Similarity-Based Experts Weighting of CBR-Based Multi-experts System in Partner Selection

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Abstract: - With the development of supply chain collaboration in agile manufacturing (AM), outsourcing has become a focus, in which partner selection is an important problem. Outsourcing decision is often related with expertise. The decision of partner selection needs to take opinions of multi-experts from various departments of enterprise into consideration. Expert system (ES) is one of the main branches that focus on expertise, and case-based reasoning (CBR) is a methodology for problem solving in complex environments. In this research, a new approach of similarity-based experts weighting in CBR-based multi-experts system (MES) was proposed to integrate expertise in outsourcing of AM. Foundational issues of expert weighting in CBR-based MES, including the R^6 model, assumption of delaminating structure of case and similarity-based experts weighting, were firstly discussed. Based on the R^6 model and assumptions, experts weighting mechanism in CBR-based MES was then built up, including weighting founded on consensus-based similarity and that founded on case-based similarity. Finally, the application of multi-experts weighting approach in supplier selection carried out.

Key-Words: - Outsourcing; Experts weighting; Case-based reasoning; Multi-experts System; Partner selection

1 Introduction

The global trend of outsourcing has resulted in companies' more dependent on their suppliers in agile manufacturing (AM) which is believed to be the strategy for being more competitive [1], [2]. Companies are now adopting intensive relationships with their supply base when realizing AM [3], which is one of the common features shared by the so-called virtual enterprise [4], extended enterprise [5], and supply chain. In general, the lifecycle of multi-firms' cooperation has three stages: creation, operation, and dissolution. Firms always choose some key suppliers to develop collaborative relationships with them in creation stage. Partner selection in companies' outsourcing strategy of AM has called broad attention. Various theories, such as AHP [6], Goal Programming Model [7], Ant Colony Optimization [8], etc., have been introduced into this area. In recent years, the development of artificial intelligence techniques provides a new way to research outsourcing partner selection in AM. The introduction of artificial intelligence technologies into outsourcing management could lead to the management of supplier intelligence.

Case-based reasoning (CBR) was employed to development an expert system (ES) for outsourcing operations [9]. In fact, partner selection in outsourcing strategy of AM is a typical multi-experts decision problem. When deciding which supplier is important and suitable for the supply chain cooperation in the framework of CBR-based ES, several departments of various firms in the same supply chain, such as outsourcing department, financial department, etc. should be involved in the decision process. Because outsourcing partners selection in AM is not just a one person decision. When a partner taking part in the AM strategy of a firm, there are always transactions and trades between it and the firm and its cooperators. That is to say, CBR-based ES in outsourcing management of AM, which is an expert system build-up in the framework of CBR, is always in the form of group decision. Hence, CBR-based multi-experts system (MES), which is an expert system build-up in the framework of CBR and multi-experts decision, is a more applicable way to realize outsourcing partner selection of AM.

Multi-experts decision is usually understood as the reduction of different individual preferences by knowledge. Its main goal is to get a final group consensus from individual preferences. CBR in outsourcing decision of AM carries on based on the group consensus. When a situation involves multi-experts, each with different knowledge, the final consensus will be integrated between this expert's preferences and those of others. In the integrated process, expert weighting is an inevitable problem that had to be studied in MES. Hence, when CBR is employed into the building-up of partner selection in companies' outsourcing strategy of AM, experts weighting in the framework of CBR-based MES is an inevitable research problem.

In this research, similarity-based experts weighting approach in CBR-Based MES is proposed to tackle expertise problem in outsourcing management of AM. The new approach can truly utilize experts' knowledge. The rest of the paper is divided into 4 sections. Section 2 is a discussion on several foundational issues of CBR-based MES in experts weighting of outsourcing partner selection, following by the building up of experts weighting mechanism in section 3. Section 4 is an application of similarity-based experts weighting process into supplier selection. Section 5 makes conclusion.

2 Foundational Issues of Experts Weighting in CBR-Based MES

2.1 Experts Weighting in MES

ES was developed in the mid-1960s, whose traditional basic idea is that expertise is transferred from a human to a computer and called on by users for specific advice as needed [10]. The development of such a knowledge-base system involves: identifying a real world problem solving task, representing key components, and implementing the inference process, the last two of which are involved in knowledge engineering process [11]. The task of developing a reasoning mechanism would be simpler, if the mechanism of producing a construction of the real-world knowledge is perfect. Whereas, expert knowledge is always qualitative and quantification value of experts' knowledge is subject to imprecision, uncertainty, and inconsistency, which is hard to be represented perfectly by knowledge engineering.

