameter \(a\) of the bell activation function is as following:

\[
\Delta a = -2 \frac{\partial E}{\partial a} = -2 \frac{\partial E}{\partial \tilde{\mu}_1} \frac{\partial \tilde{\mu}_1}{\partial a} = \frac{1}{1 + (\tilde{\mu}_1 a)^2} \cdot \frac{1}{2} \cdot 2b \cdot (x_1 - a)^{2b-1} \cdot (-1)
\]

(15)

\[
\Delta a = -\partial E \partial (y_d - y)/(1) \frac{\partial \tilde{\mu}_1 (1 - \tilde{\mu}_2)}{\partial a} = \frac{1}{1 + (\tilde{\mu}_1 a)^2} \cdot \frac{1}{2} \cdot 2b \cdot (x_1 - a)^{2b-1} \cdot (-1)
\]

(16)

where

\[
\frac{\partial \tilde{\mu}_1}{\partial a} = \frac{1}{1 + (\tilde{\mu}_1 a)^2} \cdot \frac{1}{2} \cdot 2b \cdot (x_1 - a)^{2b-1} \cdot (-1)
\]

(17)

Similarly, parameters \(b\) and \(c\) can be corrected through this approach. \(\Delta a, \Delta b, \text{and } \Delta c\) are the correction parameters that adjust, respectively, the centre, width and slope of the new bell activation function of neuron \(i\) based on the training data. The new membership functions tuned by learning algorithm are used in generating scenarios.

**Step 4: Sensitivity analysis:**

Sensitivity analysis is pertaining to the effects of the variation of inputs on outputs and the effect of changes in the amount of training data and occurrence probabilities of rules is measured. As input variables are uncertain and will be changed, sensitivity analysis helps to determine which variables have more effects on the output.

Fig. 2 shows the flowchart of the scenario generation by using ANFIS methodology. In this flowchart, steps 1, 2 and 4 are the same.
as described before and step 3 is divided into three sub-steps: loading training data, setting initial membership function and training algorithm. Next section explains the details of two case studies demonstrating the applicability of the proposed methodology for hybrid intelligent scenario generator.

3. Case studies

In this section, two different case studies are used for demonstration of the proposed methodology. Case study I uses a hybrid intelligent scenario generator to determine a strategic option based on two uncertain variables. Case study II shows the practical use of the proposed framework in developing a marketing strategy.

3.1. Case study I

A virtual case study is used to show the details of the proposed methodology for generating scenarios. It presumes that a company is going to select a strategic option in responding to two uncertain variables: market share (X1) and relationship with suppliers (X2). Table 1 shows the basic rules and the assumed ANFIS weight of each rule related to the uncertain fuzzy inputs. For example, it is considered that if X1 is “good” and X2 is “bad” then experts recommend “D1” strategy with 0.7 ANFIS weight.

In this case study, the ANFIS weight for a specific strategy is considered as an objective function, designated as Y. If Y is not a function of input variables then the zero-order Sugeno fuzzy inference system should be used (Negnevitsky, 2002). This results in no forward pass for ANFIS training algorithm because $A^TA$ is singular and it is not possible to account for the pseudo inverse of A. Table 2 presents the training and checking data to generate scenarios on the basis of experts’ knowledge. It contains the information about the strategic option and assumed ANFIS weight for a specific X1 and X2.

There are nine fuzzy rules and the number of epochs is 300. The learning rate and acceptance error are set to 0.02 and 0.005, respectively. At the end of 300 training periods, the network error convergence curve can be derived as shown in Fig. 3. Figs. 4 and 5 illustrate the initial and final membership function of input data (X1 and X2).

After training algorithm, the system has the ability to identify a strategic option and also calculate the ANFIS weight for specific in-
The result of sensitivity analysis on ANFIS weight of training data leads to changes in the strategic options. It also affects the final membership function for other training data (T2 to T4). Another sensitivity analysis test can be performed by introducing uncertainty into X1 or X2 of each training data. If the X1 in T1 is shifted from 20 to 20.5, the new strategic option will be selected to be D1 instead of D4. Furthermore, it modifies the final membership function of X2 especially the “Bad” curve as shown in Fig. 6. The extent of modification is based on the correction vector (Δa, Δb, and Δc) which was described in previous section.

