A dynamic feedback model for partner selection in agile supply chains

Chong Wu
School of Management, Xiamen University, Xiamen, China, and
David Barnes
Westminster Business School, University of Westminster, London, UK

Abstract

Purpose – The purpose of this paper is to present a four-phase dynamic feedback model for supply partner selection in agile supply chains (ASCs). ASCs are commonly used as a response to increasingly dynamic markets. However, partner selection in ASCs is inherently more complex and difficult under conditions of uncertainty and ambiguity as supply chains form and re-form.

Design/methodology/approach – The model draws on both quantitative and qualitative techniques, including the Dempster-Shafer and optimisation theories, radial basis function artificial neural networks (RBF-ANN), analytic network process-mixed integer multi-objective programming (ANP-MIMOP), Kraljic’s supplier classification matrix and principles of continuous improvement. It incorporates modern computer programming techniques to overcome the information processing difficulties inherent in selecting from amongst large numbers of potential suppliers against multiple criteria in conditions of uncertainty.

Findings – The model enables decision makers to make efficient and effective use of the vastly increased amount of data that is available in today’s information-driven society and it offers a comprehensive, systematic and rigorous approach to a complex problem.

Research limitations/implications – The model has two main drawbacks. First, practitioners may find it difficult to match supplier evaluation criteria with the strategic objectives for an ASC. Second, they may perceive the model to be too complex for use when speed is of the essence.

Originality/value – The main contribution of this paper is that, for the first time, it draws together work from previous articles that have described each of the four stages of the model in detail to present a comprehensive overview of the model.

Keywords Supply chain management, Supplier evaluation, Partner selection, Agile supply chains, Dynamic feedback model, Dempster-Shafer theory, RBF-ANN, ANP-MIMOP

Paper type Research paper

1. Introduction

Partner selection is the process of choosing which supplier an organisation should purchase its requirements of resource inputs from. It is one of most important tasks in operations management (Dickson, 1966; Kraljic, 1983; Weber et al., 1991; De Boer et al., 2001). The choice of supplier can affect the quality, quantity, availability and price of goods purchased (Dulmin and Mininno, 2003; Sarkis et al., 2007; Wu and Barnes, 2009b).

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The term “partner”, which has been gaining currency over “supplier”, recognises the dependency of a supply chain on its constituent members. Partner selection has become increasingly important in an environment in which competition is increasingly between supply chains rather than between individual firms (Lambert and Cooper, 2000; Christopher and Towill, 2001).

Partner selection is a complex problem as it is multi-objective in nature (Ho et al., 2010). In what is now considered classic research, Dickson (1966) identified 23 criteria that might be applied in such decision making. Subsequent researchers have sought to modify the number and relative importance of these criteria in the light of the changing business environment. Although there is broad agreement that partner selection criteria should relate to operational performance and competitive priorities such as cost, quality, delivery and flexibility (Verma and Pullman, 1998; Lin and Chen, 2004), increasingly demanding business conditions point to the need for a wider range of criteria (Ngai et al., 2004). The partner selection process is particularly complex when viewed from a supply chain perspective as it involves a series of inter-related decisions about suppliers, which impact both the formation and the performance of the supply chain as a whole.

As business environments have become more turbulent and dynamic (Hakansson and Snehota, 2006), the response of many firms has been to adopt the concept of the agile supply chain (ASC) (Christopher, 2000; Prater et al., 2001). Although the concept of agility arose from the manufacturing environment (Goldman and Preiss, 1991) it has been increasingly applied to the entire supply chain (Lin et al., 2006). An ASC is a network of member companies that is capable of responding rapidly to changing market conditions (Lee, 2004; Ismail and Sharifi, 2006; Swafford et al., 2006; Jain et al., 2008; Li et al., 2008). The successful operation of an ASC depends on its ability to select the most appropriate supply partners in any given situation. However, in ASCs, the partner decision-making process involves increased uncertainty and ambiguity because selection criteria are likely to need to change over time (Sarkis et al., 2007; Baker, 2008). Furthermore, different potential partners may have different characteristics with regard to different performance criteria (Xia and Wu, 2007).

Whilst the globalization of world trade provides increased opportunities for sourcing goods and services in other countries (Crispim and de Sousa, 2010), incorporating off-shore partners into supply chains can be particularly challenging (Millington et al., 2006). It not only increases the number of potential partners to consider but makes the task of collecting and analysing data about them more challenging. This highlights the need for partner selection to be conducted in as comprehensive and thorough manner as possible. However, assessing multiple aspects of performance implies that large quantities of data about potential partners will need to be collected and analysed.

In short, decision making about partner selection in an ASC is particularly challenging, because of the complexity of putting together a supply network under dynamic conditions. In recent work that directly addresses this challenge, Luo et al. (2009) present a “four-phase conceptual model for supplier selection in ASCs”. In this and related work, the same researchers separately detail each of four stages of the model (Wu and Barnes, 2009a, 2010; Wu et al., 2009). The model incorporates modern computer programming techniques to overcome the information processing difficulties inherent in selecting suitable partners from amongst large numbers of potential suppliers against multiple criteria in conditions of uncertainty. In so doing, it aims to offer a comprehensive and rigorous approach to partner selection in ASCs. The aim
of this paper is to review the work presented in these four papers, to integrate their content and so present a comprehensive overview of the complete model for the first time. In so doing the paper will assess the benefits of the model to both the academic community, by assessing its contribution in the context of the extant literature, and to practitioners, by assessing its potential to offer support to managerial decision making.

The paper is structured as follows. This introduction is followed by Section 2, a literature section which reviews previous approaches to partner selection in order to provide a rationale for the four-phase model for partner selection in ASCs. This is then presented in Section 3, and each of the four phases of the model described in more detail. Section 4 concludes the paper by critically assessing the potential contribution that the application of the model could make to partner selection in ASCs from both an academic and a practitioner perspective. Finally, some suggestions for future research are made.

