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An intuitionistic fuzzy OWA-TOPSIS method for collaborative network formation considering matching characteristics

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Abstract. Collaborative Network (CN) as a new emerging paradigm can rapidly answer market demands by effective collaboration and coordination between enterprises. Nowadays, it has become a potential solution for different organizations to manage their business issues effectively. Thus, selecting a suitable partner combination is critical to CN success. Matching characteristic is very important for partner combination selection in the CN formation, while it is neglected in the existing research. This paper proposes a method and model for partner combination selection of CN considering matching utility. Firstly, the matching factors are developed from four aspects, supply capability, goal, culture, and technology. Then, a hybrid approach is designed to integrate Intuitionistic Fuzzy Ordered Weighted Averaging (IFOWA) operators into the a Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) procedure. Moreover, matching utility combination method amongst multi-partners is advanced to establish the partner combination model. Moreover, a decision support system is applied in a practical enterprise to illustrate the advantage of the proposed method. Finally, a sensitivity analysis is conducted to investigate the robustness of solutions ranking to changes by the matching factor. The result shows that ranking the solutions for forming CN is relatively sensitive to the matching factor.

1. Introduction

The fierce global competition and rapid technology development faced by manufacturing industry have forced enterprises, especially SMEs, to evolve at an unprecedented rate [1,2]. In order to be successful in a very competitive and rapidly changing environment, SMEs need to enhance competitiveness by improving business models, strategies, organizational and governance principles, processes and technological levels to rapidly respond to different market opportunities.

The rapid development of ICT has provided a possible opportunity for SMEs to change business model sustainably to meet demander's requirements ranging from traditional product development mode (serial design mode), manufacture model (make-to-stock), and distribution mode (distributor) to concurrent engineering (concurrent design mode), mass customization (make-to-order), and Electronic Commerce (EC) & the third Party Logistics (3PL) distribution mode in networked manufacturing environment. Therefore, in order to survive and succeed in such a turbulent and dynamic environment, SMEs present various business organization patterns adapting to the new business

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models including supply chain management [1], extended enterprise [2], virtual enterprise [3], dynamic alliance [4], collaborative networked organization [5-9], etc. CNs show a high potential not only in terms of the survival capability, but also in terms of value creation by new capabilities to cope with innovation needs, uncertainty, mass customization, and fierce competition [8]. All these new organization patterns have the common features of networked enterprises: being geographically distributed, dynamic, and heterogeneous. However, selecting partners to finish collaborative tasks is the main challenge that organizations face before they attain the advantages of collaboration. Therefore, how to formulate mathematical models and propose effective decision-making methods of partner selection is important when a CN is to be established.

Nowadays, partner selection has received a great deal of attention as a topic in the literature and industrial practices; however, scope of research on partner selection of CNs remains limited. Thus, direct and indirect literature reviews with respect to partner selection of alliances were investigated. Many criteria were considered for the problem of partner selection. Wu and Barnes [10] developed certain formulating criteria for partner decision-making selection in agile supply chains which include 7 sub-criteria of production and logistics management, partnership management, financial capability, technology and knowledge management, marketing capability, industrial and organizational competitiveness, and human resource management. Also, several approaches were developed, some of which were applied broadly in practice. Rezaei [11] proposed a two-way partner selection approach to matching all the buyers and suppliers optimally. Awasthi et al. [12] presented a fuzzy BOCR-GRA approach for collaboration-type partner selection for city logistics planning in the presence of municipal freight regulations. Mat and Cheung [13] identified the top 5 criteria of partner selection in the CN by an on-line survey which targeted organizations from Malaysia, Australia, and other countries (such as India, Singapore, and Philippines), and those criteria include previous track record in business, integrity (performed task with honesty), commitment (dedicated in performing tasks), Trusted to act in the best interest of the partnership, and contributed complementary resources.

In addition, different advanced Multiple-Attribute Decision-Making (MADM) approaches have been developed to solve this problem. Feng et al. [14] advanced a fuzzy MADM approach considering the collaborative factors of resource complementarity, overlapping knowledge bases, motivation correspondence, goal correspondence, and compatible cultures to rank the partners in the codevelopment alliances formulation. Various extensions of fuzzy sets have been used for the MADM problems. Dymova et al. [15] proposed an interval type-2 fuzzy extension of the TOPSIS method. Some hesitant fuzzy methods have been also advanced based on a hesitant fuzzy set [16-18] to deal with uncertain and hesitant information for the MADM problems. Wang and Xu [19] showed the application of intuitionistic-valued hesitant fuzzy elements in a practical problem involved with supplier selection. The intuitionistic fuzzy method has been developed to extend the fuzzy set in MADM problems. Xu and Liao [20] proposed intuitionistic fuzzy AHP in which the preferences are represented by intuitionistic fuzzy values. Boran et al. [21] extended the TOPSIS method with the Intuitionistic Fuzzy Set (IFS) to select an appropriate supplier.

Based on the above-menioned issues, most literature reviews focused on the individual utility of each candidate partner, while the collaborative utility shared by pairwise partners was overlooked. However, when collaborative utilities in the process of partner selection are involved, there is still a gap regarding the performances of interaction and matching between partners. In CN, collaboration is an intentional property derived from a certain shared belief. Therefore, approaches that intended to fill this gap are developed to assess this type of performance mainly from two aspects: assessing the actual interaction between partners and considering the general capability of a company for matching others' demands. In addition, it is essential to identify the collaborative patterns and matching relationship amongst candidate partner enterprises to obtain the object. In addition, among these extensions of fuzzy set, the IFS is characterized by membership, non-membership, and hesitancy functions. Therefore, it can be warranted that, unlike other single approaches, the preference information is more comprehensive, not to mention its convenient implementation in practical applications. As a result, we apply intuitionistic fuzzy method to evaluate the matching performances amongst candidate partners in terms of the criteria evolving from collaborative patterns, and then rank the order with the proposed intuitionistic fuzzy OWA-TOPSIS approach.

The remainder of the paper is organized as follows. In the next section, we briefly introduce some basic knowledge related to Intuitionistic Fuzzy Numbers (IFNs), IFOWA, and intuitionistic fuzzy TOPSIS. Section 3 develops the collaborative patterns amongst partners in a CN and the criteria for building CNs, considering matching characteristics amongst partners. Section 4 presents the method to integrate the IFOWA operation into TOPSIS approach in intuitionistic fuzzy environment to cope with the multi-attribute group decision-making problems. The proposed intuitionistic fuzzy OWA-TOPSIS method is employed to solve CN formation in Section 5. Then, a decision support system is developed and an application case is shown in a practical enterprise in Section 6. Finally, conclusions and further research are discussed in Section 7.

2. Preliminaries

In the following, we shall briefly introduce some basic knowledge related to IFN, IFOWA, and intuitionistic fuzzy TOPSIS.

2.1. Intuitionistic fuzzy numbers

In order to enable effective partner selection for building CNs, the criteria evaluation approach based on IFS is introduced briefly in this section. Fuzzy set theory, initially proposed by Zadeh [22], proved to be very effective in handling the vagueness and uncertainty [23]. Moreover, the IFS is a generalization of the concept of a fuzzy set. IFS theory has been applied to different areas such as pattern recognition [24] and decision-making problems [25]. The basic concept of IFS is reviewed as below to facilitate a deeper understanding of the following sections.

Definition 1 [26]. Let $X = \{x_1, x_2, ...x_n\}$ be a finite universal set. IFS A on X is an object in the form of $A = \{x, \mu_A(x), v_A(x))|x \in X\}$, where functions $\mu_A : X \to [0,1]$ and $V_A : X \to [0,1]$ assign the degree of membership and the degree of non-membership to the element, respectively; further, they are constrained by $0 \leq \mu_A(x) + v_A(x) \leq 1$.

In addition, for each IFS A, $\pi_A(x) = 1 - \mu_A(x) - v_A(x)$ is called the degree of indeterminacy or hesitancy, depicted as in Figure 1. The larger $\pi_A(x)$ is, the more uncertain about x we will be; on the contrary, we can be more certain about x if $\pi_A(x)$ is smaller.