3.2. Case study II

Marketing strategy is the means by which the marketing objectives will be achieved (Li, 2000b; McDonald, 1996). There are some intelligent systems to help decision makers develop a marketing strategy (e.g., (Arinze, 1990; Belardo, Duchessi, & Coleman, 1994; Li et al., 1997; Little, 1979; Moormann & Lochte-Holtgreven, 1993; Wilson & McDonald, 1994)). This case study is based on Li’s work in development of a hybrid intelligent system to define an appropriate marketing strategy. Li’s hybrid intelligent system has been developed to attain the following objectives (Li, 2000b):
- to help strategic analysis; to couple strategic analysis with managers’ judgement; to integrate the strengths of diverse support techniques and technologies; to combine the benefits of different strategic analysis models; and to help strategic thinking. In this case study, another module will be added into Li’s framework to enable the tuning of the membership function related to the uncertain inputs. Fig. 7a and b show the steps of Li’s and the proposed framework, respectively.

**Module 1: The neural network forecasting module**

This module facilitates managers to have a better estimation about the market growth and share by using the back propagation learning algorithm based on the previous trends. The results of this module will be saved to use as an input data for the next module. The topology of the Artificial Neural Networks (ANNs) model with 1 year of lead time is as follows (Li, 2000b):

- **Input neurons:** t - 1, l(t - 2), l(t - 3).
- **Hidden neurons:** four hidden neurons.
- **Output neuron:** O(t).

### Table 3

The result of sensitivity analysis on ANFIS weight of training data

<table>
<thead>
<tr>
<th>Training data</th>
<th>Initial ANFIS weight</th>
<th>Strategic option</th>
<th>Final ANFIS weight</th>
<th>New strategic option</th>
</tr>
</thead>
<tbody>
<tr>
<td>T1</td>
<td>0.2</td>
<td>D4</td>
<td>0.26</td>
<td>D1</td>
</tr>
<tr>
<td>T1</td>
<td>0.2</td>
<td>D4</td>
<td>0.14</td>
<td>D4</td>
</tr>
<tr>
<td>T2</td>
<td>0.25</td>
<td>D4</td>
<td>0.3</td>
<td>D4</td>
</tr>
<tr>
<td>T2</td>
<td>0.25</td>
<td>D4</td>
<td>0.2</td>
<td>D4</td>
</tr>
<tr>
<td>T3</td>
<td>0.4</td>
<td>D4</td>
<td>0.45</td>
<td>D4</td>
</tr>
<tr>
<td>T3</td>
<td>0.4</td>
<td>D4</td>
<td>0.35</td>
<td>D4</td>
</tr>
<tr>
<td>T4</td>
<td>0.55</td>
<td>D4</td>
<td>0.5</td>
<td>D4</td>
</tr>
<tr>
<td>T4</td>
<td>0.55</td>
<td>D4</td>
<td>0.6</td>
<td>D4</td>
</tr>
</tbody>
</table>

Fig. 4. Membership function of the market share (X1).

Fig. 5. Membership function of the supplier relationship (X2).

Fig. 6. Membership function of the supplier relationship (X2).
where $t$ is the year of predicted growth rate or share, $I(t)$ the growth rate or share at year $t$, and $O(t)$ is the predicted growth rate or share at year $t$.

