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ORIGINAL ARTICLE

A survey of partner selection methodologies for virtual enterprises and development of a goal programming–based approach

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Abstract A virtual enterprise (VE) is a platform that enables dynamic collaboration among manufacturers and service providers with complementary capabilities in order to enhance their market competitiveness. The performance of a VE as a system depends highly on the performance of its partner enterprises. Hence, choosing an appropriate methodology for evaluating and selecting partners is a crucial step toward creating a successful VE. In this paper, we begin by presenting an extensive review of articles that address the VE partner selection problem. To fill a significant research gap, we develop a new goal programming (GP)–based approach that can be applied in extreme bidding conditions such as tight delivery timelines for large demand volumes. In this technique, fuzzy analytic hierarchy process (F-AHP) is used to determine customer preferences for four main criteria: proposed unit price, on-time delivery reliability, enterprises' past performance, and service quality. These weights are then incorporated into the GP model to evaluate bidders based on customers' preferences and goals. We present a case study in which we implement the F-AHP-GP technique and verify the model's applicability, as it provides a more flexible platform for matching customers' preferences.

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Keywords Virtual enterprise · Partner selection · Fuzzy AHP · Goal programming

Abbreviations

ACO	Ant colony optimization
AHP	Analytic hierarchy process
AI	Artificial intelligence
ALFA COSME	ALFA Project's Conceptual Mexican
VE	Virtual Enterprise
ANN	Artificial neural network
ANP	Analytic network process
B&B	Branch and bound
CA	Cluster analysis
CBR	Case-based reasoning
COWORK	Concurrent Project Development Tools for SMEs Networks
FIS	Fuzzy inference system
GA	Genetic algorithm
GA-BHTR	Genetic algorithm–binary heap and transitive reduction
GP	Goal programming
IP	Integer programming
MASSYVE	Multi-agent Manufacturing Agile Scheduling Systems for Virtual Enterprises
MAUT	Multi-attribute utility theory
MCDM	Multi-criteria decision making
MILP	Mixed integer linear programming
PRODNET	Production Planning and Management in an Extended Enterprise
PROMETHEE	Preference ranking organization method for enrichment of evaluations
PSO	Particle swarm optimization
QEA	Quantum evolutionary algorithm
SME	Small and medium enterprise

TOPSIS	Technique for order of preference by similarity to ideal solution
TS	Tabu search
VIRTEC	Virtual Enterprise for Formation of High Technology Based Enterprises

1 Introduction

Manufacturing enterprises are challenged by today's extremely competitive global market conditions. Increasingly, companies are feeling pressure to diversify their product or service offerings in order to satisfy customers' dynamically changing expectations and maintain market competitiveness. To achieve these goals, enterprises must introduce high-quality, competitively priced products and services to the market quickly, which requires significant investments in corporate infrastructures. Although large enterprises have the advantage of extensive financial and human resources, in many cases, progress is hindered by rigid organizational structures. In contrast, small- and medium-sized enterprises (SMEs) have more dynamic organizational structures but lack sufficient resources. Therefore, a collaborative platform that enables both types of enterprises to capitalize on these complementary advantages—vast resources and operational flexibility—would solve many challenges associated with diversification. This is why modern production strategies such as virtual enterprise (VE) have emerged in recent decades.

By definition, VE is a temporary alliance of autonomous, diverse, and sometimes geographically dispersed enterprises that share core resources or competencies [1]. The primary purpose of VE is to enhance collaboration among multiple enterprises with different capabilities through an internet-based network to capitalize on specific market opportunities. Therefore, selecting the best consortium partners is one of the key issues in constructing a successful VE collaboration [2].

Like all decision making problems, partner selection involves trade-offs among conflicting criteria. Certainly, a company that provides a high-quality product at a cheap price is the ideal alternative. But, this typically is not the case in real life. High-quality products normally cost more to produce and are sold at higher prices. So, a customer must determine the relative importance of quality and price then make a trade-off between these two. In other words, the decision maker might have to sacrifice one in order to get the other. However, since human judgments are typically uncertain and vague, preferences may be inconsistent. There also may be uncertainty about partners' performance due to incomplete information or knowledge. Clearly, partner selection is a challenging problem; hence, an extensive number of articles have been published in this domain.

In Sect. 2, we present a review of relevant literature on VE implementations and, specifically, the formation of VE consortiums. Our review reveals an important research gap—namely, a need to extend and improve effective models to meet current market needs. Specifically, goal programming (GP)–based selection has not yet been applied to model the partner selection problem. This approach would be beneficial because it provides a flexible structure for choosing enterprises based on customer goals. Thus, in Sect. 3, we propose a novel fuzzy analytic hierarchy process–goal programming (AHP-GP) method for VE partner selection and illustrate the model using a case study in Sect. 4. Finally, in Sect. 5, we present some final thoughts and suggest opportunities for future research.

2 Literature review

In this section, we briefly review and discuss the performance of implemented VE systems. As the success of a VE depends highly on its partners' performance and coherence, we review and analyze VE partner selection techniques in depth and identify important research gaps.

2.1 VE tools and implementations

In recent years, VE systems have been implemented for different purposes, and various tools and applications have been developed to fulfill different VE requirements. Among the notable attempts in this era are the Production Planning and Management in an Extended Enterprise (PRODNET) I and II projects [3]. In these projects, a multi-layered information communications technology (ICT) architecture for VE systems was proposed and different tools and applications were developed to evaluate and select partners' resources and capabilities [4]. Virtual Enterprise for Formation of High Technology Based Enterprises (VIRTEC), Conceptual Mexican Virtual Enterprise (ALFA COSME-VE), and Concurrent Project Development IT Tools for Small–Medium Enterprises Networks (COWORK) are the similar projects which aimed to develop an enterprise pool for potential partners using special criteria and management system architectures. [5–7]. Recently, human–software hybrid systems have been developed to satisfy the high automation and flexibility requirements of VE systems. One of these hybrid systems was introduced in the Multi-agent Manufacturing Agile Scheduling Systems for Virtual Enterprises (MASSYVE) project, which is benefiting from an agent-based approach for selecting partners and generating intra- and inter-organizational schedules.

Rival SMEs in a molding industry collaborated in order to capitalize on market opportunities by strengthening cooperation and increasing their market compatibility in TECHMOULD project. In order to swiftly and flexibly respond to customers' needs, they developed a decision support system (DSS) to select the most appropriate VE partners, and a broker system to collect bids from potential partners. This DSS was based on a tool from the Multi-agent Manufacturing Agile Scheduling Systems for Virtual Enterprises (MASSYVE) project that had been developed by the same researchers. Outcomes from DSS tool are sent to members of the TECHMOULD management board, who provide final approval. This is a good example of a hybrid structure for partner selection [8, 9].

Various implementations of VE projects in industry have revealed the need for reliable partner selection methods and strategies. This fact inspired many researchers to focus on this topic and conduct advanced research. The next section provides a comprehensive review on published partner selection methods and techniques in VE systems.

2.2 Categorical review of partner selection techniques

In this section, we review journal articles specifically related to the VE partner selection problem and retrieved using the keywords “partner selection” and “virtual enterprise,” excluding conference proceedings, master’s theses, doctoral dissertations, and publications in languages other than English. Articles addressing supplier selection, supply chain, and strategic alliances are excluded, although there may be significant overlaps with our field of study. Based on these criteria, 46 articles matched the scope of our review.

Reflecting the multi-disciplinary nature of the virtual enterprise topic, the articles reviewed in this section were published in computer, industrial, mechanical and manufacturing engineering, mathematics, economics, informatics, business, and management journals. Table 1 provides the distribution of articles with respect to the journals in which they appeared. Most of the papers were published in *International Journal of Production Research*, followed by *International Journal of Advanced Manufacturing Technology* and *Computer Integrated Manufacturing*.

We review a total of 46 articles, 42 of which present a methodology for solving the partner selection problem specifically. These methodologies can be classified into three main categories: optimization, multi-criteria decision making (MCDM), and other. A detailed classification of partner selection approaches is presented in Fig. 1. The numbers in parentheses indicate the number of studies employing the corresponding technique.

2.2.1 Optimization approaches

The VE partner selection problem can be approached as an optimization problem where the goal is to assess decision makers’ priorities and maximize their satisfaction. Customer consent depends on several factors such as cost, quality, risk, trust, and many others. Maximizing satisfaction requires maximizing some parameters, such as quality, trust, reliability, and service level, and minimizing others, such as cost and risk. These factors are considered to be the objectives of the model; however, due to resource limitations, some constraints may need to be defined as well. For instance, minimizing lead time is not accomplished by simply choosing the shortest production cycle, but by also considering and managing constraints in the process related, for example, to task requirements and manufacturing sequences. Partner selection problems can be characterized by a single or multiple objective functions those are going to be optimized under a number of constraints.

Of the 46 approaches identified in the literature to solve the VE partner selection problem, 22 employed optimization techniques. Optimization is the most frequently used approach to the partner selection problem mainly because a wide variety of exact methods and artificial intelligence (AI) techniques exist for solving optimization problems.

Exact methods Algorithms that solve mathematical programming problems exactly are called exact methods. Two exact methods are relevant to our context: integer programming and mixed integer linear programming.

Integer programming Integer programming is a mathematical solution methodology in which objectives and constraints must be integers. Generally, task assignments are represented by $\{0, 1\}$, where 0 indicates that a task has not been assigned to a partner and 1 indicates that a task has been assigned to a partner [10].

One of the earliest studies in this area was conducted by Wu et al. in 1999, who proposed an integer programming model with the objective of minimizing the total cost of performing all tasks and the transportation cost [11]. In 2004, the authors improved the previous model by adding time constraint. They transformed the integer programming (IP) formulation into a graph-theoretical formulation and developed a two-phase algorithm to solve the problem [12].

Ip et al. implemented a branch and bound (B&B) algorithm to obtain the solution of a model described by integer programming with an objective function of cost minimization. A limitation of branch and bound method is that it cannot solve large-scale problems within an acceptable amount of time [10].

Hsieh et al. developed a framework for partner selection using reverse auctions to minimize the cost of VE project tasks. They developed a solution algorithm based on Lagrangian relaxation technique; although the algorithm does not guarantee the generation of an optimal solution, in practice it often generates optimal or near-optimal solutions [13].

Zeng et al. proved that the partner selection problem with a due date constraint is NP-complete, and constructed the cost minimization non-linear integer programming model which was solved using a branch and bound algorithm [14].