Definition 2 [26]. Let $A = \{(x, \mu_A(x), v_A(x))|x \in X\}$ and $B = \{(x, \mu_B(x), v_B(x))|x \in X\}$ be two IFSs and λ be a positive real number. The following relations and operations are valid:

$$A \cap B = \{(x, \min(\mu_A(x), \mu_B(x)), \max(v_A(x), v_B(x)))|x \in X\},$$

$$A \cup B = \{(x, \max(\mu_A(x), \mu_B(x)), \min(v_A(x), v_B(x)))|x \in X\},$$

$$A \oplus B = \{(x, \mu_A(x) + \mu_B(x) - \mu_A(x)\mu_B(x), v_A(x)v_B(x))|x \in X\},$$

$$A \otimes B = \{(x, \mu_A(x)\mu_B(x), v_A(x) + v_B(x) - v_A(x)v_B(x))|x \in X\},$$

$$\lambda A = \{(x, 1 - (1 - \mu_A(x))^\lambda, (v_A(x))^\lambda)|x \in X\}.$$

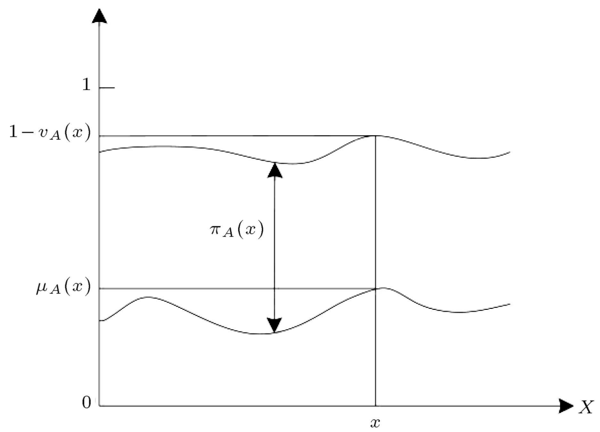

Figure 1. An example of IFS.

For convenience, Xu and Yager [27] called $\alpha = (\mu_\alpha, v_\alpha)$ an IFN, where:

$$\mu_\alpha \in [0,1], \qquad v_\alpha \in [0,1], \qquad \mu_\alpha + v_\alpha \leq 1,$$

and:

$$\pi_\alpha = 1 - \mu_\alpha - v_\alpha.$$

Definition 3 [27]. Let $\alpha = (\mu_\alpha, v_\alpha)$ be an IFN, a score function, s_α, and accuracy function, h_α, of α can be defined, respectively, as follows:

$$s_\alpha = \mu_\alpha - v_\alpha, \qquad s_\alpha \in [-1,1], \tag{1}$$

$$h_\alpha = \mu_\alpha + v_\alpha, \qquad h_\alpha \in [0,1]. \tag{2}$$

Based on the score and accuracy functions, a comparison law for IFNs is introduced as below [27,28]:

Definition 4. Let $\alpha = (\mu_\alpha, v_\alpha)$ and $\beta = (\mu_\beta, v_\beta)$ be IFNs, s_α and s_β be the score functions of α and β, respectively, h_α and h_β be accuracy functions of α and β, respectively, and then:

1. If $s_\alpha < s_\beta$, then $\alpha < \beta$,
2. If $s_\alpha = s_\beta$, then $\begin{cases} h_\alpha < h_\beta \Rightarrow \alpha < \beta \\ h_\alpha = h_\beta \Rightarrow \alpha = \beta \end{cases}$

Definition 5 [29]. Let $\alpha = (\mu_\alpha, v_\alpha)$ and $\beta = (\mu_\beta, v_\beta)$ be IFNs, and then the Euclidean distance between α and β is calculated as follows:

$$d(\alpha,\beta) = \sqrt{\frac{1}{2}\left\{(\mu_\alpha - \mu_\beta)^2 + (v_\alpha - v_\beta)^2 + (\pi_\alpha - \pi_\beta)^2\right\}}. \tag{3}$$

2.2. Intuitionistic fuzzy OWA

The OWA operator is an important aggregation with the rational aggregation result in terms of the situations between the "and" and "or" [30]. However, the OWA operator can only be used where the aggregated arguments bring about exact numerical values. Hence, it is essential to extend it to the fuzzy environment. Xu [28] generalized the OWA to the IFS and induced the IFOWA operator given as follows.

Definition 6. Let $a_i = (\mu_{a_i}, v_{a_i})\ i = (1, 2, ..., n)$ be a collection of n IFNs, and then an IFOWA operator on the collection is defined as follows:

$$\begin{aligned}&\mathrm{IFOWA}_{W^*}(a_1, ..., a_n)\\&= \mathrm{IFOWA}_{W^*}((\mu_{a_1}, v_{a_1}), ..., (\mu_{a_n}, v_{a_n}))\\&= w_1^* a_{\alpha(1)} \oplus w_2^* a_{\alpha(2)} \oplus ... \oplus w_n^* a_{\alpha(n)}\\&= \left(1 - \prod_{i=1}^{n}(1 - \mu_{a_{\alpha(i)}})^{w_i^*}, \prod_{i=1}^{n}(v_{a_{\alpha(i)}})^{w_i^*}\right), \qquad (4)\end{aligned}$$

where $a_{\alpha(i)}$ is the ith largest of IFN in the order relation and the associated weight vector $W^* = (w_1^*, w_2^*, ..., w_n^*)^T$, constrained by $w_i^* \in [0, 1]$, $i = 1, 2, ..., n$ and $\sum_{i=1}^{n} w_i^* = 1$.

Obviously, the aggregated value using the IFOWA operator is also an IFN.

2.3. Intuitionistic fuzzy TOPSIS

TOPSIS was proposed by Hwang and Yoon [31], whose very basic idea is simple and intuitive: measuring alternatives' distances to predefined positive-ideal and negative-ideal points first; then, aggregating separate distance information to reach overall evaluation results. The intuitionistic fuzzy TOPSIS analysis procedure is presented in [21,32] and summarized as in the following steps:

Step 1. Construct intuitionistic fuzzy decision matrix $P = [p_{ijk}]_{m\times n\times l}$ to measure the performances of m alternatives based on n criteria by l experts;

Step 2. Develop the weighted normalized decision matrix by the associated weights of the criteria as:

$$r_{ijh} = w_{jh} p_{ijh} \quad i = 1, 2, ..., m; \quad j = 1, 2, ..., n; \quad h = 1, 2, ..., l, \qquad (5)$$

where w_{jh} is the weight of the jth attribute or criterion by the hth expert, and $\sum_{j=1}^{n} w_{jh} = 1$; $h = 1, 2, ...l$;

Step 3. Construct aggregated weighted intuitionistic fuzzy decision matrix, $F = [f_{ij}]_{m\times n}$:

$$f_{ij} = r_{ij1} \oplus r_{ij2} \oplus ... \oplus r_{ijl} \qquad i = 1, 2, ..., m; \quad j = 1, 2, ..., n. \qquad (6)$$

Step 4. Define positive-ideal points, F_j^+, and negative-ideal ones, F_j^-:

$$\begin{aligned}F_j^+ &= \{f_1^+, f_2^+, ..., f_n^+\}\\&= \left\{\left(\max_{i=1}^{m} f_{ij}|j \in B\right), \left(\min_{i=1}^{m} f_{ij'}|j' \in C\right)\right\}, \qquad (7)\end{aligned}$$

$$\begin{aligned}F_j^- &= \{f_1^-, f_2^-, ..., f_n^-\}\\&= \left\{\left(\max_{i=1}^{m} f_{ij'}|j' \in C\right), \left(\min_{i=1}^{m} f_{ij}|j \in B\right)\right\}, \qquad (8)\end{aligned}$$

where B is associated with benefit criteria, and C is associated with cost criteria;

Step 5. Calculate the Euclidean distances from f_{ij} to f_j^+ and f_j^- with Eq. (3):

$$\begin{aligned}D_i^+ &= d(f_{ij}, f_j^+)\\&=\sqrt{\frac{1}{n}\sum_{j=1}^{n}\left\{(\mu_{f_{ij}}-\mu_{f_j^+})^2+(v_{f_{ij}}-v_{f_j^+})^2+(\pi_{f_{ij}}-\pi_{f_j^+})^2\right\}}, \qquad (9)\end{aligned}$$

and:

$$\begin{aligned}D_i^- &= d(f_{ij}, f_j^-)\\&=\sqrt{\frac{1}{n}\sum_{j=1}^{n}\left\{(\mu_{f_{ij}}-\mu_{f_j^-})^2+(v_{f_{ij}}-v_{f_j^-})^2+(\pi_{f_{ij}}-\pi_{f_j^-})^2\right\}}. \qquad (10)\end{aligned}$$

Step 6. Calculate the relative closeness to the ideal solution. The overall distance of the alternative ith can be defined as follows:

$$D_i^* = \frac{D_i^-}{D_i^- + D_i^+} \qquad i = 1, 2, ..., m. \qquad (11)$$

Step 7. Rank the preference order. Obviously, a larger value of D_i^* represents a better overall performance of alternative i.