Case-based reasoning (CBR), which was firstly proposed by professor Schank, is one of the main problem solving methodology employed in ES [12], [13]. It is able to utilize the specific knowledge of previously experienced, concrete problem situations, instead of relying solely on general knowledge. As a result, CBR-based ES has called broad attention [14], [15], [16]. It is a feasible way to employ CBR-based MES in outsourcing partner selection. To enhance the efficiency of reasoning, implementing knowledge reasoning in the presence of experts had to be introduced as a supplementary of traditional reasoning implementation in the absence of experts. The parameters of experts' weights are a key to reasoning process in the situation of MES. Common methodologies traditionally used in experts weighting are those exiting ones of criterion weighting process such as directly giving weight, Analytic Hierarchy Process (AHP), Simos's procedure, etc., on the assumption of introducing a supra-actor [17], [18], [19]. Nevertheless, experts weighting and criterion weighting are not two sides of the same icon. Thus, some new methods of expert weighting must be developed in the situation of CBR-based MES.

2.2 R^6 Process-Oriented Model in CBR-Based MES

The traditional process-oriented model of CBR-based ES is the R4 model proposed by Aamodt and Plaza [20], [21] i.e. Retrieve, Reuse, Revise, and Retain. Because CBR is heavily dependent on the structure and content of case collection, Finnie and Sun [22] integrated case construction into the R4 model and proposed a R5 model. Hence, core problems addressed by CBR research society can be grouped into five areas, i.e. knowledge representation, retrieval methods, reuse methods, revise methods, and retain methods. The two Rx models can be shown in Fig. 1.

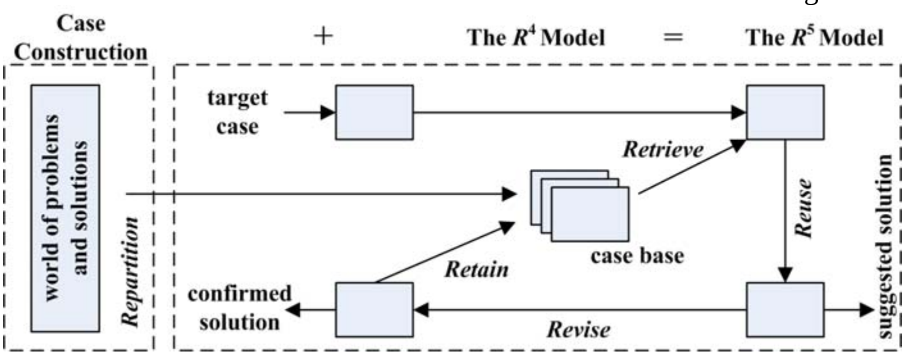

Fig. 1. The two R^x process-oriented models in CBR-based ES

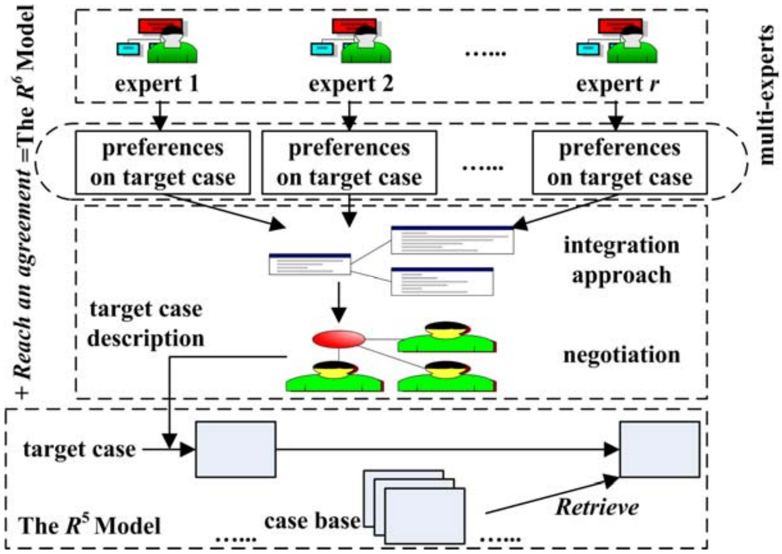

Fig. 2. The R^6 process-oriented model in CBR-based MES

In the situation of CBR-based MES, multi-experts are introduced into the traditional process-oriented model to strengthen retrieval methods. Thus, Reach an agreement is another R process. In many domain problems, especially in related areas of outsourcing management in AM, descriptions on target case are a hard job that involved lots of qualitative factors. Taking the sub-feature, promotion, of the feature, market mix, as an example [16], different experts may have different opinions on promotion of a firm. When dealing with these types of features, multi-experts decision is a feasible way to reduce individual preferences based on their knowledge and make the retrieval process more reasonable and effective. The difference between process-oriented model of CBR-based MES and the R5 model is mainly on retrieval process. In the retrieval process, multi-experts firstly draw out individual opinion on target case on the foundation of their expertise. In the following step, preferences on target case of each individual expert are integrated to form group consensus through integration approach, in which experts weighting is always employed. Then, multi-experts negotiate on the consensus. Finally, multi-experts' preferences on target case are formed. The R6 model can be shown in Fig. 2.

