Computational Intelligence to Model the Export Behavior of Multinational Corporation Subsidiaries in Malaysia

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The academic literature suggests that the extent of exporting by multinational corporation subsidiaries (MCSs) depends on their strategic role in the multinational corporation (MNC), their age and size, and whether their products are targeted at niche or commodity markets. In particular, it is claimed that MNCs seek to invest in a particular country if its resources adopt a vertically integrated structure, if the country grants regional or global sales mandates to their subsidiaries, or if it has been established in a host market for a longer time and is thus more likely to promote subsidiary exports. Our aim in this article is to model the complex export pattern behavior of multinational corporation subsidiaries in Malaysia using a Takagi–Sugeno fuzzy inference system. The proposed fuzzy inference system (FIS) is optimized by using neural network learning and evolutionary computation. Empirical results clearly show that the proposed approach could model the export behavior reasonably well compared to a direct neural network approach.

Introduction

Malaysia has been pursuing an economic strategy of export-led industrialization (Ariff & Hill, 1985; Doraisami, 1996; Gomez & Jomo, 1997). To facilitate this strategy, foreign investment is courted through the creation of an attractive incentive package. This primarily entails taxation allowances and more liberal ownership rights for investments (Jomo, 1998; Levitt, 1983). The quest to attract foreign direct investment (FDI) has proved to be highly successful. Of the manufacturing projects that were approved by the Ministry of International Trade and Industry in the mid-1990s, 25.6% were wholly Malaysian-owned, 43.0% were international joint ventures between Malaysian and foreign investors, and 31.5% were wholly foreign owned ventures (Lyles, Salaiman, Barden, & Kechik, 1999). The bulk of investment has gone into export-oriented manufacturing industries.

Several specific subsidiary features identified in the international business literature are particularly relevant when seeking to explain multinational corporation (MNC) subsidiary export behavior. The location factors attracting FDI to the country, the subsidiary's functional roles, size, and age, and whether subsidiary products are targeted at niche or broader markets, have all been perceived to be determinants of export behavior. In this article, we are concerned with the manner in which the structure and strategy of MNCs that have invested in Malaysia affect the export intensity of their subsidiaries. Prior to going into the details of the study, it is important to explain that there are two related aspects of export behavior. One aspect is the probability of a firm exporting at all. The other aspect is the relationship between the percentage of total sales exported and the size of the firm. According to the literature, larger firms are more likely to export. However, there is no clear relationship between size of the firm and export intensity. For example, Bonnaccorsi (1992) found that, although larger firms were more likely to export, there was no significant difference between the export intensity of small, medium, or large firms. Wolff and Pett (2000) also found no significant difference in export intensity between small, medium, and large firms. They argued that the type of resources available is a key factor,

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specifically, that with the appropriate type of resource, a small firm can use the same competitive patterns utilized by larger firms with the same effectiveness. Wagner (2001) notes that for any industry or country, greater firm size is not necessary or sufficient.

In this article, we concentrate on the subsidiary's strategic role and size and their influences on export behavior. Multinational corporation subsidiaries (MCSs) strategic role is statistically expressed through their manufactured product, resources, tax protection, involvement strategy, financial independence, and suppliers' relationship with a multinational corporation. The size of MCSs is statistically presented through their customers and markets.

To model an export pattern behavior is obviously a multi-objective problem. Solving multi-objective problems is, generally, a very difficult goal because the objectives often conflict across a high-dimension problem space and consequently may require extensive computational resources. For this research, we have used the EvoNF framework, which is an integrated computational framework to optimize a fuzzy inference system using neural network learning and evolutionary computation (Abraham, 2002a). The hierarchical evolutionary search framework could adapt the membership functions (MF; shape and quantity), rule base (architecture), fuzzy inference mechanism (T-norm and T-conorm operators), and the learning parameters of neural network learning algorithms. In addition to evolutionary learning (global search), neural learning could be considered as a local search technique to optimize the parameters of the rule antecedent/consequent parameters and the parameterized fuzzy operators.

In the next section, what is known so far is explained, i.e., the influence of the subsidiary's strategic role and the MCS's size in relation to its exporting. In the following section, neural networks and some theoretical foundations of neuro-fuzzy modeling are introduced with algorithm details of the proposed EvoNF approach to model the export behavior presented in the section thereafter. Then, the experimentation results based on data provided by Malaysian MCSs are given in the next-to-last section with concluding remarks shared in the final section.

What Is Known

Subsidiary's Strategic Role

The traditional view of the MNC hierarchy involves the notion that the parent company should maintain tight control of the roles of its subsidiaries. However, the modern approach to subsidiary management embraces the idea that subsidiary managers may take strategic initiatives beyond the mandate of the subsidiary. An MNC subsidiary operating in the global market may be encouraged to be proactive in developing its activities (Delany, 2000), which has implications for export behavior. Pearce (1989) identifies three major types of subsidiary, each with particular roles and with different implications for export behavior: truncated miniature replica subsidiaries, rationalized producer subsidiaries, and world product mandate subsidiaries.

