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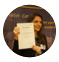

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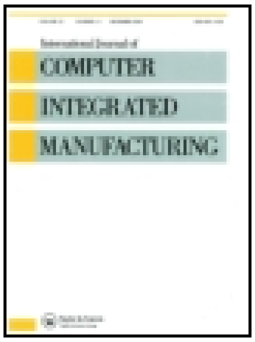

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An ontology-based multi-agent virtual enterprise system (OMAVE): part 2: partner selection

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A virtual enterprise (VE) is a collaboration model between multiple business partners in a value chain. The VE model is particularly feasible and appropriate for small- and medium-sized enterprises (SMEs) and industrial parks containing multiple SMEs that have different vertical competencies. The VE consortium's success highly depends on its members. Therefore, it is crucial to select the most appropriate enterprises when forming a VE consortium. In this study, a new multi-agent hybrid partner selection algorithm is developed for application in the development of an ontology-based multi-agent virtual enterprise (OMAVE) system. In this platform, the agent's interactions are supported by agent ontology, which provides concepts, properties and all message formats for the agents. Different types of agents collaborate and compete with each other so that unqualified or inefficient enterprises are eliminated from the enterprise pool. Only the remaining enterprises would be allowed to enter the negotiation process and propose in the bidding. The agent-based auctioning platform is coupled with a fuzzy–AHP–TOPSIS algorithm to evaluate partners based on their proposals and background. Accordingly, the winning enterprise for each task is identified and the whole project can be accomplished by assigning tasks to the responsible partners. To test and verify the functionality of the developed OMAVE system, a sample module using OMAVE applications and tools was manufactured. The last section of this paper presents the results of this case study, which validate the applicability of the proposed technique.

Keywords: virtual enterprise; partner selection; multi-agent systems; bidding

Introduction

Turbulent global market conditions impose a tremendous pressure on enterprises. To keep their market share competitive, enterprises need to get customer consent by introducing more innovative products with higher qualities. In this respect, modern manufacturing platforms such as just-in-time manufacturing, lean manufacturing and the virtual enterprise (VE) model have emerged. The main idea behind VE is to create a temporary alliance among enterprises with different core competences in order to respond to a specific demand (Unver and Sadigh 2013). The VE concept was proposed deliberately to empower small- and medium-sized enterprises (SMEs) to accomplish a project by sharing their resources and capabilities with other SMEs with different complementary competencies.

As a cooperation platform, a VE highly depends on the performance of its partners for success. Therefore, selecting the most appropriate enterprises to participate in a VE is of great importance. Candidate enterprises are chosen from an enterprises pool called virtual breeding environment and then evaluated. In order to construct a reliable evaluation process, it is necessary to consider different aspects of the evaluation. In that respect, selecting the best partners is not a simple optimisation problem (Sari, Sen, and Kilic 2008) mainly because the partner selection problem generally deals with several conflicting objectives. For instance, if there is an alternative that provides a high-quality product at a low price, the selection would be straightforward. Generally, however, this is not the case in real-life situations as high-quality products are usually offered for sale at high prices. Therefore, customer's preferences need to be identified accurately since the evaluation process would be based on these priorities. It is clear that expressing such a subjective decision-making mechanism via simple mathematical formulations may not be possible.

Partner selection problem is classified as a multi-criteria decision-making (MCDM) problem by many researchers. MCDM methods provide mathematical tools to construct and solve decision-making problems. These techniques evaluate alternatives based on the decision maker's preferences. As human judgements are usually uncertain, interpreting the subjective explanation of these preferences to a mathematically applicable data is another important issue in modelling a decision-making problem.

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The importance of partner selection along with the complexity of the problem has inspired many researchers to focus on this field. Some authors mathematically represented partner selection as a cost-minimisation problem that has several constraints such as time and risk of failure. Authors approaching the partner selection problem as an MCDM problem proposed the analytical hierarchy process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and other MCDM techniques. Some studies apply agents to model this problem, where agents are used either individually or in multi-agent platforms.

However, in most of the studies in the literature, intangible factors and the uncertainty of their values are ignored. Furthermore, generally developed methods are not effective when the size of the problem grows. The importance of the topic along with the aforementioned research gaps has inspired the authors to focus on this subject. In this article, an objective partner selection procedure is developed that evaluates the volunteer enterprises using a hybrid, stepwise multi-agent algorithm based on each customer's preferences.

The remainder of this paper is organised as follows. First, a brief literature survey on different modelling approaches for partner selection in a VE is reviewed. Then, a description of the problem and the architecture of the system are presented in the 'Multi-agent system architecture' section. In the 'Methodology' section, a partner selection methodology for an ontology-based VE is described in detail. In order to verify the practical implementations of the proposed technique, a case study is provided. Finally, the 'Case study' section summarises the conclusions of this paper.

Related works

The VE concept was first introduced in 1993 by Byrne, who defined it as a 'temporary nature of interactions between independent enterprises using Information and Communication Technologies (ICT)' (Byrne, Brandt, and Port 1993). From then on, the VE concept and related topics have attracted the attention of researchers. Just a couple of years later, in 1997, a study was published by Meade, Liles and Sarkis (1997) addressing the importance of partner selection in VE for the first time. A variety of approaches have been proposed to model the partner selection problem. In the literature, generally, there are three main approaches to model and solve partner selection problems: optimisation approaches, MCDM approaches and agent-based approaches.

Optimisation approaches are characterised by a single- or a multiple-objective function. Owing to resource limitations, however, some constraints need to be added to the model as well. Wu (2005) proposed a cost-minimisation model under time constraint. The integer programming formulation of this model is transformed into a graph-theoretical formulation and is solved by a two-phase algorithm (Wu 2005). Zeng, Li and Zhu (2006) solved a similar model with the branch and bound technique. Exact algorithms do not give satisfactory solutions in a reasonable computational time to large-scale problems, that is, problems with either a large number of alternatives or different types of evaluation criteria. As a result, artificial intelligence (AI) methods were proposed in some studies. Genetic algorithm (GA) is the most frequently used AI technique to solve VE partner selection problems. Wang, Xu and Zhan (2009) applied the GA method to solve the cost-optimisation model; moreover, Zhang et al. (2012) used the same method to obtain a pareto-optimal solution. Other AI techniques such as particle swarm optimisation (PSO), ant colony optimisation and Tabu search are also used. For instance, in a study by Zhao, Zhang and Xiao (2008), PSO is suggested to solve the partner selection problem with cost objective and due date constraint. In contrast to other techniques, optimisation approaches are powerful in terms of handling a sequence of subtasks. However, they need the model to be formulated with mathematical equations, which are not straightforward (if not impossible) in the subjective environment of decision-making.

The second class of approaches is MCDM, which provides tools to solve the partner selection problem in the formation of a VE. AHP, analytical network process and TOPSIS are among the most widely used MCDM methods for choosing the best companies to form a VE consortium. Sari, Sen and Kilic (2008) and Mikhailov (2002) adopted AHP, fuzzy-AHP and fuzzy logic-based methods to model the problem. By applying fuzzy–TOPSIS, Ye (2010) considered the cost, time, trust, risk and quality in the evaluation of candidate enterprises. MCDM techniques can handle both quantitative and qualitative criteria; yet, they fail when the number of candidates increases.

The third class of approaches designs and constructs a partner selection framework by employing agents (Huang, Wong, and Wang 2004; Henry and Lau 2001). Different algorithms and methods are used in different types of agents so that the optimum result is found in terms of task allocation, negotiation process stability and production planning (Wang, Nagalingam, and Lin 2007; Choi, Kim, and Doh 2007; Lim and Zhang 2012; Wang, Wong, and Wang 2014). Kaihara, Fujii and Iwata (2006) developed an agent-based game theoretic method, whereas Lim and Zhang (2012) implemented an agent-based GA method to simplify the bidding mechanism. Another research on the VE formation stage is the CONCOISE project (Norman et al. 2004). Furthermore, ecological aspects are also considered in establishing a VE consortium (Wang, Wong, and Wang 2012). Despite the rich literature in this domain of research, to the best of our knowledge, there is a lack of methods that can evaluate the large number of enterprises based on both quantitative and qualitative criteria that consider the uncertainty of customer's preferences.

Besides partner selection, agents are used to apply this infrastructure to different phases of the VE formation. In the case of complex and dynamic system environments, like VE, multi-agent systems are more responsive than other approaches. In multi-agent systems, there are several autonomous and self-aware agents that interact with each other through an agreed-upon language and protocols. The Foundation for Intelligent Physical Agents' Agent Communication Language and Knowledge Query Manipulation Language are two such languages. The application of multi-agent approaches in a VE can roughly be divided into the following categories.

To support the dynamically changing configurations of VE architecture including general services for trading, scheduling, flexibility improvements, ordering, shop floor managing, logistic service planning etc., researchers developed multi-agent-based approaches in the literature (Aerts, Szirbik, and Goossenaerts 2002; Rabelo, Camarinha-Matos, and Afsarmanesh 1999; Rabelo 2003; Kaihara, Fujii, and Iwata 2006; Kim et al. 2008).

The use of agents would be beneficial in terms of developing a collaboration platform by sharing inter-enterprise knowledge and system integration (Nahm and Ishikawa 2005). In this respect, in a study by Shen et al. (2007), enterprises equipped with intelligent manufacturing infrastructures were targeted. In this study, the authors concentrated on implementing a service-oriented computing paradigm on a developed unified framework to integrate software agents and web services (Shen et al. 2007). An article by Wang, Shen and Hao (2006) presents a web-based workflow management system that can be integrated with the heterogeneous software and hardware systems of enterprises. To enhance inter-enterprise knowledge sharing of semantic information, Lin and Harding (2007) developed an ontology-based model of a manufacturing execution system (MES).

The use of agents is advantageous for the operation management of VE systems as well. This framework aims to monitor and control dynamic production processes using ontology and RFID technologies (Chen and Tu 2009). In this architecture, agents analyse and select manufacturing parameters to reach the optimal trade-off between economic and technique factors by using machine learning algorithms and regression models (Kruger et al. 2011).

Reviewing the literature in detail reveals that integrating semantic and machine-interpretable architecture by developing ontologies for agents and by developing an intelligent multi-agent-based negotiation process for the partner selection stage of the VE is the missing part here.