2. Literature review

2.1 Approaches to partner selection

As noted above, ASCs are likely to be most appropriate under conditions of complexity, uncertainty and ambiguity. Yet under these conditions, the problem of partner selection cannot be solved effectively and efficiently unless it is broken down into several sub-problems, which can then each be addressed and solved individually (Lorange et al., 1992; De Boer et al., 2001). Many of the decision support models that have been developed for partner selection emphasize the final stages of the process, when, typically a choice has to be made between a small number of shortlisted suppliers (Weber et al., 1991; Weber and Current, 1993; Dulmin and Mininno, 2003). However, it is risky to neglect the early stages of the process as the quality of decision making at the final choice stage is largely dependent on decisions already made in the previous stages (De Boer and Van der Wegen, 2003). Second, existing methods pay little attention to the task of selecting new suppliers (De Boer et al., 2001), which can be particularly important in ASCs. In practice many managers often rely on qualitative methods and subjective judgements when tackling the problem of partner selection (Gencer and Gurpinar, 2007). Although partner selection in ASCs presents a significant information processing challenge, recent advances in computer programming can offer decision makers the processing power necessary to conduct the level of information processing required for effective quantitative analysis. In particular, techniques such as artificial neural networks (ANN), especially radial basis function-ANN (RBF-ANN), and analytic network process-mixed integer multi-objective programming (ANP-MIMOP) appear to have the potential to help. Yet, few researchers in this field have tried to apply such techniques.

Although there is a wealth of literature on specific aspects of supplier selection, very little attention has been given to modelling the entire process of the partner selection decision-making process in ASCs. De Boer et al. (2001) have characterized supplier selection as a multi-stage process. However, their approach makes extensive use of managerial subjective judgement. On the other hand, Lin and Chen (2004) take a more quantitative approach, in developing a fuzzy decision-making framework for supplier selection. The principle underlying their approach is that of formulating a set of optimal criteria for supplier selection based on the distinctive features of the industry from which the supplier as to be selected. This not only enables best use to be made of valuable evaluation resources, but also increases the chances of selecting the best potential partner.
Another strand of supply chain partner research is that concerning customer, rather than supplier, selection. For example, Kim and Lee (2007) point out that the typical customer selection strategy, which retains profitable customers but rejects unprofitable ones, is not appropriate for a firm with goods and services that exhibit network externalities because of the strategic network value of unprofitable customers. Son and Ikuta (2007) and Son (2007) also discussed the optimal decision rules for customer selection problem within an identical framework. However, they only consider price and delivery time as the main criteria for customer selection.

Another allied strand of literature is that of strategic alliance partner selection. Hacklin et al. (2006) developed an integrated strategic partner selection process and decision support system for technology-intensive organisations. This emphasises the need to adopt a network-oriented, partnership portfolio management perspective. More recently, Chen et al. (2010) established a mechanism for partner selection that emphasizes the relationship between criteria and motivation for establishing strategic alliances based on fuzzy numbers. Solesvik and Westhead (2010) used a multiple case study methodology to explore the strategic partner selection process. Their work highlights the importance of careful initial selection and building trust-based relationships in successful alliances.

Many researchers advocate the used the multiple stages in partner selection decision making. Huang et al. (2004) proposed a two-stage framework for selecting efficient and compatible partners. Their stage 1 mainly focuses on identifying suitable partners who can offer the right products at the right time, at the right quality at the right price. Their stage 2, then focuses on the potential for collaboration and co-operation with those partners. Che (2010) also developed a two-phase model. In phase 1, suppliers are clustered according to their characteristics for meeting customer needs on multiple dimensions of cost, quality and time. In phase 2, a multi-criteria optimization mathematical model is constructed on the basis of these clusters. Mendoza et al. (2008) also described a multi-criteria method to reduce potential suppliers to a manageable number and optimize the allocation of orders by means of an ideal solution approach using the techniques of analytical hierarchical programming (AHP) and goal programming. Chen (2008) proposed a three-stage model for considering the supply chain partner selection problem with multi-product, multi-supplier, multi-vendor and multi-period, under conditions of limited capacity. The well-known multiple stage model for partner selection of De Boer et al. (2001) also identifies three main stages: “criteria formulation” and “qualification”, in which suitable partners are identified, followed by “final choice”, in which a selection is made from amongst suitably qualified partners. We now examine, in turn, the literature relevant to each of these stages.

### 2.2 Decision models for criteria formulation

The first stage of any partner selection process is that of determining what criteria to use in subsequent decision making. Dickson (1966) has argued that vendor selection and evaluation process is multi-objective in nature. There is widespread agreement that the main categories of partner selection criteria should correspond to the principal manufacturing performance and competitive priorities of cost, quality, delivery and flexibility (Wind and Robinson, 1968). These can all be important when supply has a direct impact on competitive performance and corporate strategy, as in the case of innovative and unique products (Lamming et al., 2000). Consequently, the criteria for
developing supply chain partnerships are typically driven by the expectation of quality, cost efficiency, delivery dependability, volume flexibility, information and customer service (Abratt, 1986).

Wang et al. (2004) related product characteristics to supply chain strategy and adopt supply chain operations reference model level 1 performance metrics as the decision criteria. They then built an integrated AHP and pre-emptive goal programming-based multi-criteria decision-making methodology to take into account both qualitative and quantitative factors in supplier selection. Based on multi-criteria analysis to evaluate environmental and social considerations, Boufateh et al. (2007) built a decision support system within a textile supply chain using a sustainable development perspective. Kannan and Haq (2007) used the interpretive structural modeling (ISM) methodology to describe the interactions between the criteria and sub-criteria that will influence the supplier selection decision making in a built-in-order supply chain environment. El-Maraghy and Majety (2008) considered additional criteria including first-time quality and suppliers' on-time delivery risk with and without allowing splitting of customer demand between suppliers. Additionally, Mandal and Deshmukh (1994) proposed an ISM based on group judgment to identify and summarise relationships between supplier choice criteria through a graphical model.

