Partner selection in agile supply chains: a fuzzy intelligent approach

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Partner selection in agile supply chains: a fuzzy intelligent approach

Partner selection is a fundamental issue in supply chain management as it contributes significantly to overall supply chain performance. However, such decision making is problematic due to the need to consider both tangible and intangible factors, which cause vagueness, ambiguity and complexity. This paper proposes a new fuzzy intelligent approach for partner selection in agile supply chains (ASC) by using fuzzy set theory in combination with radial basis function artificial neural network. Using these two approaches in combination enables the model to classify potential partners in the qualification phase of partner selection efficiently and effectively using very large amounts of both qualitative and quantitative data. The paper includes a worked empirical application of the model with data from eighty-four representative companies within the Chinese electrical components and equipment industry, to demonstrate its suitability for helping organizational decision makers in partner selection.

Keywords: Partner selection; agile supply chains; fuzzy set theory; artificial neural network

1. Introduction

Partner selection is a fundamental issue in supply chain management as it contributes significantly to overall supply chain performance. However, the tangible and intangible factors associated with the partner selection problem cause vagueness and ambiguity in the decision making process (Yucel and Guneri, 2011). At the same time, the vagueness of the information in this type of problem makes decision making more complicated (Amid *et al.*, 2006; Yang, 2010). Consequently, many researchers have seen the application of fuzzy set theory (FST) as offering an efficient means of handling this uncertainty effectively and of converting human judgments into meaningful results.

Luo *et al.,* (2009) developed a radial basis function artificial neural network (RBF-ANN) based intelligent model that helps overcome the information processing difficulties inherent in screening a large number of potential partners in the early stages of the partner selection process in agile supply chains (ASCs). Their model enables potential partners to be assessed against multiple criteria using both quantitative and qualitative measures. Yet, as the authors noted, building the RBF-ANN based intelligent model assumes the availability of an adequate supply of both quantitative and qualitative data on all potential partners under consideration. However, in real business situation, most of the input information is not known precisely, especially qualitative information. The values of many qualitative criteria are expressed in vague terms, such as "have good quality" but "not too high in price". Therefore, deterministic models cannot easily take this vagueness into account (Amid *et al.,* 2009). Furthermore, the decision sometimes involves much complex and imprecise information about potential partners, especially during the early stage of the process (Famuyiwa *et al.*, 2008; Wu and Barnes, 2011). In these cases, FST is one of the best tools to handle uncertainty (Erol and Ferrell 2003; Yucel and Guneri, 2011).

Building on the work of Luo *et al.*, (2009), this paper applies FST in combination with a RBF-ANN based intelligent model to propose a new fuzzy intelligent approach for partner selection, especially for the qualification phase of supplier selection, in ASCs.

The main advantages in applying both FST and RBF-ANN methodologies are twofold. Firstly, the problem of qualification in ASC is extremely complex. If we use only one of them (as Luo *et al.,* (2009), Amid *et al.,* (2009) and Wu *et al.,* (2010) did) this problem cannot be solved with efficiency and effectiveness. Because, RBF-ANN models typically only consider quantitative criteria, it creates a significant problem in considering qualitative ones. FST can overcome the shortcomings of RBF-ANN but can neither achieve high efficiency nor a high degree of automation in information processing. Secondly, the two methods are mutually reinforcing, in that the shortcomings of one method are compensated for by the strong points of the other. On the one hand, FST can consider the vagueness and uncertainty of complex human judgements, but its information processing ability and efficiency is limited, especially during the large-scale information processing associated with supplier qualification. On the other hand, RBF-ANN can solve the information processing problem very efficiently and effectively. However, it cannot consider the vagueness and uncertainty of information that is inevitable in ASC partner selection (Buyukozkan and Cifci, 2011). Using these methods in combination increases the chances of solving the qualification problem more efficiently and effectively.

After this Introduction the paper is structured as follows. Section 2 reviews the existing supply partner selection literature, highlighting the current absence of attempts to utilise FST in combination with RBF-ANN in partner selection. Section 3 then describes how these methods can be combined in a fuzzy intelligent approach to partner selection. An empirical illustration of the proposed method follows in Section 4. The paper concludes with discussions and conclusions in Section 5.

2. Literature review

Kumar *et al.*, (2006) summarized five main reasons why partner selection is considered to be a complex problem, namely multiple criteria, potential partners having different performance on different criteria, internal policy and externally imposed system constraints, production capacity constraints, and delivery time constraints. More importantly, most of these problems cannot be expressed in exact numeric terms. Such vagueness in critical information cannot be captured in a deterministic problem and therefore the optimal results of formulation may not serve the real purpose of the problem (Kumar *et al.*, 2006; Chen *et al.*, 2011). In addition, because human judgment is needed in so many areas (such as preferences on alternatives or on the attributes of partners or the class number and borders), partner selection becomes more difficult and risky (Keskin *et al.*, 2010). In building a dynamic feedback model for partner selection in ASCs, Luo *et al.*, (2009) and Wu and Barnes (2012) divide the partner selection process in ASCs into four phases, criteria formulation, qualification, final selection and application feedback (shown in Figure 1). We now use these four headings to review relevant papers on decision models in the next four sub-sections.

[Insert Figure 1 about here.]

2.1 Decision models for formulation of criteria

The first phase of the stage of the partner selection process is that of criteria formulation. This involves deciding what criteria should be used in the later stages of the process. Cost has historically been considered to be the most important criterion in most purchasing decisions. Arguably this continues to be the case. Indeed its importance may have increased in an environment when vendors increasingly seek to exploit global supply markets. However, advocates of a more strategic approach to purchasing (e.g. Kraljic, 1983) have long argued that focussing on price alone is detrimental to longer term supply performance. There has also long been evidence that practitioners do apply multiple criteria. For example, Dickson's (1966) classic study identified twenty three criteria for partner selection. Weber *et al.*'s (1991) review of seventy four papers showed that price, quality, delivery, production capacity and facility location were the most commonly used criteria. In a dynamic business environment it is likely that the relative importance of these criteria will change over time. This instability coupled with a tendency to incorporate an increasing number of criteria inevitably makes the partner selection process more complicated (Weber *et al.*, 1991).

Various methods have been developed to try to cope with this complexity. Humphreys *et al.*, (2011) pointed out that the key area of supply chain management activities for concern is strategic supplier development. Based on statistical analysis of a survey in in the Hong Kong electronics industry, they examined the role of supplier development activities in the context of buyer-supplier performance and found that effective communication, direct supplier involvement, trust, supplier evaluation and supplier strategic objectives are the five key factors. Their research could be used by Western companies when they are considering establishing partnership with Far Eastern suppliers. Lin *et al*., (2006) proposed an agility index using attribute ratings and corresponding weightings, aggregated by a fuzzy weighted average. These are generally aimed at constructing a smaller, more customized set of criteria by determining their relative importance in different procurement circumstances. However, as Wu and Barnes (2012) note, the literature contains relatively few examples of methods aimed at optimising criteria in partner selection. Lin and Chen (2004) propose a method for developing industry specific criteria based on a set of general criteria, whilst Wu and Barnes (2010) use Dempster-Shafer theory and optimisation to develop a model for formulating criteria in ASCs.

2.2 Decision models for qualification

The qualification phase involves reducing a list of all possible suppliers to a smaller set of partners deemed acceptable for the specific purchases under consideration (De Boer, 2001; Soni and Kodali, 2012). As Sarkar and Mohapatra (2006) demonstrate, such supply base reduction is a necessary prerequisite for closer more cooperative relationship with partners. Thus, qualification is a sorting process rather than a ranking process. The initial stage of qualification invariably involves constructing a set of acceptable suppliers, whilst subsequent stages are aimed at reducing this number. The methods and models applied for the qualification phase include:

2.2.1 Data envelopment analysis models

Data envelopment analysis (DEA) was initially proposed for use in supplier selection by Weber *et al.,* (1991, 1998). It is based on the concept of the efficiency of the decision alternatives (De Boer *et al.*, 2001). Wu and Blackhurst (2009) developed what they term ‘augmented DEA’, as the basis for a partner evaluation and selection model. They use weight constraints in their model to reduce the possibility of having inappropriate input and output factor weights. Thereby, they improve the discriminatory power of their method over basic DEA models through the incorporation of a range of virtual standards. Zeydan *et al.*, (2011) proposed a Fuzzy-DEA methodology that takes into account both qualitative and quantitative criteria in supplier selection for one of the biggest car manufacturing factory in Turkey. As a first step they initially use fuzzy TOPSIS (the technique for order performance by similarity to ideal solution) to rank suppliers. They then transform qualitative variables into a quantitative variable for use in DEA methodology.

2.2.2 Cluster analysis models

Cluster analysis is a statistical method that can be used to group items with similar scores for a quantifiable attribute together into a number of clusters. The technique enables differences between items within a cluster to be minimised and differences between items from different clusters to be maximised (De Boer, 2001). Hinkle *et al*., (1969) showed how cluster analysis can be used to classify groups of comparable partners using appropriate selection criteria. Subsequently, Ha and Krishnan (2008) introduced a hybrid method for cluster analysis that enables both qualitative and quantitative performance criteria to be utilised. Keskin *et al.,* (2010) applied Fuzzy Adaptive Resonance Theory (ART)'s classification ability to supplier evaluation and selection. By using Fuzzy ART, their supplier selection method can not only select the most appropriate suppliers but also cluster all of the vendors according to the chosen criteria. By segmenting and selecting suppliers after cluster analysis, Che (2010) found that unwanted candidates could be eliminated effectively, and the resulting supplier combination still meet customer needs. However, to date, cluster methods have only been used to verify clusters on a global scale. Relationships between local and global perspectives on cluster detection have yet to be explored (Wu and Barnes, 2012).