Stopford and Wells (1972) identified the truncated miniature replica as the first stage of internationalization. Multidomestic subsidiaries result from what Caves (1982) defines as horizontal integration. Such subsidiaries perform functions, including production, in essentially the same way as the parent. They are usually intended to service the markets in which they are located, possibly protected by tariffs (Pearce, 1989; White & Pointer, 1984). The domestic focus of their production implies they cannot exploit sufficient economies of scale to be internationally competitive and hence, are unlikely to have a capacity for exporting. Because of this limited export opportunity, the multidomestic is likely to be a net importer as there will most likely be some imported components for which economies of scale, or the need to protect core technology from diffusion to competitors, require production in the parent plant (D'Cruz, 1986).

Many scholars have noted a tendency over the past 30 years for MNCs with mulitdomestic strategies being restructured to fulfil a different, more specialized role in a global strategy (Birkinshaw, 1996; Bowman et al., 2000; D'Cruz, 1986; Gallagher, 1988; Levitt, 1983; Pearce, 1989). Two types of specialization have been identified: rationalization–integration and world product mandate.

Rationalization–integration occurs when a subsidiary produces a limited part of the MNC's production, possibly one not relevant to the demand of the country in which it is located (Wagner, 2001). Caves (1982) refers to this kind of structure as "vertical integration." These subsidiaries, termed *rationalized producers*, may specialize in production of particular component parts or may perform a complete stage in a vertically integrated production process. Delany (2000) classifies this as an *intermediate, enhanced mandate*, where the subsidiary does not have control of the entire value chain for an MNC, but is involved in a number of its activities. The aim is to achieve production by making optimum use of the distinctive productive capabilities of different locations accessible to the multinational corporation (Pearce, 1992). Each facility is worldscale and concentrates on becoming a low-cost producer of those parts or processes for which it is responsible (D'Cruz, 1986). The rationalized producer structure is particularly relevant where transportation costs are low relative to selling price and where market requirements are relatively standardized across the world (D'Cruz, 1986). Subsidiary exports occur automatically because production is taken up by the MNC. Much of the subsidiary's output will serve foreign markets; whereas much of the inputs will be derived from other specialized suppliers among the parent's other subsidiaries (Pearce, 1992). Vertical integration stimulates cross-border exchange; it should result in a relatively high intensity of exports.

The second role for a subsidiary in a globally organized MNC, a regional mandate is where the site has full responsibility for the development, manufacturing and marketing, including export marketing, of one or more product lines (Birkinshaw, 1996; Bonin & Peron, 1986; Crokell, 1986;

Delany, 2000; Roth and Morrison, 1992; Rugman & Douglas, 1996). The opportunity to sell its products anywhere in the region or the world implies that the subsidiary can establish a world-scale production facility and operate at a competitive unit cost level (D'Cruz, 1986). A large part of the output of this subsidiary will contribute to the net exports of the host country.

Subsidiary's Size

Several theoretical reasons can be proffered to justify the proposition that firm size is related to export intensity (Calof, 1994). First, internationalization requires a variety of resources, such as experienced personnel, financial resources, and international contacts. Resource scarcity limits the ability of smaller firms to reach advanced stages of internationalization (Dunning, 1988). Second, smaller firms may be risk-averse, because of insufficient information and the grave impact of international errors (Calof, 1994). Third, from an international life-cycle perspective, firms are likely to undertake growth within their domestic market first. At some point, when the opportunities for domestic growth become limited, the firm will commence exporting. By this stage, they will have grown larger. Consequently, exports are expected to be associated with larger and older firms. Various empirical studies have found evidence of such relationships (Calof, 1994). Fourth, economies of scale render a firm more competitive and therefore assist it in creating capacity to pursue export opportunities.

These arguments, however, have been disputed, even in their application to locally owned firms. Moen (1999) found that although small and large companies can vary in terms of competitive advantage, a smaller firm size does not automatically lead to a less competitive company in global markets, especially in the manufacturing and technology industries. Bonnaccorsi (1992) argues that a combination of acquiring export services from outside firms, hiring staff with exporting experience, investing in networks with international linkages, minimizing the entry costs by imitating strategies of successful exporters and using the relatively low-risk export entry mode, can minimize the disadvantage of being relatively small. Indeed, firms that produce niche products may be expected to exhibit greater export intensity, because the domestic niche market becomes exhausted relatively more quickly. For example, small high-technology firms may become exporters at the very beginning of their life cycle because the domestic market does not offer sufficient opportunities for growth (Bonnaccorsi, 1992; Moen, 1999).

The most recent attempt to clarify the relationship between firm size and export performance (focusing on manufacturing firms) was carried out by Verwaal and Donkers (2002) who argue that the firm size–export intensity relationship is moderated by the size of export relationships. They define an export relationship as "the series of transactions in time with a particular foreign buyer." The size of the export relationship refers to the volume of export transactions. They posit that the inconsistency of previous findings regarding firm size and export intensity arises from disregarding the size of export relationships. Their results indicate that this factor does significantly moderate the firm size–export intensity relationship. Specifically, they found that when the export relationship size is large, an insignificant or negative relationship between firm size and export intensity is found, whereas in the case of small export relationships, a positive relationship between firm size and export intensity was found (Verwaal & Donkers, 2002).