3. CN formation criteria considering matching characteristics

In this section, we firstly analyze the collaborative patterns of a CN following its concepts given by previous research papers. Then, the criteria are presented to solve the problem of building CNs considering the developed collaborative patterns and matching characteristics.

3.1. Collaborative patterns of CNs

Nowadays, more and more companies are outsourcing components and services to suppliers around the world and focusing on their own core competitiveness. The emergence of CNs paradigm offers new possibilities for effective and agile organization of future manufacturing systems and provides an essential cooperation model for SMEs. In order to comprehend the collaborative patterns of CNs, it is essential to investigate the concept and understand the connotation of CNs. Camarinha-Matos et al. [33] considered that a CN is a network consisting of a variety of entities (e.g., organizations and people) that are largely autonomous, geographically distributed, and heterogeneous in terms of their operating environment, culture, social capital and goals, yet collaborating to better achieve common or compatible goals, and thus jointly generating value, whose interactions are supported by a computer network. Another definition of CN is the collection of businesses, individuals, and other organizational entities that possess the capabilities and resources needed to achieve a specific outcome [34]. The above concepts summarize the basic characteristics of CNs and necessary capable technology which lead to the achievement of a common goal without referring to collaborative patterns. However, the discussion of collaborative patterns can be viewed from other fields; for example, Wang et al. [35] investigated nine coordination types of product development. Through investigating different cooperation patterns from other research fields and combining the connotation of CNs, the basic collaborative patterns of CNs are generalized as follows, shown in Figure 2:

- Flow type means that the output of one partner is employed by another partner. For example, automobile manufacturers purchase steels from material suppliers. This type is simple and commonly viewed;

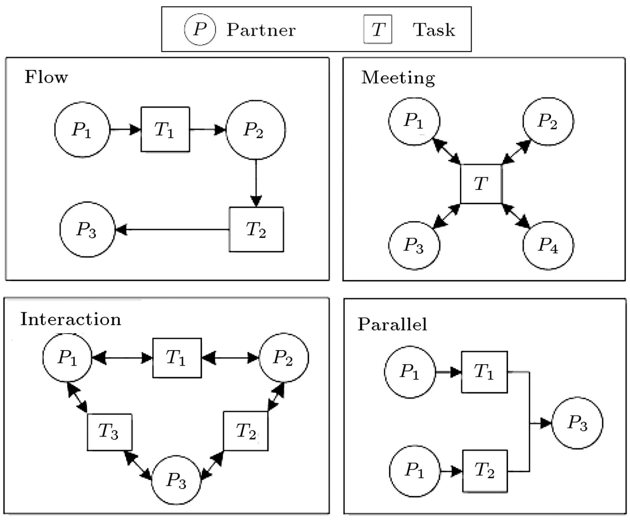

Figure 2. Collaborative patterns of CNs.

- Meeting type implies mutual engagement of participants to solve a problem together at the same time, implying mutual trust that requires time, effort, and dedication. The individual contributions to the value creation are much more difficult to determine here. Moreover, some technical meetings are held with interdisciplinary specialists to negotiate about special design information, e.g. "meeting regarding product specification negotiation with the customer." Recently, because of the advent of ICT, technical meetings are sometimes held in cyberspace with the support of design applications, e.g. virtual design support tools [36];
- Interaction type shows that two partners communicate their demands, methods, results, and goals to each other until the outputs meet the criteria; it is a typical iteration loop. Interaction is essential for the successful merge of processes in cooperation. This type and flow type can be supported by the workflow technology;
- Parallel type presents any two partners with no business relationship at the time dimension. This type can be generally ignored due to its independence.

3.2. Matching criteria for CN formation

The matching criteria can be deduced from the above collaborative patterns. Flow pattern shows the time series relationship and resources dependence between partners. Therefore, the supply matching factor can be applied to evaluate the performance of flow pattern from the view of resources supply and sharing. Interaction and meeting is essential for fulfilling the goals of collaboration where partners have to act jointly. The collaboration performance is linked to the performance of interactions. Considering the abovementioned definition of CNs, the goal, culture, and enabled technology can be employed as the evaluation indicator of interaction and meeting type. In this way, an evaluation hierarchy for partner selection of CNs is constructed, as presented in Table 1. The hierarchy involves four types of criteria, supply matching, goal matching, culture matching, and ICT matching attributes, all of which are finalized according to the aforementioned literature and the real requirements of the formation of CNs considering the matching characteristic. Brief descriptions of these sub-attributes are expounded in Table 1.

1. **Supply matching:** The supply capability of a company is essential to achieve the objective of delivering the right products with right quantity, quality, and price to the right price at the right time. Therefore, it is demanded that any partner have good production and logistics capability, involving production and manufacturing ability (e.g., production volume flexibility, capabilities to provide

Table 1. Matching criteria of partner selection for CNs.

Criteria	Sub-criteria	Descriptions
Supply matching (C_1)	Production and manufacturing ability (C_{11})	The partner has either an innovative manufacturing technology or advanced equipment to produce high-quality products with flexible volume.
	Supply reliability/ flexibility (C_{12})	The partner has supply capability which is enough flexible and reliable to deliver product at appropriate time to meet the changing customer demands.
	Supply quantity matching (C_{13})	The partner supplies products in matching quantity following the BOM of product in order to reduce the inventory.
	Task collaboration (C_{14})	This refers to the extent to which the partners finish the task collaboratively, which is important for interaction of information between partners.
Goal matching (C_2)	Goal congruence (C_{21})	The partners have a similar goal, which enhances the consistency of expectations and assures mutual gains and mitigates the conflict behavior.
	Resource complementarity (C_{22})	The partners have manufacturing resource that is distinct, yet complementing one another for the foreseen opportunity.
	Accessing to product/service/ target market (C_{23})	The partners can understand competitors and customers, predict the potential business opportunity, and share this opportunity together.
	Sharing of risks and profits (C_{24})	The partners share risks and profits to guarantee the collaboration successfully.
Culture matching (C_3)	Similar cultural background (C_{31})	The partners have similar values and briefs.
	Work motivation (C_{32})	The partners have work motivation policy to encourage the enthusiastic work of employees.
	Organization teamwork (C_{33})	The partners have organization teamwork sprint to achieve effective cooperation.
	Commitment (C_{34})	This refers to the extent to which the partner would fulfill its duties following the contracts.
	Trust (C_{35})	This refers to the extent to which the partners have an established integrity relationship.
ICT matching (C_4)	Information system construction (C_{41})	The partners have established information systems such as ERP/CRM/SCM/MES/PDM/OA or will fund to upgrade the present systems.
	Interface compatibility (C_{42})	This refers to the extent to which the partners can interoperate the heterogeneous systems in different organizations.
	Information sharing extent (C_{43})	This refers to the extent to which information will be shared among the partners.

quality product, etc.), supply reliability/flexibility (e.g., delivery capacity and reliability, order lead time, etc.), and supply quantity matching;

2. **Goal matching:** Goal matching requires relatively high levels of goal congruence and the sharing of some general paradigms helping participants determine collective interest and guaranteeing the inter-organizational cooperation between partners. Goal congruence is defined as the extent to which common goals can be achieved by firms, and multiple interactions help firms understand each other's constraints and opportunities [36,37]. Accordingly, the conflict behavior can be mitigated, leading to superior performance that is mutually beneficial. In the cooperation mode of resource interdependence and complementarity, the cooperators are sure to share risks and profits to access the product/service target market rapidly and flexibly, further expanding market share;
3. **Culture matching:** Culture matching is an important evaluation factor in inter-organization collaboration. Similar cultural background paves the path for effective communication among partners because they have compatible cognitions, expectations, mindsets, norms, values, and similar beliefs. Work motivation can increase job enthusiasm and keep employees motivated to devote themselves to jobs in companies, emboding the aggressive aspect of organization culture. Further, the inter-organization teamwork expresses a cooperation sprint, which has a potential acceleration for collaboration leading to practical benefits. In addition, commitment and trust bring about integrity in business activities between partners when performing their respective duties;
4. **ICT matching:** With the advent and development of ICT, available methods and means to support collaboration among partners have resurfaced. ICT matching mainly measures the integration and interoperation of heterogeneous systems. Funding in information system construction and upgrading is essential for the above target. In addition, interface compatibility of business information systems and information sharing extent in CNs determine the information interaction to a great degree.