2.3 Assumption of Delaminating Structure of a Case

Taking case structure in CBR based marketing plans system [16] into account, there are lots of features of a case, including case name, case company, status analysis, objective, marketing mix, and so on. While, there are some sub-features of a feature, e.g. there are three sub-features, i.e. company name, business target, and market position, in the feature of case company. And there are four sub-features, i.e. price, product, channel, and promotion, in the feature of market mix. At the same time, the feature of product also has three sub-features, i.e. main product, sub product, and brand. Obviously, there are delaminating structures of a case. What we concerned in this research is the approach of experts weighting in CBR-based MES. Therefore, we can make the assumption that there is a two-level case structure in CBR-based MES. And experts weighting in this assumption can be extended to the situation of multi-level case structure easily, and can also be simplified to the situation of one-level case structure. The two-level case delaminating structure assumption is shown in Fig. 3.

2.4 Assumption of Similarity-Based Experts Weighting

Similarity-based experts weighting is a new weighting mechanism we proposed, in which an expert' weight is computed through the similarity between each expert's individual preference and the final decision result. The assumption of similarity-based experts weighting is that expert's decision accuracy is directly influenced by his or her domain knowledge. The more abundant his/her domain knowledge is the more accurate and reasonable his/her decision is, and the more heavily he should be weighted in multi-expert decision. While, traditional used experts weighting methods such as directly giving weight, AHP, and Simos' procedure, which can be called supra-actor-based expert weighting, is directly influenced by the assumptive supra actor's individual preferences. The assumption of it is that the supra actor have the ability to distinguish an expert's knowledge is abundant or not. If the supra actor considers knowledge of an expert as abundant, the expert should be weighted more. The assumption of similarity-based experts weighting is more reasonable and objective than that of supra-actor-based experts weighting. Decision accuracy of an expert can be defined by the similarity between single expert's preferences on feature values of target case and multi-experts' consensus on target case, and the corresponding relationship between each expert's preferences and the final retrieved result. The two assumptions are shown in Fig. 4.

3 Experts Weighting Mechanism in CBR-Based MES

The experts weighting mechanism is on the foundation of two types of similarities. One is similarity between individual expert's preferences on target case and multi-experts' final consensus description on it, which can be called as consensus-based similarity. The other is similarity between individual expert's preferences on target case and final retrieved cases, which can be called as case-based similarity. These two types of similarities incarnate decision accuracy of an expert. The two types of similarities and formalization representations can be shown in Fig. 5.

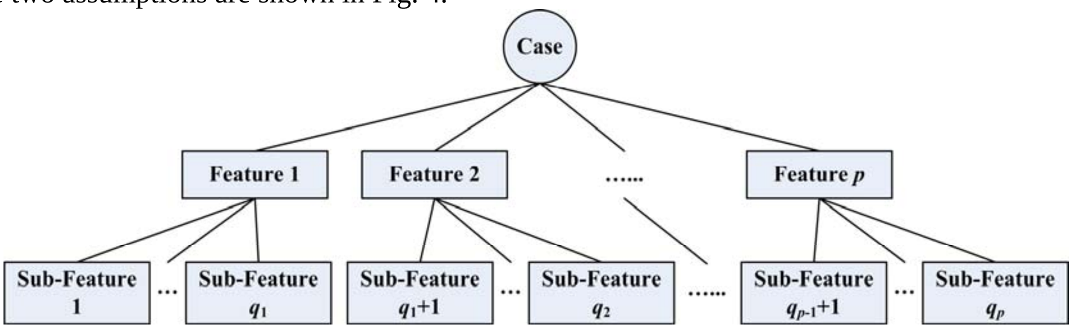

Fig. 3. Two-level case delaminating structure

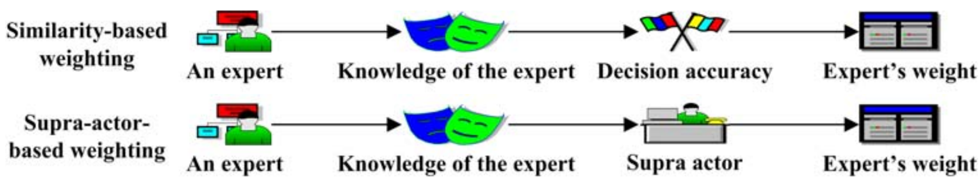

Fig. 4. Assumptions of similarity-based weighting and supra-actor-based weighting