However, the perspectives outlined in the above literature were developed mainly in relation to domestic firms. Not all of these theoretical justifications apply equally to subsidiaries of multinational corporations. Resource scarcity may be less pertinent, because the subsidiary can utilize the resources, including knowledge, of the parent. However, MNCs that invest in a foreign market are likely to expect subsidiary management to pursue the local market opportunities before they consider export markets (Andersson & Fredriksson, 1996).

Artificial Neural Networks

The study of artificial neural networks (ANNs) originated in attempts to understand and construct mathematical models for neurobiology and cognitive psychology, and their current development continues to shed light in these areas. Although significant advances have been achieved in the area of conventional expert systems for mimicking human intelligence, there is still a long way to go for the current computational techniques before realizing the capability of carrying out certain man-dependent tasks.

Human brains provide proof of the existence of ANNs that can succeed at those cognitive, perceptual, and control tasks in which humans are successful. Rough arguments from neurobiology suggest that the cycle time of an individual human neuron is 10^{-3} seconds (1 millisecond) for a clock rate of less than 1 KHz. This compares with the current computers operating on a cycle time of 10^{-9} seconds for a clock rate of about 1 GHz, a factor more than a million (10^6). Nevertheless, the brain is capable of computationally demanding perceptual acts (e.g., recognition of faces, speech) and control activities (e.g., body movements and body functions) that are now only on the horizon for computers. The advantage of the brain is its effective use of massive parallelism: the parallel computing structure and the imprecise information processing capability. The basic processing element in the nervous system is the neuron. Tree-like networks of nerve fiber called dendrites are connected to the cell body or soma, where the cell nucleus is located. Extending from the cell body is a single long fiber called the axon, which eventually branches into strands and substrands, and are connected to other neurons through synaptic junctions, or synapses. The transmission of signals from one neuron to another at synapses is a complex chemical process in which specific transmitter substances are released from the sending end of the junction. The effect is to raise or lower the electrical potential inside the body of the receiving cell. If the potential reaches a threshold, a pulse is sent down the axon—we then say the cell has "fired." In a simplified mathematical model of the neuron, the effects of the synapses are represented by *weights* that modulate the effect of the associated input signals, and the nonlinear characteristic exhibited by neurons is represented by a transfer function, which is usually the sigmoid, Gaussian, trigonometric functions, etc. The neuron impulse is then computed as the weighted sum of the input signals, transformed by the transfer function. The learning capability of an artificial neuron is achieved by adjusting the weights in accordance to the chosen learning algorithm.

Artificial neural networks have been developed as generalizations of mathematical models of biological nervous systems. They have the advantageous capabilities of learning from training data, recalling memorized information, and generalizing to the unseen patterns. Artificial neural networks are characterized by the network architecture, the connection strength between pairs of neurons (weights), node properties, and updating rules. The updating or learning rules control weights and/or states of the processing elements (neurons). It can learn by adapting its weights to changes in the surrounding environment, can handle imprecise information, and generalize from known tasks to unknown ones. Each neuron is an elementary processor with primitive operations, like summing the weighted inputs coming to it and then amplifying or thresholding the sum. Parallel implementations of ANNs offer an attractive way of speeding up both the learning and recall phases. Parallel mapping of ANN models have been implemented on various hardware platforms and processor topologies for different ANN architectures.

Back-Propagation Neural Network

The perceptron is a single layer neural network whose weights and biases could be trained to produce a correct target vector when presented with the corresponding input vector. The simple perceptron is just able to handle linearly separable or linearly independent problems. For those nonlinear problems, it is, however required that the network should have an appropriate intermediate representation of the input patterns by introducing nonlinear hidden layers. Back-propagation neural network (BPNN) utilizes the delta rule for the learning process. Back propagation is an abbreviation for the backwards propagation of error. With the delta rule, as with other types of back propagation, learning is a supervised process that occurs with each cycle or epoch (i.e., each time the network is presented with a new input pattern) through a forward activation flow of outputs, and the backwards error propagation of weight adjustments. More simply, when a neural network is initially presented with a pattern it makes a random "guess" as to what it might be. It then sees how far its answer was from the actual one and makes an appropriate adjustment to its connection weights.

The network is initially randomized to avoid imposing any of our own prejudices about an application on the network. The training patterns can be thought of as a set of ordered pairs $\{(x_1, y_1), (x_2, y_2), \ldots, (x_P, y_P)\}$ where x_i represents an input pattern and y_i represents the output pattern vector associated with the input vector x_i. The process of training the network then proceeds according to the following algorithm, which is derived as a natural result of finding the gradient of the error surface (in weight space) of the actual output produced by the network with respect to the desired result (Abraham & Nath, 2000).