4. The intuitionistic fuzzy OWA-TOPSIS method

The proposed intuitionistic fuzzy OWA-TOPSIS method provides a general framework of information aggregation regarding multiple pairs of extreme fuzzy points and multiple criteria. Chen et al. [38] generalized the OWA-TOPSIS method based on distance aggregations including internal aggregation, external aggregation I, and external aggregation II. Moreover, the aggregation process changes when OWA-TOPSIS extends to intuitionistic fuzzy environment. Firstly, we determine the weight vector of IFOWA, and then aggregate the IFOWA operator into the TOPSIS approach with IFN comparison. The intuitionistic fuzzy OWA-TOPSIS is outlined as follows:

Step 1. Constructing intuitionistic fuzzy assessment matrix, $P = [p_{ijh}]_{m\times n\times l}$, to measure the performances of m alternatives based on n criteria by l experts;

Step 2. Determining associated weight vector, $W^* = (w_1^*, w_2^*, ..., w_l^*)^T$, of IFOWA. Moreover, the fuzzy linguistic quantifier approach [30,39] is employed to obtain the associated weight vector;

Step 3. Applying IFOWA operator to aggregate the evaluation of experts on alternatives to different criteria:

$$\begin{aligned} R &= \mathrm{IFOWA}_{W^*}(p_{ij1}, p_{ij2}, ..., p_{ijh}, ..., p_{ijl}) \\ &= w_1^* p_{ij\sigma_1} \oplus ... \oplus w_k^* p_{ij\sigma_h} \oplus ... \oplus w_l^* p_{ij\sigma_l} \\ &= \left(1 - \prod_{h=1}^{l} (1-\mu_{p_{ij\sigma_h}})^{w_h^*}, \prod_{h=1}^{l} (v_{p_{ij\sigma_h}})^{w_h^*}\right), \end{aligned} \tag{12}$$

where $p_{ij\sigma_h}$ is the hth largest of IFN in the order relation. Further, the comparison between any two IFNs is detailed in Step 5. The aggregated intuitionistic fuzzy decision matrix is expressed as in $R = [r_{ij}]_{m\times n}$;

Step 4. Developing weighted evaluation matrix, $F = [f_{ij}]_{m\times n}$, by the associated weight vector of criteria $\tilde{W} = (\tilde{w}_1, \tilde{w}_2, ..., \tilde{w}_i, ..., \tilde{w}_n)$:

$$f_{ij} = \tilde{w}_j r_{ij} = (1 - (1-\mu_{r_{ij}}))^{\tilde{w}_j}, v_{r_{ij}}^{\tilde{w}_j}). \tag{13}$$

Step 5. Determining the positive-ideal and negative-ideal points of $F = [f_{ij}]_{m\times n}$. Let F_j^+ and F_j^- be intuitionistic fuzzy positive-ideal and intuitionistic fuzzy negative-ideal set for criterion j, respectively. Then, F_j^+ and F_j^- can be obtained by Eqs. (7) and (8). In this step, the essential issue is to compare two IFNs. Boran et al. [21] obtained the positive-ideal and negative-ideal points by calculating the maximum membership degree and minimum non-membership degree separately, and they overlooked the comparison of two IFNs. Xu [28] presented a method for the comparison between two IFNs by calculating score and accuracy functions. In this study, this method is employed to identify the positive-ideal and negative-ideal points.

Subsequently, the alternatives are ranked according to Steps 5-7 in Section 2.3.

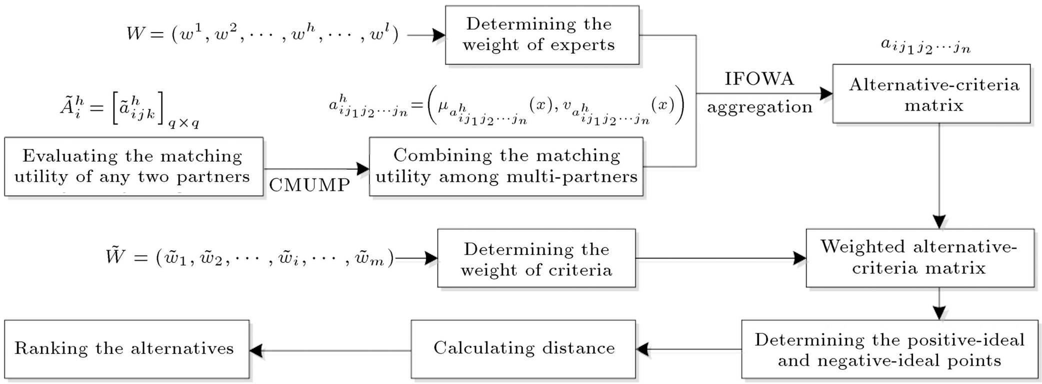

Figure 3. Partner combination selection with intuitionistic fuzzy OWA-TOPSIS.

Table 2. Linguistic terms for the importance and performance rating of each criterion.

Linguistic terms		IFS
Very High (VH)	Very Important (VM)	(0.9, 0.1-π)
High (H)	Important (I)	(0.7, 0.3-π)
Medium (M)	Medium (M)	(0.5, 0.5-π)
Low (L)	Unimportant (U)	(0.3, 0.7-π)
Very Low (VL)	Very Unimportant (VU)	(0.1, 0.9-π)
It does Not Matter (NM)	It does Not Matter (NM)	(0.0, 0.0-π)

5. The proposed partner combination model for building CNs

Based on the criteria of building CNs presented in Section 3, we propose a combination model of matching value of multi-partners to solve the CN formation problem. In the proposed model, firstly, the CNs formation problem is described. Then, the selection criteria and their weights are determined. Then, the matching value of each of two candidate partners is assessed by experts, and the matching values are combined to calculate the combination matching utility among multi-partners. Furthermore, the combination matching utility among multi-partners in the form of IFNs is mapped onto the crisp numbers by intuitionistic fuzzy OWA-TOPSIS to achieve the final ranking of all candidate partners' combination. The process is shown in Figure 3, and the details of the proposed model are presented as follows.

5.1. Problem description

Assume that an enterprise wins a manufacturing task; however, it is not able to complete the whole task due to deficiency of resources and technologies. Therefore, enterprises need to outsource the manufacturing task and call several tenderers from a manufacturing industry cluster to fulfill this task collaboratively. The enterprise decomposes the task into several subtasks and determines the number of partners to recruit to build a CN. Then, the partner selection problem in the formation of a CN is described as follows.

Let $P=\{P_j|j=1,...,q;q\geq 1\}$ be a finite candidate partner set, where P_j is the jth candidate. Let $E=\{E_h|h=1,...,l;l\geq 2\}$ be a finite expert set and E_h is the hth expert invited to conduct the partner evaluation. Let $C=\{C_i|i=1,...,m\}$ be a finite criteria set whose criterion has been discussed above. Expert E_h utilizes linguistic terms to assess the weights and matching extent of each criterion based on six scales of IFN, as depicted in Table 2 [40].

5.2. Determining the weights of evaluation experts

The importance of experts $e_h(h=1,...,l;l\geq 2)$ can be evaluated using the linguistic terms defined in Table 2. Let intuitionistic number, $E_h=(\mu_h,v_h)$ $h=(1,2,...,l)$, be the rating value of the hth expert. Then, the weight of the hth expert is obtained using Eq. (14):

$$w^h=\frac{CM_h}{\sum_{h'=1}^{l}CM_{h'}}, \tag{14}$$

where CM_h represents the complete membership score of IFN on expert h. The expert weight vector, $W=(w^1,w^2,...,w^h,...,w^l)$, can be obtained in this way.

5.3. Determining the weights of matching criteria

This section introduces a new resolution process for determining the linguistic weights of matching criteria.