Multi-agent system architecture

Any reliable decision-making model needs a wealth of information on the background that nourishes the evaluation process. In order to manage a massive amount of information, it is beneficial to use data management tools. Ontology is a tool designed to represent concepts, store domain knowledge and exchange knowledge-level messages. Furthermore, ontologies provide a suitable platform for agents and human communications. In regard to the fact that VE requires a highly dynamic domain, ontologies are implemented to construct an easily reconfigurable framework for the OMAVE system. An established ontology model contains several rules to enable a system to create inference models according to the acquired raw data and rules. The main target of developed rules is to establish possible relations between multiple available components in the model. With regard to the inferred relations in the model, enterprises qualified to join a project can be selected. This is the primary step in the partner selection process of the OMAVE system. A rule-based partner identification process is described in detail in part 1 of this study ('Domain Modeling and Rule Management'). Outcomes from this rule-based partner identification process are directed to the designed hybrid multi-agent-based partner selection process of OMAVE. This process contains several eliminations and decision-making procedures that work coherently with a multi-agent-based auctioning system. The main target of this system is to find the most appropriate choice from an arranged list of potential partners in the rule-based elimination step. The following aspects have to be considered in modelling this system:

(1) The evaluation process should be dynamic and reliable.
(2) Each customer is unique owing to its own preferences, so the evaluation process should take this diversity into account by identifying customer's priorities clearly.
(3) Uncertainty, as an inescapable part of any decision-making process, cannot be neglected.
(4) An appropriate set of criteria needs to be selected. No important criterion should be ignored, whereas including too many unnecessary criteria increases the complexity of the problem.
(5) The model should be able to handle both qualitative and quantitative parameters.
(6) The proposed technique should be flexible, maintaining its accuracy in different projects of different types.

This study focuses on developing an innovative, flexible, objective partner evaluation and selection technique to overcome the limitations spotted in the literature. A detailed description of the domain modelling and rule management of the OMAVE system can be found in part 1 of this study.

A simplified OMAVE system and the interactions between its corresponding sections are illustrated schematically in Figure 1. Task manager agent is at the centre of OMAVE architecture. It acts as a bridge between enterprise agents and customer agent. Enterprise and customer agents do not have any information about each other's actions, but their action depends on the incoming bids from other agents. It is the duty of task manager agent to collect all required information and propagate it to other active agents in the system. Dynamic information about tasks are collected through agents and historic information about companies (i.e. company past performance, quality performance etc. are obtained from system database). In each iteration during a bidding cycle, numerical formulations are serviced by OMAVE web services to all agents.

There are different stages from submission of a request for quote by customer to sign an agreement between customer and selected enterprises. These activities are shown in the diagram of the general activity of the OMAVE system illustrated in Figure 2. Related system interfaces provided for customers, enterprise users and system administrators in different stages are attached to this diagram. It is obvious that each of these activities embeds more detailed procedures and that illustrating all these detailed procedures in a single activity diagram would make the diagram very complicated and useless. In the development of OMAVE system procedures and structures, several scenarios and circumstances were predicted and the system was designed based on these ultimate situations. For instance, during the project operation phase, any of the partner enterprises could be resigned or, because of unpredicted problems, eliminated by the project manager. In this ultimate scenario, there should be a plan for the system to handle the situation. In Figure 3, a diagram of the reporting and project operation management activity is depicted. In this scenario, according to the submitted reports from partner enterprises, the task manager follows different instructions for managing the project. One of these scenarios is enterprise replacement.

Methodology

Multi-agent-based partner selection

As stated in previous sections, the VE formation phase is the most critical phase in the VE life cycle. The success of a VE consortium highly depends on its members and their performances during the operation phase. Therefore, choosing the most appropriate partners is crucial. In order to manage the partner selection process in the VE formation phase, a new multi-agent-based approach is developed. In this method, in order to find the most appropriate enterprises to join the OMAVE consortium, several agents with different responsibilities communicate, collaborate and compete with each other and with the

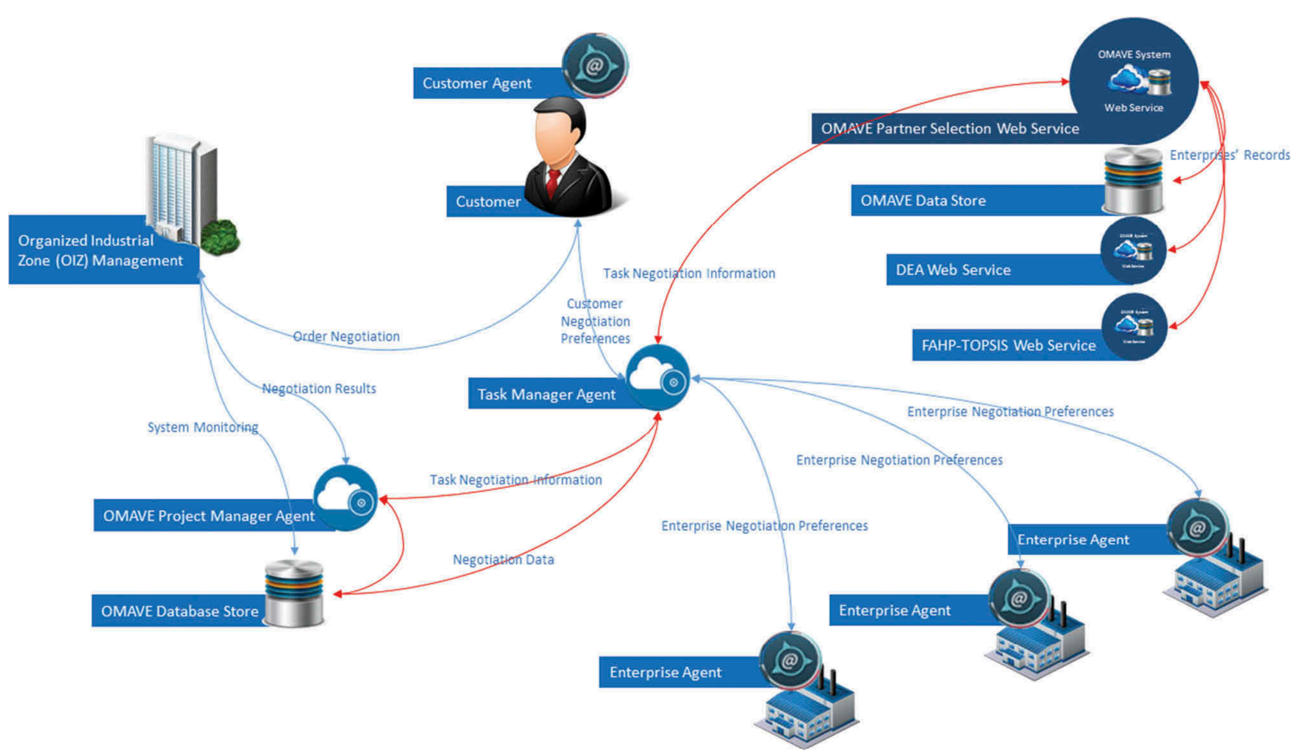


Figure 1. Architecture of the OMAVE system.

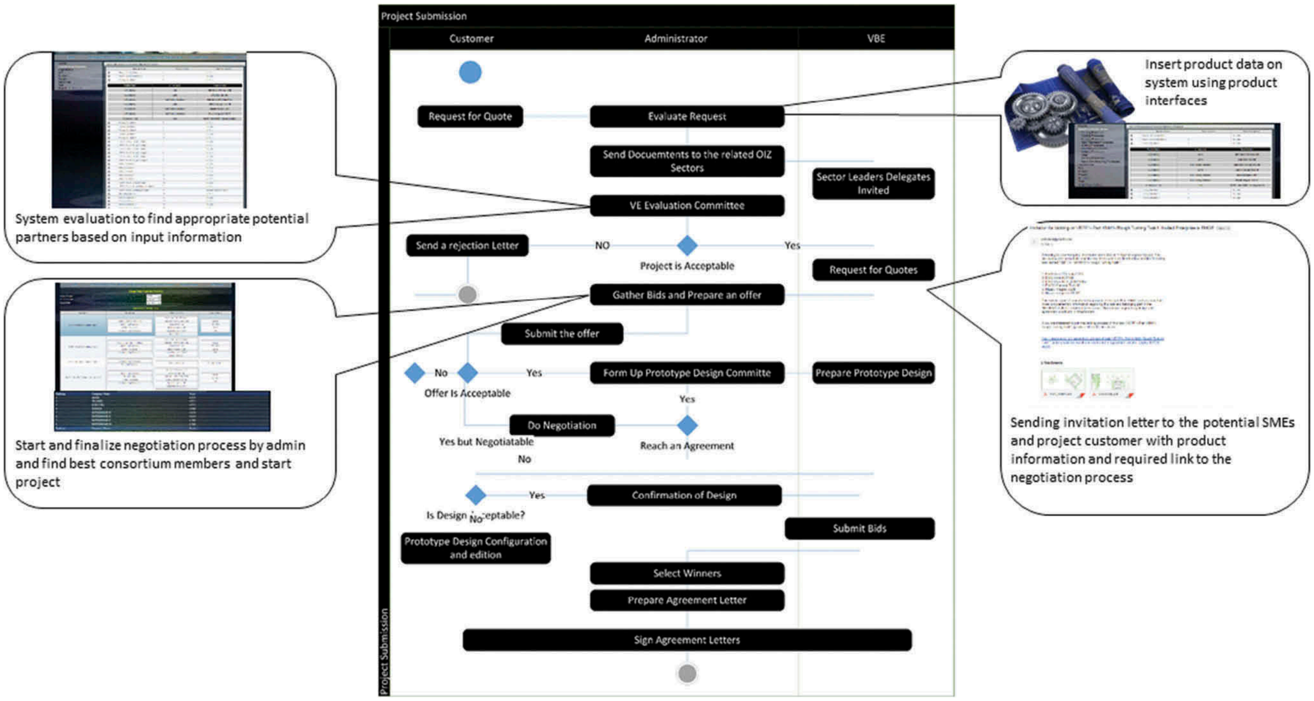


Figure 2. Diagram of the general activity of the OMAVE system.