**Module 2: The group assessment support module**

This module is one of the salient features for developing a marketing strategy by ranking the manager’s viewpoints on the market attractiveness and business strengths. For instance, The principle for the group assessment support to compute market attractiveness is stated as follows (Li, 2000b):

\[
S_j = \frac{1}{k} \sum_{i=1}^{k} S_{ij}, \quad (j = 1, 2, \ldots, n),
\]

\[
W_j = \left( \frac{1}{\sum_{j=1}^{n} k} \sum_{i=1}^{k} w_{ij} \right) \quad (j = 1, 2, \ldots, n),
\]

where

\[
W_j = \begin{pmatrix} w_{1j} & w_{12} & \cdots & w_{1n} \\ w_{2j} & w_{22} & \cdots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{kJ} & w_{k2} & \cdots & w_{kn} \end{pmatrix} \quad \text{and} \quad \sum_{i=1}^{n} W_{ij} = 1 \quad (21)
\]

$n$, $k$ are the number of strategic factors and managers in assessment group and $S_{ij}$ is the score of manager $i$ for factor $j$ with the scale of 1–10, $w_{ij}$ is the manager $i$’s weighting for factor $j$. $S_j$ and $W_j$ are the average score for factor $j$ which are computed by Eqs. (19) and (20).

The market attractiveness score $A$ is obtained using Eq. (22) where the score $A$ ranges from 1 to 10.

\[
A = \sum_{j=1}^{n} S_j \times W_j.
\]

**Module 3: Fuzzification component module**

Marketing strategy factors and some strategic analysis models can be fuzzified through converting them into membership functions (Li, 2000b). Directional Policy Matrix (DPM) is used in this module with adding the fuzzified market attractiveness and business strengths as shown in Fig. 8. In the fuzzified DPM matrix, strategic options gradually change with certain confidence due to a change in either criterion of market attractiveness or business strengths (Li, 2000b). Based on this architecture, Li has also developed a software called Marstra (Li, 2000a) as well as a web-enabled approach (Li, 2005).

Li’s framework uses fuzzy numbers for the market attractiveness and business strengths without any adjustment of initial membership function. This research develops rule-base ANNs within a fuzzy inference system which tunes the membership function of marketing strategy based on training data. Training data may be based on the specific data taken from experts and is generally focused on the border lines where it is difficult to select which strategic option should be selected. Fig. 9a and b present two different fuzzy numbers for business strengths to clarify the importance of tuning membership functions and their effects on the selected strategic option. Based on the membership function in Fig. 9a, the strategic option is “protect and refocus” but if the membership function is changed to Fig. 9b then the strategic option is changed to “manage for earnings”. This example shows that different membership functions have different results in Li’s framework. Because of the necessity of tuning of the membership function, another module is added to modify the initial membership

**Fig. 7.** (a) Li’s framework and (b) the proposed framework for developing marketing strategy.

**Fig. 8.** DPM with membership functions.
function according to experts’ viewpoints about specific organisation.

Module 4: Hybrid intelligent scenario generator

Nine fuzzy rules were considered on the basis of the fuzzy states of business strengths (low, medium and high) and market attractiveness (low, medium and high) and each of them has a specific strategic option and ANFIS weight. Table 4 shows the fuzzy rules with the assumed ANFIS weight for DPM.

Table 5 presents the training and checking representative data taken from experts. This assumed training data is used in the ANFIS learning algorithm to tune new membership functions for the market attractiveness and business strengths. Figs. 10 and 11 present the initial and final membership functions for the market attractiveness and business strengths, respectively.

In sensitivity analysis step, initial and final strategic options with different ANFIS weights are calculated for different input variables. Table 6 shows the result of this sensitivity analysis which will be discussed in next section. For example, if the business strengths and market attractiveness are considered 6 and 3.5 then

| Table 4 | Fuzzy rules based on DPM with assumed ANFIS weight |
|-----------------------------------------------|
| Business strength (X1) | Market attractiveness (X2) | Strategic options (D) | ANFIS weight |
| Strong | Low | Protect and refocus | 0.7 |
|       | Medium | Selectivity build | 0.6 |
|       | High | Protect position | 0.9 |
| Medium | Low | Manage for earning | 0.9 |
|       | Medium | Selectivity/manage for earning | 0.8 |
|       | High | Invest to build | 0.75 |
| Weak  | Low | Divest | 0.8 |
|       | Medium | Limited expansion | 0.6 |
|       | High | Build selectivity | 0.8 |