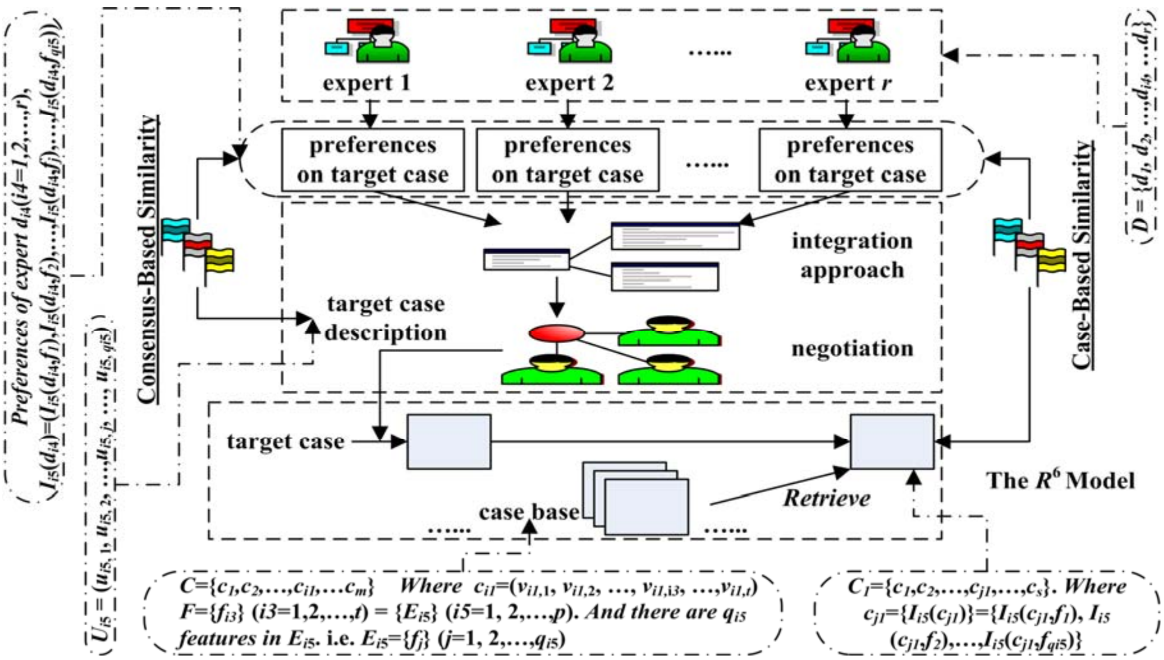

Fig. 5. Consensus-based similarity, case-based similarity and formalization representations

Case Library: Let $C=\{c_1,c_2,\ldots,c_m\}$ denote a case library and c_0 denote target case. Each case can be identified by a set of corresponding features, which can be expressed as $F=\{f_{i3}\}$ $(i3=1,2,\ldots,t)$. Based on two-level case delaminating structure assumption, $\{f_{i3}\}$ can be grouped into p classes. Each class consists of a sub-gather of features. Let E_{i5} $(i5 = 1, 2,\ldots,p)$ denote a class library. Thus, $F=\{E_{i5}\}$. Each class includes a set of sub-features, which can be denoted as $\{f_j\}$ $(j=1,2,\ldots,q_{i5})$.

Multi-experts: Let $D = \{d_1,d_2,\ldots,d_r\}$ denote an expert library. Each expert d_{i4} draws out his preferences on target case, which can be expressed as $I_{i5}(d_{i4})=(I_{i5}(d_{i4},f_1), I_{i5}(d_{i4},f_2),\ldots, I_{i5}(d_{i4},f_{qi5}))$, where $I_{i5}(d_{i4},f_j)$ corresponds to the value of feature f_j $(1\leq j\leq q_{i5})$ based on the $i4$-th expert's opinion. After integration and negotiation of multi-experts' preferences, consensus description on target case can be expressed as $U_{i5}=(u_{i5,1},u_{i5,2},\ldots,u_{i5,qi5})$, where $u_{i5,j}$ corresponds to the value of feature f_j $(1\leq j\leq q_{i5})$.
Retrieved Cases: Let $C_1=\{c_1,c_2,\ldots,c_s\}$ denote a retrieved case gather. The $j1$-th case c_{j1} in retrieved case gather can be represented as an n-dimensional vector, $c_{j1} = \{I_{i5}(c_{j1})\} = \{I_{i5}(c_{j1},f_1), I_{i5}(c_{j1}, f_2), \ldots,I_{i5}(c_{j1},f_{qi5})\}$, where $I_{i5}(c_{j1},f_j)$ corresponds to value of feature f_j.