1. Select the first training vector pair from the training pair vectors. Call this the vector pair (x, y).
2. Use the input vector x, as the out put from the input layer of processing elements.
3. Compute the activation to each unit on the subsequent layer.
4. Apply the appropriate activation function, which we denote as $f(net^h)$ for the hidden layer and as $f(net^0)$ for the output layer, to each unit on the subsequent layer.
5. Repeat steps 3 and 4 for each layer in the network.
6. Compute the error, δ^o_{pk}, for this pattern p across all K output layer units by using the formula: $\delta^o_{pk} = (y_k - o_k)f'(net^o_k)$
7. Compute the error, δ^h_{pj}, for all J hidden layer units by using the recursive formula:
$$\delta^h_{pj} = f'(net^h_j)\sum_{k=1}^{K}\delta^o_{pk}w_{kj}$$
8. Update the connection weight values to the hidden layer by using the equation: $w_{ji}(t+1) = w_{ji}(t) + \eta\delta^h_{pj}x_i$. Where η is a small value used to limit the amount of change allowed to any connection during a single pattern training cycle.
9. Update the connection weight values to the output layer by using the equation:
$$w_{kj}(t+1) = w_{kj}(t) + \eta\delta^o_{pk}f(net^h_j).$$
10. Repeat steps 2 to 9 for all vector pairs in the training set. Call this one training epoch.

Steps 1 to 10 are to be repeated for as many epochs as it takes to reduce the sum of squared error to a minimal value according to the formula

$$E = \sum_{p=1}^{P}\sum_{k=1}^{K}(\delta^o_{pk})^2$$

It has been proven that BPNN with sufficient hidden layers can approximate any nonlinear function to arbitrary accuracy. This makes BPNN a good candidate for signal prediction, forecasting, and system modeling systems. In the batched mode variant the descent is based on the gradient ∇E for the total training set.

$$\Delta w_{ij}(n) = -\varepsilon\cdot\frac{\delta E}{\delta w_{ij}} + \alpha\cdot\Delta w_{ij}(n-1)$$

The letters, ε and α are the learning rate and momentum, respectively. A good choice of both the parameters are required for training success and speed of the ANN.

Neuro-fuzzy modeling is based on a combination of neural networks and fuzzy models (Jang, 1992). It is a way of creating a fuzzy model "from data by some kind of learning method that is motivated by learning procedures used in neural networks" (Bezdek, Dubois, & Prade, 1999, Part II, Chapter 5).

TABLE 1. Complementary features of artificial neural networks (ANN) and fuzzy inference systems (FIS).

ANN	FIS
Black box	Interpretable
Learning from scratch	Making use of linguistic knowledge

A fuzzy inference system (FIS) can utilize human expertise by storing its essential components in rule base and database, and perform fuzzy reasoning to infer the overall output value. The derivation of *if–then* rules and corresponding MF depends heavily on the researcher's a priori knowledge about the system under consideration. However, there is no systematic way of transforming experiences of knowledge of human experts to the knowledge base of a FIS. There is also a need for adaptability or some learning algorithms to produce outputs within the required error rate (Abraham, 2001).

On the other hand, the ANN learning mechanism does not rely on human expertise. Due to the homogenous structure of ANN, it is hard to extract structured knowledge from either the weights or the configuration of the ANN. The weights of the ANN represent the coefficients of the hyperplane that partition the input space into the strategic role and size of the MCS with different output values. If we can visualize this hyperplane structure from the training data then the subsequent learning procedures in an ANN can be reduced. However, in reality, the a priori knowledge is usually obtained from human experts. It is most appropriate to express the knowledge as a set of fuzzy *if–then* rules and it is not possible to encode it into an ANN (Petrovic-Lazarevic, Abraham, & Coghill, 2002). Table 1 summarizes the comparison of FIS and ANN.

The drawbacks pertaining to these two approaches seem largely complementary. Therefore, it is natural to consider building an integrated system combining the concepts of FIS and ANN modeling (Abraham, 2001).

Some of the popular fuzzy inference methods are the Takagi–Sugeno–Kang (TSK) FIS (Kasabov, 1998) and the Mamdani FIS (Abraham, 2002b).

In a TKS fuzzy inference system the conclusion of a fuzzy rule is constituted by a weighted linear combination of the crisp inputs rather than a fuzzy set.

For a first-order TSK model, a common rule set with two fuzzy *if–then* rules is represented

Rule 1: If x is A_1 and y is B_1, then $f_1 = p_1x + q_1y + r_1$
Rule 2: If x is A_2 and y is B_2, then $f_2 = p_2x + q_2y + r_2$

where x and y are linguistic variables and A_1, A_2, B_1, B_2 are corresponding fuzzy sets and p_1, q_1, r_1 and p_2, q_2, r_2, are linear parameters. The TSK fuzzy controller usually needs a smaller number of rules, because their output is already a linear function of the inputs rather than a constant fuzzy set.

Most fuzzy systems employ the inference method proposed by Mamdani in which the rule consequence is defined by fuzzy sets and has the following structure (Abraham, 2001).