Table 1 Distribution of articles by journal

Name of journal	Number of published articles
Annual Reviews in Control	1
Applied Mathematics and Computation	1
Business and Economic Horizons	1
Chinese Journal of Economics	1
CIRP Annals - Manufacturing Technology	1
Computers and Industrial Engineering	1
Computers and Operations Research	1
Expert Systems with Applications	4
IEEE Transactions on Systems Manufacturing and Cybernetics	1
International Journal of Advanced Manufacturing Technology	5
International Journal of Computer Integrated Manufacturing	4
International Journal of Computer Science and Network Security	1
International Journal of Operations & Production Management	1
International Journal of Production Economics	1
International Journal of Production Research	9
International Journal of Services and Operations Management	1
Journal of Intelligent Manufacturing	1
Journal of Materials Processing Technology	1
Knowledge-Based Systems	1
Omega, The International Journal of Management Science	3
Progress in Natural Science	1
Robotics and Computer-Integrated Manufacturing	3
The Data Base for Advances in Information Systems	1
Total	46

Dissimilar to previous approaches, a hybrid form of IP is developed by Sha et al. They integrated IP with analytic hierarchy process (AHP) and multi-attribute utility theory (MAUT) [15].

Mixed integer linear programming In addition to the integer programming models mentioned above, the partner selection problem can also be modeled through mixed integer linear programming. In contrast to IP, the unknowns of

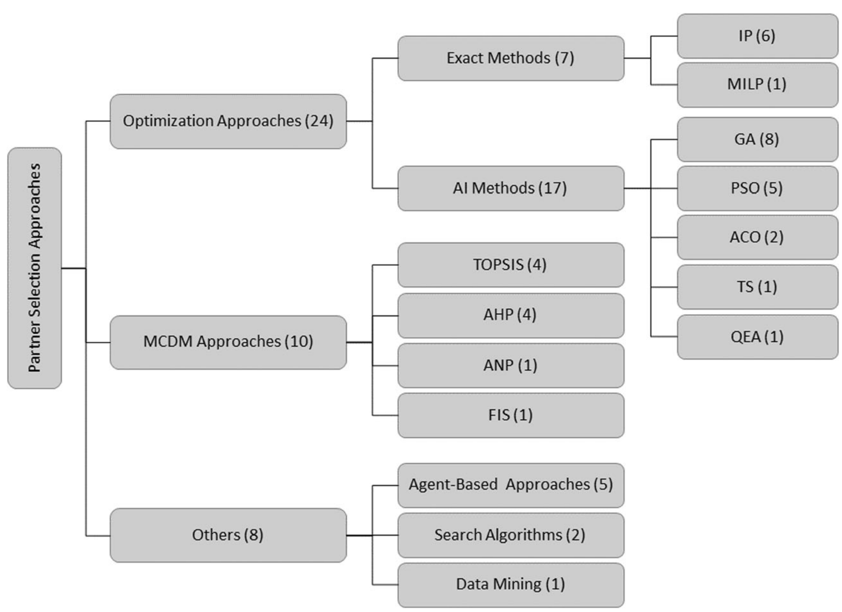

Fig. 1 Classification of partner selection techniques

mixed integer programming (MIP) can be either integers or non-integers.

The model developed by Jarimo et al. is the only study which adapts MIP for the partner selection problem. Some consider the proposed model to have a weakness, since this method does not yield an absolute ranking of candidates and the final decision must be made by the decision maker to change among the set of Pareto efficient configurations [16].

As we mentioned previously, exact algorithms such as branch and bound generally do not provide a satisfactory solution within a reasonable amount of computational time and are not recommended for large-scale, complex problems.

Artificial intelligence methods To address the complexity of large-scale problems, researchers have adapted artificial intelligence (AI) methods (i.e., computer-aided systems) such as genetic algorithm (GA), particle swarm optimization (PSO), ant colony optimization (ACO), and tabu search (TS).

Genetic algorithm A genetic algorithm is an intelligent search algorithm that mimics the process of natural selection. As GA searches the solution domain randomly, it is more suitable for solving discrete problems such as the partner selection problem. Other AI methods such as PSO and ACO are more suitable for solving continuous solution problems [17], which explains why GA is the most frequently used AI technique in VE partner selection. GA and its revised or integrated forms have been applied to the partner selection problem in eight papers.

Ip et al. proposed a model that aimed to select the optimal combination of partners in order to minimize project risks. The objective of the problem was not linear, convex, or differentiable, so it could not be solved using general mathematical programming methods. Therefore, the authors introduced a rule-based genetic algorithm to solve the problem [18]. The criteria considered during the optimization process were risk of failure and tardiness; all qualitative criteria were neglected. Later, Wang et al. also proposed a risk-oriented model; however, they included task benefit in the objective function as an indicator of partner quality and service level [19].

GA may lead to prematurity and local convergence. Therefore, scholars proposed a hybrid genetic algorithm (HGA) that takes cost, time, and risk into account to solve the model. They compared HGA to standard GA and other versions of GA and confirmed its efficiency [20]. Moreover, implementing an adaptive GA with step size adaptation to the same model showed faster convergence compared to traditional GA [21].

These models were improved further by adding additional criteria. Tao et al. found the best partner by minimizing two criteria, total cost and risk, and maximizing two other parameters, quality and flexibility, with budget and deadline constraints. The model was solved using an evolutionary GA–binary heap and transitive reduction (GA-BHTR). Unlike a traditional GA, the authors claimed that a GA-BHTR does not converge quickly to a local solution [22]. Like many other models, since no reliable method is used to control weight parameters of objectives and constraints, the results may not be accurate.

Zhang et al. made further improvements in partner selection model in terms of environmental friendliness by developing a green partner selection model and introducing two new green criteria: carbon emissions and lead content. The objective of the model was to minimize cost, time, and carbon emissions while maximizing quality. Constraints in this model were cost, time, quality, reliability, carbon emissions, and lead content. They designed a new Pareto genetic algorithm in order to obtain the set of non-inferior solutions [17].

While the aforementioned researchers focused on modeling the partner selection problem, others tried to improve the search methodologies. For instance, Zhong et al. developed a hybrid algorithm integrating GA and ACO to minimize a single objective which could be either cost, time, or risk. The authors claimed that the GA-ACO integrated algorithm was superior to GA [23]. Another fairly novel approach was proposed by Cheng et al., who introduced performance parameters of the manufacturing tasks (PPMT) into the model. The objective was to minimize the gap between performance objectives determined by the core company and partner bids. The weights of the performance parameters of the subtasks were determined by applying an analytical hierarchy process (AHP) or an analytical network process (ANP), and the model was solved by adaptive GA [24].

Particle swarm optimization Particle swarm optimization (PSO) is a population-based stochastic search algorithm inspired by the social behavior of flocks of birds or schools of fish. Among the artificial intelligence methods, PSO is the second most frequently used optimization technique. There are five articles addressing PSO and its revised forms.

As stated in the previous section, Jian et al. claimed that HGA was superior to GA. Likewise, Gao et al. developed an algorithm with faster converging speed than GA based on discrete binary PSO for the same criteria of cost, time, and failure risk [25]. Mahapatra et al. also implemented a discrete version of PSO for the partner selection problem and claimed that discrete PSO was more effective because it avoided the particle velocity in standard PSO [26].

In another study, Zhao et al. adapted a PSO algorithm to solve the partner selection model with precedence and due date constraints, and claimed that PSO was more effective than GA and B&B [27]. Likewise, Xio et al. added two more evaluation criteria, trust and quality, to the previous criteria of cost, time, and risk. An adaptive quantum swarm evolutionary algorithm was applied to optimize the model [28].

One fact that had been neglected in previous studies was the uncertainty of information. To deal with this problem, Huang et al. used a fuzzy set to maximize the objective of meeting a minimum satisfaction threshold with precedence, cost, and due date constraints. The model was optimized by adaptive PSO [1].

Ant colony optimization Ant colony optimization (ACO) is a probabilistic technique for finding the optimal path through graphs [29]. To optimize the partner selection problem by ACO, all bids for subtasks in the network are illustrated with a directed graph from initiation to completion. The objective function value is calculated by maximizing the cumulated AHP values [30]. Unlike previous work, Niu et al. developed a model that took both quantitative and qualitative attributes into account to evaluate the candidate partners. Quantitative objectives were cost, time, and quality, and qualitative objectives were risk and reputation. They adapted fuzzy set theory for two purposes: to determine the weights of the criteria, and to represent linguistic terms as numbers. They developed an enhanced ACO to obtain the solution [29].

Tabu search Tabu search is a meta-heuristic search method for mathematical optimization based on a local or neighborhood search procedure. Ko et al. are the only researchers who have developed and published a selection methodology based solely on tabu search method. The authors developed four tabu search–based heuristic algorithms to generate optimal or near-optimal solutions for a cost minimization model [31]. While Crispim et al. also used tabu search by integrating it with technique for order of preference by similarity to ideal solution (TOPSIS), we discuss their work in detail in the section on TOPSIS-based methods since TOPSIS was the core evaluation method and tabu search was used as an aid to ensure the feasibility of the solution.

Quantum-inspired evolutionary algorithm (QEA) Han et al. introduced a novel evolutionary algorithm based on quantum computing principles and concepts in 2002 [32]. Tao et al. also proposed a quantum multi-agent evolutionary algorithm by combining agents and quantum bits to minimize costs in a VE partner selection model [33].

In summary, it can be argued that the partner selection problem is not a straightforward optimization problem [34]. Optimization approaches force decision makers to specify their preferences in terms of mathematical formulations, while it is actually a process of making decisions among number of alternatives and based on several criteria, which can be subjective.

2.2.2 MCDM approaches

Enterprise evaluation is considered to be a multi-criteria decision making (MCDM) problem based on customer preferences. MCDM approaches are decision support tools that allow decision makers to construct, evaluate, and solve problems associated with multiple conflicting criteria. Analytic hierarchy process (AHP), analytic network process (ANP), technique for order of preference by similarity to ideal solution (TOPSIS), preference ranking organization method for enrichment of evaluations (PROMETHEE), and VIKOR (from Serbian: VIseKriterijumska Optimizacija I Kompromisno Resenje, that means: multi-criteria optimization and compromise solution) are some well-known methods.