2.2.3 Artificial neural network models

Artificial neural network models make use of computer-aided systems which can, in effect, be “trained” using experts or historical data, to develop a solution to a new problem by consulting the systems models used to solve past problems. Lee and Ou-Yang (2009) developed an artificial neural network (ANN) based model to help buyers involved in partner selection negotiations. They claim that their model offers an adaptive tool for use in what can be sophisticated and challenging negotiations. However, it can be criticised for its inadequate number of input factors and its focus on price. Luo *et al.*, (2009) also offered an ANN-based model which helps overcome the information processing difficulties inherent in scanning a huge number of potential partners in the early phases of the partner selection process. They use RBF-ANN to enable potential partners to be measured against multiple criteria, both quantitative and qualitative. Aksoy and Ozturk (2011) built an ANN-based supplier selection and suppliers performance evaluation system for use in a JIT manufacturing environment. The most distinctive advantage of their model is its ability to identify improvement areas from the ANN model outputs.

2.3 Decision models for final selection

Final selection involves selecting the most suitable partners from amongst those already qualified in the previous phase. Solving this problem can become very challenging when it involves multiple business processes, multiple criteria and multiple products. Models used for this phase include:

2.3.1 Goal programming

Hajidimitriou and Georgiou (2002) developed a goal programming model for partner selection to achieve multiple goals for different levels of performance for each criterion. However, the method did not consider combinations of potential partners. Ravindran *et al.*, (2010) used goal programming to solve partner selection in two separate steps, namely qualification and order quantities allocation, by considering it to be a multiple criteria optimisation problem. Abdallah *et al.*, (2012) introduced a closed-loop supply chain formulation model which can capture the interdependency between location inventory decisions in different types of supply chains. Besides the evaluation and selection decision-making model, their research also provides a flexible framework for policy-makers to enhance the economic feasibility of reverse logistics partners in ASCs.

2.3.2 Multi-objective programming

Amid *et al.*, (2006) proposed a fuzzy multiple objectives linear model to solve the partner selection problem in supply chains by applying an asymmetric fuzzy decision making technique. Guneri *et al.,* (2009) presented an integrated fuzzy and linear programming approach for supplier selection. Firstly, the linguistic values are applied to assess weights and ratings of selection criteria. Then fuzzy positive and negative ideal solutions are used to find each supplier's closeness coefficient. Finally, order quantities were assigned using the linear programming model. Wu *et al.*, (2010) proposed a fuzzy multi-objective programming approach to decide on supplier selection, taking risk factors into consideration. This modelled the supply chain on three levels, and used simulated quantitative and qualitative data to assess the fuzzy events into the fuzzy multi-objective programming models. Chamodrakas *et al.*, (2010) introduced a supplier evaluation and selection method in electronic marketplaces. Potential suppliers were screened through the enforcement of hard constraints on the selection criteria. Then, their model applied Fuzzy Preference Programming for the final selection. This model has two advantages. Firstly, it has the potential to alleviate the information overload effect which is inherent in the environment of electronic marketplaces. Secondly, it can facilitate an easier elicitation of user preferences through the reduction of necessary user input and computational complexity.

In terms of solving the nonlinear programming problems with bounded variables, Hsu *et al.*, (2010) applied the resolution identity result to construct the membership function of a fuzzy capability-index estimate for each supplier. Therefore, the preferred suppliers can be identified by using a ranking method of fuzzy preference relations of the suppliers. Kara (2011) integrated stochastic programming model and fuzzy TOPSIS methods. Firstly, fuzzy TOPSIS is used to rank potential suppliers under the fuzzy environment. Then, a group of ranked potential suppliers is included in a two-stage stochastic programming model for evaluation. By using this methodology, supplier evaluation procedure can be done in an unknown environment.

2.3.3 Integer programming

Combining the information of House of Quality and evaluation results of the part design scheme, Tang *et al.*, (2005) constructed a 0-1 integer programming model for selection of the parts combinatorial scheme in supplier-involved part deployment processes. In their model, a two-layer fuzzy synthesis evaluation method was applied to assess the part design scheme in a supplier-involved new product development process. Drawing on FST and VIKOR methodologies, Sanayei *et al.*, (2010) employed linguistic variations to measure the weights and ratings for the selected criteria, and construct a hierarchy multi-criteria decision making model to deal with supply chain partner selection. The VIKOR method they incorporate enables a multi-criteria decision making problem to be solved whilst considering conflicting and non-commensurable criteria.

Zhang and Zhang (2011) used a mixed-integer programming approach to minimize the costs of purchase, selection, holding and shortage. However, their model can be criticised for not considering the supply risk and price discounts connected with the order quantities. Yucel and Guneri (2011) developed a weighted additive fuzzy programming model for multiple criteria supplier selection problems. As it has no computational procedure, the model can deal with the rating of factors very effectively. Chaabane *et al.,* (2011) applied multi-objective mixed-integer linear programming technique to build a comprehensive methodology to address sustainable supply chain formation problems. Their proposed model can make trade-offs between economic and environmental considerations during suppliers and sub-contractors selection process. The model was successfully applied in a Canadian steel firm facing new legislation capping carbon emissions.

2.3.4 Analytic hierarchy/network process models

Haq and Kannan (2006) constructed an integrated multi-echelon distribution inventory and supplier selection model in a produce-to-order environment by combining the fuzzy analytical hierarchy process (AHP) method with genetic algorithm. Buyukozkan *et al.*, (2008) developed a fuzzy AHP and fuzzy TOPSIS approach to rank partners under conditions of uncertainty and complexity. It would be beneficial if this model could be extended to a group decision making environment in order to avoid the bias inherent in a single decision maker. The identification of universal criteria weights is not possible as any organization forming a supply chain will have its own specific requirements. Besides the common criteria, Chan *et al.*, (2008) also discussed some of the important decision variables which can play a critical role in case of the international sourcing. They built a fuzzy based AHP to tackle both quantitative and qualitative decision factors involved in selection of global supplier. The model can provide the guidelines for the decision makers to select their global suppliers in the competitive business scenario.

Lee (2009) also proposed a fuzzy AHP model, which incorporates the benefits, opportunities, costs and risks concept, to evaluate various aspects of suppliers. In their model, multiple positive or negative factors which may affect the success of the buyer-supplier relationship were analyzed in details. In general, the methods proposed by using AHP only consider one-way hierarchical relationships between the factors.

This is a simplistic assumption that does not consider the many possible relationships. Chen *et al.*, (2011) focused on third party logistics partner selection in supply chains. In order to achieve the most effective network, they firstly applied a negotiation mechanism to select potential suppliers as outsourcing alternatives. They then used the AHP method to identify the best choice for partnership in a specific supply chain. The main feature of their methodology is that the proposed mechanism focused used FST to incorporate a level of vagueness for preferences for potential partners.

Wu *et al.*, (2009) proposed a two-stage approach to solve the problem of partner selection in ASCs by applying an analytic network process-mixed integer multi-objective programming (ANP-MIMOP) model. Stage one uses an ANP methodology to compute the different weights for different selection criteria. Stage two uses these weights in a MIMOP sub-model to determine supply chain structure and optimize order quantities. Onut *et al.*, (2009) initiated a supplier evaluation approach based on the ANP and TOPSIS methods under conditions of uncertainty. Contrary to conventional Fuzzy ANP methodology in the literature, they used triangular fuzzy numbers in all pairwise comparison matrices in the Fuzzy ANP. Hence, criteria weights were calculated as the triangular fuzzy numbers and then these fuzzy criteria weights were inserted to the fuzzy TOPSIS methodology to rank the alternatives. Buyukozkan and Cifci (2011) developed a fuzzy ANP approach within multi-person decision making schema under incomplete preference relations for sustainable suppliers' selection. These ANP models can overcome the shortcomings of AHP approaches but cannot solve the detailed lot-sizing problem.

Vinodh *et al.,* (2011) proposed a supplier selection conceptual model which encompasses various criteria and sub-criteria. In their conceptual model, the fuzzy ANP approach has been used for the supplier selection process. Based on supplier selection weighted index, the best supplier can be determined. After examining the components and elements of green supply chain management, Buyukozkan and Cifci (2012) proposed a new green supply chain management evaluation framework. By applying ANP technique, the dynamic characteristics of the green supply chain management have been analyzed. Meanwhile, to cope with ambiguity and vagueness of the decision maker's judgments, a FST extension of the ANP technique was introduced and applied in a real-case study of a pioneering company in Turkey.

2.3.5 Genetic algorithms models

Applying FST, T-transformation technology, and genetic algorithms (GA), Wang and Che (2007) developed an integrated model for modelling the change behaviour of product parts, and for evaluating alternative suppliers for each part. Based on the concepts of part change requirements, fuzzy performance indicators, and the integration of different attributes, their model allows the part supplier selection of a specific commercial product to be explored and modelled. The result of their experiment shows that the proposed GA was reliable and robust. In order to effectively assess the efficiency of configuration change schemes, Wang (2008) also applied the GA to establish a model to find near-optimal solution within a short period of time. In their model, the analysis of component parts with association graph, fuzzy theory and data T transfer were integrated. However, the main drawback of GA is that it requires users to have a level of specialised knowledge that is likely to be well beyond that possessed by most managers and organizational decision makers. In addition, a severe drawback is that some feasible solutions cannot be generated by crossover operation.