Let $\tilde{W} = (\tilde{w}_1, \tilde{w}_2, ..., \tilde{w}_i, ..., \tilde{w}_m)$ be the weight vector of criteria. We obtain weights via IFS operations based on [41,42], as described in the following steps:

1. Evaluating the importance of each criterion $e_h(h = 1, ..., l; l \geq 2)$ through $c_i(i = 1, ..., m)$ experts who employ the linguistic terms defined in Table 2. Let $U = \{\tilde{u}_i^h | i = 1, ..., m;\ h = 1, ..., l\}$ be the evaluation of the importance of matching criteria;
2. Investigating the similarity between any two experts' evaluations for each specific criterion, c_i . The similarity between $\tilde{u}_i^h$ and $\tilde{u}_i^{h'}$, which is denoted as $S(\tilde{u}_i^h, \tilde{u}_i^{h'})$, can be obtained via the following equation:

$$S\left(\tilde{u}_i^h, \tilde{u}_i^{h'}\right) = 1 - \frac{1}{2}\left(|\mu_{\tilde{u}_i^{h_1}} - \mu_{\tilde{u}_i^{h'}}| + |v_{\tilde{u}_i^{h_1}} - v_{\tilde{u}_i^{h'}}|\right). \quad (15)$$

3. Developing an agreement matrix $AM_i = [S(\tilde{u}_i^h, \tilde{u}_i^{h'})]_{l\times l}$ for showing each similarity between each pair of experts.

$$AM_i = \begin{bmatrix} 1 & S(\tilde{u}_i^1, \tilde{u}_i^2) & \dots & S(\tilde{u}_i^1, \tilde{u}_i^l) \\ S(\tilde{u}_i^2, \tilde{u}_i^1) & 1 & \dots & S(\tilde{u}_i^2, \tilde{u}_i^l) \\ \vdots & \vdots & \vdots & \vdots \\ S(\tilde{u}_i^l, \tilde{u}_i^1) & S(\tilde{u}_i^l, \tilde{u}_i^2) & \dots & 1 \end{bmatrix}. \quad (16)$$

4. Calculating the average agreement degree, AAD^h, for each single expert, e_h:

$$AAD_i^h = \frac{1}{l}\sum_{h'=1}^{l} S\left(\tilde{u}_i^h, \tilde{u}_i^{h'}\right). \quad (17)$$

5. Obtaining the relative average agreement degree, $\tilde{w}_i^h$, for each single expert, e_h:

$$\tilde{w}_i^h = \frac{AAD_i^h}{\sum_{h'=1}^{l} AAD_i^{h'}}. \quad (18)$$

6. Calculating the weighted relative average agreement degree, $\tilde{w}_i$, by aggregating the weights of experts:

$$\tilde{w}_i = \sum_{h=1}^{l} w^h \tilde{w}_i^h. \quad (19)$$

5.4. Assessing the matching utility between any two partners

The CN formation problem with IFN $\tilde{a}_{ijk}^h$ estimates partners' judgments on matching extent of candidates P_j and P_k with respect to attribute C_i. In this respect, let $\tilde{A}_i^h = [\tilde{a}_{ijk}^h]_{q\times q}$ be the decision matrix in the form of IFNs expressed in a matrix format as follows:

$$\tilde{A}_i^h = \begin{bmatrix} \tilde{a}_{i11}^h & \tilde{a}_{i12}^h & \dots & \tilde{a}_{i1q}^h \\ \tilde{a}_{i21}^h & \tilde{a}_{i22}^h & \dots & \tilde{a}_{i2q}^h \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{a}_{iq1}^h & \tilde{a}_{iq2}^h & \dots & \tilde{a}_{iqq}^h \end{bmatrix}, \quad \begin{pmatrix} h = 1, ..., l \\ i = 1, ..., m \end{pmatrix}. \quad (20)$$

In matrix $\tilde{A}_i^h$, the assessment value of matching utility between candidates P_j and P_k is equal to the one between candidates P_k and P_j due to the characteristics of matching attributes in Table 1, i.e. $\tilde{a}_{ijk}^h = \tilde{a}_{ikj}^h$. Thus, matrix $\tilde{A}_i^h$ is a symmetrical matrix.

5.5. Combining the matching utilities among multi-partners

It is essential to assess the combination matching utility in the CN. Assume that the enterprise has n subtasks, and each one has to be finished by one cooperative company. Due to the complexity of collaborative process, it is difficult to solve multi-partners selection problem with matching utility between any two partners. Therefore, we attempt to transfer matching utilities between any two partners into n partners based on the IFN operation. Therefore, the definition of combination matching utility among multi-partners is given in the following.

Definition 7. Combination Matching Utility of Multi-Partners (CMUMP) is used to measure the matching extent of multiple partners considering matching factors, such as culture, objective, and ICT, for constructing a CN. Assume that matching utility among n partners can be calculated by the matching utility among $n-1$ partners. In terms of the attitudes of experts, we introduce a matching factor $\lambda(0 \leq \lambda \leq 1)$, so the CMUMP $a_{ij_1j_2\cdots j_n}^h = (\mu_{a_{ij_1j_2\cdots j_n}^h}(x), v_{a_{ij_1j_2\cdots j_n}^h}(x))$ can be computed by integrating the optimistic CMUMP $a_{ij_1j_2\cdots j_n}^{h+}$ and pessimistic CMUMP $a_{ij_1j_2\cdots j_n}^{h-}$; the formulas are as follows:

$$\begin{cases} \mu_{a_{ij_1j_2\cdots j_n}^h}(x) = \mu_{a_{ij_1j_2\cdots j_n}^{h-}}(x) \\ \quad + \lambda\left(\mu_{a_{ij_1j_2\cdots j_n}^{h+}}(x) - \mu_{a_{ij_1j_2\cdots j_n}^{h-}}(x)\right) \\ v_{a_{ij_1j_2\cdots j_n}^h}(x) = v_{a_{ij_1j_2\cdots j_n}^{h+}}(x) \\ \quad + (1-\lambda)\left(v_{a_{ij_1j_2\cdots j_n}^{h-}}(x) - v_{a_{ij_1j_2\cdots j_n}^{h+}}(x)\right) \end{cases} \quad (21)$$

In addition:

$$\begin{aligned} a_{ij_1j_2\cdots j_n}^{h+} =& a_{ij_1j_2\cdots j_{n-1}}^{h+} \cup a_{ij_1j_2\cdots j_{n-2}j_n}^{h+} \cup \dots \\ & \cup a_{ij_1j_2\cdots j_{n-m}j_{n-m+2}\cdots j_{n-1}j_n}^{h+} \cup \dots \\ & \cup a_{ij_2\cdots j_{n-2}j_{n-1}j_n}^{h+}, \end{aligned} \quad (22)$$

and:

$$a^{h-}_{ij_1j_2\cdots j_n} = a^{h-}_{ij_1j_2\cdots j_{n-1}} \cap a^{h-}_{ij_1j_2\cdots j_{n-2}j_n} \cap \cdots \cap a^{h-}_{ij_1j_2\cdots j_{n-m}j_{n-m+2}\cdots j_{n-1}j_n} \cap \cdots \cap a^{h-}_{ij_2\cdots j_{n-2}j_{n-1}j_n}, \tag{23}$$

where:

$$j_1, j_2, ..., j_n \in P, \qquad P=\{P_j|j=1,...,q; q\geq 2\},$$

$$j_1 \neq j_2 \neq ... \neq j_n, \qquad m < n.$$

In this way, overall matching utility $a^h_{ij_1j_2\cdots j_n}$ of partners $j_1, j_2, ..., j_n$ can be computed based on $\tilde{A}^h_i$. The aggregation results of $a^h_{ij_1j_2\cdots j_n}$ still represent an IFN.

5.6. Applying intuitionistic fuzzy OWA-TOPSIS method to order-ranking process

Due to the aggregation results, $a^h_{ij_1j_2\cdots j_n} = (\mu_{a^h_{ij_1j_2\cdots j_n}}(x), v_{a^h_{ij_1j_2\cdots j_n}}(x))$ are still an IFN and they can be the inputs of the intuitionistic fuzzy OWA-TOPSIS procedure. Then, outputs of the ranking of partner combination selection problem are obtained.

6. System development and application

Ma et al. [43] developed a decision support system (*Decider*) for multi-attribute group decision-making problems. However, it is not convenient for evaluators to perform *Decider* because it cannot be available in the web environment. Moreover, *Decider* is a general system and lacks a meticulous aggregation method, which needs to be extended to solve the CN construction problems. Therefore, it is necessary to extend the existing system by integrating a new approach into the system. Herein, a decision support system of building CNs for SMEs is designed and developed, which can enable the efficient information collection, expert evaluation, and data aggregation. This section will introduce the structure and functions of the system. Then, an application case in a practical enterprise is illustrated to demonstrate the advantage of the proposed evaluation approach.