Analytic hierarchy process AHP is the most frequently used MCDM approach for both supplier selection in supply chain management and VE partner selection [35]. Developed by Thomas Saaty in the 1970s, AHP is a technique based on pairwise comparisons representing the relative importance of one criterion versus another [36]. Unlike optimization approaches, AHP can handle both tangible (quantitative) and intangible (qualitative) criteria. In one study, Chu et al. employed AHP to evaluate partners based on cost, time, quality, customer service, and financial stability factors [37]. However, assigning trustworthy scores for intangible criteria is not an easy task. Sari et al. proposed an AHP-based partner selection method that used an artificial neural network (ANN) to assess the overall past performance of each partner and implemented program evaluation review technique (PERT) to calculate the completion probability of each task. In addition to past performance and completion probability, the researchers also considered unit cost and caution cost as evaluation criteria. Caution cost was actually a measure for demonstrating the level of commitment [38].

Assigning exact numeric scores to represent preferences among criteria is another challenge for decision makers. Mikhailov made one of the main contributions to solving this aspect of the partner selection problem by introducing a fuzzy analytical approach. He used fuzzy intervals in order to assess uncertain weights of selection criteria in the AHP framework [39]. Later, Wang et al. developed a technique that could reduce the number of pairwise comparisons of Mikhailov's fuzzy AHP method [58]. In some papers, AHP was used as a tool to derive the weights of each criterion when the model's objective function was based on a cumulative sum of objectives.

Analytic network process Analytic network process (ANP), a more advanced form of AHP, was introduced by Saaty in 1996 [40]. Although both approaches use pairwise comparisons to derive weights and rank alternatives, in AHP, each factor of the hierarchy structure is considered to be independent of all others while ANP allows interconnections between factors. Furthermore, ANP overcomes the issue of rank reversal, which is a well-known limitation of AHP. Since ANP is a methodology which is capable of handling the complex relationships between criteria, Sarkis et al. suggested using it to solve the VE partner selection problem [41]. While the same problem can be solved by both ANP and AHP, ANP requires significantly more pairwise comparisons than AHP, which causes excessive complexity.

TOPSIS The technique for order preference by similarity to ideal solution (TOPSIS) is an MCDM technique developed by Hwang and Yoon. TOPSIS is based on the idea that the chosen alternative should be closest to the "positive ideal solution" and the farthest from the "negative ideal solution" [42]. In 4 out of 46 reviewed articles, researchers used TOPSIS integrated methods to solve the VE partner selection problem. This makes TOPSIS the second-most popular MCDM method for solving this type of problem.

Although TOPSIS does not provide a consistency check of judgments and preferences, the simplicity of programming encourages many authors to take advantage of the integrated forms of this method [43].

Deviation degree–based and risk factor–based TOPSIS are two extended TOPSIS models for group decision making proposed by Ye. Cost, time, trust, risk, and quality were selected as evaluation criteria [44]. A year later, in 2010, Ye developed a fuzzy TOPSIS model to address two issues: Information about the criteria for each candidate may be incomplete or uncertain, and expressing accurate judgments with exact numbers may not be possible [45].

TOPSIS is capable of dealing solely with numbers, not linguistic definitions. Therefore, to apply TOPSIS to qualitative criteria, a tool must be used to quantify subjective terminology. Crispim et al. improved a fuzzy TOPSIS approach by adding tabu search meta-heuristics. The fuzzy approach makes it possible to consider qualitative criteria, quality, and trust in addition to cost and delivery time. Tabu search is used to identify conflicts between activities in alternative scenarios and to ensure that the solution is feasible [46].

The other algorithm proposed by Crispim et al. can handle 20 criteria. The authors integrated cluster analysis, case-based reasoning (CBR), and multi-objective tabu search into a fuzzy TOPSIS method. Cluster analysis is applied to restrict the search according to the decision maker's preferences. Case-based reasoning is implemented to construct partner configurations by reusing knowledge from past. The authors designed multi-objective tabu search to approximate the Pareto front and implemented fuzzy TOPSIS to rank the alternative VE configurations [47].

TOPSIS still requires the specification of weights of objectives. Thus, a method like AHP is still required in order to determine proper objective weights. Furthermore, like AHP, TOPSIS in its standard form is deterministic and does not consider uncertainty in weights. In order to eliminate this shortcoming of TOPSIS, the authors who used this technique integrated it with fuzzy set theory.

Fuzzy inference systems A fuzzy inference system (FIS) is a popular reasoning framework based on the concept of fuzzy sets published by Zadeh in 1965 [48]. FIS makes decisions based on fuzzy rules and is accepted as an effective MCDM method [43].

Mun et al. proposed a trust-based partner selection approach in which trust is the output of fuzzy inference–based model and quality and due date are the inputs [49]. Since the model's reliability depends on establishing reasonable fuzzy rules, rules must be established correctly and precisely. Imprecise rules lead to unreliable outcomes.

2.2.3 Other approaches

Agent-based approaches In one of the earliest studies in the field of partner selection, researchers applied an agent-based concept to develop the information flow infrastructure. In this study, five types of agents were implemented in a virtual enterprise network [50]. Another agent-based approach for the VE partner selection problem combined constraint solving and quality modeling techniques [51]. Kim et al. investigated the VE configuration process and presented a simulation-based configuration but did not focus on finding optimal or near-optimal partners [52]. Choi et al. proposed a multi-agent task assignment system to select partners and assign tasks to them [53]. These authors considered price, time, and quality and neglected all other criteria, such as past performance, communication, and openness.

In contrast, Huang et al. proposed a two-stage partner selection framework that divides the evaluation criteria into hard and soft factors. Hard factors are studied in the first stage to identify the partners that are able complete a certain task on time with high quality and low price. Soft factors are considered in the second stage to evaluate partners' cooperation potential [54].

Search algorithms In two of the reviewed papers, researchers developed new decision making algorithms aimed at solving the VE partner selection problem. In the first paper, Feng and Yamashiro developed a model which finds an optimal solution with minimum comprehensive cost by following a step-by-step pragmatic approach: First, the algorithm eliminates the partners with qualitative inadequacies; then, the costs associated with eligible partner sets are calculated; and finally, the set with the lowest cost is selected [55].

In the second paper in this category, Chen et al. presented a two-stage qualitative search algorithm. In the first stage, the algorithm searches for alternative schemes of VE enterprises based on manufacturing requirements. In the second stage, these schemes are expressed mathematically. Using this model, the authors developed three search algorithms and ranked enterprises [56].

Data mining–based technique Data mining is a computational process of extracting information and patterns from a data set and interpreting them into a regulated structure. A data mining method was applied to the VE partner selection problem in just one paper, in which the authors introduced a neural online analytical processing system. An online analytical processing system (OLAP) is a data mining tool that is used to convert clusters of complex data into useful information. These data were used as input layer nodes during the training process for the neural network. Although the model provided a feasible prediction for the problem, it required massive amount of data to train the network and develop a reliable module [57].

All reviewed articles in this study are presented in Table 2.

2.3 Analysis of literature review and observations

We made several observations based on our analysis of the journal articles related to the partner selection problem, which we discuss in the following subsections.

2.3.1 Most popular criteria

Selecting the right partners is crucial to the success of a virtual enterprise, and since partners are evaluated with respect to specific criteria, choosing an appropriate set of criteria is important as well. Some characteristics of VEs make partner selection much harder than in other contexts such as supply chains [59]. For instance, VEs must be flexible to allow different types of customers and partners to participate. Moreover, different regulations, standards, and preferences may be adapted. Therefore, a comprehensive set of evaluation criteria should be considered. Conversely, considering an excessive number of criteria overinflates the problem and makes it difficult to handle. It is also important to select an appropriate set of conflicting criteria to enhance model robustness and reliability.

Baldo et al. developed a framework to help decision makers create appropriate sets of evaluation criteria. The framework is a knowledge-based model that uses performance indicators (PIs) to bias the criteria [59]. Our analysis of the literature revealed that although dozens of different criteria have been adapted by researchers, costs (and cost-related factors), which were addressed in 38 of 46 articles, are the most popular criteria, followed by time and quality, respectively (Table 3).

2.3.2 Most popular approaches

In 23 of 46 reviewed papers, VE partner selection was considered as an optimization problem rather than as an MCDM problem. In 17 articles, researchers attempted to solve these optimization problems using AI methods. GA is the most popular AI approach, followed by PSO. In eight articles, scholars addressed GA and its adaptive or integrated forms. However, this does not mean that GA is the best solution methodology for VE partner selection. Extensive use of GA could be attributed to the fact that GA steps are flexible, which helps researchers develop adaptive forms of this algorithm to solve problems.

Fuzzy set theory is the most precise way to cope with the vagueness of information in the partner evaluation process. Fuzzy set is an effective tool for mathematically describing subjective terminology. Applying fuzzy set criteria to uncertain information (i.e., enterprises' performance scores and customers' preferences) can be considered in the VE partner selection model. In ten papers, researchers integrated their approaches with fuzzy sets. Table 4 presents a list of integrated fuzzy approaches. Figure 2 shows the distribution of integrated approaches based on fuzzy sets and the three most popular methods used to solve the VE partner selection problem.

2.3.3 Most popular articles

To identify which of these papers have attracted more attention, we considered the cumulative number of citations per year. Our investigation revealed that Mikhailov's paper in which he developed an integrated fuzzy AHP approach has the most citations. Interestingly, the second-most popular article introduced an enhanced form of Mikhailov's approach by reducing the number of pairwise comparisons. The third-most popular article models risk-based partner selection using a fuzzy rule–based genetic algorithm. Table 5 presents the ten most frequently cited articles so far and reveals that integrated forms of fuzzy set theory are attracting more attention overall.

2.3.4 Chronological distribution of articles

The distribution of articles by publication year is provided in Fig. 3. The first study emphasizing the importance of the partner selection process in constructing successful virtual enterprises was published in 1997 by Meade et al.; afterward, few studies were published until 2003. In 2004, the number of published articles reached 4. The number of publications peaked in 2009 and gradually decreased thereafter.