2.4 Decision models for the application feedback

Christopher and Towill (2000) have argued that in increasingly competitive environments, there is a need to review and evaluate the application of one cycle of the supply partner selection process in order to improve its application in the subsequent cycle. Accordingly, Luo *et al.*, (2009), Wu and Barnes (2009) and Wu and Barnes (2012) introduce the additional stage of application feedback into the supply partner selection process for ASCs. Based on the methods of continuous improvement and principles of organizational learning, it aims to assist decision makers in their efforts to improve the effectiveness of the supply chain by ensuring that the most suitable partners are selected at all times. They argue that this stage is particularly important in the very dynamic environments in which ASCs are most likely to be best suited, because such conditions will give rise to an increased number of applications of the partner selection process. Najmi and Makui (2012) combined AHP and Decision Making Trial and Evaluation Laboratory methods for understanding the relationship between comparison metrics and integration to provide a value for performance measurement. The proposed methodology tries to identify the key features of a performance evaluation model. One of the main contributions of their work is that the interdependencies of the performance metrics are considered in model.

2.5 Summary of literature review

In summary, many different methods for this type of decision making problem have been proposed, including ANN, AHP, ANP, MOP and DEA. However, all of these methods lack the ability to handle the linguistic vagueness of fuzzy factors individually (Kumar *et al.*, 2006). In fact, many existing decision support models only consider quantitative criteria for partner selection. However, several influential factors (such as incomplete information, additional qualitative criteria and imprecision preferences) are often not taken into account in the decision making process (Chen *et al.*, 2006).

Fuzzy logic theory was first introduced to deal with the vagueness of human thought (Zadeh, 1965). Subsequently, many fuzzy based models/methods have been utilised for partner selection in supply chain management, as discussed in the four sub-sections above. Besides the above fuzzy based approaches, Erol and Ferrell (2003) also used fuzzy quality function deployment (QFD) to convert qualitative information into quantitative parameters and then combined this data with other quantitative data to parameterize a multi-objective mathematical programming model. Bevilacqua *et al.*, (2006) proposed a fuzzy QFD approach to support supply partner selection. This approach uses both internal and external variables to rank the potential partners. The advantage of this method lies in its ability to transform decision makers' verbal assessments to linguistic variables, which are more accurate than other non-fuzzy methods. However, it is used to rank potential partners, which is not the main objective in the early phase of partner selection. Sarkar and Mohapatra (2006) used a fuzzy set approach to rank and reduce the number of potential partners, by focusing on their performance and capability. However, this method has a compensation problem, as a potential partner's high score in one dimension may compensate for a low score in some other. Bayrak *et al.*, (2007) proposed a fuzzy approach method for partner selection by assessing delivery, quality, flexibility, and service criteria. However, a purely subjective method will inevitably depend heavily on experts' experiences.

Table 1 summaries the use of FST based models and approaches in papers that consider the partner selection process.

[Insert Table 1 about here.]

Table 2 lists the main features of the various models and methods used in some of the most recent literature on partner selection. The approach on which the model developed in this paper is based, namely that of fuzzy intelligent, is also included for comparison.

[Insert Table 2 about here.]

It is possible to identify several main approaches used for partner selection at different selection stages. Each approach has its own specific merits, but each approach also has its own shortcomings. The DEA method does not need to explicitly specify a mathematical form and is capable of handling multiple inputs and outputs. However, the results of its analysis are sensitive to the selection of inputs and outputs and you cannot test for the best specification. Cluster analysis has primary shortcomings. Firstly, only global-scale clusters are verified. Secondly, the relationships between local and global perspectives for cluster detection are yet to be explored. Mathematical programming allows decision makers to formulate the decision problem in terms of a mathematical objective functions. It is more objective than other qualitative models as it requiring the decision makers to explicitly depict the objective functions. However, mathematic programming models often can only consider quantitative criteria and cannot accommodate subjective attributes which are very common in partner selection problems. AHP does not consider the interactions between the various factors and also cannot effectively take into account uncertainty and risk (Wu and Barnes, 2012). ANP methodology can overcome the drawbacks of AHP but cannot solve the more detailed lot-sizing decision-making problem. GAs often requires very long fitness function evaluations times when finding the optimal solution to complex high dimensional, multimodal problems. Also, in some situations, GAs may also have a tendency towards local optimal solutions rather than global optimal solutions of the problem.

The model presented in this paper will integrate FST and artificial intelligence techniques in solving the partner selection problem in ASCs. Such an approach is both novel and potentially highly appropriate. It is novel in that there is no other model or method in the existing literatures which uses such a combination of techniques. It is appropriate in that it the use of FST enables vague and imprecise information to be more easily defined, collected, processed and combined with deterministic quantitative information in order to evaluate and select the most appropriate partners. At the same time, FST are also enhanced by incorporating artificial intelligent in ways that improve the information processing ability and efficiency. Furthermore, decision makers' judgments, in general, are often uncertain and cannot be estimated by an exact numerical value. Thus, the problem of partner selection has many uncertainties and difficulties. ANNs offer a way of dealing with ambiguous as well as unambiguous information. By using their information process capability, ANNs could achieve fuzzy programming and fuzzy reasoning functions, or even all of the fuzzy control functions. ANNs and FST have been widely applied and both have their own merits. Yet, there is a problem with the lack of flexibility in decision making with fuzzy numbers and in the determination of fuzzy shapes that can better represent experts' experiences (Kuo *et al.*, 2010). Combining FST and ANNs could overcome the main drawbacks of each approach, namely that FST does not have a learning capability and ANNs cannot express linguistic variations. FST combined with ANNs could also leverage the artificial intelligent approach to simulate human intelligent and improve decision making efficiency. However, as illustrated in Table 1 and Table 2, there is as yet no literature that combines Fuzzy and ANN methodologies in a single model. This paper seeks to address this gap in the current literature by proposing a model based on just such a combination of methods, which aims to enhance the efficiency and effectiveness of partner selection decision making.

3. The fuzzy intelligent approach for partner selection in ASCs

Building on Luo *et al.*, (2009)'s information processing model, the paper applies FST to build a fuzzy intelligent model to collect and evaluate decision makers' judgments on qualitative criteria. It then combines them with quantitative criteria after converting the linguistic variables into quantitative ones.

RBF (radial basis function)-ANN is a particular type of ANN model, which has a number of advantages. Firstly, one of the main distinguishing features of RBF-ANN is its self-learning ability. Once an RBF-ANN model had been constructed successfully, it can adopt and learn new "knowledge" about the partner evaluation and selection throughout its entire application (Moody and Darken, 1989; Luo *et al.*, 2009). Secondly, RBF-ANN is a very user-friendly approach to business decision making (Albino and Garavelli 1998). Thirdly, compared with other traditional methods, RBF-ANN is highly robust and has the ability to learn rapidly about changing decision making environments, which enables it to adopt and take account of new restrictions over time. Last but not least, RBF-ANN's ability to respond to fast-changing environmental and market conditions, make it particularly suitable for use in ASCs, whose membership may need to change frequently (Chen *et al.*, 1993; Luo *et al.*, 2009). In short, RBF-ANN seems to offer the prospect of solving the problem of partner selection more effectively and efficiently.

Accordingly, we present a proposed framework for a fuzzy intelligent approach to partner selection in ASCs, which is shown in Figure 2.

[Insert Figure 2 about here.]

It comprises three steps, which are now described in more detail.

3.1 Evaluation knowledge acquisition

The purpose of this step is to identify potential partners and select which evaluation criteria should be used in order to select the partners most compatible with the goals and objectives of the whole ASC. In this paper, we adopt the criteria formation methodology proposed by Wu and Barnes (2010) as the method for the formation of potential partner evaluation criteria, which is based on the development of an Optimal Hierarchy Criteria (Wu and Barnes, 2010). Appropriate data is then collected on each potential partner in order to conduct the evaluation.

3.2 Fuzzy information processing

Under many conditions, hard data are inadequate to model real-life situations. Since human judgements, including preferences, are often vague and it is difficult to estimate an individual's judgement with an exact numerical value. A more realistic approach may be based on linguistic assessments instead of numerical values (Chen *et* *al*., 2006). Linguistic variables can be defined as variables whose values are expressed in linguistic terms (Zimmermann, 1991). In the fuzzy intelligent model proposed in this paper, qualitative criteria are evaluated by decision makers or industry experts based on their knowledge and experience by using the linguistic variables. The fuzzy information processing step of the model involves defining, collecting and processing linguistic variables. This can be divided into the following three sub-phases.

3.2.1 Fuzzification of linguistic variables

The vague and imprecise nature of the information available on each qualitative criterion is characterized through membership functions. Particular forms of the fuzzy numbers, which are known as triangular and trapezoidal fully numbers, are a common tool for presentation of imprecise information (Faez *et al.*, 2009). In this paper, we use triangular membership function as shown in Figure 3. The intervals associated with different linguistic variables may overlap to reflect the existence of inherent fuzziness of adjacent words such as high and very high (Erol and Ferrell, 2003, Famuyiwa *et al.*, 2008). As the simplicity of triangular membership function, the fuzzy intelligent model uses it to measure the degree of membership of each linguistic level relative to the rating scale of 1-10. Figure 3 shows the fuzzy set definition with five membership (or linguistic variable levels) functions graphically.