If x is A_1 and y is B_1 then $z_1 = C_1$

An Integrated Computational Framework

The Role of a Fuzzy Inference System for Explaining the Export Behavior of Multinational Corporation Subsidiary

We propose an integrated computational framework, defined as architecture of EvoNF (Abraham, 2002a), to optimize FIS by using a neural network learning technique and evolutionary computation. The proposed framework could adapt to Mamdani, Takagi–Sugeno, or other FIS. The architecture and the evolving mechanism can be considered as general framework for adaptive fuzzy systems. That is a FIS can change their MF (quantity and shape), rule base (architecture), fuzzy operators, and learning parameters according to different environments without human intervention.

We propose a 5-tier evolutionary search procedure wherein the MF, rule base (architecture), fuzzy inference mechanism (T-norm and T-conorm operators), learning parameters, and finally the type of inference system (Mamdani, Takagi–Sugeno, etc.) are adapted according to the environment. Figure 1 illustrates the interaction of various evolutionary search procedures. For every FIS, there exists a global search of learning algorithm parameter, inference mechanism, rule base, and MF in an environment decided by the problem. Thus, the evolution of FIS will evolve at the slowest time scale while the evolution of the quantity and type of MF will evolve at the fastest rate. The function of the other layers could be derived similarly.

Hierarchy of the different adaptation layers (procedures) will rely on the prior knowledge. For example, if there is more prior knowledge about the architecture than the inference mechanism, then it is better to implement the architecture at a higher level. If we know that a particular FIS will best suit the problem, we could also minimize the search space. For fine-tuning the FIS all the node functions are to be parameterized.

Parameterization of membership functions. A fuzzy inference system is completely characterized by its MF. For example, a generalized bell MF is specified by three parameters (p, q, r) and is given by:

$$\text{Bell}\,(x, p, q, r) = \frac{1}{1 + \left|\dfrac{x - r}{p}\right|^{2q}}$$

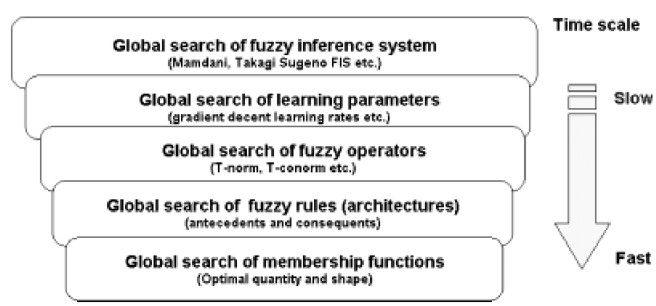

FIG. 1. General computational framework of EvoNF.

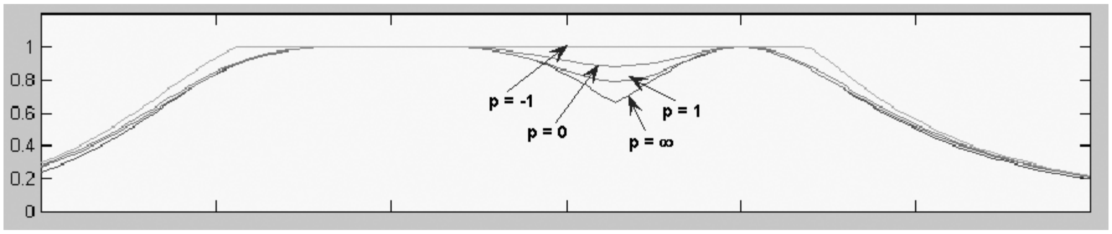

FIG. 2. Effects of changing p of T-conorm operator.

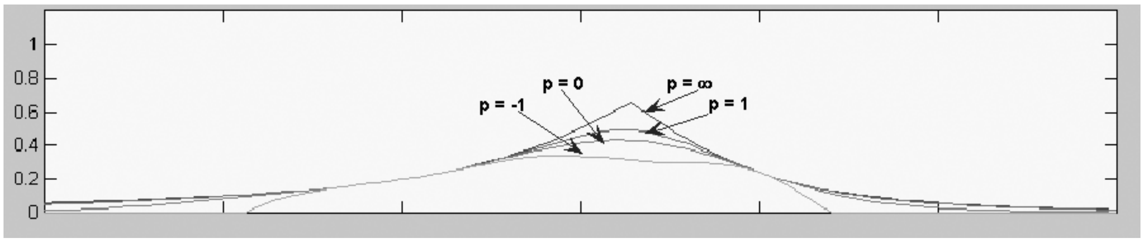

FIG. 3. Effects of changing p of T-norm operator.

Parameterization of T-norm operators. T-norm is a fuzzy intersection operator, which aggregates the intersection of two fuzzy sets A and B while T-conorm operators compute fuzzy union of two fuzzy sets A and B. The Schweizer and Sklar's T-norm and T-conorm operator can be expressed as:

$$\text{T} - \text{norm } T(a, b, p) = [\max\{0, (a^{-p} + b^{-p} - 1)\}]^{-\frac{1}{p}}$$

$$\text{T} - \text{conorm } S(a, b, p) = 1 - [\max\{0, ((1 - a^{-p}) + (1 - b^{-p}) - 1)\}]^{-\frac{1}{p}}$$

It is observed that

$$\lim_{p \to 0} T(a, b, p) = ab$$
$$\lim_{p \to \infty} T(a, b, p) = \min\{a, b\}$$

which correspond to two of the most frequently used T-norms in combining the membership values on the premise part of a fuzzy *if–then* rule.