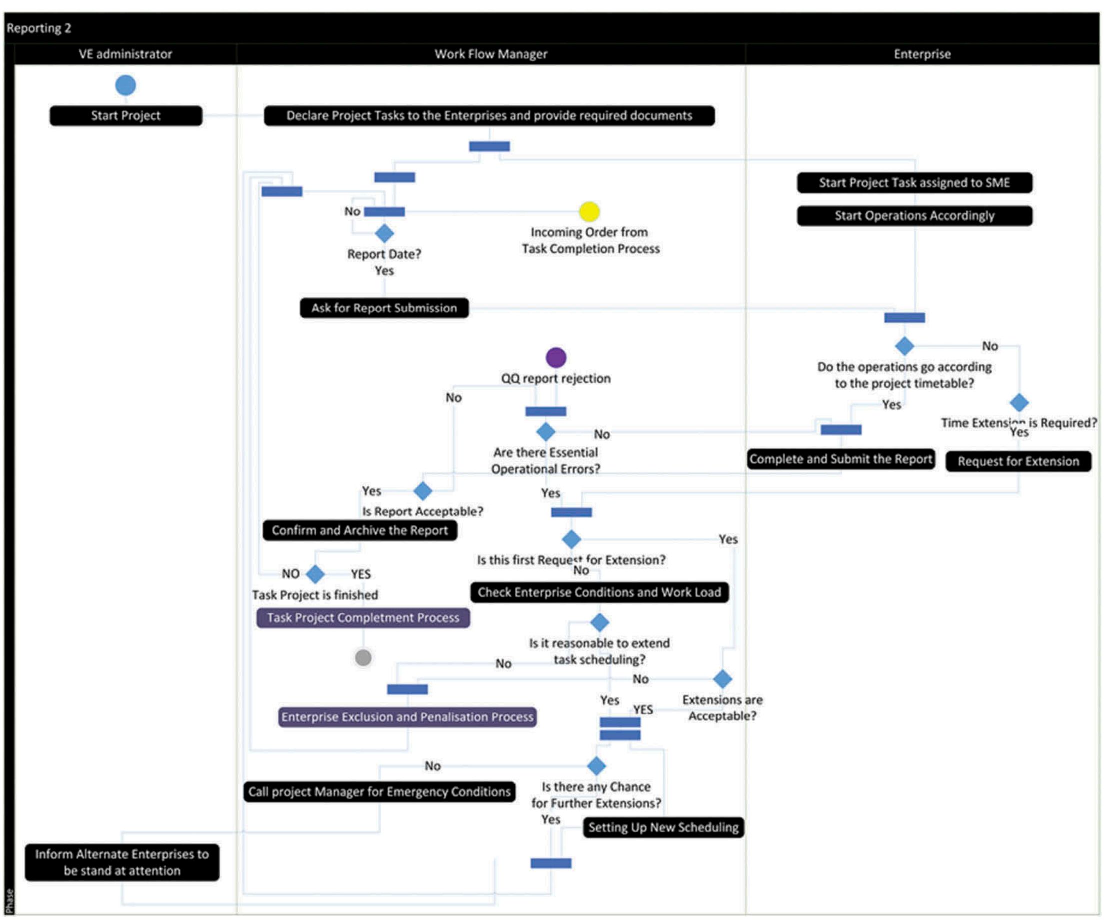


Figure 3. Diagram of the OMAVE system reporting and penalising activity.

system's web services to accomplish the partner selection process. Before the agents' deployment, several elimination processes should be accomplished to refine the selection process. Each elimination step aims to eliminate the unqualified enterprises in terms of customer or manufacturing requirements. The initial elimination steps are done by semantic rules designed and implemented in the OMAVE model. Reasoner engines create inference models based on the data stored in a system database and on the designed semantic rules. According to the deduced data from the reasoning process, a list of nominated enterprises capable of accomplishing the specified task is generated. Then, basic customer requirements are checked again by related rules in the model and a nominated enterprise list is refined further (this process is described comprehensively in part 1 of this study). By implementing a data envelopment analysis (DEA) technique, the system can eliminate inefficient enterprises from the list of potential partners. The efficiency of enterprises is evaluated by considering the specified inputs and outputs of the DEA. Afterwards, the results are sent to the system administrator. The system administrator activates the negotiation procedure, and the agent's deployment process begins. The next step is the deployment of the task manager agent. The task manager agent invites all efficient partners to the negotiation process and assigns an enterprise agent to all eager, responding enterprises and also customer enterprises. These agents gather all the required information from associated enterprises and system databases, and then the negotiation procedure starts, which is managed by the task manager agent. An integrated structure between the partner selection algorithms and the multi-agent-based negotiation procedure was designed here. To finalise the negotiation procedure, the fuzzy–AHP–TOPSIS technique is applied to obtain a ranked list of bidding enterprises. The iteration corresponding to the receipt of bids and evaluation of the proposals is repeated until the *i*th ranked partner is obtained. For instance, *i* should be set to 3 if the VE management is interested to obtain the first three bidders for the negotiations. Consequently, the ranked list of bidding enterprises is presented to the system administrator. The enterprise that ranked first is considered as the winner of the bargaining process, and the rest are announced as reserve partners. The overall partner selection framework and agent interactions are demonstrated in Figure 4.

A detailed description of the rule-based elimination process to identify qualified partners is described in part 1 of this study. Agents' interactions and the stepwise partner selection procedure are presented in the following sections.

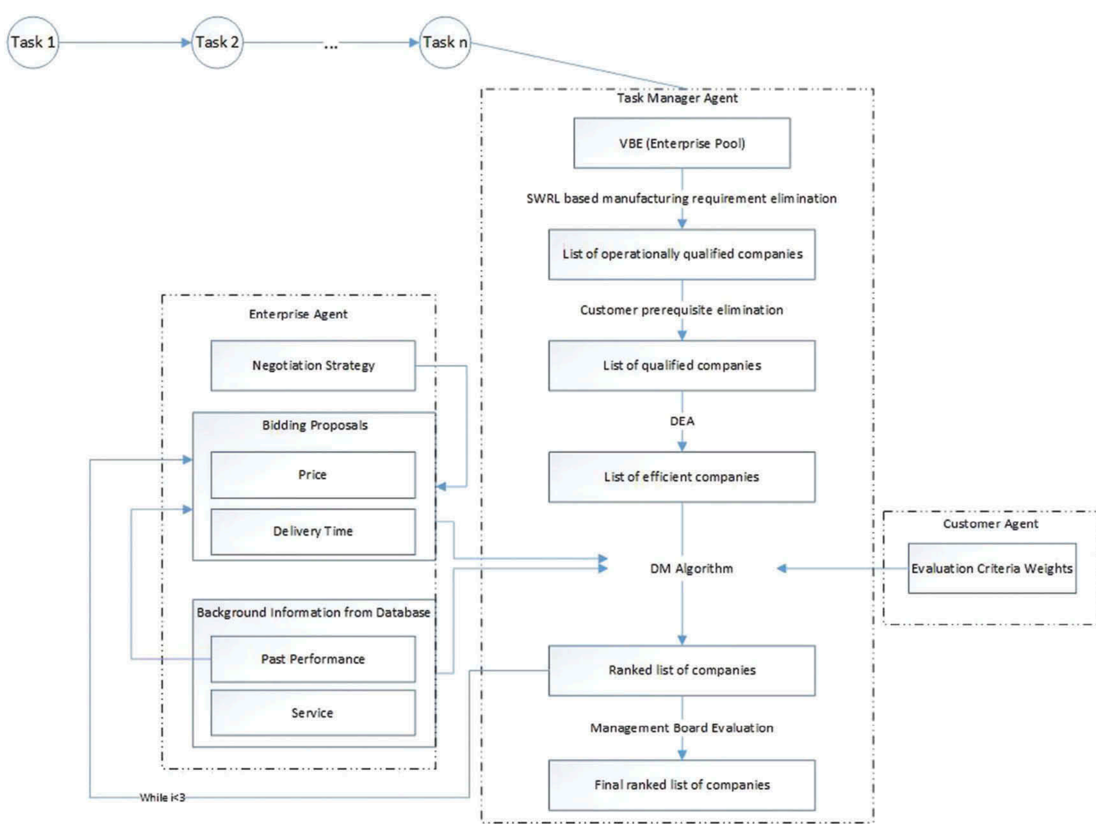


Figure 4. Structure of the interactions between agents in the partner selection process.

DEAs

DEA empirically measures the efficiency of alternatives by deducing the efficiency frontier. The efficiency score of each enterprise is calculated with respect to its inputs and outputs (Charnes, Cooper, and Rhodes 1978). Alternatives that serve more output using less input are considered to be more efficient alternatives. Applying DEA in the evaluation steps will be beneficial in several aspects:

- Among the list of criteria needed to be taken into account in evaluating enterprises, some are chosen to be considered in the DEA. Meanwhile, the number of criteria left for the next stages of decision-making will be easier to handle.
- If there are too many candidates, DEA detects the inefficient enterprises and excludes them from the list. So, they lose the chance to participate in the negotiation process. In the literature, most of the partner selection techniques are stuck when the number of candidates is large.
- Including just efficient enterprises in forming a VE increases the chance of satisfactory performance during the operation phase.

Among the variety of assets of each enterprise, five main inputs are selected to be included in the model. These are total energy consumption, total machinery value, total area, total human resources and total working hours. Any company can employ different types of inputs to acquire the output. The following two outputs are selected as a representative of the companies' outcomes: total sales value and working capital. The mathematical formulation of DEA is modelled as follows and solved with linear programming techniques:

$$\text{Max}\, E = \sum_{k=1}^{K} Y_{ok} v_k \tag{1}$$

$$\sum_{k=1}^{K} Y_{ik} v_k - \sum_{j=1}^{J} X_{ij} u_j \leq 0 \tag{2}$$

$$\sum_{j=1}^{J} X_{oj} u_j = 1 \tag{3}$$

$$v_k, u_j \geq 0 \tag{4}$$

where i is the number of enterprises, J is the number of inputs (assumed to be 5), K is the number of outputs (assumed to be 2), E is the enterprise efficiency ratio, X_{ij} is the amount of input j used by enterprise i, Y_{ik} is the amount of output k generated by enterprise i, X_{oj} is the amount of input for the enterprise being evaluated, Y_{ok} is the amount of output for the enterprise being evaluated, u_j is the coefficient assigned by DEA to input j and v_k is the coefficient assigned by DEA to input k.

By implementing DEA, the system can determine an efficient frontier and exclude inefficient enterprises from the list. It should be noted that the DEA step is applied only if there are too many qualified enterprises. In other words, DEA is not used to rank the alternatives. It is just embedded in the algorithm's structure to reasonably decrease the number of candidate enterprises if required.

In the next step, call for proposals are sent to the (previously identified) efficient candidates. Enterprise agents of volunteer enterprises are deployed to determine the enterprise strategies and bidding proposals. After the activation of the enterprise and customer agents, these agents acquire their needed data and information from their associated enterprises and enter the negotiation procedure. The negotiation process encapsulates two different types of auction procedures.