Since 2011, researchers have focused on adapting optimization approaches to model the problem. Most of them have used enhanced AI techniques, some of which are integrated with fuzzy set theory. As solution methodologies are enhanced, evaluation criteria are also improved. With the help

Table 2 List of reviewed articles

Index	Core technique	Method	Reference
Optimization approaches			
Op1	Integer programming	IP, graph theory	Wu, Mao, & Qian, 1999 [11]
Op2	Integer programming	IP, graph theory	Wu & Su, 2004 [12]
Op3	Integer programming	IP, B&B	Ip, Yung, & Wang, 2004 [10]
Op4	Integer programming	IP, Lagrangian relaxation	Hsieh & Lin, 2012 [13]
Op5	Integer programming	B&B	Zeng, Li, & Zhu, 2006 [14]
Op6	Integer programming	IP, MAUT, AHP	Sha & Che, 2004 [15]
Op7	Mixed integer programming	B&B	Jarimo & Salo, 2009 [16]
Op8	Genetic algorithm	Fuzzy R-GA	Ip, Yung, & Wang, 2004 [10]
Op9	Genetic algorithm	GA	Wang, Xu, & Zhan, 2009 [19]
Op10	Genetic algorithm	HGA	Jian, Bo, Xiubo, & Cong, 2010 [20]
Op11	Genetic algorithm	Adaptive GA	Simona & Raluca, 2011 [21]
Op12	Genetic algorithm	GA-BHTR	Tao, Qiao, Zhang, & Nee, 2012 [22]
Op13	Genetic algorithm	Pareto GA	Zhang et al., 2012 [12]
Op14	Genetic algorithm	GA-ACO	Zhong, Jian, & Zijun, 2009 [23]
Op15	Genetic algorithm	Adaptive GA, AHP/ANP	Cheng, Ye, & Yang, 2009 [24]
Op16	PSO	Discrete binary PSO	Gao, Gui, Zhao, & Liu, 2006
Op17	PSO	Discrete PSO	Mahapatra, Nayak, Prasanna, & Beriha, 2011 [26]
Op18	PSO	PSO	Zhao, Zhang, & Xiao, 2008 [27]
Op19	PSO	Adaptive quantum, PSO	Xio, Liu, Huang, & Cheng, 2014 [28]
Op20	PSO	Adaptive fuzzy PSO	Huang, Gao, & Chen, 2011 [1]
Op21	ACO	ACO, AHP	Fischer, Jahn, & Teich, 2004 [30]
Op22	ACO	Fuzzy enhanced ACO	Niu, Ong, & Nee, 2012 [29]
Op23	TABU	TABU	Ko, Kim, & Hwang, 2001 [31]
Op24	QEA	Multi-agent QEA	Tao, Zhang, Zhang, & Nee, 2010 [33]
MCDM approaches			
MC1	AHP	AHP	Chu, Tso, Zhang, & Li, 2002 [37]
MC2	AHP	AHP, ANN	Sari, Sen, & Kilic, 2007 [38]
MC3	AHP	Fuzzy AHP	Mikhailov, 2002 [39]
MC4	AHP	Fuzzy AHP	Wang & Chen, 2007 [58]
MC5	ANP	ANP	Sarkis, Talluri, & Gunasekaran, 2007 [41]
MC6	TOPSIS	Interval valued TOPSIS	Ye & Li, 2009 [44]
MC7	TOPSIS	Fuzzy TOPSIS	Ye, 2010 [45]
MC8	TOPSIS	Fuzzy TOPSIS Tabu	Crispim & Sousa, 2010 [46]
MC9	TOPSIS	Fuzzy TOPSIS Tabu, CBR, CA	Crispim & Sousa, 2009 [47]
MC10	Fuzzy inference system	FIS	Mun, Shin, Lee, & Jung, 2009 [49]
Other approaches			
Ot1	Agent-based		Lau & Wong, 2001 [50]
Ot2	Agent-based		Norman T. et al., 2004 [51]
Ot3	Agent-based		Kim, Son, Kim, & Kim, 2008 [52]
Ot4	Agent-based		Choi, Kim, & Doh, 2007 [53]
Ot5	Agent-based		Huang, Wong, & Wang, 2004 [54]
Ot6	Search algorithms		Feng & Yamashiro, 2006 [55]
Ot7	Search algorithms		Chen, Chen, & Lee, 2007 [56]
Ot8	Data mining technique		Lau, Chin, Pun, & Ning, 2000 [57]

IP integer programming, *B&B* branch and bound algorithm, *MAUT* multi-attribute utility theory, *AHP* analytic hierarchy process, *GA* genetic algorithm, *HGA* hybrid genetic algorithm, *BHRT* binary heap and transitive reduction, *ACO* ant colony optimization, *ANP* analytical network process, *PSO* particle swarm optimization, *QEA* quantum-inspired evolutionary algorithm, *TOPSIS* technique for order of preference by similarity to ideal solution, *CA* cluster analysis

Table 3 Most popular criteria

Reference	Cost	Time	Quality	Risk of failure	Service	Trust/ reliability	Financial stability	Completion probability	Flexibility	Past performance/ reputation	Carbon emissions	Caution cost	Collaboration efficiency
Wu, Mao, & Qian, 1999 [11]	✓												
Wu & Su, 2004 [12]	✓	✓											
Ip, Yung, & Wang, 2004 [10]	✓	✓											
Hsieh & Lin, 2012 [13]	✓												
Zeng, Li, & Zhu, 2006 [14]	✓												
Sha & Che, 2004 [15]	✓	✓	✓		✓								
Jarimo & Salo, 2009 [16]	✓			✓						✓			
Ip, Yung, & Wang, 2004 [10]		✓		✓									
Wang, Xu, & Zhan, 2009 [19]	✓		✓	✓	✓								
Jian, Bo, Xiubo, & Cong, 2010 [20]	✓	✓		✓									
Simona & Raluca, 2011 [21]	✓	✓		✓									
Tao, Qiao, Zhang, & Nee, 2012 [22]	✓		✓	✓					✓				
Zhang et al., 2012 [17]	✓	✓	✓			✓					✓		
Zhong, Jian, & Zijun, 2009[a] [23]	✓	✓		✓									
Cheng, Ye, & Yang, 2009 [24]	✓	✓	✓										
Gao, Gui, Zhao, & Liu, 2006 [25]	✓	✓		✓									
Mahapatra, Nayak, Prasanna, & Beriha, 2011 [26]	✓	✓		✓									
Zhao, Zhang, & Xiao, 2008 [27]	✓	✓											
Xio, Liu, Huang, & Cheng, 2014 [28]	✓	✓	✓	✓		✓							
Huang, Gao, & Chen, 2011 [1]	✓	✓											
Fischer, Jahn, & Teich, 2004 [30]	✓	✓						✓					
Niu, Ong, & Nee, 2012 [29]	✓	✓	✓										
Ko, Kim, & Hwang, 2001 [31]	✓												
Tao, Zhang, Zhang, & Nee, 2010 [33]	✓												
Chu, Tso, Zhang, & Li, 2002 [37]	✓	✓	✓		✓		✓						
Sari, Sen, & Kilic, 2007 [38]	✓							✓		✓		✓	
Mikhailov, 2002 [39]	✓		✓		✓		✓						
Wang & Chen, 2007 [58]	✓		✓		✓		✓						
Ye & Li, 2009 [44]	✓	✓	✓	✓		✓							
Ye, 2010 [45]	✓	✓	✓	✓		✓							
Crispim & Sousa, 2010 [46]	✓		✓						✓				
Mun, Shin, Lee, & Jung, 2009 [49]													
Lau, Chin, Pun, & Ning, 2000 [57]													
Norman et al., 2004 [51]	✓	✓	✓										
Kim, Son, Kim, & Kim, 2008 [52]	✓	✓	✓										

Table 3 (continued)

Reference	Cost	Time	Quality	Risk of failure	Service	Trust/reliability	Financial stability	Completion probability	Flexibility	Past performance/reputation	Carbon emissions	Caution cost	Collaboration efficiency
Choi, Kim, & Doh, 2007 [53]	✓	✓	✓										
Huang, Wong, & Wang, 2004 [54]	✓	✓	✓										✓
Feng & Yamashiro, 2006 [55]	✓	✓											
Total	35	24	17	12	5	4	3	2	2	2	1	1	1

[a] Model considers any of these criteria (i.e., cost OR time OR risk)

Table 4 Integrated fuzzy approaches

Method	Reference
Fuzzy ACO	Niu, Ong, & Nee, 2012 [29]
Fuzzy TOPSIS	Ye & Li, 2009 [44]
Fuzzy TOPSIS	Ye, 2010 [45]
Fuzzy TOPSIS	Crispim & Sousa, 2009 [47]
Fuzzy TOPSIS TABU	Crispim & Sousa, 2010 [46]
Fuzzy R-GA	Ip, Yung, & Wang, 2004 [10]
Fuzzy AHP	Mikhailov, 2002 [39]
Fuzzy AHP	Wang & Chen, 2007 [57]
Fuzzy PSO	Huang, Gao, & Chen, 2011 [1]
Fuzzy inference system	Mun, Shin, Lee, & Jung, 2009 [49]

ACO ant colony optimization, *TOPSIS* technique for order of preference by similarity to ideal solution, *GA* genetic algorithm, *AHP* analytic hierarchy process, *PSO* particle swarm optimization

of fuzzy set theory, qualitative criteria such as flexibility, reliability, reputation, and degree of customer satisfaction have been incorporated, and environmental parameters such as carbon emissions and lead content have also been considered.

2.3.5 Literature gap

Our extensive review of the literature revealed that although valuable research has been performed on the topic of VE partner selection, some emerging decision making techniques have not yet been investigated. For example, the fireworks algorithm and cuckoo search technique are two useful evolutionary algorithms which can be used to model the problem [60, 61]. We suggest these as two potential avenues for research in future studies, as it is probable that they can be useful if they are modeled properly.