[Insert Figure 3 about here.]

3.2.2 Development and application of the fuzzy "if-then rules"

In this sub-phase, fuzzy "if-then rules" will be developed to relate the evaluation criteria with compatibility drivers. A fuzzy if-then rule assumes the form:

If a is X, then b is Y

where X and Y are the linguistic values defined by fuzzy sets on the universe of discourse a and b, respectively. In general, "a is X" is called the antecedent or premise, while "b is Y" is called the consequence or conclusion. Historical data, expert knowledge and the experience of decision makers are used to formulate the interactions between the compatibility drivers and compatibility criteria in the form of fuzzy “if-then rules”. Table 3 shows a fuzzy “if-then rules” example that will be used in the following empirical illustration. For instance, “If one *input is low and the other is very low*, then *the output is very low*”.

[Insert Table 3 about here.]

3.2.3 Defuzzification of the fuzzy outputs

The third phase of this step focuses on transforming qualitative data in the form of linguistic variables into a format that can be used along with quantitative data.

The output of each rule is a fuzzy set, but in general, we want the output for an entire collection of rules to be a single number. Therefore, the output fuzzy sets for each rule, are first aggregated into a single output fuzzy set. Then the resulting set is defuzzified to a single number. The smallest of max (Z_{SOM}) and largest of max (Z_{LOM}) defuzzification methods are not used as the other three dufuzzification methods because of their obvious bias (Famuyiwa *et al.*, 2008). However, the centroid of area (Z_{COA}), which can be defined as $Z_{COA} = \frac{\int_Z \mu_A(Z) Z dZ}{\int_Z \mu_A(Z) dZ}$, is the most widely used method and it is the one adopted in the model presented in this paper (the different defuzzification schemes are shown in Figure 4). Therefore, the inputs are always hard numerical values limited to the universe of discourse of the input variables and the output is a fuzzy degree of membership in the qualifying linguistic level in the interval between zero and one. Figure 5 shows a fuzzy rules reasoning process surface based on the fuzzy “if-then rules” listed in Table 3.

[Insert Figure 4 and 5 about here.]

3.3 Construction and application of the fuzzy intelligent model

3.3.1 Construction of the fuzzy intelligent model

Use of an RBF-ANN information processing model to solve the qualification and classification problem and reduce the solution space of the partner selection problem has the potential to improve the efficiency of the partner selection process and reduce the cost of final selection (Luo *et al.*, 2009; Wu and Barnes, 2012). RBF-ANN has only one hidden layer and can simulate any function within any precision. Therefore, we construct a three-layer feed forward network, comprising an input layer, hidden layer and output layer. The hidden layer applies the radial basis function, which is a Gauss function, as the activation function. The inputs of every neural cell in the hidden layer are the differences between the weight vector W_{ij} of input layer and the input vector x^q multiplied by the threshold value b_j. The values of W_{ij} and b_j are determined by the RBF-ANN's precision and accuracy when the network is being constructed (Moody and Darken, 1989). The inputs of i^{th} neural cell in the hidden layer are: $t_i^q = \sqrt{\sum_j (W_{ij} - x_i^q)^2} \times b_j$. The outputs of j^{th} neural cell in hidden layer are: $r_j^q = \exp(\sqrt{\sum_j (W_{ij} - x_i^q)^2} \times b_j)$. The inputs of output layer are weighted sum of the output of the hidden layer. Because of the activation function is pure linear function, the output is: $y_k^q = \sum_j (r_j \times V_{jk})$. (Please see Luo *et al.*, (2009) for more detailed mathematics.)

As to the numbers of neural cells at input layer, it depends on the evaluation criteria built for the partner qualification and classification. For the numbers of neural cells at output layer, we follow Luo *et al.*, (2009)'s research which applied Kraljic (1983)'s classic partner classification matrix (see Figure 6) and used (0,0) to represents a *routine partner*; (0,1) for a *leverage partner*; (1,0) for a *preference partner* and (1,1) for a *strategic partner.* Thus, the resulting fuzzy intelligent model proposed is depicted in Figure 7.

[Insert Figure 6 and 7 about here.]

3.3.2 Application of the fuzzy intelligent model

The application of the model involves the following steps:

- *Step 1: Obtain the evaluation data.* The quantitative criteria are determined from publically available historical data (e.g., annual reports), which also need to be pre-processed by applying linear processing techniques. The qualitative criteria are determined by industry experts or organizational decision makers, who need to assign linguistic values to the qualitative criteria according to triangular membership function shown as Figure 3. During this process, the information vagueness will be captured. The linguistic variables will then be converted to quantitative ones by applying the fuzzy "if-then rules" and the centroid of area (Z_{COA}) dufuzzification method before they combining with the quantitative criteria. After combining, the process of the information vagueness is captured and combined with the deterministic criteria.
- *Step 2: Construct the training samples* ($\vec{X}$, $\vec{Y}$). For every pair of training samples, input vector $\vec{X}$ is constructed by combining the quantitative criteria and the defuzzified qualitative criteria in order. The expectation outputs $\vec{Y}$ are synthetically analyzed and quantified with reference to Figure 6.
- *Step 3: Apply the training samples* ($\vec{X}$, $\vec{Y}$) to construct the fuzzy intelligent model. RBF-ANN has two notable characteristics. Firstly, the network constructing process is also the network training process. Secondly, there is no need to set up network precision, the number of neural cells in the hidden-layer and initialization weight in advance (Moody and Darken, 1989). During this step, the weights of different criteria will be decided automatically according to the minimum system errors principle.
- *Sept 4: Testing the network* by using part of the training data or new data to confirm the precision of the fuzzy intelligent partner selection model.
- *Step 5: Calculate the input vector* $\vec{X}'$, using the given criteria to quantify the sub-criteria of the potential partners as per the methods in step 1 and 2 above.

- *Step 6: Input the vector* $\overrightarrow{X}'$ into the network in order to obtain the output values for $\overrightarrow{Y}'$.
- *Step 7: Classify the potential partners* (in accordance with Figure 6), based on the values of the output $\overrightarrow{Y}'$.

4. Empirical illustration

This section gives an empirical illustration to show how the fuzzy intelligent model can be used in practice by applying it to eighty-four representative companies within the Chinese electrical components and equipment industry.

4.1 Evaluation knowledge acquisition

In order to focus on the application of the fuzzy intelligent model itself, Wu and Barnes methodology has been used to form the Optimal Hierarchy Criteria for partner qualification and classification. See Wu and Barnes (2010) for details of the process of the criteria formation. The outcomes are shown in Table 4.

[Insert Table 4 about here.]

As Table 4 shows, there are seven criteria at the middle level to evaluate the potential partners. There are Production and logistics management, Partnership management, Technology and knowledge management, Marketing capability, Industrial and organizational competitiveness, Human resource management, and Financial capability. Each of them has their own sub-criteria. It is easy to category these criteria into quantitative and qualitative ones. As for the quantitative criteria, we collected the data on the quantitative criteria of the eighty four potential partners from the database of Wind Information Co. Ltd. (In this paper, only parts of the original data are shown in Table 5 due to space limitations.) Then, the linear normalization method is used to pre-process the original data. The processed data are shown in Table 6.

[Insert Table 5 and Table 6 about here.]

The qualitative criteria are evaluated by industry experts and researchers (three in China and two in the U.K.) based on their knowledge and experience by using linguistic variables. Parts of the evaluation results are shown in Table 7.

[Insert Table 7 about here.]

The same industry experts and researchers also classified the potential partners into the four categories of partners (applying Kraljic (1983)'s classic partner classification matrix). The ideal outputs of the potential partners are shown in Table 8.

[Insert Table 8 about here.]

4.2 Fuzzy information processing

We applied the Fuzzy Logic Toolbox, the mature product of the MATH WORKS CO. as our fuzzy reasoning environment for two main reasons. Firstly, the Fuzzy Logic Toolbox is a powerful and user-friendly toolbox. It has the capability to handle the fuzzy modelling problem in these decision making situations. Secondly, the Fuzzy Logic Toolbox is compatible with Luo *et al.*, (2009)'s information processing model which is constructed in ANN toolbox 4.0.3, which is also a product of the MATH WORKS CO.

Based on the fuzzy "if-then rules" listed in Table 3, it is convenient to model the calculation and defuzzification process. For this illustration, Fuzzy Logic module based on Mamdami is used in performing the fuzzy reasoning process. Figure 5 shows one of the fuzzy rules reasoning process surface after the fuzzy "if-then rules" modelled in the Fuzzy Logic Toolbox programming environment. After inputting the linguistic variables which got from the industry experts into the fuzzy model, we can get the defuzzified qualitative criteria (parts of defuzzified qualitative data are shown in Table 9).

[Insert Table 9 about here.]