The first auction procedure is semi-English auction, which runs on the customer side. An English auction is an open auction process for ascending the price during the negotiation. It means that bidders offer higher bids in each round of auction. This type of auction has two different versions (Kunimoto 2008). In the first version, the starting price comes from the bidders, but in the other type, the auctioneer conducts an opening price and the bidders increase their bids later. The bidding procedure continues until only one bidder remains. However, here in the OMAVE negotiation procedure, there is only one bidder, which is the customer agent. The customer agent increases the price according to the mean price coming from enterprise agents. This price is announced by the task manager agent to the customer agent at the end of each iteration. In the following section, the customer agent's behaviour is discussed in details.

The second auction procedure is reverse auction, which runs on the enterprise side. In this auction, the roles of buyers and sellers are reversed. Sellers as suppliers place their bids to get the buyers' interests. Buyers have the opportunity to select the most appropriate offer from the suppliers and buy services or stuffs as cheap as possible (Schoenherr and Mabert 2007).

In the OMAVE partner selection auction process, a hybrid system of reverse auction and English auction is used. In this research, to get the customer offer, English auction-based approach is used, with the aim of getting the maximum possible price from the customer. Complete conditions of the English auction and its predefined concepts cannot be implemented here because only one customer is participating in the negotiation and this customer's price increment is a function of the customer negotiation strategy, defined price limitations, and, definitely, price changes on the enterprise side.

On the enterprise side, however, typical reverse auction conditions are established and suppliers (here enterprises) compete to offer the best minimum price for the auctioned stuff (product or service) to get the job.

The auctioneer here is the task manager agent who manages both auctions simultaneously and continuously compares offered bids from both sides. If one of the enterprise agents accepts the customer offer, the task manager agent ends the negotiation process and announces the final incoming bids. If none of the agents were able to get the customer offer, however, the negotiation process would be ended by the task manager agent without obtaining any results.

Project manager agent

In order to simplify the main project, it should be decomposed into its components (if necessary). Let's assume that the aim of the project is to manufacture a complex assembled product. First, it should be disassembled to its constituent parts. To manufacture each part, several tasks are needed to be operated and each task is decomposed into the individual manufacturing processes. Corresponding tasks and operations are defined for each project based on design specifications and production necessities. The project manager agent is responsible for getting the information regarding the required tasks and their properties. The next step is to deploy the task manager agent by the project manager agent.

Enterprise agent

If an enterprise volunteers to participate in a VE, the enterprise agent collects from company authorities different pieces of information such as the opening price, maximum price and company strategy during the negotiation process. Based on these information items and the companies' past performance score collected from the system database, enterprise proposals are set by the agent. The enterprise agent enters the negotiation with these bidding proposals.

In the negotiation procedure, enterprise agents compete with each other to give the most competitive price to the customer, who here is the task manager agent. In order to calculate the next bid from an enterprise in the VE partner selection negotiation process, following main equation is used:

$$a_i = \left(\frac{b_{i-1}+f(\alpha)}{2}\right) - E_{\mathrm{pp}} \cdot C_{\mathrm{p}}\left(\frac{b_{i-1}-f(\alpha)}{2}\right) \tag{5}$$

where a_i is the next bid of the enterprise in the bidding procedure (next iteration price of the enterprise), E_{pp} is the enterprise's past performance, C_{p} symbolises how severe the negotiation process is for the company, $f(\alpha)$ is the price estimation formula in each step for each company, and b_{i-1} is the best offer of the last iteration. In this formula, E_{pp} is obtained from the system database and C_{p} is calculated from the relation below:

$$C_{\mathrm{p}} = \frac{b_{i-1} - a_{\min}}{a_{i-1} - a_{\min}} \tag{6}$$

where $a_{\min}$ is the minimum price of the company in the negotiation process, a_{i-1} is the last bidding price of the company and α and β are the fixed factors for the enterprise strategy. The enterprise strategy determines the policy of the enterprise and of the corresponding agent in the negotiation process. Here, as shown in Figure 5, the enterprise clarifies its strategy in the negotiation, which it desires to win in any way or it only considers to win with a considerable profit margin. According to the enterprise selection, the α and β factors are determined in a way that $\alpha + \beta = 10$. The value of 10 is the scale factor, which is assumed by the authors. It could be any amount, however. The important thing here is the enterprise's chosen strategy for the negotiation process.

In order to avoid radical bidding policies in the VE negotiation process, and to prevent the negotiation process from collapsing in the very first steps, some restrictions and stoppages are designed. In each step, companies are allowed to bid in a secure bidding range, which is between $a_{i\min}$ and $a_{i\max}$. $a_{i\min}$ is the minimum value that agents can bid for the next iteration. Correspondingly, $a_{i\max}$ is the maximum value for bidding for the agents. The secure bidding range was proposed to prevent enterprises from bidding aggressively and from putting their minimum price in the very first stages of the negotiation, which could break the system. Therefore, the minimum band of secure bidding range was designed to be the average of the minimum price of the enterprise and of the best price of the last iteration. On the other hand, if enterprises want to keep prices as high as possible, then they will try to keep the price close to the best price of the last iteration. Therefore, if the last iteration price is not below the company's minimum price, enterprise's next offer will be below the best price of the last iteration (Figure 6).

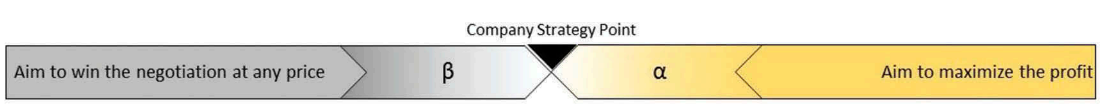


Figure 5. Enterprise strategy point.

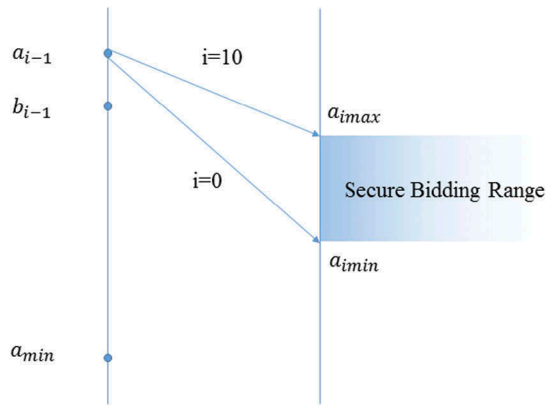


Figure 6. Possible bidding band of an enterprise agent for the next bidding round.

These values are calculated from Equations 7 and 8:

$$a_{i\min} = \frac{a_{\min} + b_{i-1}}{2} \quad (7)$$

$$a_{i\max} = b_{i-1} \quad (8)$$

Also, Equation 9 is used to determine the secure bidding range gap:

$$\gamma = a_{i\max} - a_{i\min} = \frac{b_{i-1} - a_{\min}}{2} \quad (9)$$

Based on these relations, the formula for calculating the next bidding price of the enterprise is derived, which is assumed as a third-degree cubic equation with coefficients *a, b, c* and *d* as shown in Equation 10.

$$f(\alpha) = a\alpha^3 + b\alpha^2 + c\alpha + d \quad (10)$$

Considering the boundary conditions, the next bidding price of the enterprise equation is reduced to

$$f(\alpha) = a\alpha^3 - 15a\alpha^2 + 75a\alpha + a_{i\min} \quad (11)$$

As defined in Equation 9, $a_{i\max} - a_{i\min} = \gamma$ and considering $f(0)$ and $f(10)$, the coefficient 'a' can be calculated as follows:

$$a = \frac{a_{i\max} - a_{i\min}}{250} = \frac{\gamma}{250} = 0.004\gamma \quad (12)$$

and using 'a' in Equation 10, final form of the new pricing formula will be as in the following equation:

$$f(\alpha) = 0.004\gamma\alpha^3 - 0.06\gamma\alpha^2 + 0.3\gamma\alpha + a_{i\min} \quad (13)$$

By replacing Equations 7 and 9 in formula above, pricing formula can be given as follows:

$$f(\alpha) = \left[\frac{b_{i-1} - a_{\min}}{2}\right]\left[0.004\alpha^3 - 0.06\alpha^2 + 0.3\alpha\right] + \frac{a_{\min} + b_{i-1}}{2} \quad (14)$$

Finally, in order to include the E_{pp} and C_p factors to the final enterprise bid and calculate the bidding price of the enterprise, the following function is derived:

$$a_i = b_{i-1} \cdot \left(\frac{1 - E_{pp} \cdot C_p}{2}\right) + f(\alpha) \cdot \left(\frac{1 + E_{pp} \cdot C_p}{2}\right) \quad (15)$$

Combining Equations 14 and 15, Equation 16 is obtained:

$$a_i = b_{i-1} \cdot \left(\frac{1 - E_{pp} \cdot C_p}{2}\right) + \left[\left(\frac{b_{i-1} - a_{\min}}{2}\right)[0.004\alpha^3 - 0.06\alpha^2 + 0.3\alpha] + \frac{a_{\min} + b_{i-1}}{2}\right] \cdot \left[\frac{1 + E_{pp} \cdot C_p}{2}\right] \quad (16)$$

In the next step, bidding proposals, quality and past performance scores are sent to the task manager agent. These scores will be used to evaluate the candidates by applying a logical partner selection algorithm, which is described technically in the 'fuzzy–AHP–TOPSIS' section. The output of this algorithm is the ranked list of candidates.

Customer agent

Evaluation, ranking and selection of enterprises are conducted based on customer preferences. The customer agent extracts the weights of the criteria and sends them to the task manager agent.

Customer agent bidding policy is based on the average of the last bids submitted by enterprise agents. As in a closed bidding system, all agents' prices are sealed and the price information of other agents cannot be seen by other agents; customer agent behaviour regarding enterprise agents thus faces a dead end. In order to give the required information to the customer agent, in each iteration, the average of incoming bids from enterprise agents is revealed to the customer agent by the task manager agent. According to the new proposed average price, the customer agent sets its new offer for the next iteration. Setting a new customer default price is necessary. Both customer and bidding enterprise agents should forego their benefits to reach an agreement. When one of the bidding enterprise agents accepts the new price offered by the customer, the negotiation will be stopped.

In order to avoid a dead end in the negotiation process and reach an agreement, it is critical to encourage the customer agent to change its price in each iteration.

Similar to enterprise agents, a new constant δ is defined for the customer agent. Here, however, instead of α, the constant δ is used to express the eagerness of the customer agent to change the price and to set its strategy in the negotiation process. For this purpose,

if $\delta = 0$, then the change rate of the customer agent's price is set to 0%;

if $\delta = 10$, then the change rate of the customer agent's price is set to 100%.