| Table 5 | Training and checking data with assumed ANFIS weight |
|-----------------------------------------------|
| Training data | |
| Row | Business strength (X1) | Market attractiveness (X2) | Strategic option | ANFIS weight |
| T1  | 2 | 3 | Divest | 0.8 |
| T2  | 5 | 7 | Invest to build | 0.6 |
| T3  | 7.5 | 4.5 | Selectivity build | 0.4 |
| T4  | 2 | 5 | Limited expansion or harvest | 0.7 |

| Checking data | |
| Row | Business strength (X1) | Market attractiveness (X2) | Strategic option | ANFIS weight |
| C1  | 6 | 4 | Selectivity/manager for earnings | 0.65 |
| C2  | 6 | 5 | Selectivity/manager for earnings | 0.7 |
| C3  | 7 | 9 | Protect position | 0.6 |
| C4  | 4 | 6 | Manage for earnings | 0.25 |

Fig. 9. The comparison of two different DPM membership functions.

Fig. 10. Initial and final Membership function of the business strength.

Fig. 11. Initial and final Membership function of the Market attractiveness.
the strategic option is changed from “manage for building” with 25.43 ANFIS weight to “selectivity build” with 5.65 ANFIS weight. This sensitivity analysis shows the importance of tuning of membership function for choosing the appropriate strategic option which will be discussed in next section.

4. Discussion

In case study I, the membership functions associated with market share and supplier relationship indicate the experts’ views about the future event. The hybrid scenario generator tuned the membership function of the two uncertain inputs. For supplier relationship membership function, “bad” curve is much wider and “good” curve approaches to a crisp shape in the final membership function. For market share membership function, all three curves (bad, average and good) are close to crisp shape in final membership function. In sensitivity analysis, some of the training data were arbitrarily varied to show the importance of sensitivity analysis and the effects of uncertainties after selecting a strategic option. It can be inferred that the strategic option is changed if the ANFIS weight of one rule changes only 6% or the market share modified by 0.5%. This explicitly shows that the organisation should not rely on only one strategic option. There is a need that organisations have some alternatives for a chosen strategic option because of the high level of uncertainty in future.

In case study II, the hybrid intelligent scenario generator changed the initial membership function based on the training data. As membership function is tuned based on the expert’s viewpoints, DPM are found to be more useful in developing a marketing strategy. The result of sensitivity analysis presents that the strategic options are sensitive especially when the market attractiveness and business strengths are very close to border lines. For example, if it is considered the market attractiveness and business strengths are 6 and 7 accordingly, the initial strategic option will be changed from “invest to build” to “protect position” with the ANFIS weight changing from 25.58% to 14.32% if membership functions were tuned by hybrid intelligent scenario generator. It is possible that there is a change only in ANFIS weight for example, initial and final strategic options are “selectivity/manager for earnings” if the market attractiveness and business strengths are 3.5 and 5, respectively. The result of this sensitivity analysis shows that the strategic option and its ANFIS weight may be changed by the final membership functions, therefore; it is recommended that organisations should carefully choose a strategic option and it is better to consider other strategic options which are close to the selected strategic option in DPM as other possible solutions.

5. Conclusion

The development of a hybrid intelligent scenario generator has been described in this paper. The hybrid architecture is the central point of the proposed methodology which allows having fuzzy rules and a learning algorithm in scenario generation. ANNs bring out the ability to learn from experts and fuzzy logic gives a consensus to express the ambiguity in human thinking and is able to mimic the human reasoning process. Therefore the developed methodology has the ability to learn and correct experts and also translate the linguistic experts’ rules. Moreover, ANFIS combines the classical back propagation methods with the minimum least square methods to modify the fuzzy numbers for uncertain variables. In this paper, two case studies are also presented to demonstrate the applicability of the hybrid intelligence scenario generator. The results of case studies show that the inputs greatly affect the selected strategic option and highlight the need for an optimisation strategy for finding the best strategic option.

References