6.1. Structure of the system

The system is developed using the ASP.NET programming language for running on the web environment to cater for the distributed users. Moreover, the system is constructed for SMEs to select matching collaborators, thereby integrating the existing manufacturing resources into CNs to cover shortages of each enterprise. It is currently composed of four main modules, i.e. information collection, expert evaluation, data aggregation, and result analysis. Of course, some basic system settings and data management are added into the system in order to make it more flexible and configurable. The four main modules are interpreted in detail as follows.

6.1.1. Information collection

In terms of the information of criteria, experts, and candidates involved in the decision-making process, this module provides an input interface for this information. It is critical to collect information of candidates around each criterion. Generally, this information is expressed in the form of a text. Therefore, the alternatives need to provide a detailed description to support the evaluation of each criterion. For the criterion of manufacturing ability, for example, the candidate enterprise needs to provide some data such as machine capability and utilization, processed capability, and production volume of each part and product.

6.1.2. Expert evaluation

From the above discussion, criteria to be used in building CNs include production and manufacturing ability, supply reliability/flexibility, supply quantity matching, task collaboration, goal congruence, resource complementarity, accessing product/service/target market, sharing of risks and profits, similar cultural background, work motivation, organization teamwork, commitment, trust, information system construction, interface compatibility and information sharing extent. Experts are given the task of assessing the matching criteria using the linguistic terms in Table 2 to produce the importance rating, and the weights of criteria can be determined by the method depicted in Section 5.3. On the basis of the data from alternatives, the experts need to evaluate the matching utility of each of two enterprises, and evaluation results are expressed and represented as IFNs.

6.1.3. Data aggregation

This module is crucial to the system, which realizes the data aggregation process shown in Figure 3. We also integrate some existing aggregation methods, such as IFWA-TOPSIS [21], into the system. During the combination matching process, different matching factors can be employed to show the matching attitudes of experts. In addition, the pessimistic CMUMP, optimistic CMUMP, and average CMUMP can be obtained. Furthermore, we can apply different operators to obtain the ranks of alternatives.

6.1.4. Result analysis

After execution of data aggregation process, the overall assessments of alternatives are displayed to the user. The users can analyze the results based on cooperation experience and modify the model parameter to facilitate adaption to the practical application.

6.2. Case study

6.2.1. An application case

The system has been used and tested in a medium-sized manufacturing firm (*Sinima-TS*) which produces building materials equipment, such as rotary kiln, tube mill, and vertical mill, to select the optimal partner combination to finish the cement grinding mill assembling task. The cement grinding mill includes five parts, i.e. Feeding Device (FD), Feed-End Slipper Bearing (FESB), rotating part (RT), Discharge End Slipper Bearing (DESB), and Discharging Device (DD). Moreover, the assembling task is decomposed into 6 sub-tasks, producing RT, FD, FESB, DESB and DD, assembling FD and FESB as Front Part (FP), assembling DESB and DD as End Parts (EP), and assembling FP, RT, and EP. In order to focus on the core assembly ability, the three production tasks need to be outsourced to other three enterprises. By investigating five candidates, enterprises are shown to have the capability to finish the tasks. In order to obtain highly efficient collaboration among these enterprises, four experts are invited from building materials equipment industry to assess matching extent. Further, the importance weights of the four experts are assessed by decision-makers. The matching utilities of any two partners are evaluated by four experts, as shown in Figure 4. Further, the matching utilities of three partners are aggregated based on matching factor λ=(0.50, 0.60, 0.60, 0.40, 0.60, 0.40, 0.60, 0.40, 0.60, 0.55). The associated weight vector is determined based on the fuzzy linguistic quantifier approach [30,39], and the fuzzy linguistic quantifier is set as $\alpha = 0.5$, i.e. $W^* = (0.500, 0.207, 0.159, 0.134)$. Furthermore, the final ranking results shown in Figure 5 can be obtained with intuitionistic fuzzy OWA-TOPSIS approach. The result shows that the combination of partners ranking in the descending order is P_{245}, P_{345}, P_{124}, P_{235}, P_{125}, P_{135}, P_{234}, P_{123}, P_{145}, and P_{134}.

6.2.2. Comparison analysis

In this subsection, the comparison analysis has been done from aggregation operation and selection strategy.

1. IFOWA operator: In order to show the advantage of the proposed approach, we make a comparison analysis between IFWA and IFOWA aggregation into TOPSIS. If we do not consider the order weights in the TOPSIS procedure, the IFOWA operator reduces to IFWA one, and the TOPSIS procedure with IFOWA will be also reduced to TOPSIS procedure with IFWA. Herein, we set 5 experiments by changing associated weight vectors, shown in Table 3.

   Subsequently, we rank the alternatives using two different aggregation operators. The results are shown in Table 4. The ranking results are almost consistent for the IFOWA operator in terms of different associated weight vectors, and the best alternative is P_{245}, while the best one is P_{345} for

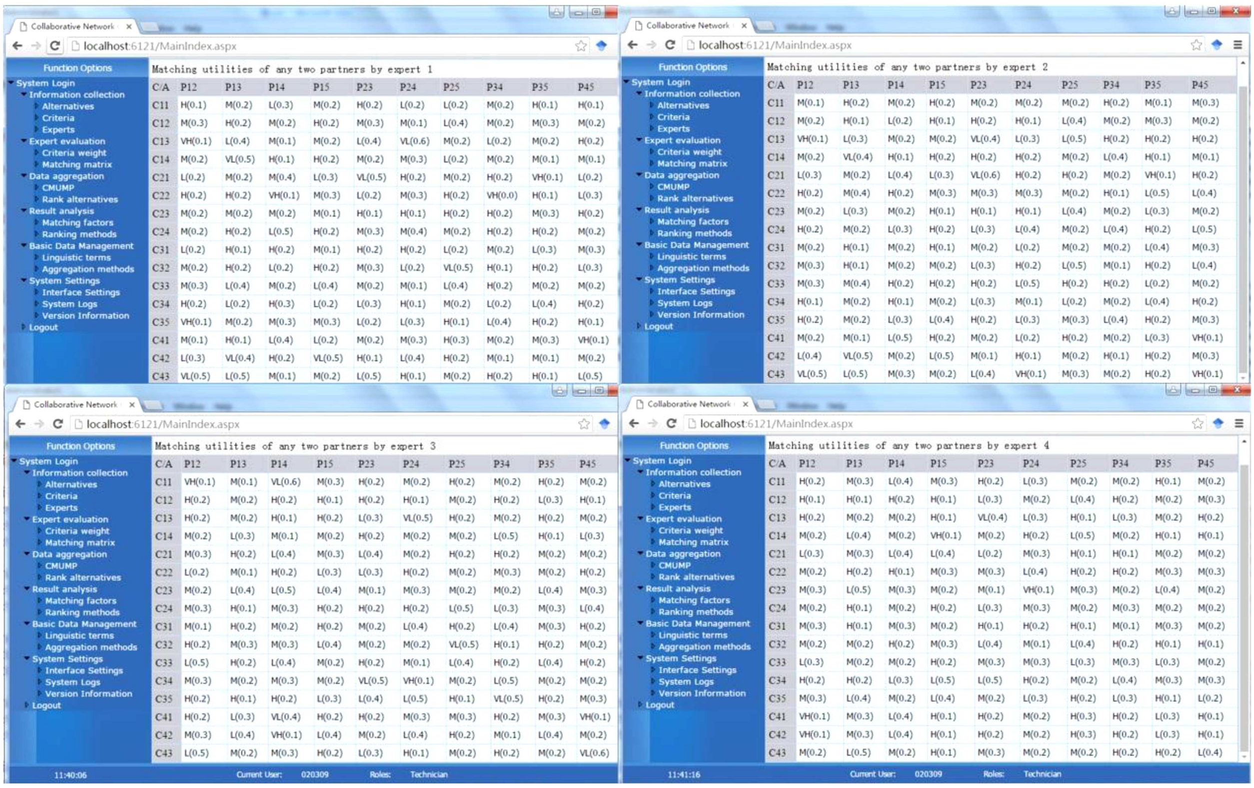

Figure 4. Matching utilities of any two partners evaluated by experts.