The logic behind the actions of the customer enterprise is to alter its proposed price. First, in Equation 17, the overall total of the enterprise agents' bids for each iteration is calculated. Here, E_j^i means the bid of enterprise agent in the ith iteration and T^i is the total sum of the enterprise agents' bids in the ith iteration:

$$\forall i : T^i = \sum_{j=1}^{m} E^i{}_j = E_1^i + E_2^i + E_3^i + \cdots + E_m^i \tag{17}$$

For the ith iteration, the total number of bids coming from m enterprises is calculated. Then, the average of the bids at this iteration is considered:

$$\forall i : A^i = \frac{T^i}{m} \tag{18}$$

In two consequent iterations, the average price change rate is found from Equation 19:

$$\theta = \frac{A^{i-1} - A^i}{A^{i-1}} \tag{19}$$

As the change rate of the enterprise agents' price increases, the customer tries to decrease the price change rate and vice versa. Therefore, the change rate of the customer agent's price should be proportional to the reverse of the enterprise's average price changes. So,

$$\bar{\theta} = 100 - \theta \tag{20}$$

Equation 21 is the relation used to calculate the customer's next proposed price:

$$C^i = \bar{\theta} \cdot \delta \cdot \left(C_{\max} - C^{i-1}\right) + C^{i-1} \tag{21}$$

Task manager agent

Customer agent behaviour is highly dependent on incoming bids from enterprise agents. In other words, the customer agent inspects the enterprise agents' acts and behaviours then takes appropriate actions accordingly. It should be noted, however, that the customer agent cannot see incoming bids from enterprise agents since all bids are sealed. To solve this problem, the task manager agent acts as a bridge between a customer agent and enterprise agents. It also manages the negotiation procedure. The task manager agent collects all bids from enterprise agents and also gets the customer agent's offer. Then, it first finds the minimum price offered by the enterprise agents and compares this price with the maximum price offered by the customer. If the best enterprise bid is greater than the customer offer, then the negotiation continues and the task manager agent announces the best bid of the last iteration to all enterprise agents. Furthermore, it also calculates the average bid of the last iteration and announces it to the customer agent to decide about the next round offer. This loop continues until an enterprise agent accepts the customer's offer. In this case, the task manager agent stops the bidding process and final bidding proposals are set and announced.

Fuzzy–AHP–TOPSIS

In order to evaluate the enterprises' proposals, it is necessary to assess two types of parameters. The first type is dynamic criteria, which are provided by enterprise authorities, and the second type is static criteria, which are obtained from the OMAVE system database. Dynamic criteria include price and delivery time. Static criteria, which reflect an enterprise's background, include past performance and service level. Past performance of the company is assessed in terms of delivering high-quality products on time. Service level is the other decisive parameter, which aggregates the after-sales service, communication skills and environmental friendliness of enterprise performance. The evaluation criteria and their corresponding sub-criteria are arranged in a hierarchy, as shown in Figure 7.

VE as a dynamic system may encounter different customers with different desires and attitudes. Therefore, it should be equipped with a tool to determine the customer's preferences and choose the best alternative with respect to the weight of the preferences. AHP has proved to be a powerful technique for determining the relative importance of each criterion by using pairwise comparisons (Saaty 1980). Conventional AHP methods use crisp values to illustrate the preferences among criteria, since mapping exact values to subjective judgements is not an easy task without applying fuzzy set theory. The fuzzy–AHP technique proposed by Buckley (1985) is an extension of AHP, which uses triangular fuzzy membership functions rather than Saaty's crisp 1–9 scales. Table 1 and Figure 8 show the fuzzy scales for linguistic variables.

The evaluation matrix, **A**, is constructed by pairwise comparison of the main criteria based on Table 1. Matrix **A** is an $n \times n$ matrix, where n is the number of criteria.

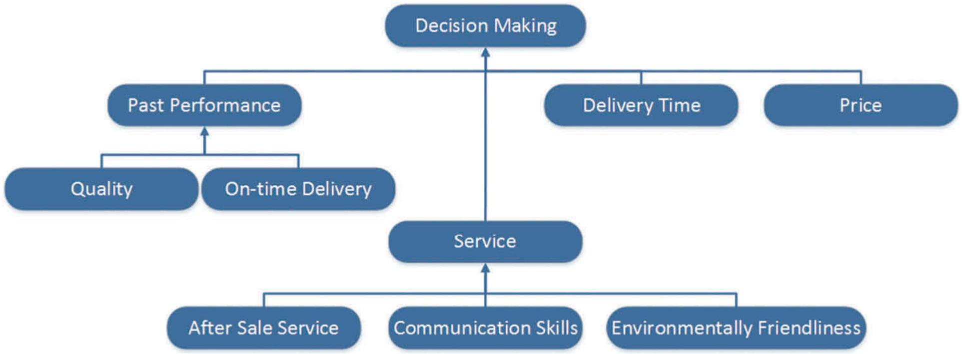


Figure 7. Hierarchical structure of the partner selection criteria.

Table 1. Pairwise comparisons of linguistic variables using fuzzy numbers.

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

a_{ij}s are the elements of matrix **A**, where $a_{ij} \odot a_{ji} \approx 1$. In fuzzy operations, $\odot$ is the multiplication of fuzzy numbers and $\oplus$ is the add operation of fuzzy numbers. Next, by applying the geometric mean method, the technique can obtain the fuzzy weights of each criterion (w_i) as follows:

$$w_i = u_i \odot (u_1 \oplus u_2 \oplus \cdots \oplus u_n)^{-1} \tag{22}$$

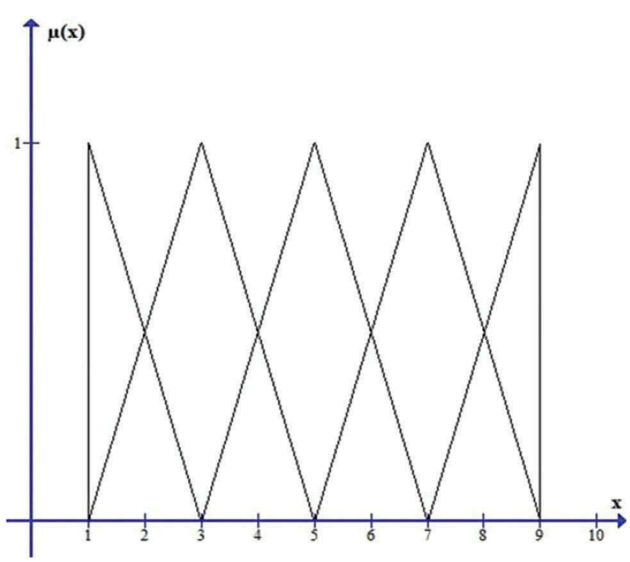


Figure 8. Membership functions of fuzzy scales.

where

$$u_i = (a_{i1} \odot a_{i2} \odot \cdots \odot a_{in})^{1/n} \tag{23}$$

Fuzzy weights are defuzzified by the centre of area defuzzification method, so the crisp weight of each criterion is concluded. These weights demonstrate the customer preferences and will be used later in the TOPSIS method. The concept of TOPSIS is based on the fact that the chosen alternative should be the closest to the positive ideal solution (PIS) and the farthest from the negative ideal solution (NIS). The performance of alternatives with respect to the criteria is expressed in a matrix known as the decision matrix 'X.' The performance matrix is an $m \times n$ matrix, where m is the number of enterprises associated with n number of criteria. The performance score of each criteria has its own unit; eliminating the effects of unit normalisation is essential. The normalised performance matrix is constructed as follows:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum^{i=1} mx_{ij}^2}} \tag{24}$$

As a result of multiplying the normalised performance matrix by criteria weights (obtained from fuzzy–AHP), the weighted normalised performance matrix is obtained.

$$u_{ij} = w_j r_{ij} \tag{25}$$

The next step is to determine the PIS and NIS using Equations 26 and 27, respectively.

$$\text{PIS} = A^{+} = \left(\max_i u_{ij} | j \in J\right), \left(\min_i u_{ij} | j \in J'\right) \quad |i = 1, 2, 3, \ldots, m \tag{26}$$

$$\text{NIS} = A^{-} = \left(\min_i u_{ij} | j \in J\right), \left(\max_i u_{ij} | j \in J'\right) \quad |i = 1, 2, 3, \ldots, m \tag{27}$$

where $J = \{j = 1, 2, \ldots, n | j \text{ associated with benefit criteria}\}$ and $J' = \{j = 1, 2, \ldots, n | j \text{ associated with benefit criteria}\}$.

The separation value of each alternative from PIS and NIS is measured by the Euclidean distance as follows:

$$s_i^+ = \sqrt{\sum_{n}^{j=1} \left(u_{ij} - u_i^+\right)^2} \tag{28}$$

$$C_i^+ = \frac{S_i^-}{(S_i^+ + S_i^-)} \tag{29}$$

where

$$C_i^+ \in [0, 1] \forall i = 1, \ldots, n.$$

The preference order of alternatives is ranked according to the decreasing order of C_i^+. To sum up, the fuzzy–AHP–TOPSIS model provides the ranked list of enterprises based on customer preferences obtained from the fuzzy–AHP method and implements it in the TOPSIS's conventional model. By finalising this step, the model can rank the enterprises, announce the winner and give the task to the winning enterprise. The overall sequence diagram for the designed agents and web services interactions is illustrated in Figure 9.

Beside studying the reliability of the model, its computational complexity will also be compared with another partner selection technique to verify its effectiveness. In this respect, the model is compared with the fuzzy–AHP technique in terms of number of calculations to obtain the result (Mikhailov 2002). The fuzzy–AHP technique is the most frequently cited technique in articles about partner selection in VE (Nikghadam et al. 2015).

Although both the fuzzy–AHP and fuzzy–AHP–TOPSIS techniques evaluate partner performances by considering the fuzziness of the data available, the number of mathematical operations (multiplications) is not the same. So, these two approaches were compared in this respect.

Let n and m denote the number of partner enterprises and number of criteria, respectively. The computational complexity of fuzzy–AHP is given by Equation 30 (Lima Junior, Osiro, and Carpinetti 2014).

$$T_{n.m}^{\text{F-AHP}} = n^2(m + 1) + m(7n + 6) = O\left(n^2 m\right) \tag{30}$$

However, the computational complexity of fuzzy–AHP–TOPSIS is as Equation 31.

$$\begin{aligned} T_{n.m}^{\text{F-AHP-TOPSIS}} = {} & 4(m + 1) + 4m + m(m + 2) \\ & + 2n(m) + 2m(n - 1) \\ & + 2n(2m + 2) + 2n \end{aligned} \tag{31}$$

$$T_{n.m}^{\text{F-AHP-TOPSIS}} = 4(m + 1) + 4m + 11nm + 6n = O(nm) \tag{32}$$

According to Equations 31 and 32, the computational complexity of the fuzzy–AHP technique is of order $O(n^2 m)$, whereas it is $O(nm)$ for the fuzzy–AHP–TOPSIS technique. This proves that, as the number of alternatives increases, the fuzzy–AHP–TOPSIS technique can obtain the results in a fewer number of calculations.