Figures 2 and 3 give a general idea of how the parameter p affects the T-conorm and T-norm operators for two bell-shaped membership functions.

Chromosome modeling and representation. The antecedent of a fuzzy rule defines a local region, while the consequent the behavior within the region via various constituents. Basically, the antecedent part remains the same regardless of the inference system used. A different consequent describes a constituent's result in different FIS. For applying evolutionary algorithms, problem representation (chromosome) is very important as it directly affects the proposed algorithm. Referring to Figure 1 each layer (from fastest to slowest) of the hierarchical evolutionary search process has to be represented in a chromosome for successful modeling of EvoNF. A typical chromosome of the EvoNF would appear as shown in Figure 4 and the detailed modeling process is as follows.

Layer 1. The simplest way is to encode the number of MF per input variable and the parameters of the MF. Figure 5 depicts the chromosome representation of n *bell* MF specified by its parameters p, q, and r. The optimal parameters of the MF located by the evolutionary algorithm will be fine-tuned later by the neural network-learning algorithm. A similar strategy could be used for the output MF in the case of a Mamdani FIS. Experts may be consulted to estimate the MF shape-forming parameters to estimate the search space of the MF parameters.

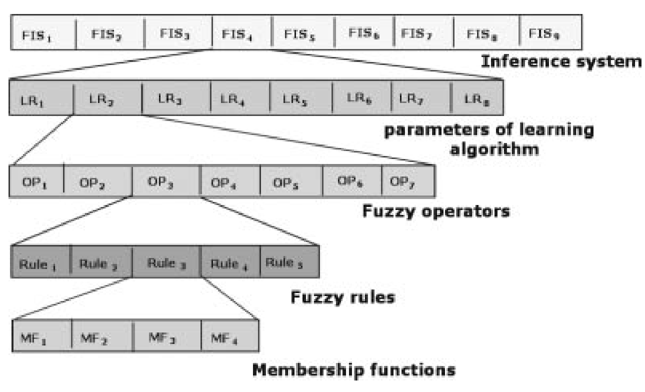

FIG. 4. Chromosome structure of the EvoNF model.

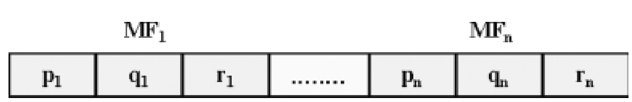

FIG. 5. Chromosome representing n MF for every input/output variable coding the parameters of a bell-shape MF.

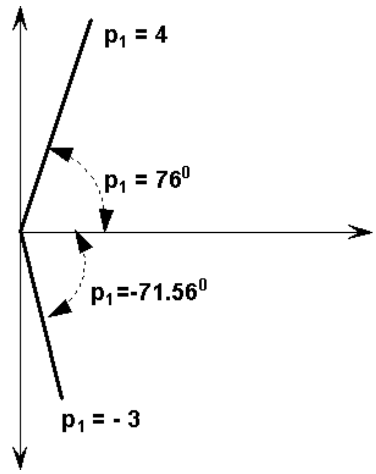

FIG. 6. Angular coding technique of rule consequent parameters of Takagi–Sugeno inference system.

We used the angular coding method proposed by Cordón, Herrera, Hoffmann, and Magdalena (2001) for representing the rule consequent parameters of the Takagi–Sugeno inference system. Rather than directly coding the consequent parameters, the "transformed" parameters represent the direction of the tangent $\alpha_i = \arctan p_i$. The range for the parameters α_i is the interval $(-90°, +90°)$, such that the parameters p_i can assume any real value. A single input Takagi–Sugeno system $Y = p_1 X + p_0$ defines a straight line. The real value p_1 is simply the gradient between this line and the X-axis. Parameter p_0 determines the offset of the straight line (intercept) along the Y-axis. Angular coding is advantageous, because the value of p_0 varies between different rules and it is difficult to use some fixed interval to exploit the search space. The procedure is illustrated in Figure 6.

Layer 2. This layer is responsible for the optimization of the rule base. This includes deciding the total number of rules, representation of the antecedent and consequent parts. The number of rules grows rapidly with an increasing number of variables and fuzzy sets. The simplest way is that each gene represents one rule, and "1" stands for a selected and "0" for a nonselected rule. Figure 7 displays such a chromosome structure representation. To represent a single rule a position-dependent code with as many elements as the number of variables of the system is used. Each element is a binary string with a bit per fuzzy set in the fuzzy partition of the variable, meaning the absence or presence of the corresponding linguistic label in the rule. For a three input and one output variable, with fuzzy partitions composed of 3, 2, 2 fuzzy sets for input variables and 3 fuzzy sets for output variable, the fuzzy rule will have a representation as shown in Figure 8.