Many authors have also highlighted the importance of adopting a broad set of criteria that encompass a long-term perspective (Dulmin and Minnino, 2003), which might include the ability of the partner to provide design and technological capabilities to the customer, the partner’s geographic location, which can be critical in the context of JIT purchasing, a willingness to share information, which characteristic is typical of partnership sourcing, or legal terms (Ellram, 1990). However, including a broad range of criteria makes partner selection decisions complex (Weber et al., 1991). Parker (1990) claims that the majority of buyers cannot take more than eight or nine factors into account in their decision-making process. Consequently, researchers have put much effort into methods that aim to develop a smaller, more customized set of attributes by determining the relative importance of the selection criteria in various procurement situations.

There are relatively few examples in the literature of methods aimed at identifying the best criteria for partner selection. Lin and Chen (2004) proposed a systematic method to build a general set of criteria which can then be modified for a specific industry. However, a weakness in their method is that they do not consider partner selection as a dynamic problem, which makes it unsuitable for ASCs. Lin et al. (2006) developed a fuzzy agility index, comprising attribute ratings and corresponding weights, aggregated by a fuzzy weighted average. Xia and Wu (2007) proposed an integrated approach to simultaneously determine the number of suppliers to employ and the order quantity allocated to these suppliers, with multiple criteria and with supplier’s capacity constraints.

Table I presents a summary of representative studies on evaluation and formulation partner selection criteria in chronological order.

2.3 Decision models for qualification
The qualification stage involves reducing the set of all possible partners to a smaller number of acceptable suppliers (De Boer et al., 2001). Dowlatshahi (2000) argues that this is necessary in order to reduce supplier development costs, because substantial business can be awarded to only a limited number of suppliers, and because close working relationships can only be developed with a limited number of suppliers.

Partner selection in ASCs
<table>
<thead>
<tr>
<th>Researchers</th>
<th>Respondents/empirical cases</th>
<th>Measurement approach</th>
<th>Main evaluation criteria</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wind and Robinson (1968)</td>
<td>20 purchasing agents from a single company</td>
<td>Thurstonian scale</td>
<td>1. Quality/price ratio, 2. delivery, 3. technical ability, 4. information and market services, 5. reputation, 6. location, 7. technical innovativeness, 8. previous contact with buyer, 9. reciprocity and 10. personal benefits received by buyer</td>
</tr>
<tr>
<td>Abratt (1986)</td>
<td>Purchasers of high-tech products from 54 on a seven-point scale organisations</td>
<td>Ratings of importance</td>
<td>1. Technical service, 2. product reliability, 3. after-sales support, 4. reputation, 5. ease of maintenance, 6. ease of operation, 7. price, 8. confidence in salesperson and 9. product flexibility</td>
</tr>
<tr>
<td>Ellram (1990)</td>
<td>Literature review and case studies</td>
<td>Interviews</td>
<td>1. Financial issues, 2. technology, 3. organisational culture and strategy and a group of miscellaneous factors</td>
</tr>
<tr>
<td>Dulmin and Mininno (2003)</td>
<td>A mid-sized Italian public road and rail firm</td>
<td>The PROMETHEE approach</td>
<td>1. Make-up, 2. processing time, 3. prototyping time, 4. quality system, 5. co-design and 6. technological levels</td>
</tr>
<tr>
<td>Wang et al. (2004)</td>
<td>A hypothetical car manufacturer producing various functional components</td>
<td>AHP (pair-wise comparisons)</td>
<td>1. Delivery performance, 2. fill rate, 3. lead time, 4. perfect order fulfilment, 5. supply chain response time, 6. production flexibility, 7. total logistics management cost, 8. value-added productivity, 10 warranty cost or returns processing cost, 11. case-to-cash cycle time, 12. inventory days of supply and asset turns</td>
</tr>
<tr>
<td>Lin et al. (2006)</td>
<td>A Taiwan-based international IT products company</td>
<td>Fuzzy logic and aggregate fuzzy ratings and weights</td>
<td>1. Collaborative relationships, 2. process integration, 3. information integration and 4. customer/marketing sensitivity</td>
</tr>
</tbody>
</table>
Therefore, qualification is a sorting rather than a ranking process. The first step of this process always consists of defining and determining the set of acceptable partners while possible subsequent steps serve to reduce the number of partners to consider. The methods used can be classified as follows.

### 2.3.1 Data envelopment analysis models

Weber et al. (1991, 1998) have discussed the application of data envelopment analysis (DEA) in partner selection in a number of publications. Subsequently, Liu et al. (2000) proposed a simplified DEA model for evaluating the overall performances of suppliers with the strategic objective of being able to reduce the number of suppliers, and providing improvement targets for suppliers. Owing to the multi-criterion nature of supplier selection, using DEA with an objective of improving the efficiency of suppliers seems to be a useful approach. Ramanathan (2007) highlighted how DEA could be advantageously employed to combine the objective and subjective information provided by the results of the total cost of ownership and AHP approaches for vendor selection by extending the analysis presented by Bhutta and Huq (2002).

### 2.3.2 Cluster analysis models

Hinkle et al. (1969) were one of the first researchers to apply cluster analysis to this problem. By 30 years later, Holt (1998) introduced a new cluster analysis model. However, two major drawbacks exist in cluster methods. First, only global-scaled clusters have been verified. Second, the relationship between global and local perspectives on cluster detection has not been explored. Keskin et al. (2010) built a partner selection model by applying fuzzy adaptive resonance theory which has the ability to classify potential suppliers. The model cannot only select the most appropriate suppliers, but also clusters them according to the chosen criteria.