Moreover, goal programming (GP) is a widely used technique for solving multi-objective problems in various

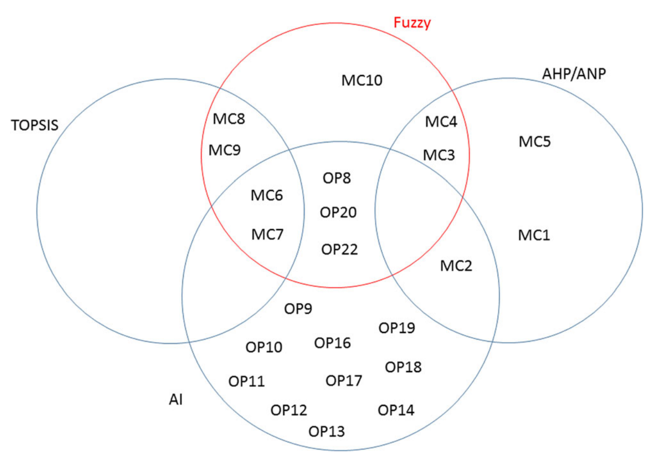

Fig. 2 Distribution of integrated approaches based on fuzzy sets and the three most popular methods

Table 5 Distribution of articles based on their citations

Rank	Reference	Method	Total no. of citations	No. of citations per year
1	Mikhailov, 2002 [39]	Fuzzy AHP	281	23.4
2	Wang & Chen, 2007 [58]	Fuzzy AHP	156	22.3
3	Ip, Huang, Yung, & Dingwei, 2003 [18]	Fuzzy R-GA	230	21.0
4	Norman et al., 2004 [51]	Agent-based	205	20.5
5	Ye, 2010 [45]	Fuzzy TOPSIS	79	19.7
6	Wu & Su, 2004 [12]	IP, graph theory	149	16.5
7	Ye & Li, 2009 [44]	Fuzzy TOPSIS	78	15.6
8	Fischer, Jahn, & Teich, 2004 [30]	ACO AHP	128	12.8
9	Camarinha-Matos & Afsarmanesh, 2007 [34]	–	83	11.8
10	Sarkis, Talluri, & Gunasekaran, 2007 [41]	ANP	81	11.5

AHP analytic hierarchy process, *GA* genetic algorithm, *TOPSIS* technique for order of preference by similarity to ideal solution, *ACO* ant colony optimization, *ANP* analytical network process

application domains that has not yet been implemented in VE systems [62]. This approach would be beneficial for providing an appropriate partner selection platform based on a customer's goals. A novel integrated form of a GP technique for solving the VE partner selection problem is presented in the next section.

3 Methodology

When a customer places an order with a VE, partners are selected from the VE pool to complete the project. First, the main project is divided into q ($q=1, 2, \ldots$) subprojects. Among the partners in the VE pool, n ($n=1, 2, \ldots$) enterprises voluntarily submit bids for the subprojects. The bidders are then evaluated with respect to m ($m=1, 2, \ldots$) evaluation criteria and the most qualified partners are selected. Therefore, the very first step to constructing a reliable partner selection technique is to define the candidate evaluation criteria.

Among the dozens of parameters studied in the literature, which are listed in Table 3, the most frequently used parameters are arranged in a hierarchy in Fig. 4.

In order to be able to evaluate the enterprises based on these criteria, customer preferences with respect to these aspects must first be identified. We use fuzzy AHP, one of the most popular techniques for handling data uncertainty, to model the problem. Fuzzy AHP uses triangular fuzzy membership functions to represent linguistic terminology. Table 6 shows the linguistic terms and their corresponding fuzzy numbers for assigning values to pairwise comparisons [63]. The corresponding membership functions are illustrated in Fig. 5.

The customer fills out the questionnaire by answering questions comparing two criteria (i.e., pairwise comparisons).

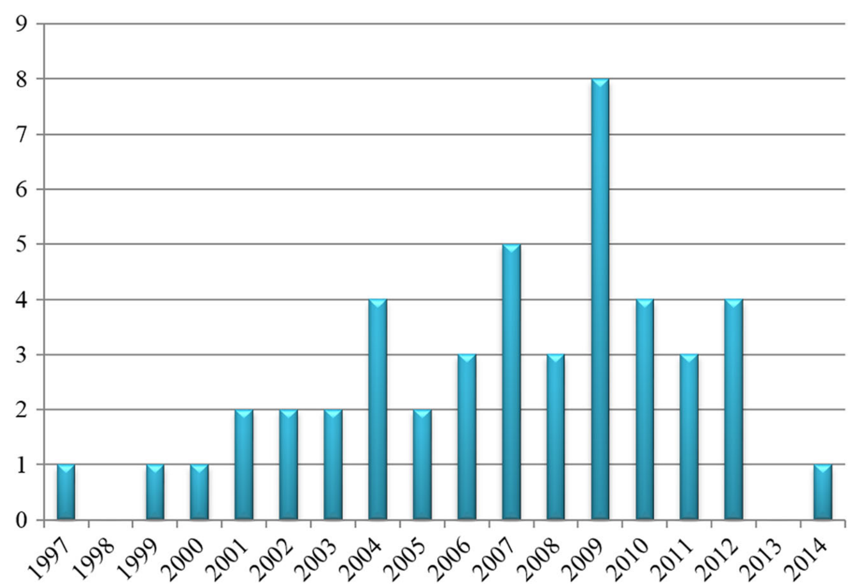

Fig. 3 Chronological distribution of articles

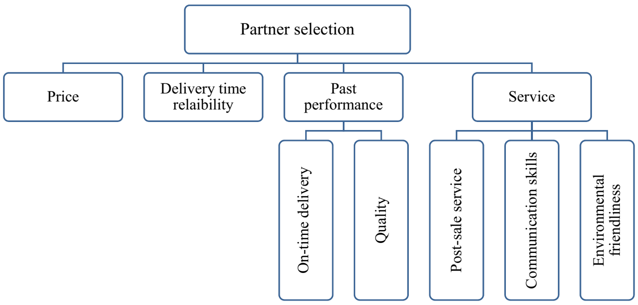

Fig. 4 Evaluation criteria hierarchy

(Our problem has four main criteria: price, delivery time, past performance, and service quality.) Fuzzy scales are applied to the results of these comparisons and evaluation matrix A is constructed. Matrix A is an $n \times n$ matrix where n is number of criteria (in our model n=4), $\widetilde{a_{ij}} \odot \widetilde{a_{ji}} = 1$. The geometric mean method is then employed to calculate the fuzzy weights of each criterion as follows [63]:

$$\widetilde{w_i} = \widetilde{u_i} \odot \left(\widetilde{u_1} \oplus \widetilde{u_2} \oplus \cdots \oplus \widetilde{u_n} \right)^{-1} \tag{1}$$

where

$$\widetilde{u_1} = \left(\widetilde{a_{i1}} \odot \widetilde{a_{i2}} \odot \cdots \odot \widetilde{a_{in}} \right)^{1/n} \tag{2}$$

A center of area (COA) defuzzification method is used to obtain the final weight of each criterion. If the customer's responses are reliable with a consistency ratio (CR) of less than 0.1, the preference weight of each criterion is denoted by $w = \{w_j | j = 1, \ldots, m\}$. The greater the weight of a criterion, the more important it is. Fuzzy AHP enables the customer's preferences among four main criteria to be identified while accounting for vagueness in his/her judgements.

In addition to the questions about criteria preferences, the customer is asked about the desired delivery time frame for the order. The VE's production planning experts analyze the manufacturing requirements and estimate the amount of time it will take to complete the order. If customer's delivery timeframe is reasonable, each subproject is allocated to a

Table 6 Pairwise comparisons of linguistic variables using fuzzy numbers

Linguistic scale for importance	Fuzzy numbers	Triangular fuzzy scale
Equally important (Eq)	$\tilde{1}$	(1,1,3)
Weakly important (W)	$\tilde{3}$	(1,3,5)
Strongly important (S)	$\tilde{5}$	(3,5,7)
Very strongly important (VS)	$\tilde{7}$	(5,7,9)
Extremely important (Ex)	$\tilde{9}$	(7,9,9)

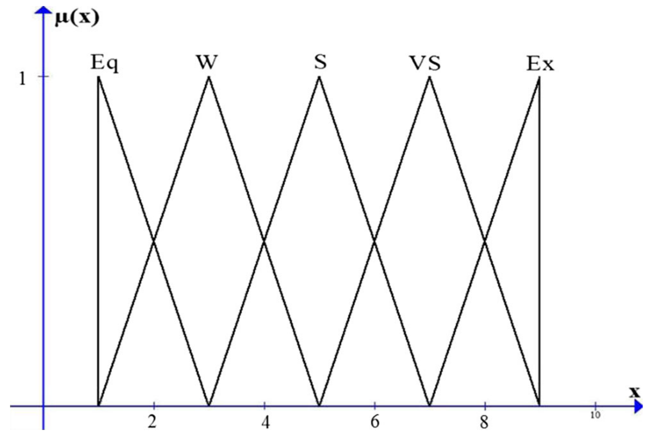

Fig. 5 Membership functions of fuzzy scales

single enterprise. However, this might not be always the case in reality. In some strict bidding situations when deadlines are too tight to accommodate the demand volume, the capacity limitations of manufacturing units may not allow them to finish the jobs individually within the specified time frames. In these extreme cases, a VE must search for more than one partner for each subproject. Thus, the problem transforms into finding the best "team" of enterprises that can meet the requirements of a subproject. Constructing a suitable partner selection methodology for forming a consortium under strict bidding conditions would provide mutual benefit for both VE members with unfilled capacity and customers who are seeking to fulfill time-critical requests. We developed a fuzzy AHP-GP model for this purpose. Figure 6 illustrates the overall structure of the proposed model schematically.

Solving the problem entails finding the alternative that fulfils the project requirements at an inexpensive price by the specified due date with lower risk and higher service support. By applying the GP technique introduced by Charnes and Cooper to the VE partner selection problem, we were able to develop a mathematical model for it [62].

Equations 3–13 formulate the problem considering the customer's preferences and goals. The objective function of GP is to minimize the weighted sum of deviations from aspirational levels. W_js represent the penalties assigned to deviations, D_js, where $W_j = (W_p, W_{DT}, W_{pp}, W_s)$. In the proposed model, W_js are the weights of criteria derived by applying fuzzy AHP; this is where GP is integrated:

$$Min\ W_p D_P^+ + W_{DT} D_{DT}^- + W_{pp} D_{pp}^- + W_s D_s^- \tag{3}$$

Subject to

$$\sum_{i=1}^{m} \sum_{k=1}^{K} P_{ik} X_{ik} Y_{ik} - D_p^+ + D_p^- = P_g \tag{4}$$

$$\sum_{i=1}^{m} \sum_{k=1}^{K} DT_{ik} X_{ik} Y_{ik} - D_{DT}^+ + D_{DT}^- = 1 \times D_T \tag{5}$$