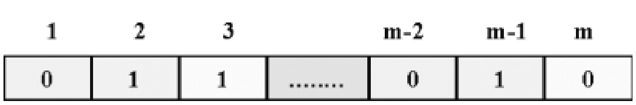

FIG. 7. Chromosome representing the entire rule base consisting of m fuzzy rules.

FIG. 8. Chromosome representing an individual fuzzy rule (three input variables and one output variable).

Layer 3. In this layer, a chromosome represents the different parameters of the T-norm and T-conorm operators. Real-number representation is adequate to represent the fuzzy operator parameters. The parameters of the operators will be fine-tuned using gradient descent techniques.

Layer 4. This layer is responsible for the selection of optimal learning parameters. Performance of the gradient descent algorithm directly depends on the learning rate according to the error surface. We used real-number representation to represent the learning parameters. The optimal learning parameters decided by the evolutionary algorithm will be used to tune MF and the inference mechanism.

Layer 5. This layer basically interacts with the environment and decides which FIS (Mamdani type and its variants, Takagi–Sugeno type, Tsukamoto type, etc.) will be the optimal according to the environment.

Once the chromosome representation, C, of the entire EvoNF model is done, the evolutionary search procedure could be initiated as follows:

1. Generate an initial population of N numbers of C chromosomes. Evaluate the fitness of each chromosome depending on the problem.
2. Depending on the fitness and using suitable selection methods, reproduce a number of children for each individual in the current generation.
3. Apply genetic operators to each child individual generated above and obtain the next generation.
4. Check whether the current model has achieved the required error rate or the specified number of generations has been reached. Go to Step 2.
5. End

Analysis and Results

Model Evaluation and Experimentation Results

For simulations we have used data provided from a survey of 69 Malaysian multinational corporation subsidiaries. Each subsidiary's data set were represented by the subsidiary strategic role and size with the following input variables.

Subsidiary strategic role represented by:

1. Product manufactured (1–5 scale representing fully independent from the parent and fully dependent)
2. Resources (1–5 scale representing fully independent from the parent and fully dependent)

TABLE 2. Parameter settings of EvoNF framework.

Population size	40
Maximum no. of generations	35
FIS	Takagi Sugeno
Rule antecedent MF	2 MF (parameterised Gaussian) per input variable
Rule consequent parameters	Linear parameters
Gradient descent learning	10 epochs
Ranked based selection	0.50
Elitism	5%
Starting mutation rate	0.50

3. Tax protection (1–5 scale representing tax protection and no tax protection)
4. nvolvement strategy (1–4 scale representing subsidiary, subsidiary and parent, parent alone, and equal share)
5. Financial independence (1–5 scale representing fully independent from the parent and fully dependent)
6. Suppliers relationship (1–5 scale representing fully independent from the parent and fully dependent)

Subsidiary size represented by:

7. Customers and market (1–4 scale representing the geographical distribution of the customers)

EvoNF Training

We used the popular grid partitioning method (clustering) to generate the initial rule base. This partition strategy requires only a small number of MF for each input. We used 90% of the data for training and the remaining 10% for testing and validation purposes. The initial populations were randomly created based on the parameters shown in Table 2. We used a special mutation operator, which decreases the mutation rate as the algorithm greedily proceeds in the search space 0. If the allelic value x_i of the i-th gene ranges over the domain a_i and b_i the mutated gene is drawn randomly uniformly from the interval $[a_i, b_i]$.

$$x_i' = \begin{cases} x_i + \Delta(t, b_i - x_i), & \text{if } \omega = 0 \\ x_i + \Delta(t, x_i - a_i), & \text{if } \omega = 1 \end{cases}$$

where ω represents an unbiased coin flip $p(\omega = 0) = p(\omega = 1) = 0.5$, and

$$\Delta(t, x) = x\left[1 - \gamma^{(1-\frac{t}{t_{max}})^b}\right]$$

defines the mutation step, where γ is the random number from the interval [0,1] and t is the current generation and t_{max} is the maximum number of generations. The function computes a value in the range $[0, x]$ such that the probability of returning a number close to zero increases as the algorithm proceeds with the search. The parameter b determines the impact of time on the probability distribution Δ over $[0, x]$. Large values of b decrease the likelihood of large mutations in a small number of generations. The parameters mentioned in Table 2 were decided after a few trial and error approaches. Experiments were repeated 3 times and the average performance measures are reported. Figure 9 illustrates the meta-learning approach for training and test data combining evolutionary learning and gradient descent technique during the 35 generations. The 35 generations of meta-learning approach created 76 *if–then* Takagi–Sugeno-type fuzzy *if–then* rules compared to 128 rules using the grid-partitioning method. Empirical results for the test data (13 MCS) are depicted in Figure 10 (fuzzy modeled values are indicated in *).

We also used a feed forward neural network with 12 hidden neurons (single hidden layer) to model the export output for the given input variables. The learning rate and momentum were set at 0.05 and 0.2, respectively, and the network was trained for 10,000 epochs. The network parameters were decided after a trial and error approach. The obtained training and test results are depicted in Table 3.