4.3 Construction and application of the fuzzy intelligent model

The structure of the fuzzy intelligent model for this empirical illustration is 19 – H – 2 (input layer – hidden layer – output layer). Here, nineteen represents the numbers of combined input criteria including defuzzified qualitative ones (6) and the quantitative ones (13). H represents the number of neural cells at the hidden layer, which will generate automatically during the network construction and training phase depending on system standard errors. We choose eighty pairs of data, j = 1, 2 , …, 8, 10, …, 25, 27, …, 44, 46, …, 75, 77, … 84, for network training and the rest of four, j = 9, 26, 45 and 76, for network testing, randomly. To construct the network, we need to choose an appropriate RBF-Spread only. This is because the larger spread is the smoother the function approximation. However, on the one hand, too large a spread means many neurons are required to fit a fast-changing function. On the other hand, too small a spread means lots of neurons are required to fit a smooth function, and the final network would not construct easily. Therefore, by computer programming, we tested different RBF-Spreads and tried to identify the optimal one. The test results are shown in Table 10, Figure 8 and Figure 9.

[Insert Table 10, Figure 8 and Figure 9 about here.]

Based on the minimum system errors principle, we choose Spread = 2 as the RBF-Spread. Figure 10 and Figure 11 show the RBF-ANN system standard error after the whole network constructed.

[Insert Figure 10 and Figure 11 about here.]

The network standard errors are about 8x10^{-7}, which fulfils the demand of the real application. After construction and training of the network, we tested the fuzzy intelligent partner selection model by inputting testing samples $\overrightarrow{X_j}$ (j = 9, 26, 45 and 76) to obtain the output $\overrightarrow{Y_j}^*$ (j = 9, 26, 45 and 76). The results are shown in Table 11. It is clear that the test results are located in the acceptable area.

[Insert Table 11 about here]

The outputs of testing demonstrate that the proposed fuzzy intelligent model for partner selection could handle the huge amounts of qualitative as well as quantitative data necessary effectively and efficiently. Thus, the model is capable of helping organizations to classify potential partners in preparation for the final selection phase.

5. Discussions and conclusions

The proposed model can be widely used in different decision making situations and environments at the qualification phase of partner selection in ASCs. It can help decision makers qualify and classify potential partners efficiently and effectively.

As the above empirical illustration shows, the application of the proposed fuzzy intelligent model achieved a favourable effect in the electrical components and equipment industry, in which product lifecycle is relatively short. In this kind of industry, supply chain agility is essential, as managers need to re-form and re-construct their supply chains much more frequently than in more traditional industries in order to meet fast changing customer demands. Therefore, the selection of appropriate partners is vital for the success of an ASC. Furthermore, the timeliness of decision making is critical as the market may change rapidly. In short, these decision making situations require the application of a model/method that is highly efficient as well as highly effective. The proposed fuzzy intelligent model is very suitable for such highly demanding decision making situations. Consequently, industries that share these same decision making requirements could have much to gain through the application of the proposed fuzzy intelligent model.

Additionally, the proposed model could also be applied in different information integrity environments. Unlike the above empirical illustration, in which decision information is rich and determined as it mostly comes from the open databases of the companies listed on stock markets, the proposed model could also be used in decision making environments where decision making information is vague and uncertain, or even deficient. This is because both FST and RBF-ANN can tolerate vague and uncertain, or even deficient information. These specific characteristics mean that there are likely to be many more practical applications for the type of fuzzy intelligent model proposed.

In real cases, decision makers typically lack precise input data for potential partners. However, they usually do have intangible information about decision criteria rather than exact and complete information, especially for qualitative criteria. Due to the limited historical data available on potential partners and the reluctance of most corporations to share proprietary information, decision makers often have to rely on vague, imprecise, and even subjective information when selecting potential partners.

The fuzzy intelligent partner selection model proposed in this paper advances the work of Luo *et al.,* (2009). In particular, by combining FST with RBF-ANN it overcomes the weakness of the original information processing model. By using FST, vague and imprecise information can more easily be defined, collected, processed and combined with the deterministic quantitative information to evaluate and select the most appropriate partners in ASCs. At the same time, FST approaches are also enhanced by incorporating artificial intelligent in ways that improve information processing ability and efficiency. These are both unique aspects of this study. Furthermore, the proposed approach is novel and appropriate. It addresses the gap in the current literature by proposing a fuzzy intelligent model based on combination of methods. On the one hand, combining FST and ANNs overcomes the main drawbacks of each approach. On the other hand, FST combined with ANNs also leverages the artificial intelligent approach to simulate human intelligent and improve decision making efficiency. The approach can thus provide significant advantages to practitioners as it offers them increased simplicity and speed in achieving a more effective solution to the supplier selection problem whilst being able to draw upon extensive amounts of both qualitative and quantitative data.

In short, a fuzzy intelligent partner selection model has the following advantages: firstly, the fuzzy intelligent model is more comprehensive than formal intelligent processing models, such as Luo *et al.*, (2009)'s, as the information vagueness is captured and combined with the deterministic criteria in this model. By incorporating such factors, we can certainly improve the probability and stability of success of the entire ASC (Famuyiwa *et al.*, 2008). Secondly, in practical situations of designing the fuzzy intelligent model, the decision makers are not required to give deterministic values to the system's parameters, such as threshold value, joint weight and activation value etc. Thirdly, the implementation of the fuzzy intelligent model is both affordable and user-friendly for the decision makers. The fuzzy intelligent model allows both qualitative and quantitative data to be included while using FST as a translator for the linguistic inputs, so all members have direct inputs into the artificial intelligent decision making support model.

However, it needs to be noted that there are also several disadvantages to the proposed model. Firstly, as the numbers of sub-criteria within each qualitative criteria increase, the numbers of fuzzy rules increases more quickly, to the extent that they may be out of control if the numbers of sub-criteria within each qualitative criterion exceed six. Therefore, there is an economic scale for the number of sub-criteria within each qualitative criterion. However, there are ways of overcoming this disadvantage. For example, selecting the most important sub-criteria and increasing the number of groups utilised whilst making sure each group has an acceptable scale. Secondly, as is the case with the previous RBF-ANN model, the fuzzy intelligent model requires a relatively long time for data collecting and pre-processing. However, the fuzzy intelligent model makes the decision makers' task less burdensome than the RBF-ANN model through its use of FST. Using the linguistic variables enables decision makers to evaluate qualitative data on potential partners more easily and effectively.

This paper highlights the benefits of the use of fuzzy processing methodology in partner selection, particularly in the qualification phase of the process. Future research is now needed to explore the potential for the use of this methodology in other phases of the partner selection process (Wu and Barnes, 2012). This might involve seeking to combine the use of FST with other decision models such as ANN-MIMOP and Dempster-Shafer theories.

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Tables

Table 1: Review of literature drawing on fuzzy set theories for partner selection

Phase of partner selection	Combined methodologies		Authors/Publications		
Decision models for formulation of criteria	FST		Lin *et al*., (2006)		
Decision models for qualification	FST & Data Envelopment Analysis		Zeydan *et al.*, (2011)		
	FST & Cluster Analysis		Keskin *et al.*, (2010)		
	FST & Artificial Neural Network		Not found		
Decision models for final selection	FST & Mathematic Programming	Goal Programming	Famuyiwa *et al.*, (2008)		
		Multi-Objective Programming	Amid *et al.*, (2006) Chamodrakas *et al.*, (2010)	Guneri *et al.*, (2009) Hsu *et al.*, (2010)	Wu *et al.*, (2010) Kara (2011)
		Integer Programming	Tang *et al.*, (2005) Yucel and Guneri (2011)	Sanayei *et al.*, (2010)	
	FST & Analytic Hierarchy Process		Haq and Kannan (2006) Chan *et al.*, (2008)	Buyukozkan *et al.*, (2008) Lee (2009)	Chen *et al.*, (2011)
	FST & Analytic Network Process		Onut *et al.*, (2009) Vinodh *et al.*, (2011)	Wu *et al.*, (2009) Buyukozkan and Cifci (2011, 2012)	
	FST & Genetic Algorithms		Wang and Che (2007)	Wang (2008)	
	FST with other methodologies		Erol and Ferrell (2003) Bevilacqua *et al.*, (2006)	Sarkar and Mohapatra (2006) Bayrak *et al.*, (2007)	
Decision models for application feedback			Not found		

Table 2: A comparison of existing methods used in partner selection with the proposed model

Models/Methods categories	Authors/Publications	Types of criteria	Structures of criteria	Criteria aggregation	Characteristics
FST	Lin *et al.*, (2006)	Qualitative	Three levels hierarchical	Fuzzy weighted average	Aimed at constructing a smaller but more customized set of criteria by determining their relative importance in different procurement circumstances
DEA	Zeydan *et al.*, (2011)	Qualitative	Two levels hierarchical	Distance measurement	The model applies fuzzy TOPSIS to rank suppliers initially, and then transform qualitative variables into a quantitative variable for use in DEA methodology.
Cluster analysis	Keskin *et al.*, (2010)	Qualitative	Flat	Weighted	The method can not only select the most appropriate suppliers but also cluster all of the vendors according to the chosen criteria by using Fuzzy ART.
Goal programming	Famuyiwa *et al.*, (2011)	Qualitative	Three levels hierarchical	Weighted average	Based on fuzzy logic/goal programming to analyze the vague, imprecise, and subjective information regarding the compatibility of potential suppliers during the early formation of partnership.
Multi-objective programming	Wu *et al.*, (2010)	Quantitative	Flat	N/A	Modelled the supply chain on three levels, and used simulated quantitative and qualitative data to assess the fuzzy events into the fuzzy multi-objective programming models.
Integer programming	Yucel and Guneri (2011)	Qualitative	Flat	Weighted sum up	The model can deal with the rating of factors very effectively as it has no computational procedure.
AHP	Chan *et al.*, (2008)	Qualitative	Three levels hierarchical	Relative score comparing	The model can provide the guidelines to select global suppliers in the competitive business scenario while tackling both quantitative and qualitative factors involved in selection of suppliers.