The number of calculations for the case with $m = 4$ criteria is graphically represented in Figure 10.

The other important aspect needed to be highlighted is that, unlike fuzzy–AHP, the number of alternative partners in fuzzy–AHP–TOPSIS is not limited to 9. In Saaty's (1980) article, the author reported that the number of criteria or alternatives in AHP should be limited to 9 so that its consistency is not compromised. However, since the fuzzy–AHP–TOPSIS model uses the AHP approach only in evaluating the customer's preferences with respect to four criteria, the rest of the evaluation would be based on the TOPSIS technique, with no limitations in the number of partners.

To sum up, this study has proposed a novel multi-agent system-based partner selection methodology to support the dynamic structure of VE in the formation phase. By applying the fuzzy–AHP–TOPSIS technique, the proposed model can consider the uncertainty of the customer's decisions while evaluating the bidder's performance.

Case study

To test and verify the implemented system and evaluate the results, a pilot implementation at the OSTIM Organized Industrial Zone (OIZ) in Ankara, Turkey, was carried out. The target was to produce a sample product by using OMAVE system tools. A technical drawing and an image of the product are shown in Figures 11 and 12, respectively. This assembly product consists of eight different parts named Part KNM1–Part KNM8. In this paper, part KNM1 is taken as a sample to implement the multi-agent system partner selection in the OMAVE system.

Based on design specifications and manufacturing necessities, the production process of the part KNM1, shown in Figure 13, was decomposed into individual manufacturing processes. Then, corresponding product process plans were created. Consecutive similar manufacturing processes (automatically distinguished by the system) were selected and combined together to create a single manufacturing task. The operational tasks for producing the part KNM1 are turning, milling, heat treatment, grinding and, finally, coating.

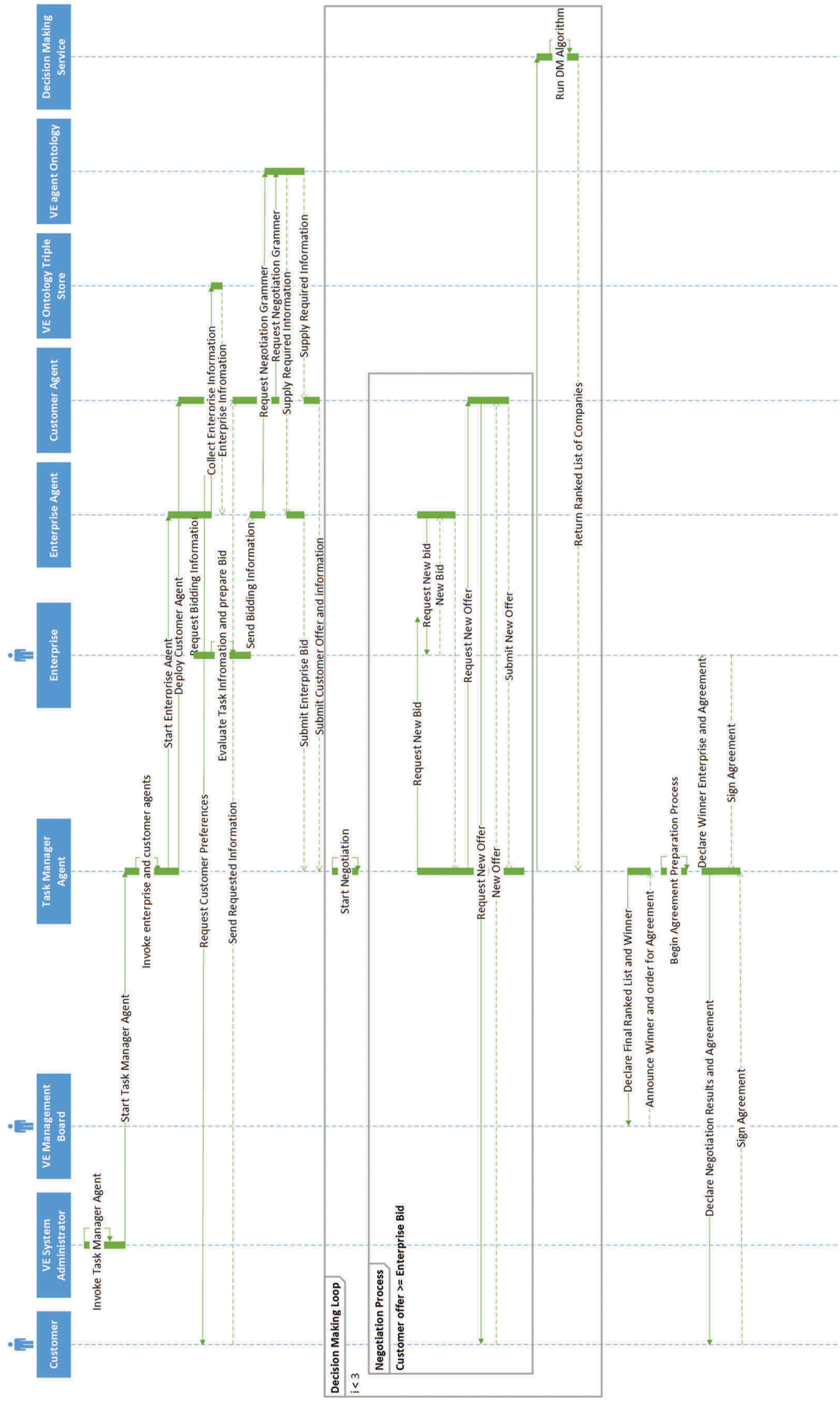
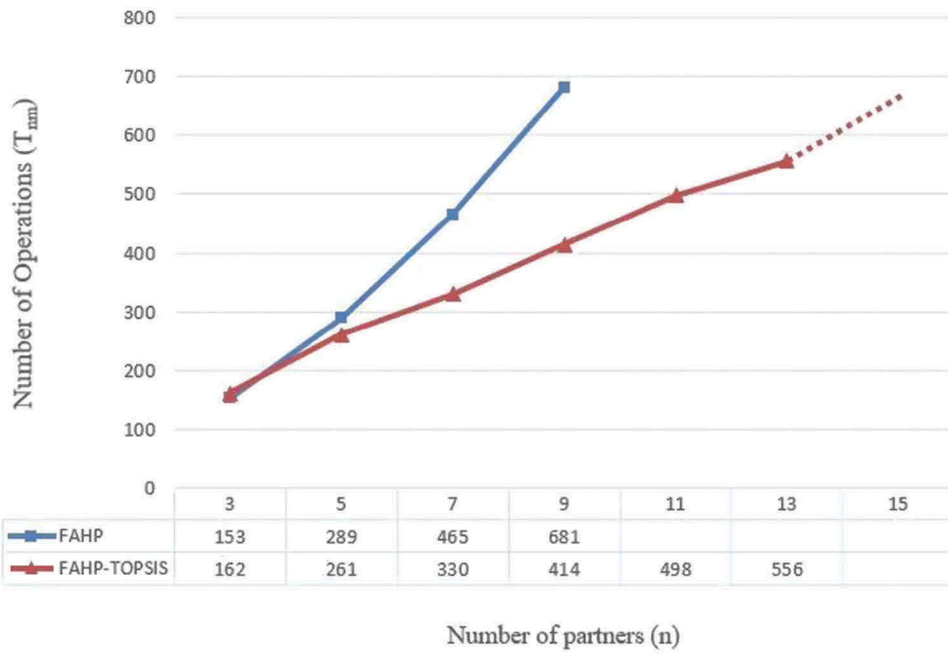


Figure 9. Sequence diagram of the agent-based bidding procedure.



	3	5	7	9	11	13	15
FAHP	153	289	465	681			
FAHP-TOPSIS	162	261	330	414	498	556	

Figure 10. Comparison between the fuzzy–AHP and the fuzzy–AHP–TOPSIS techniques.

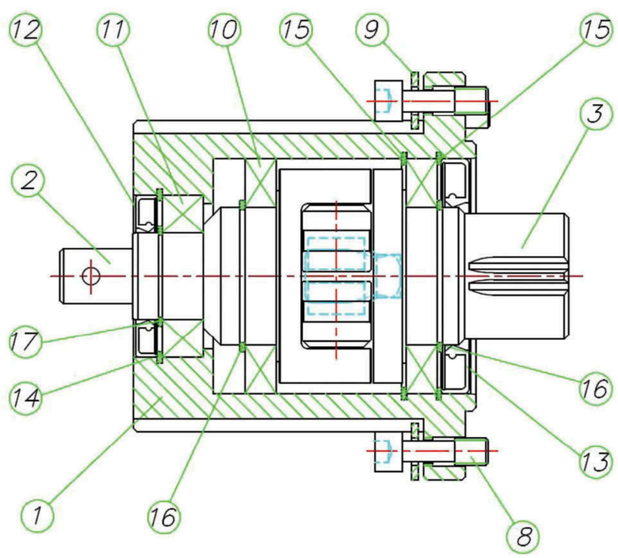


Figure 11. Sketch of the ordered product.

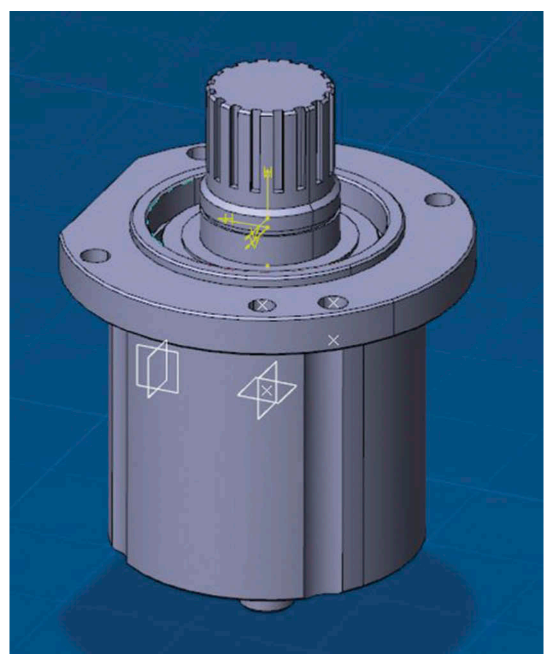


Figure 12. Solid model of the ordered product in CATIA.