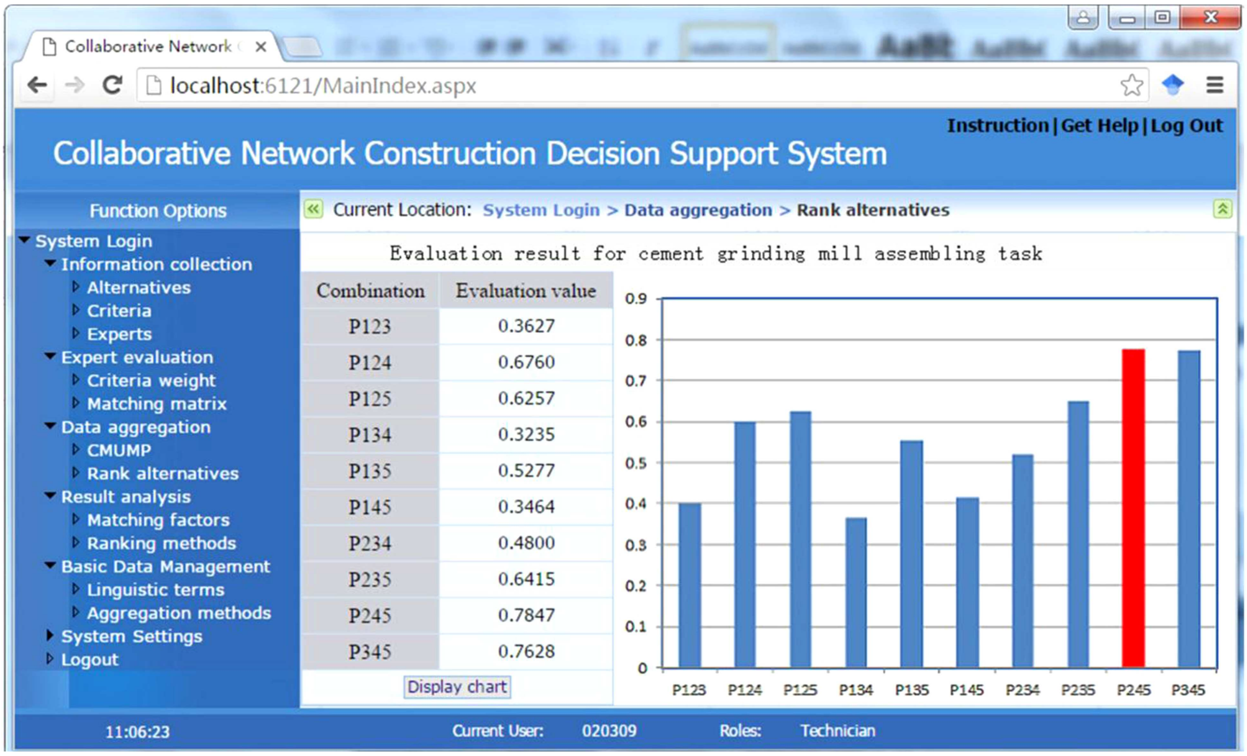

Figure 5. Final ranking results for partner combination selection.

Table 3. Ordered weights for different α.

Weights	$\alpha = 0.1$	$\alpha = 0.5$	$\alpha = 1$	$\alpha = 2$	$\alpha = 5$
r_1	0.871	0.500	0.250	0.063	0.001
r_2	0.062	0.207	0.250	0.187	0.030
r_3	0.039	0.159	0.250	0.313	0.206
r_4	0.028	0.134	0.250	0.437	0.763

IFWA operator, which is also different from the one with IFOWA operator and $\alpha = 1$. Therefore, they are two different operators. IFOWA operator weights only the ordered positions of the evaluation values, instead of weighting evaluation values themselves. In addition, the difference in the ranking orders with IFOWA can be found; for example, the best alternative is P_{345} for $\alpha = 5$, and P_{245} as the best alternative is considered for the other four α values with matching strategy. The results of the IFOWA operator have good robustness to associated weight vectors. The changes in order-ranking process based on different associated weight vectors can moderately reduce the influence of unfair arguments on the final results by assigning low-order weights to those unduly high or low ones;

2. Matching strategy: The proposed aggregation method realizes the CN formation for the firm case from the matching perspective view, called matching strategy. The matching strategy is different from the traditional partner selection. Obtaining the best partner based on its evaluation value is often reported in most partner selection academic papers [21,44], and we call the traditional method as the best strategy. In order to show the advantage of the proposed approach, a comparison

Table 4. Comparisons between two different aggregation operators.

Experiments		P_{123}	P_{124}	P_{125}	P_{134}	P_{135}	P_{145}	P_{234}	P_{235}	P_{245}	P_{345}
IFWA	—	0.4243	0.6870	0.6987	0.3596	0.6332	0.4535	0.5742	0.5245	0.7430	0.7449
IFOWA	$\alpha = 0.1$	0.3453	0.6826	0.5840	0.3088	0.4736	0.3082	0.4574	0.6275	0.7307	0.7152
	$\alpha = 0.5$	0.3627	0.6760	0.6257	0.3235	0.5277	0.3464	0.4800	0.6415	0.7847	0.7628
	$\alpha = 1$	0.3758	0.6394	0.6702	0.3078	0.5730	0.3818	0.5060	0.6594	0.8062	0.8037
	$\alpha = 2$	0.3670	0.5880	0.6406	0.3364	0.5969	0.4118	0.5078	0.6740	0.8142	0.8117
	$\alpha = 5$	0.3365	0.5327	0.5991	0.3760	0.5931	0.4099	0.5039	0.6851	0.8035	0.8098

analysis is made between two different strategies. Herein, we set 10 experiments by changing associated weight vectors shown in Table 3.

Next, the alternatives are ranked using two different strategies. Herein, we can calculate the average value of each matching group as the final result for the traditional partner selection method. The comparison results are shown in Table 5, and the changes of the final ranking in two different strategies are depicted in Figure 6.

As shown in Table 5, the ranking result is almost consistent for the two strategies in terms of different associated weight vectors. As shown in Figure 6, it is not very difficult to observe that the ranking results of those two strategies are obviously different. The most desirable alternative, P_{245}, is obtained by the matching strategy, while the best result is P_{345} for the best strategy. At the same time, the ranking order obtained by the matching strategy is different from the order presented through the best strategy. Moreover, we have conducted a survey about the performances of the system from the application enterprise *Sinima*-TS. The survey responses indicate that the proposed aggregation method can help *Sinima*-TS to select proper partners for finishing a manufacturing task collaboratively. Some performance indexes are improved such as project duration, on-time delivery, and response to task change.

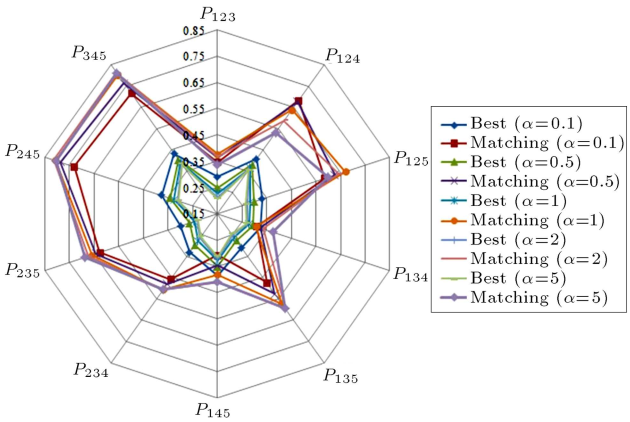

Figure 6. Comparison result of two different strategies.

The matching strategy considers the matching characteristic before the aggregation, fulfilling the practical needs for collaboration of multiple enterprises in the CN operation, while the best strategy overlooks the matching factors during the aggregation process. Therefore, the ranking order obtained by the proposed method with matching strategy is more suitable for CN formation than the traditional partner selection strategy.

6.2.3. Sensitivity analysis

A sensitivity analysis is conducted in order to investigate the impact of changes in matching factor, λ, on the solutions ranking. Herein, we overlook the weighting of IFOWA operator and set $\alpha = 1$. A slight variation in the original matching factor is as follows: $\lambda_i = \lambda_i \pm 0.05$ and twenty experiments are designed. Table 6 presents the details of the experiment. It can be seen in Table 6 that the value of λ in Ex. 1 is the same as that in the application case, undergoing different changes from Ex. 2 to Ex. 21.