### 2.3.3 Artificial intelligence models

Vokurka et al. (1996) developed an expert system for a multiple phase supplier selection process, which incorporates the formulation of supplier selection criteria. Choy and Lee (2003) presented an intelligent generic supplier management tool by using the case-based reasoning technique for outsourcing to suppliers. The benefit of the tool is that it can be fully implemented in a case-based reasoning engine with little human involvement, so the tool can solve the problem of losing supplier selection knowledge when any experienced key staff leave.

Table II provides a summary of the models on qualification in the literature.

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### 2.4 Decision models for final choice

Final selection involves selecting which of the previously qualified suppliers to use for specific purchases. The relevant literature on each of these techniques is discussed below.

#### 2.4.1 Linear weighting models

Ko et al. (2001) suggested an idea for selecting partners in a distributed dynamic manufacturing environment, which enables companies to share their machine capacities. They proposed a model to minimize the sum of the operations and transportation costs based on alternative process plans considering several kinds of operational characteristics. Ng (2008) constructed a weighted linear program for the multi-criteria supplier selection problem by using a transformation technique which could solve the problem without applying an optimizer. The benefit of the model is that it does not require the user to learn any optimization technique.

#### 2.4.2 Mathematical programming models

Geoffrion and Graves (1974) undertook early mathematical work in the area of supply chain design. Subsequently, a number of different mathematical programming models have been proposed. They can be classified into the following three sub-categories:
Goal programming. Hajidimitriou and Georgiou (2002) applied goal programming to partner selection, thereby achieving multiple goals for different levels of performance of the corresponding attributes. However, this method did not consider how different combinations of potential partners might result in better solutions for the whole supply chain. Feng and Yamashiro (2003) applied a pragmatic approach for optimal partner selection by formulating a comprehensive manufacturing cost function. However, their approach only considered one factor, namely cost. Ravindran et al. (2010) used the goal programming approach to develop two types of risk models, value at risk and miss the target, solving the partner selection problem in two separate steps.

Multi-objective programming. Dahel (2003) proposed a multi-objective-mixed integer programming approach, which considers volume discounts, to determine the number of vendors to employ and the order quantities to allocate in a multiple product, multiple supplier competitive sourcing environment. In this context, vendors offer discounts on the total sales volume not on the quantity or variety of products purchased from them.

Integer linear programming. Talluri and Baker (2002) utilised a three-phase mathematical programming approach for partner selection by combining the pair-wise efficiency game model with integer and linear programming. Whilst this approach does overcome the limitations of unrestricted weight flexibility, it also risks sub-optimisation by potentially filtering out the optimal solution. Basnet and Leung (2005) solved the supplier selection problem in a multi-period inventory lot-sizing scenario. Comparing with the enumerative search algorithm they proposed, the heuristic, which is based on the traditional lot-sizing-based heuristic algorithm, is fast enough for practical problems.

2.4.3 Analytic hierarchy/network process models. Masella and Rangone (2000) applied an AHP approach to the design of vendor selection systems for different types of customer-supplier relationships. Using the minimum criteria of time and cost, their models...
could be used not only for supplier selection but also for monitoring the evolution of customer performance and resources status. Based on the multi-criteria decision-making approach and software agent techniques, Chen and Huang (2007) developed a scheme that integrated AHP with bi-negotiation agents. This enabled quantitative and qualitative supplier selection attributes to be used in negotiation simultaneously. However, AHP does not explicitly consider the interactions between the various factors/clusters. Sarkis et al. (2007) built a strategic model for partner selection using analytical network process (ANP) methodology, which overcomes the problem of rank reversal which is also a limitation of AHP. However, as they themselves acknowledge, without incorporating secondary criteria, the final solutions may not be clearly defined.

2.4.4 Fuzzy sets models. Ordoobadi (2009) introduced a fuzzy logic methodology to address the issue of selection of the appropriate supplier. The strong point of the methodology is that it incorporates a consideration of the both subjective nature of the decision makers’ preferences and a quantitative ranking system without having to trade off one for the other. However, the criteria used in the proposed model are based solely on academic studies; they could be enriched by incorporating a practitioner’s point of view. Bayrak et al. (2007) also introduced a fuzzy sets approach, using delivery, quality, flexibility and service as assessment criteria. However, it is a purely subjective method, as it is heavily dependent on the experience and expertise of the experts utilised. Buyukozkan et al. (2008) proposed a fuzzy AHP and fuzzy technique for order preference by similarity to ideal solution approach to rank partners under conditions of uncertainty and complexity. To avoid the single decision maker’s bias, it would be beneficial to extend the model in a group decision-making environment.

Table III summarizes the approaches to final decision making in recent literature. Of these four methods, each has its own specific merits and shortcomings. Linear weighting is very simple but it relies heavily on human judgment. Mathematic programming models are more objective than rating models because they force the decision maker to explicitly state the objective function. On the other hand, they often only consider the more quantitative criteria and this may cause a significant problem in considering qualitative factors. Third, AHP does not consider the interactions among the various factors. ANP can overcome the shortcomings of AHP but cannot solve the detailed sourcing problem. Finally, whilst fuzzy set theoretic analysis does allow simultaneous treatment of precise and imprecise variables, it is difficult for the users to understand the rationale for the output results.

The next section of the paper shows how the model for supplier selection in ASC developed by Luo et al. (2009) builds on the respective literature outlined above in each of its four phases.