Step 1: First, according to product specifications, enablers (like physical and software resources) who are capable of fulfilling the tasks should be identified. Semantic rules of the OMAVE model realise this step automatically. These rules detect the most appropriate resources (e.g. machine tools) to accomplish each manufacturing task.

Step 2: Once the list of machine tools is extracted, the system would search for enterprises that own corresponding machine tools. This step is also done by applying the rules on the triple store established from the OMAVE model. The same process determines the selected machine tool owners and adds these enterprises to the list of potential partners for that specified task. The list of enterprises that are qualified to carry on the task and thus to enter the bidding process for the

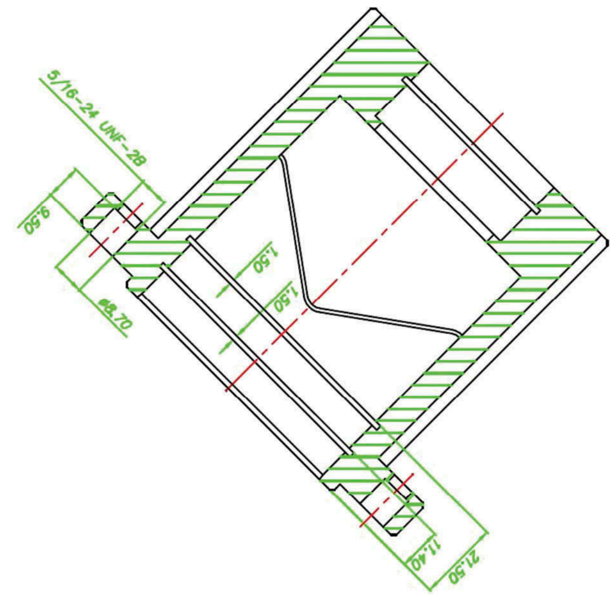


Figure 13. Drawing of the part KNM1.

'VEPP1-Part KNM1 – Rough Turning Task 1' is shown in Table 2. Here, VEPP1 is the name of created OMAVE project.

Step 3: In this step, DEA is adopted to determine the efficient companies. Here, DEA is not used to rank the enterprises, but just detects the inefficient companies based on their inputs and outputs, and then eliminates them, if any is found. Call for proposals is sent to the remaining members of the enterprise pool. The second column of Table 2 shows the efficient enterprises. Based on the data gathered from these companies and applying DEA, the system found enterprise G to be less efficient in comparison to its competitors, so it eliminated this enterprise from the pool.

Table 2. List of enterprises qualified to operate the turning process of part KNM1.

Qualified enterprises name	Efficient enterprises	Enterprises
Enterprise A	✗	✗
Enterprise B	✓	✓
Enterprise C	✗	✗
Enterprise D	✗	✗
Enterprise E	✓	✓
Enterprise F	✓	✓
Enterprise G	✓	
Enterprise H	✓	✓
Enterprise I	✓	✓
Enterprise J	✓	✓
Enterprise K	✓	✓
Enterprise L	✓	✓

Step 4: The list of companies coming from the third step is the list of efficient partners eligible to join the VE consortium. In this step, the system administrator opens the task for the negotiation procedure. By opening the task for auctioning, the system administrator enables the system to automatically send emails to the list of efficient enterprises and customer to invite them for the auctioning procedure. Moreover, by starting the bidding process, the system administrator enables the system to automatically deploy the task manager agent. The task manager agent collects all the required information about its assigned task and gets ready to deploy enterprises and customer agents.

Step 5: Each nominated enterprise gets a detailed email regarding the auction process conditions, rules, agreements, product detailed information, drawings and any complementary document. In the case of replying to the invitation, an enterprise agent specifically assigned to an enterprise will be deployed by the task manager agent. The enterprise agent acquires the necessary information for the negotiation procedure from assigned enterprise authorities. The necessary pieces of information are as follows:

- **Minimum price**: The enterprise's minimum acceptable price for this task. It means that the enterprise agent is not allowed to put bids below this amount.
- **Opening price**: The first bid put by an enterprise in the auction procedure. Based on enterprise policy and its strategy in the negotiation procedure, the first bid could be high or low, but this parameter is very critical in winning the auction.
- **Delivery date**: The optimum date for an enterprise to deliver the ordered product to the customer.
- **Strategy**: This parameter actually shows the enterprise auction policy for an agent. This is a parameter between 0 and 10, where 0 indicates an active approach to the negotiation and 10 indicates a more conservative policy in the auction. If an enterprise asks an agent to win this task auction in any way, it should adopt a more aggressive strategy and choose lower amounts for the strategy and vice versa.

Besides these criteria, an enterprise agent also gathers an enterprise's history and its reserved information from the OMAVE database. These additional pieces of information are as follows:

- **Past performance**: An enterprise's past performance is calculated with respect to two sub-criteria:

its quality background and record of on-time delivery.

- **Service**: Degree of customer satisfaction, after-sales service, and environmental friendliness are sub-criteria that are used to evaluate an enterprise's service performance. The reputation of the enterprise agent is shaped after collecting all these pieces of information. It is a very rare possibility that two companies have exactly the same conditions. Therefore, the possibility is very high that each enterprise will have its own specific enterprise agent. Agents' performance and their behaviour are based on their internal algorithms, which are described in the 'enterprise agents' section. Agents' next move is usually unpredictable.

The same procedure is used to enter the negotiation process. If a customer accepts the conditions and the invitation, it will be redirected to a customer agent interface. Here, different criteria are asked from a customer regarding the negotiation procedure. The customer agent's requested criteria are as follows:

- **Maximum price**: The maximum acceptable price for an ordered product that a customer may pay in the case of reaching an agreement.
- **Opening price**: Customer's intended opening price.
- **Delivery period**: The most reasonable time period for a customer to get the product ordered. Enterprises that meet the preferred delivery dates will have more advantages.
- **Strategy**: This parameter represents the customer's flexibility in raising its opening price.

Step 6: This step is performed to evaluate the customer preferences by applying the fuzzy–AHP method. It is assumed that the customer answers the questionnaire as shown in the program's interface, which is depicted in Figure 14. The collected data are interpreted following matrix $\tilde{A}$. Fuzzy numbers and their linguistic scales are previously presented in Table 1.

$$\tilde{A} = \begin{bmatrix} \tilde{1} & \tilde{3} & \tilde{5} & \tilde{7} \\ \widetilde{0.33} & \tilde{1} & \tilde{3} & \tilde{5} \\ \widetilde{0.2} & \widetilde{0.33} & \tilde{1} & \tilde{3} \\ \widetilde{0.14} & \widetilde{0.2} & \widetilde{0.33} & \tilde{1} \end{bmatrix} \tag{33}$$

Considering these values, it could be said that the most important criterion for the first customer is price, with 0.529 of overall weight, followed by delivery time, past performance and service, respectively. In the next step, the TOPSIS technique is used to find the best partner with respect to these weights.

Step 7: To evaluate the enterprises, it is necessary to assess their scores with respect to each criterion. The values of the unit price and delivery time are obtained from enterprise proposals, whereas the past performance and service scores of each enterprise are obtained from the OMAVE system's database. Bidding proposals and enterprises' background information are shown in Table 3. Table 4 demonstrates the normalised scores of Table 3, and, consequently, from Equation 28, the weighted normalised matrix is obtained, as shown in Table 5.

The definitions of PIS and NIS are given as follows:

$$\text{PIS} = [0.148, 0.052, 0.056, 0.025].$$

$$\text{NIS} = [0.259, 0.157, 0.031, 0.014].$$

The closeness rate, which is used to rank the enterprises, is calculated by Equations 28 and 29. C_i^* values are shown in Table 6. So, the ranked list of enterprises with given bidding proposals for customer 1 is as shown in Table 7. Briefly, among 12 enterprises, A–L, registered in the OMAVE system,

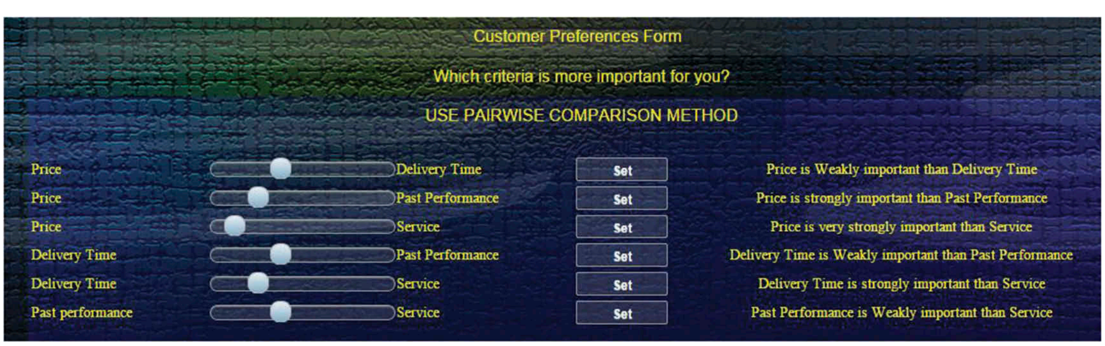


Figure 14. Preferences of the first customer.

Table 3. Enterprises' bidding information for KNM1 – rough turning task 1 (for 100 parts).

Enterprise name	Opening price ($)	Minimum price ($)	Delivery time (days)	Past performance (0–1)	Service (0–1)	Strategy (0–10)
Enterprise B	9500	8500	4	0.6	0.7	4
Enterprise E	15,000	10,300	6	0.5	0.5	2
Enterprise F	9300	8400	3	0.5	0.6	5
Enterprise H	12,000	10,000	4	0.5	0.5	3
Enterprise I	10,000	9200	3	0.9	0.9	5
Enterprise J	10,500	9350	3	0.9	0.9	4
Enterprise K	10,000	9000	4	0.9	0.9	6
Enterprise L	12,000	9900	2	0.9	0.9	5

Table 4. Normalised scores of enterprises with respect to each criterion.

Enterprise name	Price	Delivery time	Past performance	Service
Enterprise B	0.279	0.373	0.288	0.327
Enterprise E	0.490	0.560	0.240	0.233
Enterprise F	0.279	0.280	0.240	0.280
Enterprise H	0.392	0.373	0.240	0.233
Enterprise I	0.303	0.280	0.432	0.420
Enterprise J	0.343	0.280	0.432	0.420
Enterprise K	0.297	0.373	0.432	0.420
Enterprise L	0.392	0.187	0.432	0.420

Table 5. Weighted normalised scores of enterprises with respect to each criterion.