Models/Methods categories	Authors/Publications	Types of criteria	Structures of criteria	Criteria aggregation	Characteristics
ANP	Buyukozkan and Cifci (2012)	Qualitative	Network	Supermatrix raising	The FST extension of the ANP technique was introduced and applied to cope with ambiguity and vagueness of the decision maker's judgments.
Genetic algorithms	Wang (2008)	Quantitative	Single	Genetic algorithm	The analysis of component parts with association graph, fuzzy theory and data T transfer were integrated.
House of quality	Bevilacqua *et al.*, (2006)	Qualitative	Flat	Fuzzy suitability index	The method is able to transform decision makers' verbal assessments to linguistic variables, which are more accurate than other non-fuzzy methods.
FST	Sarkar and Mohapatra (2006)	Qualitative & Quantitative	Flat	Fuzzy set algorithm	The method has a compensation problem, as a potential partner's high score in one dimension may compensate for a low score in some other.
Fuzzy intelligent	Proposed model	Quantitative & Qualitative	Three levels hierarchical	RBF activation function	Vague and imprecise information can more easily be defined, collected, processed and combined with the deterministic quantitative information to evaluate and select the most appropriate partners by using FST. At the same time, FST are also enhanced by incorporating artificial intelligent in ways that improve information processing ability and efficiency.

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Table 3: Fuzzy rule base structure for three inputs and one output variables (based on Nepal *et al*., 2005 and Famuyiwa *et al*., 2008)

									Output	
				Input					**Output**	
All	Very Low								Very Low	
All	Low								Low	
All	Average								Average	***5 Rules***
All	High								High	
All	Very High								Very High	
2	Very Low	&	1	Low					Very Low	
2	Very Low	&	1	Average					Low	***12 Rules***
2	Very Low	&	1	High					Low	
2	Very Low	&	1	Very High					Low	
2	Low	&	1	Very Low					Very Low	
2	Low	&	1	Average					Low	***12 Rules***
2	Low	&	1	High					Average	
2	Low	&	1	Very High					Average	
2	Average	&	1	Very Low					Low	
2	Average	&	1	Low					Low	***12 Rules***
2	Average	&	1	High					Average	
2	Average	&	1	Very High					High	
2	High	&	1	Very Low					Average	
2	High	&	1	Low					Average	***12 Rules***
2	High	&	1	Average					High	
2	High	&	1	Very High					Very High	
2	Very High	&	1	Very Low					Average	
2	Very High	&	1	Low					High	***12 Rules***
2	Very High	&	1	Average					Very High	
2	Very High	&	1	High					Very High	
1	Very Low	&	1	Low	&	1	Average		Low	
1	Very Low	&	1	Low	&	1	High		Low	
1	Very Low	&	1	Low	&	1	Very High		Low	
1	Very Low	&	1	Average	&	1	High		Average	
1	Very Low	&	1	Average	&	1	Very High		Average	***60 Rules***
1	Very Low	&	1	High	&	1	Very High		Average	
1	Low	&	1	Average	&	1	High		Average	
1	Low	&	1	Average	&	1	Very High		Average	
1	Low	&	1	High	&	1	Very High		High	
1	Average	&	1	High	&	1	Very High		High	

Total number of rules are 125

Table 4: Hierarchy criteria of the partner selection in agile supply chain

Criteria	**Sub-criteria**
Production and logistics management	Variation in types of products or services (Choy *et al.*, 2003) Order lead time (Chung *et al.*, 2005) Distribution network performance and quality (Lin and Chen, 2004)
Partnership management	Cost to integration (Ip *et al.*, 2003) Relationship building flexibility (Lin and Chen, 2004) Willingness to reveal financial records (Choi and Hartley, 1996)
Technology and knowledge management	Partner's ability to acquire your firm' special skills (Xia and Wu, 2007) Willingness to share expertise (Ngai *et al.*, 2004) Technology innovation (Choy *et al.*, 2003)
Marketing capability	Rapid market entry (Hajidimitriou and Georgiou, 2002) General reputation (Choy *et al.*, 2002) Marketing expertise/knowledge (Harvey and Lusch, 1995)
Industrial and organizational competitiveness	Strategic orientation (Luo, 1998) Complementarity of product lines (Cavusgil *et al.*, 1995) Unique competencies (Dacin *et al.*, 1997)
Human resource management	Quality of local personnel (Sarkar and Mohapatra, 2006) Learning ability (Luo, 1998) Corporate culture (Talluri *et al.*, 1999)
Financial capability	Liquidity ratio (Wu and Barnes, 2010) Inventory turnover (Wu and Barnes, 2010) Earnings per share of stock (Wu and Barnes, 2010) Net operating margin (Mikhailov, 2002) Asset/Liability ratio (Luo, 1998) Net profits growth rates (Lin and Chen, 2004) Assets rates of increment (Dacin *et al.*, 1997) Accounts receivable turnover (Wu and Barnes, 2010) Stockholders' equity ratio (Wu and Barnes, 2010) Cash flow per share (Wu and Barnes, 2010) Debt/equity ratio (Harvey and Lusch, 1995) Total revenue (Chung *et al.*, 2005) Gross profit margin (Gencer and Gurpinar, 2007)

(Adapted from Wu and Barnes, 2010: 286-287)

Table 5: Potential partners' original financial data (Partial)

No.	Companies	Liquidity ratio	Inventory turnover	Earnings per share of stock	Net operating margin	Asset/ Liability ratio	Net profits growth rates
1	XJDQ	1.829	2.650	0.388	28.754	52.077	0.130
2	WJL	1.063	4.302	0.188	26.484	59.696	-0.110
3	DBDQ	1.199	3.307	0.002	21.222	62.482	-0.401
4	STHK	0.798	4.284	-0.340	24.716	72.761	-0.388
5	STSD	1.216	2.066	0.038	25.081	58.759	0.679
6	DFDZ	3.103	5.287	0.021	31.716	21.244	0.095
7	YHKJ	1.533	2.450	-0.087	24.225	63.352	-0.140
8	STAJ	0.702	2.937	0.010	21.507	78.903	1.653
9	HZDJ	1.298	5.451	0.190	20.975	73.482	0.066
10	SFGK	1.405	17.661	0.050	8.052	51.891	0.729

(Source: Wind Information Co., Ltd)

Table 6: Potential partners' quantitative criteria (Partial)

No.	Companies	Liquidity ratio	Inventory turnover	Earnings per share of stock	Net operating margin	Asset/ Liabilityratio	Net profits growth rates
1	XJDQ	0.078	0.082	0.255	0.348	0.428	0.008
2	WJL	0.035	0.165	0.185	0.314	0.498	0.004
3	DBDQ	0.043	0.115	0.120	0.235	0.523	0.000
4	STHK	0.021	0.164	0.000	0.287	0.617	0.000
5	STSD	0.044	0.053	0.133	0.293	0.489	0.016
6	DFDZ	0.148	0.214	0.127	0.392	0.147	0.007
7	YHKJ	0.061	0.072	0.089	0.280	0.531	0.004
8	STAJ	0.015	0.097	0.123	0.240	0.673	0.030
10	SFGK	0.054	0.833	0.137	0.038	0.426	0.016

(Source: Calculated by authors based on Table 5)

Table 7: Potential partners' lingual variation on qualitative criteria (Partial)

No.	Companies	Variation in types of products or services	Order lead time	Distribution network performance and quality	Cost to integration	Relationship building flexibility	Willingness to reveal financial records
1	XJDQ	Very High	High	Low	Low	Very High	Very Low
2	WJL	Low	High	Very Low	Average	Very Low	Low
3	DBDQ	Very Low	High	Low	Average	Low	Low
4	STHK	Very High	Average	Low	Very High	Average	Low
5	STSD	Very High	Average	High	Very Low	Very Low	High
6	DFDZ	Average	Very High	Very High	Average	Average	Low
7	YHKJ	High	Very High	High	High	Average	Average
8	STAJ	Average	Very Low	High	Very High	Very High	Very Low
9	HZDJ	Very Low	Very Low	Very High	High	High	High
10	SFGK	Low	Average	Average	Very High	Average	Low

Table 8: Potential partners' classification and its ideal outputs (Partical)

No.	Companies	Classification	Output Node 1 ideal output	Output Node 2 ideal output
1	XJDQ	Leverage partner	0	1
2	WJL	Preference partner	1	0
3	DBDQ	Strategic partner	1	1
4	STHK	Routine partner	0	0
5	STSD	Routine partner	0	0
6	DFDZ	Leverage partner	0	1
7	YHKJ	Routine partner	0	0
8	STAJ	Strategic partner	1	1
10	SFGK	Preference partner	1	0

Table 9: Potential partners' defuzzified qualitative criteria evaluation (Partial)

No.	Companies	Production and logistics management	Partnership management	Technology & knowledge management	Marketing capability	Industrial and organizational competitiveness	Human resource management
1	XJDQ	0.541	0.291	0.147	0.554	0.446	0.345
2	WJL	0.345	0.250	0.222	0.459	0.500	0.184
3	DBDQ	0.345	0.239	0.345	0.222	0.345	0.665
4	STHK	0.500	0.554	0.345	0.345	0.345	0.250
5	STSD	0.595	0.345	0.345	0.595	0.757	0.222
6	DFDZ	0.696	0.304	0.500	0.500	0.655	0.778
7	YHKJ	0.683	0.500	0.405	0.250	0.500	0.291
8	STAJ	0.345	0.595	0.554	0.239	0.250	0.500
9	HZDJ	0.345	0.709	0.709	0.446	0.500	0.345
10	SFGK	0.304	0.500	0.500	0.595	0.696	0.243