3. The four-phase dynamic feedback model
The model is a development of the three-stage model of De Boer et al. (2001). Figure 1 shows Luo et al.’s (2009) model as a two-dimensional framework. The horizontal axis shows the extent of information available to the purchasing organisation, ranging from low to high. The vertical axis shows the number of combinations of potential partners, ranging from many to few. As the selection process advances through the phases from 1 to 4, the information available becomes more detailed, whilst the number of potential combinations reduces. Use of this step-by-step approach provides an effective means of solving what would otherwise be a highly complex problem.
<table>
<thead>
<tr>
<th>Methods/models categories</th>
<th>Author(s) and research publication years</th>
<th>Method/model types</th>
<th>Structure of criteria</th>
<th>Types of criteria</th>
<th>Criteria aggregation</th>
<th>Assignment of weights</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear weighting models</td>
<td>Ko et al. (2001)</td>
<td>Linear weighting</td>
<td>Flat</td>
<td>Quantitative</td>
<td>Linear aggregation</td>
<td>No weights consideration</td>
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<td></td>
<td>Ng (2008)</td>
<td>Weighted linear</td>
<td>Flat</td>
<td>Quantitative</td>
<td>Linear aggregation</td>
<td>By decision makers</td>
</tr>
<tr>
<td></td>
<td>Hajidimitriou and Georgiou (2002)</td>
<td>Goal programming</td>
<td>Flat</td>
<td>Quantitative</td>
<td>Linear aggregation</td>
<td>By users</td>
</tr>
<tr>
<td></td>
<td>Talluri and Baker (2002)</td>
<td>Integer linear programming</td>
<td>Flat</td>
<td>Quantitative</td>
<td>Linear aggregation</td>
<td>By brokers</td>
</tr>
<tr>
<td></td>
<td>Feng and Yamashiro (2003)</td>
<td>Non-linear mixed integer programming</td>
<td>Flat</td>
<td>Quantitative</td>
<td>Non-linear programming</td>
<td>No weights consideration</td>
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<td></td>
<td>Dahel (2003)</td>
<td>Multi-objective mixed integer programming</td>
<td>Flat</td>
<td>Quantitative</td>
<td>Multi-objective programming</td>
<td>No weights consideration</td>
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<td></td>
<td>Basnet and Leung (2005)</td>
<td>Integer linear programming</td>
<td>Flat</td>
<td>Quantitative</td>
<td>Linear aggregation</td>
<td>No weights consideration</td>
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<td></td>
<td>Ravindran et al. (2010)</td>
<td>Goal programming</td>
<td>Flat</td>
<td>Quantitative</td>
<td>Min-max GP model</td>
<td>Decision makers and group preferences</td>
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<tr>
<td></td>
<td>Chen and Huang (2007)</td>
<td>AHP</td>
<td>Hierarchical</td>
<td>Quantitative and qualitative</td>
<td>Linear aggregation</td>
<td>Pair-wise comparisons</td>
</tr>
<tr>
<td></td>
<td>Sarkis et al. (2007)</td>
<td>Analytical network process (ANP)</td>
<td>Network</td>
<td>Quantitative and qualitative</td>
<td>Supermatrix</td>
<td>Pair-wise comparisons</td>
</tr>
<tr>
<td></td>
<td>Bayrak et al. (2007)</td>
<td>Fuzzy set approach</td>
<td>Flat</td>
<td>Quantitative</td>
<td>Fuzzy weighted mean operators</td>
<td>By users and fuzzy algorithm</td>
</tr>
<tr>
<td></td>
<td>Buyukozkan et al. (2008)</td>
<td>Fuzzy AHP and fuzzy technique</td>
<td>Hierarchical</td>
<td>Quantitative and qualitative</td>
<td>Ranked according to the relative closeness to the ideal solution</td>
<td>Using linguistic weighting</td>
</tr>
<tr>
<td></td>
<td>Ordoobadi (2009)</td>
<td>Fuzzy logic methodology</td>
<td>Hierarchical</td>
<td>Quantitative and qualitative</td>
<td>Centroid method</td>
<td>Using linguistic scales</td>
</tr>
</tbody>
</table>

Source: Based on Wu et al. (2009, p. 258)
More details of these phases are now presented.

3.1 Phase 1 – partner selection preparation
This phase is an extension of De Boer et al.’s “criteria formulation” phase. In this phase, organisational decision makers develop a set of customized selection criteria based on their own specific requirements, in order to assess potential partners. This is done by applying Dempster-Shafer theory (DST) and optimisation theory, which enable the problem to be solved efficiently under conditions of resource constraint. It is described in detail in Wu and Barnes (2010). The approach used follows that of Lin and Chen (2004) in formulating a set of optimal criteria based on an analysis of the distinctive features of the industry from which the supplier as to be selected. The prudent selection of evaluation criteria is critical to the decision-making process. It is important to limit the number of evaluation criteria to be used. The more criteria, the greater the chance of interdependencies and the more resources consumed. Accordingly, Wu and Barnes (2010) propose a three-stage model for this phase (Figure 2).
(1) General hierarchy criteria formulation. In the first stage, Wu and Barnes (2010) generate a set of general hierarchy criteria (GHC) for partner selection which could be applied to any industry. From a literature review, they identify 116 generic partner evaluation attributes that could be applied in any industry. They then assign all these to one of seven main categories (production and logistics management, partnership management, financial capability, technology and knowledge management, marketing capability, industrial and organisational competitiveness and human resource management) to construct a three-level hierarchy for criteria for ASCs partner selection. The first level is the objective of the ASCs partner selection, namely evaluation of potential partners in ASCs. The second level of the hierarchy comprises the seven categories of criteria listed above. The third level consists of all the 116 sub-criteria that make up the seven main criteria of the second level (Table IV).

(2) Industry-oriented hierarchy criteria formulation. In the second stage, a set of industry-oriented hierarchy criteria (IHC), specific to the industry under consideration is extracted from the GHC on the basis of the judgement of organisational decision makers. Using the GHC as the basis for IHC has advantages of adaptability and flexibility. The GHC can be tailored and adapted to meet specific needs within the constraints of available evaluation resource. However, because the available information on evaluation criteria may be incomplete and inaccuracy, there is always some risk of judgement bias. This can be accounted for by use of the DST, which is based on developing a belief acceptability index to represent the bias of decision makers due to information uncertainty (Beynon et al., 2000).