3.1 Weighting Founded on Consensus-Based Similarity

The similarity between a single expert's preferences on feature values of target case and multi-expert's consensus description on it represents decision accuracy of the expert in the process of reach an agreement. Hence, weighting founded on consensus-based similarity can be defined as follows:

Definition 1. $\forall d_{i4}\in D$, $\forall E_{i5}\in F$, $\forall f_j\in E_{i5}$, $\forall i4\in[1,r]$, $\forall i5\in[1,p]$, $\forall j\in[1,q_{i5}]$. The value of feature f_j based on the opinion of expert d_{i4} is expressed as $I_{i5}(d_{i4},f_j)$. After integration and negotiation of multi-experts' preferences, consensus description on target case in E_{i5} can be expressed as $U_{i5}=(u_{i5,1}, u_{i5,2},\ldots,u_{i5,qi5})$. Define each expert's standard preferences $I'_{i5}(d_{i4},f_j)$ and multi-experts' standard consensus preferences $u'_{i5,j}$ as:

$$I'_{i5}(d_{i4},f_j)=I_{i5}(d_{i4},f_j)\Big/\max_{i4}(I_{i5}(d_{i4},f_j),u_{i5,j}) \quad (1)$$

$$u'_{i5,j}=u_{i5,j}\Big/\max_{i4}(I_{i5}(d_{i4},f_j),u_{i5,j}) \quad (2)$$

Where $\max\limits_{i4}(I_{i5}(d_{i4},f_j),u_{i5,j})$ denotes the maximal value of feature f_j in an experts' preferences and multi-experts' consensus. As a result, $U'_{i5}=(u'_{i5,1},u'_{i5,2},\ldots,u'_{i5,qi5})$. Hence, a single expert's preferences on target case can be expressed as $I'_{i5}(d_{i4})=(I'_{i5}(d_{i4},f_1), I'_{i5}(d_{i4},f_2),\ldots, I'_{i5}(d_{i4},f_{qi5}))$. Experts' standard preferences on feature values of target case in E_{i5} can be denoted as:

$$x_{i5}=\begin{pmatrix} I'_{i5}(d_1,f_1) & I'_{i5}(d_1,f_2) & \cdots & I'_{i5}(d_1,f_{q_{i5}}) \\ I'_{i5}(d_2,f_1) & I'_{i5}(d_2,f_2) & \cdots & I'_{i5}(d_2,f_{q_{i5}}) \\ \vdots & \vdots & \ddots & \vdots \\ I'_{i5}(d_r,f_1) & I'_{i5}(d_r,f_2) & \cdots & I'_{i5}(d_r,f_{q_{i5}}) \end{pmatrix} = (I'_{i5}(d_{i4},f_j))_{r\times q_{i5}}\ (i5=1,2,\ldots,p) \quad (3)$$

Definition 2. $\forall d_{i4}\in D$, $\forall E_{i5}\in F$, $\forall f_j\in E_{i5}$, $\forall i4\in[1,r]$, $\forall i5\in[1,p]$, $\forall j\in[1,q_{i5}]$. Grey correlation degree between $u'_{i5,j}$ and x_{i5} can be defined as $\zeta_{i5,\,i4,\,j}$:

$$\zeta_{i5,\,i4,\,j}=\frac{\inf\limits_{i4}(u'_{i5,j}-I'_{i5}(d_{i4},f_j))+k\sup\limits_{i4}(u'_{i5,j}-I'_{i5}(d_{i4},f_j))}{|u'_{i5,j}-I'_{i5}(d_{i4},f_j)|+k\sup\limits_{i4}(u'_{i5,j}-I'_{i5}(d_{i4},f_j))} \quad (4)$$

Where $\inf(u'_{i5,j} - I'_{i5}(d_{i4},f_j))$ and $\sup(u'_{i5,j} - I'_{i5}(d_{i4},f_j))$ respectively represent the minimal and maximal distances of values between each expert's standard consensus and multi-experts' standard preferences on the j-th feature. $|u'_{i5,j} - I'_{i5}(d_{i4},f_j)|$ denotes the distance between multi-experts' standard consensus and a single expert's preferences on the j-th feature. $k\in[0,1]$ is the environmental parameter. The gather of $\zeta_{i5,\,i4,\,j}$ can be denoted as:

$$\zeta_{i5,\,j}=\begin{pmatrix} \zeta_{i5,1,1} & \zeta_{i5,1,2} & \cdots & \zeta_{i5,1,q_{i5}} \\ \zeta_{i5,2,1} & \zeta_{i5,2,2} & \cdots & \zeta_{i5,2,q_{i5}} \\ \vdots & \vdots & \ddots & \vdots \\ \zeta_{i5,r,1} & \zeta_{i5,r,2} & \cdots & \zeta_{i5,r,q_{i5}} \end{pmatrix}=(\zeta_{i5,i4,j})_{r\times q_{i5}} \quad (5)$$