TABLE 3. Training and test performance of the different intelligent paradigms.

Export Output	Intelligent paradigms					
	EvoNF			Neural network		
	RMSE		CC^a	RMSE		CC^a
	Train	Test		Train	Test	
	0.0013	0.012	0.989	0.0107	0.1261	0.946

[a]CC = Correlation coefficient.

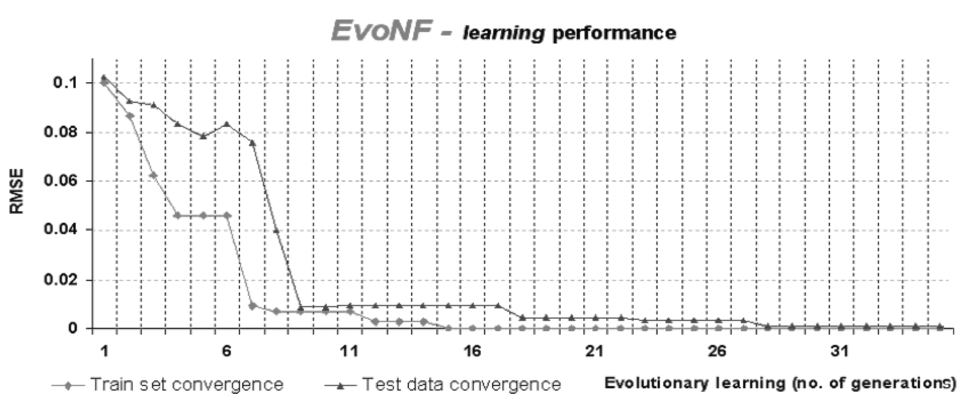

FIG. 9. Meta-learning performance (training and test performance) of EvoNF framework.

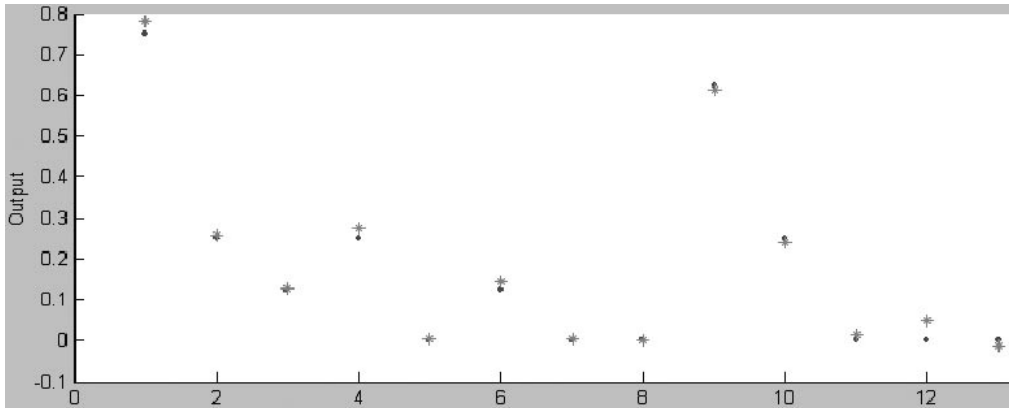

FIG. 10. Test results showing the EvoNF designed export output (scaled values) for 13 MCSs with respect to the desired values (in blue color).

Conclusions

In this article, we have modeled the complex export pattern behavior of 69 Malaysian MCSs based on their strategic role and their size to find out whether these characteristics influence the export value. The product manufactured, resources, tax protection, involvement strategy, financial independence, and suppliers' relationship with a MNC determined the strategic role. The MCSs' size, however, was manifested through their customers and markets. Each strategic role variable as well as size variable was underpinned with a corresponding Likert scale.

We have developed an integrated computational framework, defined as architecture of EvoNF, to optimize FIS by using a neural network learning technique and evolutionary computation. The proposed framework has adapted Takagi–Sugeno FIS. The architecture and the evolving mechanism were considered as a general framework for adaptive fuzzy systems. The FIS has changed quantity and shape of MF, rule base fuzzy operators, and learning parameters according to export volume requirements.

The developed EvoNF has learned the chaotic patterns and modeled the export behavior of Malaysian MCSs by using an optimized Takagi–Sugeno FIS. Given the approximate values of strategic role elements and a strategic size element we have provided the actual export pattern behavior of the MCSs. These findings justify the proposition in the modern literature that MCS size and its strategic role are related to its export intensity.

As illustrated in Figure 10 and Table 3, we have successfully adapted input variables to achieve desired output for Malaysian MCSs. The proposed method has shown that we can easily approximate the export behavior within the tolerance limits. When compared to a neural network approach, EvoNF performed better (in terms of lowest RMSE) and higher correlation coefficient. Our experiment results also reveal the importance of all the key input variables (six that relate to subsidiary strategic role and one relating to subsidiary size) to model the behavior within the required accuracy limits. These techniques might be useful not only to managers in MNCs, but also to government administrators for the long-term strategic management of the economy. As a future research project, we plan to incorporate more data mining techniques and improve the modeling aspects of the export behavior.

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