(3) Optimal hierarchy criteria formulation. The third stage is that of formulating a set of optimal hierarchy criteria (OHC), from the IHC by optimizing the total belief acceptability level under limited evaluation resources. In practice, there are typically large costs associated with acquiring performance information on potential suppliers. Thus, decision makers need to ensure that the information they obtain is as complete and accurate as possible within the time and budgetary constraints. The objective of this stage is to determine the final evaluation criteria which possess the maximum total belief acceptability. This is done by developing a 0-1 nonlinear programming model which is used to generate the OHC with limited evaluation resources.

Wu and Barnes (2010) offer a worked empirical example of how partner selection criteria can be formulated in practice by applying these three stages of formulation using data from the Chinese electrical and equipment manufacturing industry.

3.2 Phase 2 – pre-classification
This phase replaces De Boer et al.’s “qualification” stage. It aims to avoid excluding any potential partners without careful assessment (Van Weele, 2005). In this phase,

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<thead>
<tr>
<th>Hierarchy level</th>
<th>Selected criteria</th>
</tr>
</thead>
<tbody>
<tr>
<td>First</td>
<td>Evaluation for potential partners in ASC</td>
</tr>
<tr>
<td>Second</td>
<td>Production and logistics management, partnership management, financial capability, technology and knowledge management, marketing capability, industrial and organisational competitiveness and human resource management</td>
</tr>
<tr>
<td>Third</td>
<td>See Wu and Barnes (2010)</td>
</tr>
</tbody>
</table>

Table IV. GHC for partner selection in ASCs

Source: Based on Wu and Barnes (2010, p. 286)
decision makers apply the criteria developed in phase 1, using RBF-ANN to reduce the numbers of potential partners to a more manageable level by classifying potential partners into different categories. It is described in detail in Luo et al. (2009). They argue for the use of Kraljic’s (1983) model to enable potential partners to be categorised into four different types according to two variables – their impact on the purchasing organisation’s bottom line and the degree of supply risk involved. Combining these variables yields a two-by-two matrix, each of whose quadrants characterizes one of four different supplier types (Figure 3):

1. Strategic suppliers, with whom purchasing organisations should look to build long term, close relationships.
2. Preference suppliers, with whom purchasing organisations should concentrate on securing continuity of supply, if necessary at additional cost.
3. Leverage suppliers, for whom a multiple sourcing strategy is most appropriate.
4. Routine suppliers, with whom purchasers should look to reduce costs through strategies such as supplier base reduction.

Using such an analysis not only enables the potential supply market to be segmented in a way that not only simplifies the selection problem by reducing the solution space, but also enables decision makers to select within in the category that is most appropriate to their supply strategy. It can, thereby, enable the whole supply chain to be managed more effectively and improve competitiveness.

An acknowledged weakness of Kraljic’s model is that it is essentially, qualitative in nature, relying on the subjective judgment of decision makers to assess a supplier’s position on the matrix. Luo et al. (2009) overcome this by quantifying the criteria used for placement within the matrix by using 1 and 0 to represent high and low supply risk and suppliers impact on financial results, respectively. Thus, for example, (0, 1) would represent leverage suppliers and (1, 0) would represent preference suppliers. The use of Kraljic matrix in this way alongside RBF-ANN enables the otherwise very daunting task of evaluating all potential suppliers against all required criteria to become a more practical proposition.

![Figure 3. Classification matrix of suppliers](image-url)
Luo et al. (2009) argue that their use of RBF-ANN offers a way of overcoming the information processing difficulties inherent in assessing a large number of potential suppliers against multiple criteria. They construct a three-layer feed forward network, comprising an input layer, hidden layer and output layer. The hidden layer applies the RBF, which is a Gauss function, as the activation function. (Please see equations (1)-(3) in Luo et al. (2009) for the detailed mathematical expression of RBF-ANN construction.) The resulting RBF-ANN information processing model proposed is shown in Figure 4.

The network needs to be tested using data from a stratified sample from the whole population of potential suppliers. After successful network testing, the model can then be used to assess all other potential suppliers, classifying them into one of the four categories at low cost.

### 3.3 Phase 3 – final selection

This is the same as De Boer et al.’s third stage of final choice. In this phase, decision makers choose the most appropriate suppliers from within one of the appropriate categories provided in phase 2 as well as allocating the order quantities to each supplier that will optimize the performance of the entire supply chain. As detailed in Wu et al. (2009), the model does this through the use of an ANP-MIMOP model. Wu et al. (2009) combine the use of both ANP and MIMOP methodologies, arguing that the two methods are mutually reinforcing. ANP can take account of the complex set of relationships, both internal and external, between the different assessment criteria. MIMOP can solve the detailed sourcing problem of the optimization of order quantity allocation. As such, Wu et al. (2009) overcome the inherent complexity of the final selection problem effectively and efficiently, by splitting it into two sub-problems.

---

**Figure 4.**
RBF-ANN partner selection information processing model

**Source:** Luo et al. (2009, p. 257)
Calculating the priorities of the different evaluation criteria. Wu et al. (2009) propose doing this by applying an ANP methodology to solve what is a complex system problem. First, they identify the relationships between the relevant performance criteria. They propose four clusters of criteria:

(1) FC – flexibility (in establishing relationships with partners) criteria;
(2) QC – quality (in terms of both production quality and service quality) criteria;
(3) CC – cost (of both raw materials and production) criteria; and
(4) TC – time (for both transportation and distribution) criteria.

The relationships between these are shown in the resulting ANP network structure shown in Figure 5.

From Figure 5, they build a supermatrix (Figure 6), which can then be used to calculate the priorities for the different criteria. (In Figure 6, $W_{CC,K}^{TC}$ denotes that cluster CC depends on cluster TC, and so on. Clusters, with no interactions are shown with zero.)