Definition 3. $\forall d_{i4}\in D$, $\forall E_{i5}\in F$, $\forall f_j\in E_{i5}$, $\forall i4\in[1,r]$, $\forall i5\in[1,p]$, $\forall j\in[1,q_{i5}]$. Let $W_{i5}=\{w_{i5,1}, w_{i5,2},\ldots,w_{i5,qi5}\}$ denote feature weights, where $w_{i5,j}$ corresponds to weight of the j-th feature in E_{i5}. They can be calculated through traditional criterion weighting methods or some other intelligent weighting methods. Based on Euclidean distance, partial decision accuracy in E_{i5} of an expert in the process of reach an agreement can be defined as:

$$simp(U'_{i5},I'(d_{i4}))=1-\sqrt[h]{\sum_{j=1}^{q_{i5}}[w_{i5,j}\times(1-\zeta_{i5,\,i4,\,j})]^h}\quad \begin{pmatrix} i4\in[1,r] \\ i5\in[1,p]\end{pmatrix} \quad (6)$$

Hereby, the gather of $simp(U'_{i5}, I'_{i5}(d_{i4}))$ can be denoted as a matrix ζ:

$$\zeta=\begin{pmatrix} simp(U'_1,I'(d_1)) & simp(U'_2,I'(d_1)) & \cdots & simp(U'_p,I'(d_1)) \\ simp(U'_1,I'(d_2)) & simp(U'_2,I'(d_2)) & \cdots & simp(U'_p,I'(d_2)) \\ \vdots & \vdots & \ddots & \vdots \\ simp(U'_1,I'(d_r)) & simp(U'_2,I'(d_r)) & \cdots & simp(U'_p,I'(d_r)) \end{pmatrix}=(simp(U'_{i5},I'(d_{i4})))_{p\times r} \quad (7)$$

Definition 4. $\forall i4\in[1,r]$, $\forall i5\in[1,p]$. Let $W=\{w_1, w_2,\ldots,w_p\}$ denote level weights, where w_{i5} corresponds to the weight of E_{i5}. Decision accuracy of an expert in the process of reach an agreement, which is named as the so-called consensus-based similarity, can be defined as:

$$simco(U', I'(d_{i4})) = 1-\sqrt[h]{\sum_{i5=1}^{p}[w_{i5}\times(1-simp(U'_{i5}, I'(d_{i4})))]^{h}} \quad (i4\in[1,r]) \tag{8}$$

Definition 5. $\forall i4\in[1,r]$, $\forall i5\in[1,p]$. Weight of an expert d_{i4} computed by consensus-based similarity can be defined as $weicon(d_{i4})$:

$$weicon(d_{i4}) = simco(U'_{i5}, I'(d_{i4}))\Big/\sum_{i4=1}^{r} simco(U'_{i5}, I'(d_{i4})) \tag{9}$$

3.2 Weighting Founded on Case-Based Similarity

The similarity between a single expert's preferences on target case and retrieved stored-cases based on consensus description represents decision accuracy of the expert in retrieve process. Hence, weighting founded on case-based similarity can be defined as follows:

Definition 6. $\forall d_{i4}\in D$, $\forall E_{i5}\in F$, $\forall f_j\in E_{i5}$, $\forall i4\in[1,r]$, $\forall i5\in[1,p]$, $\forall j\in[1,q_{i5}]$, $\forall j1\in[1,s]$. The value of feature f_j of retrieved case c_{j1} is expressed as $I_{i5}(c_{j1},f_j)$. The value of feature f_j based on opinion of expert d_{i4} is expressed as $I_{i5}(d_{i4},f_j)$. Define standard feature value $I'_{i5}(c_{j1},f_j)$ and each expert's standard preferences $I''_{i5}(d_{i4},f_j)$ as:

$$I'_{i5}(c_{j1}, f_j) = I_{i5}(c_{j1}, f_j)\Big/\max_{j1}\max_{i4}(I_{i5}(c_{j1}, f_j), I_{i5}(d_{i4}, f_j)) \tag{10}$$

$$I''_{i5}(d_{i4}, f_j) = I_{i5}(d_{i4}, f_j)\Big/\max_{j1}\max_{i4}(I_{i5}(c_{j1}, f_j), I_{i5}(d_{i4}, f_j)) \tag{11}$$