Enterprise name	Price	Delivery time	Past performance	Service
Enterprise B	0.148	0.105	0.037	0.020
Enterprise E	0.259	0.157	0.031	0.014
Enterprise F	0.148	0.079	0.031	0.017
Enterprise H	0.207	0.105	0.031	0.014
Enterprise I	0.160	0.079	0.056	0.025
Enterprise J	0.181	0.079	0.056	0.025
Enterprise K	0.157	0.105	0.056	0.025
Enterprise L	0.207	0.052	0.056	0.025

Table 6. Candidates' closeness to the ideal solutions.

	Distance from PIS	Distance from NIS	Closeness
Enterprise B	0.056	0.123	0.6879
Enterprise E	0.155	0.000	0.0000
Enterprise F	0.037	0.136	0.7858
Enterprise H	0.084	0.074	0.4679
Enterprise I	0.029	0.129	0.8163
Enterprise J	0.043	0.114	0.7281
Enterprise K	0.053	0.118	0.6885
Enterprise L	0.059	0.120	0.6690

9 of them were identified as qualified enterprises capable of fulfilling the KNM1 rough turning task 1, although Enterprise G was detected as an inefficient company and was thus eliminated from the pool. Once the bidding started, assuming that all of the enterprises volunteered to get the job, submitted proposals were evaluated. The developed partner selection algorithm chose Enterprise I as the winner and Enterprise F as a reserve.

Table 7. Enterprises' bidding information for KNM1 rough turning task 1.

Rank	Enterprise name	Obtained points (0–1)
1	Enterprise I	0.816
2	Enterprise F	0.786
3	Enterprise J	0.728
4	Enterprise K	0.689
5	Enterprise B	0.688
6	Enterprise L	0.669
7	Enterprise H	0.468
8	Enterprise E	0.000

As claimed before, the ranking would be different for customers with different preferences. In this case, three customers with different preferences were considered. Figures 15 and 16 show the preferences of customers 1 and 2. Moreover, Table 8 shows the ranking results consequently for the same case, without any change in enterprises' proposals. Apparently, the results show how the winning enterprise might change for various customers with different attitudes.

The partner selection process is described above for Turning Task 1 of part KNM1, in detail. The same selection procedure should be applied for all tasks of a part for forming a complete consortium. Different enterprises can win the bids for separate tasks. In the end, a consortium list, including each task, should be established for each part of a product (Table 9).

It should be noted that not only the manufacturing process, but also any processes such as logistics, transportation, assembly etc. can be opened up for bidding when it is required. In the case of the example of this study, all the volunteer companies are located in the same industrial park, so the transportation cost was negligible in comparison to the production cost. Moreover, the negotiation protocols were prepared accordingly. In

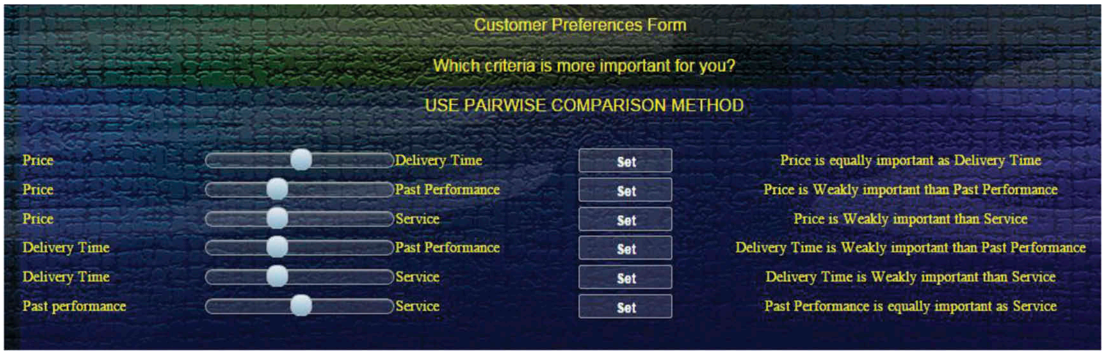


Figure 15. Preferences of the first customer.

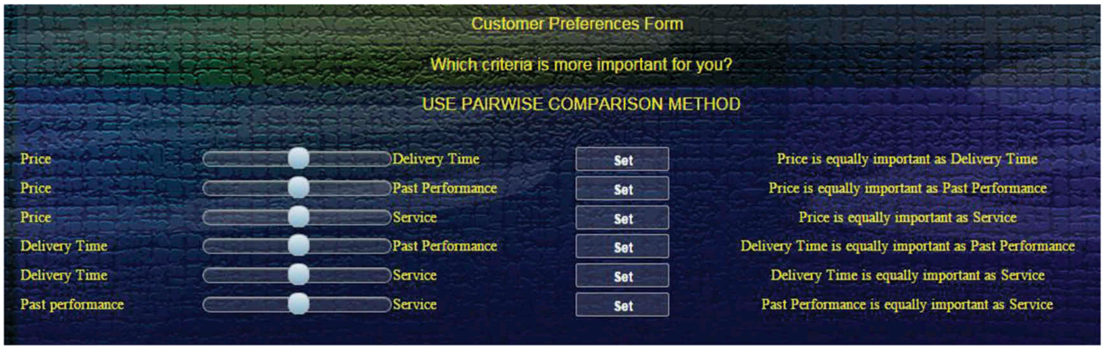


Figure 16. Preferences of the second customer.

Table 8. Ranking of the results for customer's with different preferences.

Customer Enterprise 1			Customer Enterprise 2			Customer Enterprise 3		
Rank	Enterprise name	Gained points	Rank	Enterprise name	Gained points	Rank	Enterprise name	Gained points
1	Enterprise I	0.816	1	Enterprise I	0.797	1	Enterprise I	0.827
2	Enterprise F	0.786	2	Enterprise L	0.749	2	Enterprise J	0.787
3	Enterprise J	0.728	3	Enterprise J	0.746	3	Enterprise L	0.782
4	Enterprise K	0.689	4	Enterprise F	0.720	4	Enterprise K	0.692
5	Enterprise B	0.688	5	Enterprise K	0.635	5	Enterprise F	0.584
6	Enterprise L	0.669	6	Enterprise B	0.611	6	Enterprise B	0.566
7	Enterprise H	0.468	7	Enterprise H	0.457	7	Enterprise H	0.370
8	Enterprise E	0.000	8	Enterprise E	0.000	8	Enterprise E	0.000

Table 9. Consortium members of part KNM1.

Part name	Task name	Name of winning enterprise
Part KNM1	Turning Task 1	Enterprise I
	Turning Task 2	Enterprise I
	Milling Task 1	Enterprise L
	Milling Task 2	Enterprise K
	Painting Task 1	Enterprise X
	Grinding Task 1	Enterprise Y

other words, bidders were aware that their bidding proposals should include the average transportation cost per unit of product.

The above discussions have shown that the proposed model would maintain its reliability for different VE projects with different tasks, necessities and customer types. In fact, this is exactly what the dynamic, customer-oriented VE requires.

Limitations of the model

Besides all the advantages of the proposed approach, there are still some aspects that limit the performance of the model. First, the model highly depends on the scores of each bidder, but there is no controlling approach to check the trustworthiness of these values. For instance, assigning numeric values to past performance and service are not an easy task since these criteria are subjective in nature. On the other hand, an enterprise may overestimate its capabilities when proposing competitive proposals by being well ahead of its rivals. Thereby, it would probably win the bid, but it would collapse in operation phase.

The authors believe that further studies in these aspects would improve the overall performance of the system in the future.

Conclusion

The partner selection process is the most challenging step in the VE formation phase. Selection of the most appropriate partners for a VE consortium enhances its chance of success. Therefore, to select the best possible alternatives, it is required to design a flexible, neutral, objective and unpredictable partner selection tool. To reach these goals, it is inevitable to develop a system that is capable of minimising human interruptions, coping with decision uncertainties arising from customer preferences and orders variation, facing with dynamic and changing VE environments, and using effective decision-making parameters. To deal with these issues, a hybrid multi-agent-based partner selection process was designed and implemented within the OMAVE system.

The main contributions of this research are fourfold. First, a multi-agent-based negotiation process was developed to replace human interactions during the auction process. Second, in order to reduce the problem size and alleviate problem complexity, the system applies the DEA method. By applying the DEA method before beginning the partner evaluation process, the system can eliminate inefficient enterprises from the list of nominated partners eligible to enter the negotiation procedure. Third, to cope with uncertainties arising from customer preferences and order variation, the system uses the fuzzy–AHP method to interpret subjective customer preferences to arithmetic data. Forth, a decision criteria hierarchy was established by considering the most crucial criteria in the evaluation of partners. Two types of criteria are considered in this system. One is static parameters, which consist of enterprise past performance and service level. The other is dynamic parameters such as opening, maximum and minimum prices, and delivery time. According to each enterprise condition and parameter, unique agents with different characteristics would be deployed. Assigning completely different agents for different enterprises makes the negotiation procedure difficult to prognosticate. The multi-agent platform works coherently with the fuzzy–AHP–TOPSIS partner evaluation algorithm to find the best possible partners to join a VE consortium and produce ordered product component(s).

This system was implemented at the OSTIM OIZ in Ankara, Turkey, and its performance was tested and validated by producing a sample product with the participation of three enterprises. As mentioned before, the system output benefits both enterprises and customers. Enterprises can take the advantage of the ability to produce products beyond their single-handed capabilities, and customers can obtain their desired products with better quality at a more reasonable price. Two different approaches were proposed by the OSTIM OIZ management. The system was installed at OSTIM Technology A.S.,[1] and customers (big international or national companies looking for appropriate suppliers) may benefit from the system by being able to find their requested enterprises from the OMAVE system. The second approach is the direct use of the OSTIM management to establish the most suitable consortiums that will respond to submitted customer orders. In both of these approaches, the management (OSTIM Technology A.S.) charges a fixed percentage for the project and covers the running and maintenance costs of the system. On the other hand, customers may easily find their suppliers and partners, and system partners may also use their unused capacity and increase their productivity as well.

A couple of future works are being considered so as to improve the OMAVE system performance. One of these is the implementation of a multi-agent-based operation management platform in the OMAVE operation phase. The other is the development of complementary tools and applications like light material resource planning systems and MESs to transfer real-time data regarding SMEs' available capacities and their current situation. In the case of enhancing partner evaluation, a procedure that implements agents based on an AI approach would be beneficial.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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Note

1. OSTIM Technology A.S. was originally established to enhance the collaboration between universities and industries, with contributions from academics at universities and from companies at the OSTIM Organized Industrial Zone.

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