Table 10: Mean and standard deviation of errors for different spread values

Spread	2	3	4	5	6	7
Mean of Errors	9.4407e-007	2.6640e-006	4.6773e-006	1.0149e-005	1.8154e-005	1.7024e-005
Standard deviation	7.9254e-007	2.1584e-006	3.6393e-006	7.8700e-006	1.3622e-005	1.3562e-005

Table 11: Testing the fuzzy intelligent model using the validation set

	j = 9	j = 26	j = 45	j = 76
Output of node 1	1.0318	0.1882	0.02737	0.60419
Output of node 2	0.3149	1.2276	0.54454	0.72262
Types of partner	Preference Partner	Leverage Partner	Leverage Partner	Strategic Partner

Figures

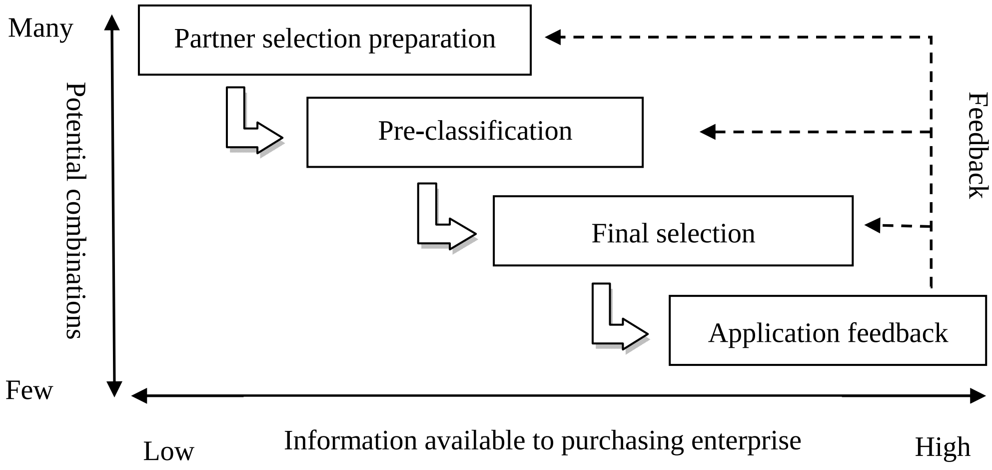

Figure 1. Four-phase dynamic feedback model for partner selection in ASC (adapted from Wu and Barnes, 2012: 89)

Step 1: Evaluation knowledge acquisition

- Identify potential partners
- Adopt the criteria from Optimal Hierarchy Criteria (Wu and Barnes, 2010)
- Data collection with respect to each potential partner

↓

Step 2: Fuzzy information processing

- Fuzzification of linguistic variables
- Develop fuzzy "if-then rules"
- Application of the fuzzy rules
- Defuzzification of the fuzzy outputs

↓

Step 3: Application of the Fuzzy Intelligent Model

- Construction of the fuzzy intelligent model
- Combine the defuzzified fuzzy variables and the deterministic variables into the fuzzy intelligent model
- Verify and test the outputs of the fuzzy intelligent model

Figure 2: The framework of the fuzzy intelligent model for partner selection

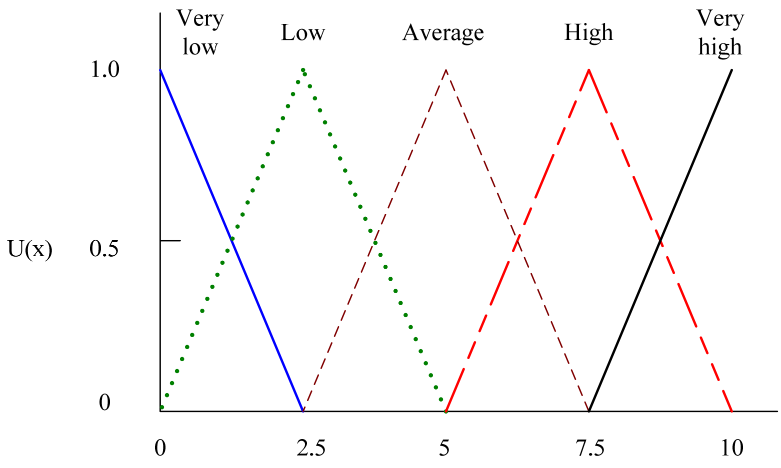

Figure 3: Membership functions for linguistic variables

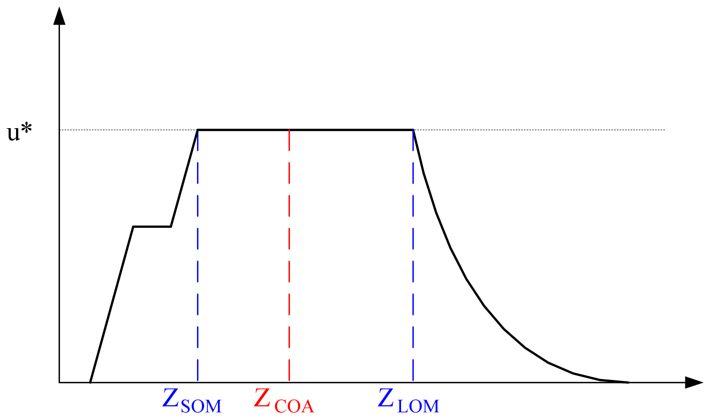

Figure 4: Various defuzzification schemes

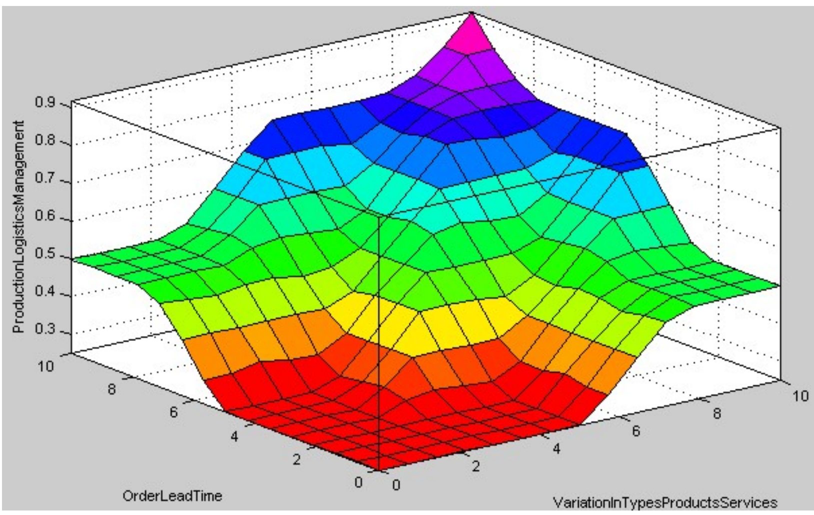

Figure 5: Fuzzy rules reasoning process surface

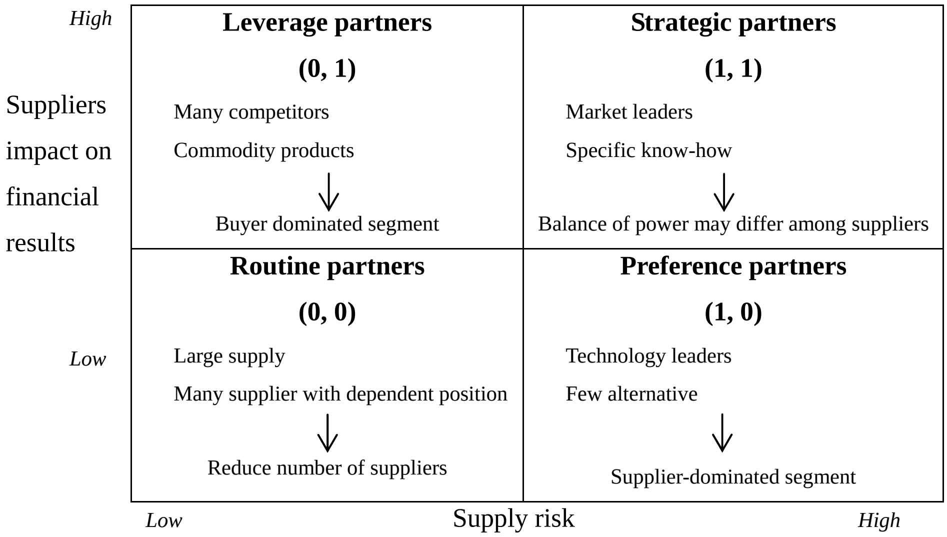

Figure 6: Classification matrix of potential partners (Kraljic, 1983; Luo *et al.*, 2009)