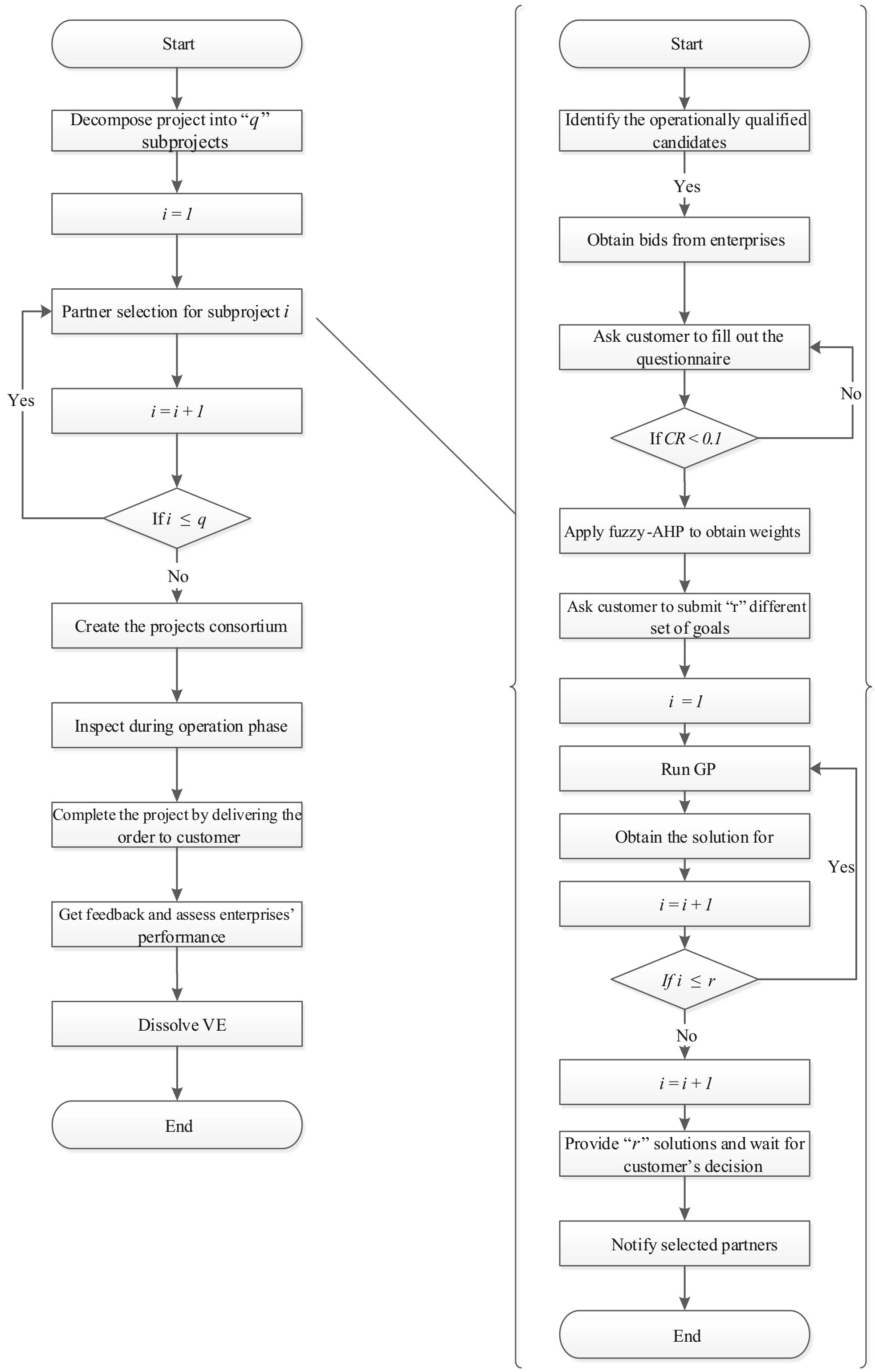

Fig. 6 An integrated fuzzy AHP-GP algorithm for VE partner selection

$$\sum_{i=1}^{m}\sum_{k=1}^{K} PP_i X_{ik} Y_{ik} - D_{pp}^{+} + D_{pp}^{-} = 1 \times D_T \tag{6}$$

$$\sum_{i=1}^{m}\sum_{k=1}^{K} S_i X_{ik} Y_{ik} - D_{s}^{+} + D_{s}^{-} = 1 \times D_T \tag{7}$$

$$\sum_{i=1}^{m}\sum_{k=1}^{K} X_{ik} = D_T \tag{8}$$

$$L_{ik} Y_{ik} \le X_{ik} \le U_{ik} Y_{ik} \quad \forall i = 1, \ldots, m \ \ and \ \ k = 1, \ldots, K \tag{9}$$

Table 7 Notations used in the goal programming formulation

Notation	Description
P_{ik}	Unit price proposed by kth bid of enterprise i
DT_{ik}	Delivery reliability score of kth bid of enterprise i
PP_i	Past performance score of enterprise i
S_i	Service quality score of enterprise i
X_{ik}	Number of products ordered from kth bid of enterprise i
Y_{ik}	Decision variable for selecting kth bid of enterprise i
L_{ik}	Lower limit of product number proposed by enterprise i for kth bid
U_{ik}	Upper limit of product number proposed by enterprise i for kth bid
D_T	Total demand from customer
i	Number of enterprises
k	Number of bid proposals for different order quantities
P_g	Aspirational price level specified by customer
DT_g	Aspirational delivery time specified by customer
D_p^+	Deviation above the aspirational price level
D_p^-	Deviation below the aspirational price level
D_{DT}^+	Deviation above the aspirational delivery time
D_{DT}^-	Deviation below the aspirational delivery time
D_{pp}^-	Deviation below the past performance goal
D_s^-	Deviation below the service quality goal

$$\sum_{j=1}^{K} Y_{ik} \leq 1 \quad \forall i = 1, \ldots, m \tag{10}$$

$$Y_{ij} = \begin{cases} 1, & \text{if job is allocated to } j\text{th bid of enterprise } i \\ 0, & \text{if job is not allocated to } j\text{th bid of enterprise } i \end{cases} \tag{11}$$

$$X_{ik} \geq 0 \tag{12}$$

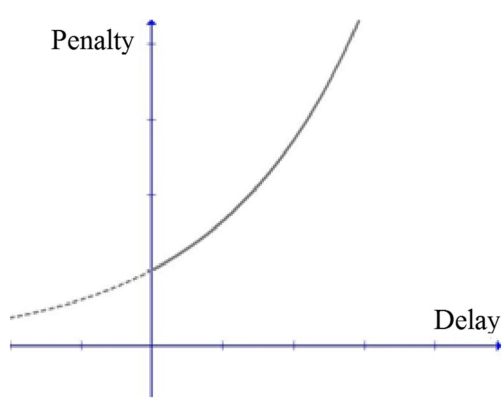

Fig. 7 Penalty/delivery delay diagram

Table 8 Bill of materials and processes for the toolbox case study

Part no.	No. of parts	Part name	Manufacturing processes	Assigned subproject
1	1	Lower body	Sheet metal cutting Sheet metal bending Spot welding Drilling Coating	Subproject 1 Subproject 1 Subproject 1 Subproject 1 Subproject 3
2	1	Upper lid	Sheet metal cutting Sheet metal bending Spot welding Drilling Coating	Subproject 1 Subproject 1 Subproject 1 Subproject 1 Subproject 3
3	1	Handle	Plastic molding Drilling	Subproject 2 Subproject 1
4	2	Lock	Sheet metal cutting Sheet metal bending	Subproject 1 Subproject 1
5	2	Hinge	Metal cutting Metal bending Spot welding	Subproject 1 Subproject 1 Subproject 1
6	6	Foot	Plastic molding	Subproject 1
7	8	Bolt	Metal cutting	Subproject 1
8	14	Washer M4	Metal cutting	Subproject 1
9	8	Nut M4	Metal cutting	Subproject 1
10	8	Nut M5	Metal cutting	Subproject 1
11	8	Washer M5	Metal cutting	Subproject 1

$$X_{ik} \in Z \tag{13}$$

Equation 3 demonstrates the objective function of the model. Equations 4–7 adjust the deviations from price, delivery time, past performance, and service goals, respectively. The aspirational price level and delivery time frame are provided by the customer, while past performance (i.e., reliability) and service quality are set to their maximum values (i.e., 1).

Values of first goals are inquired from customer, while past performance and service goals are set as their maximum

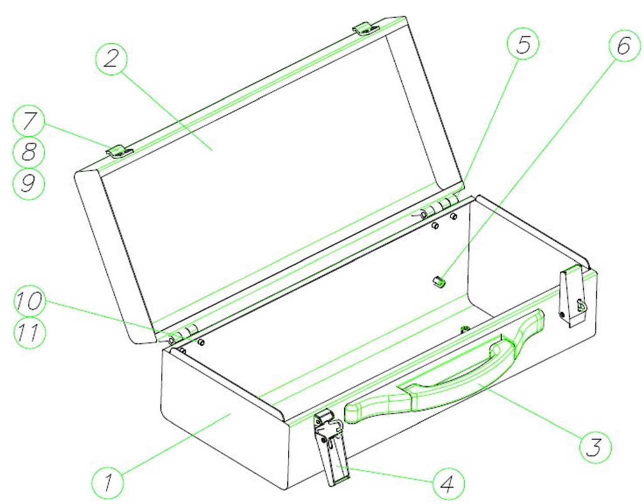

Fig. 8 Sketch of the case study product

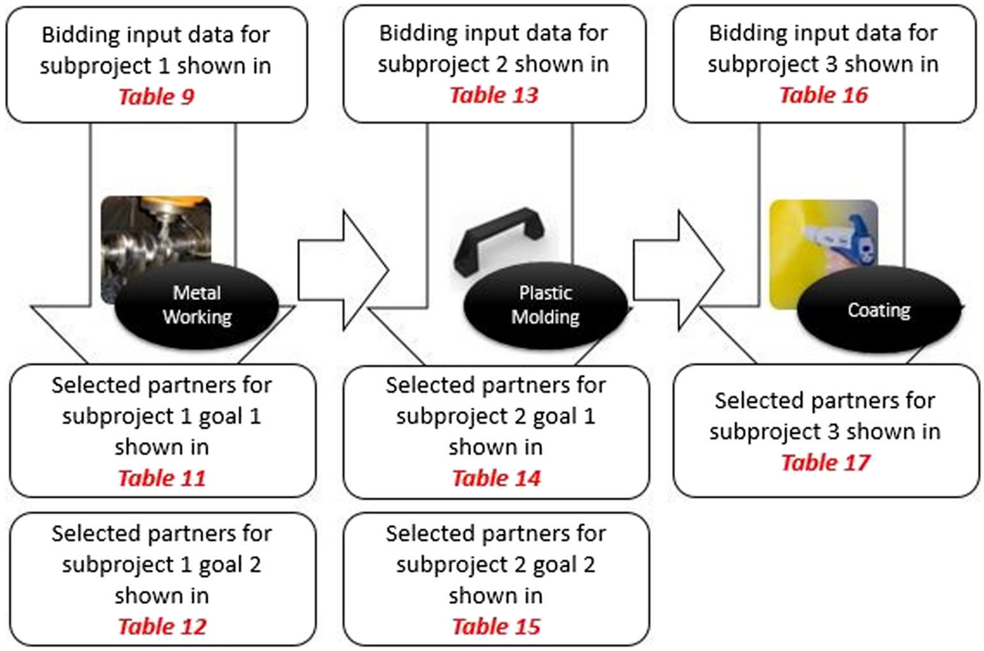

Fig. 9 Process for forming a consortium in this case study

possible value (or 1). The rest of the constraints are exactly the same as in previous models: The constraint in Eq. 8 ensures that the total demand is fulfilled; the constraint in Eq. 9 controls the quantity of each bid to remain within the indicated domain; the constraint in Eq. 10 stipulates that no more than one bid is selected from among the various proposals submitted by each enterprise; Eq. 11 is the variable constraint; the constraint in Eq. 12 imposes the non-negativity of X_{ik}, D_j^+, and D_j^-; and the constraint in Eq. 13 shows that X_{ik} can only take integer values. The notations used in the formulation of these equations are presented in Table 7. The mathematical model of GP is MILP, which can be solved by OR techniques such as B&B.