Source: Wu et al. (2009, p. 259)
Optimizing the allocation of order quantities to the most suitable partners. Wu et al. (2009) use the MIMOP method to assign the most suitable order quantities to the most appropriate partners, arguing that it offers both simplicity and flexibility. They illustrate its use with a model of the simple supply chain comprising suppliers, producers, distribution centres and customer zones, as shown in Figure 7.

They apply MIMOP in order to simultaneously achieve optimal solutions across the whole supply chain for the following objectives:

1. minimising the cost of raw materials supplied by different suppliers;
2. minimising the production cost of the different products produced by different producers;
3. minimising the complexity of transportation by minimising the total cost of transportation of each product from producer to distribution centre;
4. maximising the efficiency of the distribution of products by minimising the total distribution cost from different distribution centres to different customer zones;
5. maximising the flexibility of establishing relationship with supply chain partners by minimising costs associated with the building of new relationships and the dismantling of old relationships;
6. maximising quality by minimising the defective rate for all products; and
7. maximising the total service level in each customer zone.

At the same time, the MIMOP method is used to account for the various constraints that are relevant. Wu et al. (2009) identify constraints arising from:

- competing demands for the same materials in different product structures (as indicated in their respective bills of material);
- any single supplier only having the capacity to provide quantities of raw materials up to some limit;
- any single producer only having the capacity to produce any product up to some limit;
- any single distribution centre only having the capacity to distribute products up to some limit;
- the sum of the assigned order quantities for each distribution centre needing to meet the demand from each customer zone;
- the defect rate for each product produced by each different producer needing to be less than the maximum defect rate deemed acceptable within the ASC;

Figure 7.
The positions of different partners and notations

Source: Wu et al. (2009, p. 261)
for each distribution centre, the product input quantity needing to be equal to the product output quantity in a single period; and

all quantities needing to be positive integral numbers.

See Wu et al. (2009) for the detailed mathematics and for an illustrative application. As they point out, the model can be easily amended, incorporating different criteria, to suit different decision contexts.

3.4 Phase 4 – application feedback
An important feature of Luo et al.’s model is the addition of a fourth phase, namely that of application feedback. This phase which is described in Wu and Barnes (2009a), adds a dynamic feedback element to the model. Decision makers use qualitative and quantitative methods to assess the strengths and weaknesses of the selection process just applied in the previous three phases in order to improve subsequent applications. This phase of the model aims to provide organisational decision makers with feedback about their efforts to optimise the performance of the supply chain by ensuring that only the most appropriate suppliers are selected at all times. The process of application feedback and continuous improvement for partner selection in ASCs is shown in Figure 8.

![Figure 8. Application feedback and continuous improvement model for partner selection in ASCs](image)

Source: Wu and Barnes (2009a, p. 87)
This phase integrates the principle of continuous improvement, one of the most important aspects of quality management, into the partner selection process. Continuous improvement is itself based on the concept of organisational learning. Power et al. (2001) argue that this is particularly important in partner selection in ASCs. However, to date, such a stage has not been adopted by other researchers. Wu and Barnes (2009a) argue that such a stage is important and necessary in today’s highly competitive business environments. Consequently, we propose to rename the model as the “four-phase dynamic feedback model” in order to emphasise the importance of the incorporation of this dynamic feedback element into the partner selection processes in ASCs.

The application feedback phase of the model is based on Deming’s (2000) famous plan-do-check-act (PDCA) continuous improvement model which applies systems principles (Von Bertalanffy, 1968) to quality management. In applying this, an ASC can be seen as a system to achieve customer satisfaction and loyalty. The “plan” stage can be seen as the formulation of the four-phase model, through its application of the DST, RBF-ANN and ANP-MIMOP models and the use of multiple objectives in partner selection. The “do” stage is the application of the various models from constructing the OHC, building the RBF-ANN network and ANP structure to allocating the right-order quantities to the right partners. The “check” stage involves validating the structure of the supply chain, the selection of the partners and the allocation of order quantities by assessing the performance of the entire supply chain. The “act” stage involves taking action to address any problems identified in the check stage. These arise from monitoring supply chain performance and reviewing the effectiveness of the process. This stage closes the continuous improvement loop and thus provides an organic mechanism to respond to any changes whether arising from internal requirements or external environment influences (Chan and Chan, 2004).

In evaluating the use of the various models used in the partner selection process, Wu and Barnes (2009a) build on the work of De Boer and Van der Wegen (2003) and Bevilacqua et al. (2006) to propose 16 criteria, grouped according to two dimensions, namely complexity-fit and cost-benefit (Table V). The criteria in the complexity-fit dimension measure the intricateness and suitability of the model, whereas the criteria in the cost-benefit dimension measure the costs and returns associated with applying the model.

Wu and Barnes (2009a) argue that the application of these criteria will provide decision makers with sufficient relevant information about the merits and drawbacks of using the various models in practice that can then be used to inform subsequent decision-making cycles.

4. Discussion and conclusion
Efficient ASCs are considered to be the solution to meet the frequently changing customer demands for high quality, short lead times, low costs and high customer service levels. It is generally accepted that the successful performance of an ASC depends heavily on the construction of the supply network and the especially the ability to choose the right partners.