Where $\max_{j1}\max_{i4}(I_{i5}(c_{j1}, f_j), I_{i5}(d_{i4}, f_j))$ denotes the maximal value of feature f_j in each expert's preferences and retrieved cases. Hence, a single expert's preferences on target case can be expressed as $I''_{i5}(d_{i4}) = (I''_{i5}(d_{i4},f_1), I''_{i5}(d_{i4},f_2), \ldots, I''_{i5}(d_{i4},f_{qi5}))$. Experts' standard preferences on feature values of target case in E_{i5} can be denoted as:

$$x'_{i5} = \begin{pmatrix} I''_{i5}(d_1,f_1) & I''_{i5}(d_1,f_2) & \cdots & I''_{i5}(d_1,f_{q_{i5}}) \\ I''_{i5}(d_2,f_1) & I''_{i5}(d_2,f_2) & \cdots & I''_{i5}(d_2,f_{q_{i5}}) \\ \vdots & \vdots & \ddots & \vdots \\ I''_{i5}(d_r,f_1) & I''_{i5}(d_r,f_2) & \cdots & I''_{i5}(d_r,f_{q_{i5}}) \end{pmatrix} = (I''_{i5}(d_{i4}, f_j))_{r\times q_{i5}} (i5=1,2,\ldots,p) \tag{12}$$

And standard feature values of retrieved cases in E_{i5} can be denoted as:

$$y_{i5} = \begin{pmatrix} I'_{i5}(c_1,f_1) & I'_{i5}(c_1,f_2) & \cdots & I'_{i5}(c_1,f_{q_{i5}}) \\ I'_{i5}(c_2,f_1) & I'_{i5}(c_2,f_2) & \cdots & I'_{i5}(c_2,f_{q_{i5}}) \\ \vdots & \vdots & \ddots & \vdots \\ I'_{i5}(c_s,f_1) & I'_{i5}(c_s,f_2) & \cdots & I'_{i5}(c_s,f_{q_{i5}}) \end{pmatrix} = (I'_{i5}(c_{j1}, f_j))_{s\times q_{i5}} (i5=1,2,\ldots,p) \tag{13}$$

Definition 7. $\forall d_{i4}\in D$, $\forall E_{i5}\in F$, $\forall f_j\in E_{i5}$, $\forall i4\in[1,r]$, $\forall i5\in[1,p]$, $\forall j\in[1,q_{i5}]$, $\forall j1\in[1,s]$. The grey correlation degree $\xi_{i5,\,i4,\,j1,\,j}$ between $I''_{i5}(d_{i4})$ and y_{i5} can be defined as:

$$\xi_{i5,\,i4,\,j1,\,j} = \frac{\inf_{j1}(I''_{i5}(d_{i4}, f_j) - I'_{i5}(c_{j1}, f_j)) + k\sup_{j1}(I''_{i5}(d_{i4}, f_j) - I'_{i5}(c_{j1}, f_j))}{|I''_{i5}(d_{i4}, f_j) - I'_{i5}(c_{j1}, f_j)| + k\sup_{j1}(I''_{i5}(d_{i4}, f_j) - I'_{i5}(c_{j1}, f_j))} \tag{14}$$

Where $\inf(I''_{i5}(d_{i4},f_j)-I'_{i5}(c_{j1},f_j))$ and $\sup(I''_{i5}(d_{i4},f_j)-I'_{i5}(c_{j1},f_j))$ respectively represent the minimal and maximal distances of values between preferences on the j-th feature values of target case of expert d_{i4} and standard feature value of retrieved cases on the j-th feature. $|I''_{i5}(d_{i4},f_j)-I'_{i5}(c_{j1},f_j)|$ denotes the distance between preferences on the j-th feature values of target case of expert d_{i4} and standard feature value of retrieved cases on the j-th feature. $k\in[0,1]$ is the environmental parameter. Hereby, the gather of $\xi_{i5,\,i4,\,j1,\,j}$ can be denoted as a matrix $\xi_{i5,\,i4,\,j}$:

$$\xi_{i5,\,i4,\,j1} = \begin{pmatrix} \xi_{i5,\,i4,\,1,\,1} & \xi_{i5,\,i4,\,1,\,2} & \cdots & \xi_{i5,\,i4,\,1,\,q_{i5}} \\ \xi_{i5,\,i4,\,2,\,1} & \xi_{i5,\,i4,\,2,\,2} & \cdots & \xi_{i5,\,i4,\,2,\,q_{i5}} \\ \vdots & \vdots & \ddots & \vdots \\ \xi_{i5,\,i4,\,s,\,1} & \xi_{i5,\,i4,\,s,\,2} & \cdots & \xi_{i5,\,i4,\,s,\,q_{i5}} \end{pmatrix} = (\xi_{i5,\,i4,\,j1,\,j})_{s\times q_{i5}} \tag{15}$$