The model variables are enterprises' scores for four main criteria: price, delivery time, past performance, and service quality. Their values are calculated with corresponding formulations for each. The unit price value (P_{ik}) is simply a normalized value of the bids collected during the negotiation phase. Although delivery dates are also submitted by enterprises, they should be interpreted as a parameter that represents the probability of delivering the order on time based on the customer's ideal delivery timeframe. This parameter is called the delivery reliability score (DT_{ik}).

Applying a delivery reliability score instead of directly using the proposed delivery times is beneficial in situations with tight delivery timeframes in which extra attention must

Table 9 Bidding input data for subproject 1

Enterprise	Indices	Quantity	Price per part	Delivery domain		Past performance	Service quality
				Start	End		
A	X_{11}	[5–30]	1300	5	6	0.82	0.90
	X_{12}	(30–70]	1060	6	8	0.82	0.90
	X_{13}	(70–100]	1100	8	11	0.82	0.90
B	X_{21}	[40–60]	1350	6	7	0.92	0.80
	X_{22}	(60–90]	1200	7	8	0.92	0.80
	X_{23}	(90–110]	1380	8	12	0.92	0.80
D	X_{31}	[15–40]	1250	4	5	0.85	0.76
	X_{32}	(40–75]	1100	5	7	0.85	0.76
	X_{33}	(75–110]	1300	7	12	0.85	0.76
E	X_{41}	[10–40]	1220	4	5	0.60	0.72
	X_{42}	(40–70]	1350	7	11	0.60	0.72
F	X_{51}	(70–100]	1280	8	10	0.58	0.55

Table 10 Bidding input data for subproject 1, interpreted by the system

Enterprise	Indices	Quantity	Price per part	Delivery reliability for goal 1	Delivery reliability for goal 2	Past performance	Service quality
A	X_{11}	[5–30]	1300	1.000	1.00	0.82	0.90
	X_{12}	(30–70]	1060	1.000	1.00	0.82	0.90
	X_{13}	(70–100]	1100	0.999	0.84	0.82	0.90
B	X_{21}	[40–60]	1350	1.000	1.00	0.92	0.80
	X_{22}	(60–90]	1200	1.000	1.00	0.92	0.80
	X_{23}	(90–110]	1380	0.930	0.50	0.92	0.80
D	X_{31}	[15–40]	1250	1.000	1.00	0.85	0.76
	X_{32}	(40–75]	1100	1.000	1.00	0.85	0.76
	X_{33}	(75–110]	1300	0.960	0.73	0.85	0.76
E	X_{41}	[10–40]	1220	1.000	1.00	0.60	0.72
	X_{42}	(40–70]	1350	1.000	0.93	0.60	0.72
F	X_{51}	[70–100]	1280	1.000	1.00	0.58	0.55

be paid to the delivery criterion. Assume that a customer's desired delivery timeframe is $[a, b]$, where a is the earliest desired delivery date and b is the latest desired delivery date. It means that products delivered within this timeframe are on time, while the times before a and after b are considered to be early and late delivery domains, respectively. Enterprises' proposed delivery time frames are going to be evaluated and scored against the $[a, b]$ domain. In their subproject bids, enterprises specify the delivery domain $[Tik, Fik]$ for specific products. The DT_{ik} score for each enterprise's proposal is calculated using Eqs. 14–16:

$$\mu_{ik} = \frac{F_{ik} + T_{ik}}{2} \tag{14}$$

$$\sigma_{ik} = \frac{F_{ik} - T_{ik}}{6} \tag{15}$$

$$DT_{ik} = \begin{cases} f(b, \mu_{ik}, \sigma_{ik}) = \dfrac{1}{\sigma_{ik}\sqrt{2\pi}} e^{-\frac{(b-\mu_{ik})^2}{2\sigma_{ik}^2}} & if \quad F_{ik} > b \\ 1 & if \quad F_{ik} < b \end{cases} \tag{16}$$

By applying the normal distribution function, the DT_{ik} score for each enterprise can be confidently estimated, since 99.7 % of the values are within 3 standard deviations. By applying these equations, different DT_{ik} scores are obtained for different customer delivery goals and incorporated into the model.

P_{ik} and DT_{ik} data are obtained from enterprise proposals during the negotiation phase; however, two other criteria, past performance and service quality scores, represent how the enterprises performed on previous projects. An enterprise's past performance score, PP_i, is calculated using Eqs. 17–20:

$$Quality\ score = \frac{number\ of\ accepted\ parts}{total\ number\ of\ parts\ ordered} \tag{17}$$

$$On\,time\ delivery\ score = 1 - r_i e^{l_i} \tag{18}$$

where

$$r_i = \frac{number\ of\ late\ delivered\ parts}{total\ number\ of\ parts\ ordered} \tag{19}$$

$$l_i = \frac{delay\ duration}{total\ delivery\ time} \tag{20}$$

The term $r_i \ e^{l_i}$ in Eq. 18 formulates the penalty function of late delivery as an exponential function. As shown in Fig. 7,

Table 11 Selected partners for subproject 1 based on goal set 1: target price of \$120,000 and delivery domain of 9–11 days

Criterion	Individual enterprise					Consortium
	A	B	D	E	F	
Order quantity	70	0	50	0	0	120
Price	1060×70	–	1100×50	–	–	129,200
Delivery trust	1	–	1	–	–	1
Past performance	0.82	–	0.85	–	–	0.833
Service quality	0.90	–	0.76	–	–	0.842

Table 12 Selected partners for subproject 1 based on goal set 2: target price of \$140,000 and delivery domain of 7–10 days

Criterion	Individual enterprise					Consortium
	A	B	D	E	F	
Order quantity	30	90	0	0	0	120
Price	1060×30	1200×90	–	–	–	139,800
Delivery trust	1	1	–	–	–	1
Past performance	0.82	0.92	–	–	–	0.900
Service quality	0.90	0.80	–	–	–	0.825

Table 13 Bidding input data for subproject 2

Enterprise	Indices	Quantity	Price per part	Delivery domain		Past performance	Service quality
				Start	End		
L	X_{11}	[20–30]	590	1	2	0.90	0.70
	X_{12}	(30–60]	480	1	2	0.90	0.70
	X_{13}	[60–110]	520	4	6	0.90	0.70
	X_{14}	(110–120]	570	4	7	0.90	0.70
M	X_{21}	[40–60]	510	2	3	0.82	0.75
	X_{22}	(60–100]	500	4	5	0.82	0.75
N	X_{31}	[10–20]	560	2	3	0.88	0.80
	X_{32}	(20–80]	550	3	5	0.88	0.80
	X_{33}	[80–100]	520	4	5	0.88	0.80
O	X_{41}	[10–40]	510	1	3	0.68	0.65
	X_{42}	[40–90]	490	3	6	0.68	0.65
	X_{43}	[90–110]	520	3	7	0.68	0.65
P	X_{51}	[30–50]	530	3	4	0.72	0.70
	X_{52}	[50–90]	500	3	7	0.72	0.70

the penalty increases exponentially as the length of delay increases.

An enterprise's service quality score, S_i, is a simple average of three sub-criteria—post-sale service, communication skills, and environmental friendliness—based on customer feedback.

By applying the developed formulation for our fuzzy AHP-GP approach, a VE would be able to find the best partners for each set of customer goals and present the solution to the decision maker. In the next section, we present a case study in which we implemented the developed model to test its applicability.

4 Case study

In our example case, a leader company in the OSTIM industrial zone in Ankara is an administrative unit for a VE system. This VE system consists of 2500 SMEs in different sectors with different core competencies and resources. This case is based on an order for parts to make 120 toolboxes to be delivered within 22 days.

Table 8 shows the operations required to manufacture the toolbox illustrated in Fig. 8. This project is divided into three main subprojects: Subproject 1 is metal working, subproject 2 is plastic molding, and subproject 3 is coating. Each of these subprojects is opened for bidding; the proposals are received and candidate enterprise partners are evaluated.

According to the schedule prepared by the VE's production planning experts, the delivery time frame of 22 days (specified by the customer) is equal to almost half of the time required to respond to the order, and it will not be possible to meet this requirement unless more than one enterprise is involved in each subproject. Hence, the problem is modeled using a GP-based approach. Moreover, the customer is willing to pay \$200,000 if the products are delivered within 22 days, and \$220,000 if the products are delivered within 18 days. So, the first request is recorded as goal 1 and the second is recorded as goal 2.