The four-phase dynamic feedback model reviewed in this paper, offers a comprehensive and detailed method for tackling the partner selection problem in ASCs. The approach contained in the model improves the partner selection process in ASCs in following main ways. First, unlike much of the existing literature, it considers
the partner selection process as a whole, which enables the entire system to be optimized by considering the sequence and connections between different phases. Second, it makes dynamic feedback practical for those involved in partner selection and provides them with continuous improvement opportunities. As such, it can enhance an organisation’s ability to choose the most appropriate partners when seeking to form or re-form the most competitive ASCs. Third, it enables the most appropriate methods to be chosen for each of the phases of supplier selection, thereby improving the effectiveness of the process as a whole. In particular, the model enables decision makers to make use of recent advances in computing that are incorporated within its various techniques. In more detail, the formation of OHC enables interdependencies between attributes to be considered by applying the DST, whilst at the same time considering the limitations of the resources needed to obtain information on evaluation attributes. The use of Kraljic’s (1983) matrix alongside RBF-ANN enables the otherwise very daunting task of evaluating all potential partners against all required criteria to become a realistic proposition. The use of the classification matrix also increases the visibility of the assessment of each potential partner’s strength and weakness, enabling decision makers to make more rational judgments. The use of ANN-MIMOP is flexible enough to allow the investigation of different scenarios with minimal effort, thus providing alternative solutions and trade-offs between several tangible and intangible factors with different priorities. Individually and collectively these techniques offer the prospect of more informed and considered decision making. In summary, the use of the four-phase model provides decision makers with the ability to make efficient and effective use of the vastly increased amount of data that is available on potential partners in today’s information-driven society.

There are, however, some drawbacks to the model, which may tend to make the model more attractive to academics than to practitioners. First, determining which factors to take into account is difficult in practice. These must be matched to the objectives of the ASC,

<table>
<thead>
<tr>
<th>Dimensions</th>
<th>Criteria</th>
</tr>
</thead>
<tbody>
<tr>
<td>Complexity-fit</td>
<td>C1: Do the models aggregate information in a proper way?</td>
</tr>
<tr>
<td></td>
<td>C2: Do the models utilise available information sufficiently?</td>
</tr>
<tr>
<td></td>
<td>C3: Are the models easy to use?</td>
</tr>
<tr>
<td></td>
<td>C4: Do the models save valuable time?</td>
</tr>
<tr>
<td></td>
<td>C5: Is it (to a satisfactory extent) possible to incorporate opinions and beliefs?</td>
</tr>
<tr>
<td></td>
<td>C6: Is it (to a satisfactory extent) possible to achieve a fair participation of individual members in case of a group decision?</td>
</tr>
<tr>
<td>Costs-benefits</td>
<td>C7: Are the models sufficiently flexible for changes in the decision situation?</td>
</tr>
<tr>
<td></td>
<td>C8: Is the outcome of the decision models useful?</td>
</tr>
<tr>
<td></td>
<td>C9: Is the outcome of the decision models accurate?</td>
</tr>
<tr>
<td></td>
<td>C10: Are the models sufficiently user-friendly?</td>
</tr>
<tr>
<td></td>
<td>C11: Are the required investments justifiable?</td>
</tr>
<tr>
<td></td>
<td>C12: Are the models sufficiently flexible for changes in the decision situation?</td>
</tr>
<tr>
<td></td>
<td>C13: Is the way the decision models work sufficiently clear?</td>
</tr>
<tr>
<td></td>
<td>C14: Do the decision models increase the insight in the decision situation?</td>
</tr>
<tr>
<td></td>
<td>C15: Do the decision models enhance communication?</td>
</tr>
<tr>
<td></td>
<td>C16: Do the decision models improve decision-making skills?</td>
</tr>
</tbody>
</table>

Source: Wu and Barnes (2009a, p. 89)
which is difficult in fast-changing market conditions. However, use of the model forces decision makers to address this issue explicitly, which should improve the decision-making process by encouraging partner selection to be aligned with strategic objectives. Second, the process may appear too complex to organisational decision makers, particularly when speed is of the essence. They are likely, at least initially, to need the help and support of experts in the application of the various methods employed in the model, which has obvious resource implications. Third, obtaining information, particularly quantitative data, that is accurate, meaningful and reliable poses significant challenges in many organisational settings. Getting such information from potential suppliers can be particularly problematic. Even getting the data required from internal organisational sources may be costly and time consuming.

The main contribution of the paper is theoretical in that, for the first time, it draws together work from previous articles that have described each of the four stages of the model in detail to present a comprehensive overview of the model. As such, the paper is likely to be of most interest to other academic researchers in this field. Additional research is now required to further develop the model. Further detailed work is required in each phase in order to develop the techniques in sufficient detail to enable them to be applied in practice. Initially this is likely to involve their application under conditions which simulate real world contexts. However, the efficacy of the model can only be truly established by its application in live organisational situations. This would enable any shortcomings to be identified and subsequently addressed in order to further improve and refine the model. Undertaking real world testing would enable the gap theory and practice to be bridged, thereby making the model of interest to supply chain practitioners as well as academics. Applications of the model in real organisations would help meet the challenge of gaining support for its use by confronting the inevitable concerns of practitioners about its costs and difficulties compared to the potential benefits available from improved partner selection in ASCs.

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About the authors
Chong Wu is an Assistant Professor of Operations Management at the School of Management, Xiamen University. He received his BSc and PhD in Management from Business School, Central South University. His main research interests include supply chain management and information management. From 2007 to 2009, he was a visiting academic at Royal Holloway University of London, supported by grants from the Chinese government scholarship. He has published several papers in quality journals such as International Journal of Production Economics, Production Planning & Control, Journal of Purchasing & Supply Management, and Knowledge and Process Management.

David Barnes is Head of the Department of Business Information Management and Operations at Westminster Business School, University of Westminster. He has held lecturing posts with Royal Holloway, University of London, the Open University and Thames Valley University, and was a visiting Research Fellow at the University of Cambridge. He holds a BSc (Eng) from Imperial College London, a MBA from the Open University and a PhD from Staffordshire University. His research interests encompass the strategic management of operations, performance management and the impact of e-business on operations. He has published extensively in leading academic journals, including International Journal of Operations & Production Management, International Journal of Production Economics, Production Planning & Control, and Journal of Manufacturing Technology Management. David Barnes is the corresponding author and can be contacted at: D.Barnes@westminster.ac.uk

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