Figure 7 depicts the changes in the final ranking of the solutions to form manufacturing CN when the matching factor changes. Based on Table 6 and Figure 7, out of 20 experiments, solution P_{245} has the highest score in 17 experiments (Ex. 2-Ex. 13, Ex. 15-Ex. 17, Ex. 19, and Ex. 20), which is the same as that in

Table 5. Comparisons between two different strategies.

Experiments		P_{123}	P_{124}	P_{125}	P_{134}	P_{135}	P_{145}	P_{234}	P_{235}	P_{245}	P_{345}
$a = 0.1$	Best	0.2902	0.4072	0.3327	0.3259	0.3094	0.3847	0.3314	0.2978	0.3755	0.4332
	Matching	0.3453	0.6826	0.5840	0.3088	0.4736	0.3082	0.4574	0.6275	0.7307	0.7152
$a = 0.5$	Best	0.2488	0.3814	0.3004	0.2947	0.2755	0.3502	0.2972	0.2630	0.3422	0.4043
	Matching	0.3627	0.6760	0.6257	0.3235	0.5277	0.3464	0.4800	0.6415	0.7847	0.7628
$a = 1$	Best	0.2270	0.3657	0.2826	0.2786	0.2598	0.3298	0.2788	0.2443	0.3243	0.3905
	Matching	0.3758	0.6394	0.6702	0.3078	0.5730	0.3818	0.5060	0.6594	0.8062	0.8037
$a = 2$	Best	0.2129	0.3593	0.2705	0.2720	0.2507	0.3203	0.2655	0.2304	0.3104	0.3844
	Matching	0.3670	0.5880	0.6406	0.3364	0.5969	0.4118	0.5078	0.6740	0.8142	0.8117
$a = 5$	Best	0.2063	0.3545	0.2660	0.2682	0.2454	0.3137	0.2590	0.2279	0.3076	0.3826
	Matching	0.3365	0.5327	0.5991	0.3760	0.5931	0.4099	0.5039	0.6851	0.8035	0.8098

Table 6. Experiments for sensitivity analysis.

Experiments	λ	P_{123}	P_{124}	P_{125}	P_{134}	P_{135}	P_{145}	P_{234}	P_{235}	P_{245}	P_{345}
Ex. 1	λ	0.3758	0.6394	0.6702	0.3078	0.5730	0.3818	0.5060	0.6594	0.8062	0.8037
Ex. 2	$\lambda_1 - 0.05$	0.3119	0.6470	0.6684	0.3228	0.5855	0.3828	0.5108	0.6613	0.8093	0.8068
Ex. 3	$\lambda_1 + 0.05$	0.4288	0.6345	0.6661	0.3012	0.5695	0.3766	0.5002	0.6585	0.8058	0.8028
Ex. 4	$\lambda_2 - 0.05$	0.3737	0.5667	0.6735	0.3026	0.5766	0.3795	0.5057	0.6621	0.8096	0.8082
Ex. 5	$\lambda_2 + 0.05$	0.3712	0.7054	0.6621	0.3039	0.5659	0.3770	0.5002	0.6559	0.8013	0.7991
Ex. 6	$\lambda_3 - 0.05$	0.3823	0.6430	0.6127	0.3138	0.5847	0.3849	0.5209	0.6667	0.8149	0.8097
Ex. 7	$\lambda_3 + 0.05$	0.3671	0.6252	0.7185	0.3007	0.5608	0.3731	0.4965	0.6487	0.7945	0.7920
Ex.8	$\lambda_4 - 0.05$	0.3867	0.6473	0.6783	0.2757	0.5808	0.3929	0.5157	0.6609	0.8077	0.8055
Ex. 9	$\lambda_4 + 0.05$	0.3529	0.6321	0.6617	0.3554	0.5701	0.3617	0.4952	0.6581	0.8043	0.8021
Ex. 10	$\lambda_5 - 0.05$	0.3757	0.6430	0.6735	0.3121	0.5228	0.3830	0.5086	0.6610	0.8082	0.8058
Ex. 11	$\lambda_5 + 0.05$	0.3678	0.6376	0.6565	0.3050	0.6307	0.3758	0.5007	0.6573	0.8072	0.7974
Ex. 12	$\lambda_6 - 0.05$	0.3758	0.6394	0.6702	0.3078	0.5730	0.3296	0.5060	0.6594	0.8062	0.8037
Ex. 13	$\lambda_6 + 0.05$	0.3758	0.6394	0.6702	0.3078	0.5730	0.4396	0.5060	0.6594	0.8062	0.8037
Ex. 14	$\lambda_7 - 0.05$	0.3795	0.6465	0.6722	0.3120	0.5797	0.3866	0.4514	0.6612	0.8075	0.8078
Ex. 15	$\lambda_7 + 0.05$	0.3682	0.6152	0.6516	0.3007	0.5614	0.3696	0.5698	0.6522	0.7947	0.7929
Ex. 16	$\lambda_8 - 0.05$	0.3767	0.6396	0.6706	0.3088	0.5730	0.3854	0.5078	0.6608	0.8065	0.8041
Ex. 17	$\lambda_8 + 0.05$	0.3694	0.6352	0.6664	0.3004	0.5681	0.3745	0.5002	0.6808	0.8059	0.8034
Ex. 18	$\lambda_9 - 0.05$	0.3828	0.6393	0.6771	0.3123	0.5791	0.3881	0.5195	0.6620	0.7791	0.8058
Ex. 19	$\lambda_9 + 0.05$	0.3659	0.6311	0.6464	0.3037	0.5625	0.3696	0.4993	0.6551	0.8354	0.8021
Ex. 20	$\lambda_{10} - 0.05$	0.3777	0.6426	0.6728	0.3094	0.5783	0.3835	0.5095	0.6612	0.8095	0.7748
Ex. 21	$\lambda_{10} + 0.05$	0.3729	0.6335	0.6642	0.3055	0.5689	0.3783	0.5010	0.6569	0.8037	0.8308

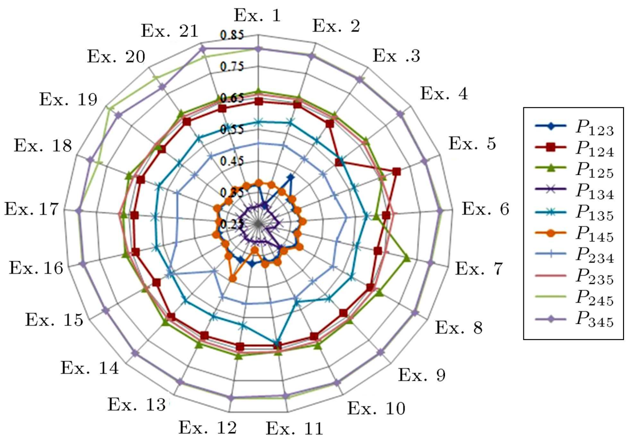

Figure 7. Result of sensitivity analysis.

Ex. 1. In the remaining 3 experiments, solution P_{345} has the highest matching value. The matching value significantly changes, while other solutions' rankings slightly change as its matching factor changes. For example, the matching value of P_{124} in Ex. 4 and Ex. 5 changes from 0.5667 to 0.7054, while the value fluctuates nearly 0.64 in other experiments. Hence, ranking the solutions for forming CN is relatively sensitive to the matching factor.

7. Conclusions

Partner selection is a critical issue in the formation of the CN and key to success of a CN. During the CN formation process, the matching utility amongst candidate partners was often ignored in previous researches. Therefore, this paper proposed a combination method for partner selection of CNs considering their matching utility. Next, a hybrid approach was designed to integrate IFOWA operators into the TOPSIS analysis procedure to achieve diverse fuzzy information aggregations to select the appropriate partner combination for CNs based on the matching factors developed as the criteria of CN formation. The proposed approach was compared with the traditional partner selection strategy. Moreover, the results show that the proposed method with matching strategy is more suitable for processing the collaboration utility for the CN formation. In addition, a sensitivity analysis was conducted to investigate the robustness of solutions ranking to changes in matching factor, λ. Further, the result shows that ranking the solutions for forming CN is relatively sensitive to its matching factor.

Moreover, it should be pointed out that the formation of CNs is a complicated problem in terms of different industries. Besides matching utility considered in this paper, non-matching utility (profit, risk, etc.) may be involved at the same time. Therefore, further research needs to be conducted to assess the risk during the CN formation process with regard to product structures and cost factors, and then improve the system.

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