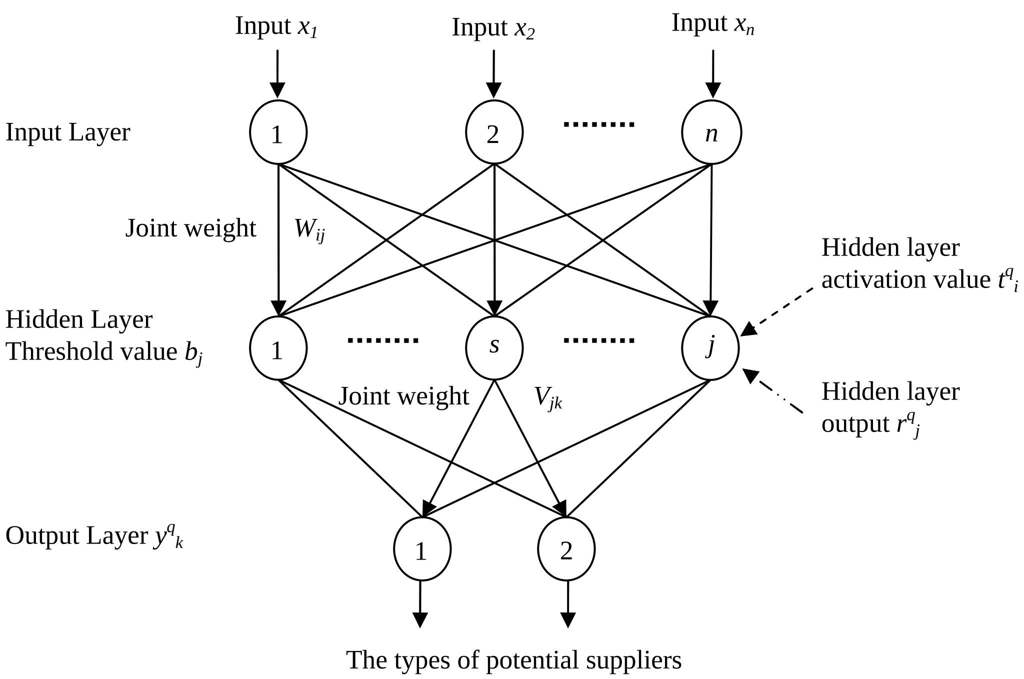

Figure 7: Fuzzy intelligent model for partner selection

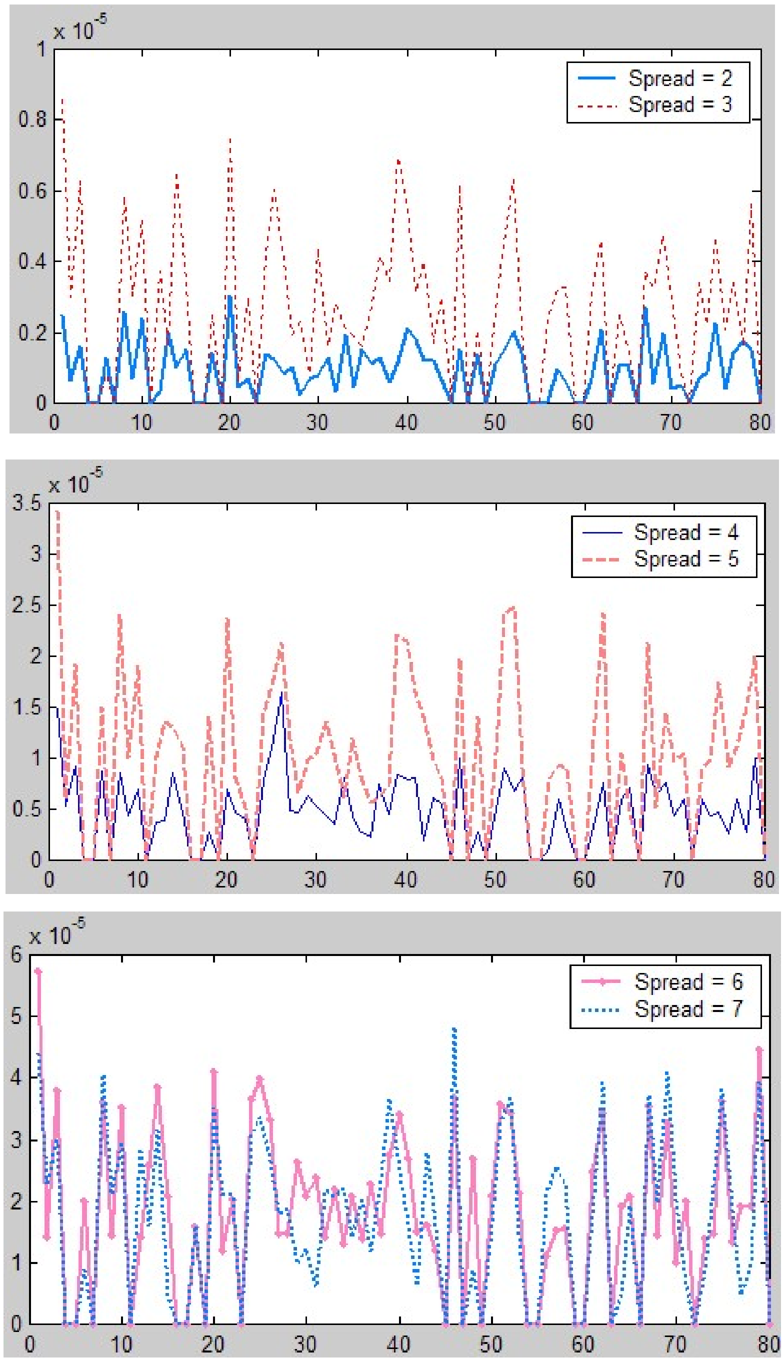

Figure 8: Comparison of the system errors with different spread values

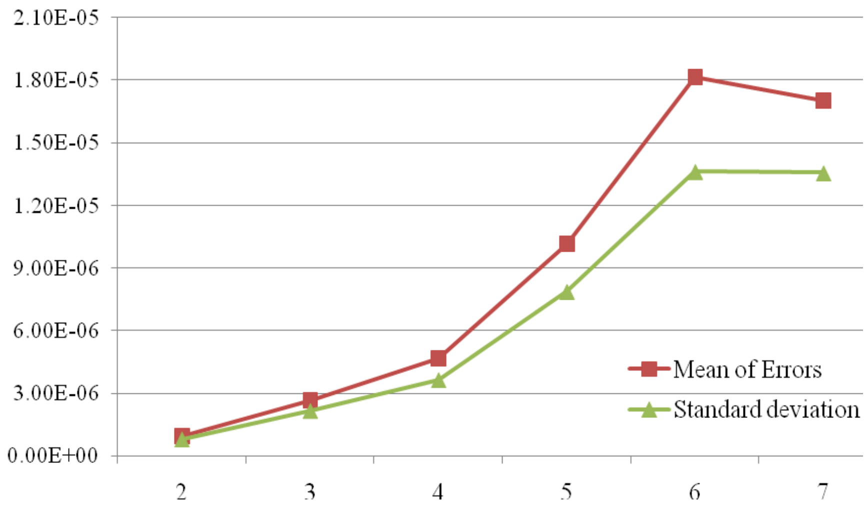

Figure 9: Mean and standard deviation of errors for different spread values

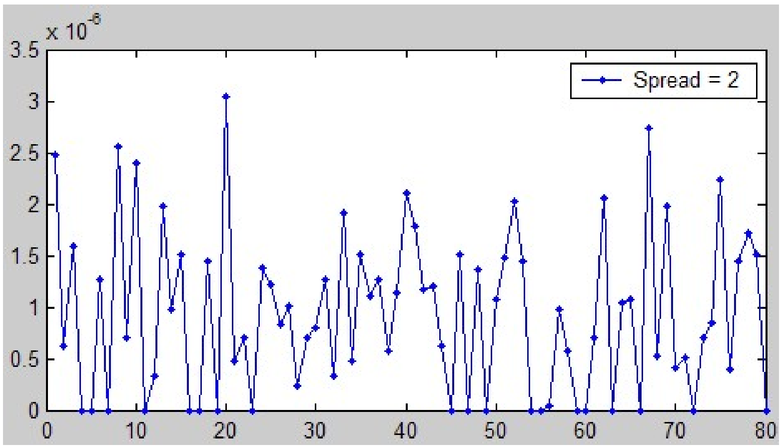

Figure 10: The system errors of the Fuzzy Intelligent Model for partner selection

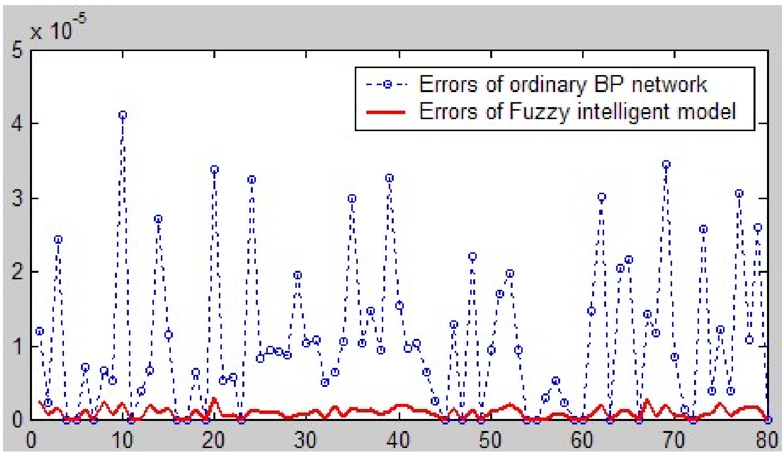

Figure 11: Comparison of the system errors of two different methodologies