Table 14 Selected partners for subproject 2 based on goal set 1: target price of \$50,000 and delivery domain of 4–6 days

Criterion	Individual enterprise					Consortium
	L	M	N	O	P	
Order quantity	60	60	0	0	0	120
Price	480×60	510×60	–	–	–	59,400
Delivery trust	1	1	–	–	–	1
Past performance	0.9	0.82	–	–	–	0.860
Service quality	0.7	0.75	–	–	–	0.725

Table 15 Selected partners for subproject 2 based on goal set 2: target price of \$60,000 and delivery domain of 4–5 days

Criterion	Individual enterprise					Consortium
	L	M	N	O	P	
Order quantity	60	40	20	0	0	120
Price	480×60	510×40	550×20	–	–	60,200
Delivery trust	1	1	1	–	–	1
Past performance	0.9	0.82	0.88	–	–	0.870
Service quality	0.7	0.75	0.80	–	–	0.733

Table 16 Bidding input data for subproject 3

Enterprise	Indices	Quantity	Price per part	Delivery domain		Past performance	Service quality
				Start	End		
R	X_{11}	[10–50]	190	1	2	0.80	0.58
	X_{12}	[50–110]	200	2	3	0.80	0.58
S	X_{21}	[1–50]	185	1	2	0.68	0.46
	X_{22}	[50–100]	180	2	3	0.68	0.46
T	X_{31}	[80–120]	210	2	4	0.72	0.48
U	X_{41}	[10–60]	180	1	2	0.70	0.44
	X_{42}	[60–80]	170	1	3	0.70	0.44

The customer's preferences in terms of evaluation criteria are compiled in a matrix form of Eq. 21. In this matrix, $a_{21} = \tilde{5}$ and $a_{31} = \tilde{3}$, denoting that the delivery time is strongly more important to the customer than price, weakly more important than past performance, and so forth.

$$A = \begin{bmatrix} \tilde{1} & 1/\tilde{5} & 1/\tilde{3} & \tilde{1} \\ \tilde{5} & \tilde{1} & \tilde{3} & \tilde{7} \\ \tilde{3} & 1/\tilde{3} & \tilde{1} & \tilde{5} \\ 1/\tilde{1} & 1/\tilde{7} & 1/\tilde{5} & \tilde{1} \end{bmatrix} \tag{21}$$

The consistency ratio of the customer's answers is 0.048 so the judgements are trustworthy.

By implementing fuzzy AHP technique, the customer's preference weights are derived as $W_j = (W_p, W_{DT}, W_{pp}, W_s)$, $W_j = (0.205, 0.491, 0.253, 0.050)$. After all of the parameters regarding the customer's preferences have been obtained, enterprises voluntarily submit their proposals and bids for each subproject. Figure 9 illustrates the overall process for forming a consortium.

Detailed information for each bid and their corresponding calculations are presented one by one for each subproject. Data from proposals submitted by enterprises for subproject 1 are shown in Table 9.

Based on goals determined by the customer for the main project, VE experts calculate the goal sets for the subprojects. So, the GP model for subproject 1 must be solved once for the goal set of [price, delivery]=[\$120,000, 9–11 days] and once for the goal set of [price, delivery]=[\$140,000, 7–10 days]. Table 10 shows the data that are used to model the GP for subproject 1.

The mathematical model of this problem is formulated in Lingo software and solved once for goal set 1. The optimal solution is obtained, as shown in Table 11. Then, the model is formulated for goal set 2, as shown in Table 12.

Similar steps are followed to find partners for subproject 2. Data from the proposals received from the five enterprises are shown in Table 13. The GP model for subproject 2 must be solved based on the calculated goal sets for subproject 2, once for goal set 1 [price, delivery]=[\$50,000, 4–6 days], and once for goal set 2 [price, delivery]=[\$60,000, 4–5 days]. The selected partners and order quantities are tabulated in Tables 14 and 15.

Applying the GP model to two different goal sets results in two sets of solutions. For goal set 1, X_{12}=60, X_{21}=60, and others are 0. For goal set 2, X_{12}=60, X_{21}=40, X_{32}=20, and others are 0.

Table 16 shows the data from enterprise proposals submitted for subproject 3, coating. Subproject 3 is a simple subproject which would be completed no earlier than 2–3 days. So, different customer goals would not be reflected in scheduling of this subproject. And, the model is solved once for goal set [price, delivery]=[\$20,000, 2–3 days]. As shown in Table 17, enterprises S and U are selected as the VE partners for subproject 3.

Table 17 Selected partners for subproject 3

Criteria	Individual enterprises				Consortium
	R	S	T	U	
Order quantity	0	40	0	80	120
Price	0	190×40	0	170×80	21,200
Delivery trust	0	1	0	1	1
Past performance	0	0.68	0	0.70	0.693
Service quality	0	0.46	0	0.44	0.446

Table 18 Consortium for the case study based on goal set 1: total target price of \$200,000 and delivery within 22 days

Project	Subproject 1	Subproject 2	Subproject 3	Overall project
Enterprises	A, D	L, M	S, U	A, D, L, M, S, U
Price	\$129,200	\$59,400	\$21,200	\$209,800
Delivery reliability	1	1	1	1
Past performance	0.833	0.860	0.690	0.800
Service quality	0.842	0.725	0.450	0.67

Table 19 Consortium for the case study based on goal set 2: total target price of $220,000 and delivery within 18 days

Project	Subproject 1	Subproject 2	Subproject 3	Overall project
Enterprises	A, B	L, M, N	S, U	A, B, L, M, N, S, U
Price	$139,800	$60,200	$21,200	$221,200
Delivery reliability	1	1	1	1
Past performance	0.9	0.870	0.690	0.820
Service quality	0.825	0.733	0.450	0.669

Combining the results for each subproject, the consortium for main project would be as shown in either Tables 18 or 19, depending on what the customer decides.

In this case, the customer prefers to pay $11,400 more to receive the order 4 days earlier. Hence, the second goal set is accepted and enterprises A, B, L, M, N, S, and U are announced as the partners of the VE consortium. This combination is the best possible combination of partners based on the customer's attitudes and preferences. For a customer with different preferences and different goals, the results would change. And, this is exactly what a flexible, customer-based VE system needs to be able to do.

The sample case in this study is modeled and solved using traditional IP techniques, and a number of iterations for each scenario are derived. Figure 10 shows the number of iterations required to find the solution using the two methods (IP and GP) in different scenarios. Various numbers of decision variables and different problems are tested in different scenarios. A statistical significance test shows that the GP technique finds the solution in a fewer number of iterations. In this test, seven scenarios for different problems with different numbers of variables are considered and the p value is 0.00000005, proving that GP is statistically better than IP in terms of the number of iterations required to find a solution.

5 Conclusion

We have made several contributions with this study. First, we provided a systematic review of published articles on VE partner selection techniques. We carefully selected and reviewed 46 journal articles in detail and classified the literature into three categories: optimization approaches, MCDM approaches, and other approaches. We summarized the methodology used in each article and described the strengths and limitations of each approach. The following conclusions can be drawn based on the review:

- Most researchers considered VE partner selection as an optimization problem rather than an MCDM problem.
- Uncertainty is an inherent attribute of the decision making process; researchers apply fuzzy set theory to address this issue.
- Cost, time, and quality, respectively, are the most widely accepted evaluation parameters, as these are the key manufacturing parameters.
- Among the 46 papers, eight addressed GA and its adaptive or integrated forms. Thus, GA is the most popular approach based on the number of published articles in this domain, likely because the steps of the algorithm are flexible, so it can be improved and reconfigured easily. Moreover, compared to other AI techniques, GA is more suitable for solving discrete problems such as partner selection.
- Not only is AHP one of the most frequently used decision making methods, but it is also used as a tool to determine the relative importance of evaluation criteria.
- Mikhailov's fuzzy AHP approach is the most popular, with a total of 281 citations.
- The traditional form of TOPSIS was not used in any articles. In all four TOPSIS-based articles, scholars used fuzzy intervals instead of crisp values.

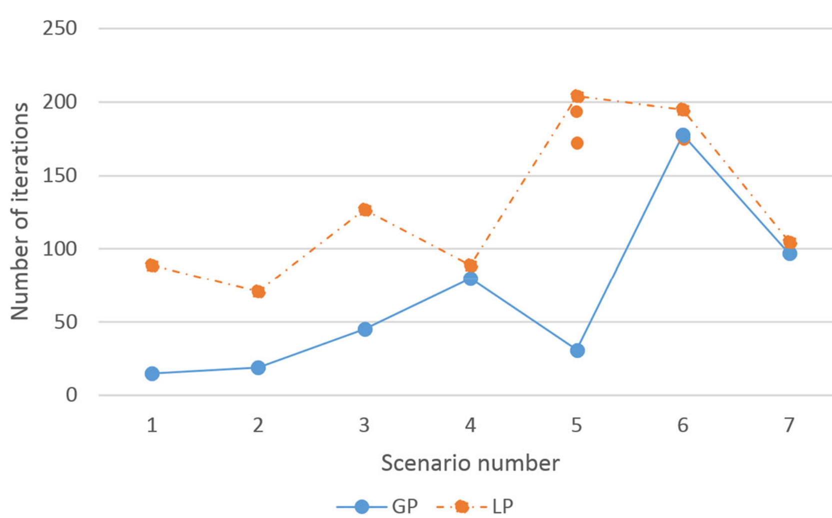

Fig. 10 Comparison of the number of iterations required by IP and GP to find a solution

- In recent years, AI techniques have attracted the most attention because they can be used to compute large amounts of data within a short period of time.

Based on this extensive review of the literature, we recommend applying fuzzy set theory to deal with data vagueness whenever possible; a primary benefit is that it can be integrated with almost all other methods. AI techniques are suitable for excessively complex problems with large amounts of data. If a model cannot be formalized, MCDM techniques are reliable methodologies for finding solutions.

We also identified a significant research gap in the literature. Despite the advantages associated with the GP technique, it had not yet been applied to model the VE partner selection problem. Therefore, we developed an integrated fuzzy AHP-GP approach to virtual enterprise consortium formation under strict bidding conditions. This approach enables VEs to respond to customer demands which are hard to fulfill due to limited capacities of individual enterprises. Some of the main characteristics of this model are as follows:

- When delivery time frames are tight, enterprise proposals are evaluated based on "on-time delivery reliability" rather than "delivery time" itself.
- GP allows the customer to have different acceptable price limits for different delivery dates and formulates the problem for each scenario; multiple solution options can then be presented to the customer.
- By defining specific goals, especially under strict bidding conditions, the partner selection technique does not search for cheaper bids if the customer is willing to pay more, thereby extending the capability of the VE system to find a mutually beneficial solution for customers and enterprises.

Our case study revealed that the model was able to find a solution that matched the customer's preferences. The customer cared most about the delivery time, followed by the past performance of partner enterprises, and this is why partners with higher scores in delivery reliability and past performance were selected to form the consortium. Furthermore, a statistical significance test proved that the GP technique solves the problem in fewer iterations compared to traditional IP-based techniques.

5.1 Limitations

Despite all of these advantages, the GP-based approach developed in this study has some limitations. First, the model proposes only an optimum solution of selected enterprises and it does not provide any information about the second-best group of partners. Another problem is that the model's outcomes are extremely sensitive to the defined goals. If the goals do not accurately represent the customer's choices, the results may be unreliable. In this respect, the model could be improved further by applying a fuzzy GP technique and setting fuzzy goals instead of crisp ones.

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