Definition 8. $\forall d_{i4}\in D$, $\forall E_{i5}\in F$, $\forall f_j\in E_{i5}$, $\forall i4\in[1,r]$, $\forall i5\in[1,p]$, $\forall j\in[1,q_{i5}]$, $\forall j1\in[1,s]$. Let $W_{i5}=\{w_{i5,1}, w_{i5,2}, \ldots, w_{i5,qi5}\}$ denote feature weights, where $w_{i5,j}$ corresponds to the weight of the j-th feature in E_{i5}. Partial decision accuracy in E_{i5} of an expert in the process of retrieve can be defined as $simp'(I''_{i5}(d_{i4}), C_1)$:

$$simp'(E_{i5}, I''(d_{i4}), C_1) = 1-\sqrt[h]{\sum_{j=1}^{q_{i5}}[w_{i5,j}\times(1-\xi_{i5,\,i4,\,j1,\,j})]^{h}} \quad \begin{pmatrix} i4\in[1,r]; \\ i5\in[1,p];\ j1\in[1,s] \end{pmatrix} \tag{16}$$

Hereby, the gather of $simp'(E_{i5},I''_{i5}(d_{i4}),C_1)$ can be denoted as a matrix $\xi_{i5,\,i4}$:

$$\xi_{i5,i4} = \begin{pmatrix} simp'(E_1,I'(d_{i4}),1) & simp'(E_1,I'(d_{i4}),2) & \cdots & simp'(E_1,I'(d_{i4}),s) \\ simp'(E_2,I'(d_{i4}),1) & simp'(E_2,I'(d_{i4}),2) & \cdots & simp'(U'_p,I'(d_{i4}),s) \\ \vdots & \vdots & \ddots & \vdots \\ simp'(E_p,I'(d_{i4}),1) & simp'(E_p,I'(d_{i4}),2) & \cdots & simp'(E_p,I'(d_{i4}),s) \end{pmatrix} = (simp'(E_{i5},I'(d_{i4}),j1))_{p\times s} \tag{17}$$

Definition 9. $\forall i4\in[1,r]$, $\forall i5\in[1,p]$, $\forall j1\in[1,s]$. Let $W=\{w_1, w_2, \ldots, w_p\}$ denotes level weights, where w_{i5} corresponds to the weight of E_{i5}. Decision accuracy of an expert in the process of retrieve, which is named as the so-called case-based similarity, can be defined as:

$$simca(C_1, I''(d_{i4})) = \sum_{j1=1}^{s}\{1-\sqrt[h]{\sum_{i5=1}^{p}[w_{i5}\times(1-simp'(E_{i5}, I''(d_{i4}), j1))]^{h}}\} \quad (i4\in[1,r]) \tag{18}$$

Definition 10. $\forall i4\in[1,r]$, $\forall i5\in[1,p]$, $\forall j1\in[1,s]$. Weight of an expert d_{i4} computed by case-based similarity can be defined as $weicas(d_{i4})$:

$$weicas(d_{i4}) = simca(C_1, I''(d_{i4}))\Big/\sum_{i4=1}^{r} simca(C_1, I''(d_{i4})) \tag{19}$$

3.3 Integrated Weights of Multi-experts

Definition 11. $\forall i4 \in [1,r]$. Define the integrated weight of an expert d_{i4} as $wei(d_{i4})$:

$$wei(d_{i4}) = b \times weicon(d_{i4}) + (1-b) \times weicas(d_{i4}) \cdot \quad \textbf{(20)}$$

In which, $b\in[0,1]$ is the environmental parameter. In real-world applications, experts weighting can be integrated by supra-actor-based experts weighting and similarity-based weighting, because the supra-actor may be responsibility for the real-world problem-solving.

4 Application

Supplier selection is one of the key processes in outsourcing management of AM. Concerning the role of a firm in supply chain cooperation, it can be grouped as production partner, sale partner, design partner, logistic partner, and so on. Taking production partner selection in supply chain based on CBR-based MES as an example, we applied the new similarity-based experts weighting method to compute weights of multi-experts in production partner selection.

The basic idea of applying CBR-based MES in supplier selection is as follows. A virtual benchmark is produced by firstly taking the most preferred value of each feature of candidate-partners then negotiating among experts. Then, similarities between the virtual benchmark and candidate-partners are computed. The bigger the similarity is, the more the corresponding candidate-partner is similar to the benchmark, and the more it is preferred. In production partner selection in supply chain based on CBR-based MES, the gather of candidate-partners corresponds to the gather of stored cases C. Candidate-partner corresponds to stored case c_{i1}. The virtual benchmark corresponds to target case c_0. And multi-experts participating in partner selection approach compose the gather D. Parameters in the application are as follows:

(1) There are five supply chain operational experts participating in the approach. That means: r=5, i_4 = {1, 2, …, 5.}

(2) The number of candidate-partners above threshold is six. That means: s=6, j_1 = {1, 2, …, 6}.

(3) In the application, one-level case structure is adopted, which means: p=1, i_5 = 1.

(4) In this application, U_{i5} corresponds to multi-experts consensus preferences on the virtual benchmark.

(5) Feature gather used is {product throughput, product development competency, time in dealing with production emergency, compatibility of cooperation cultures}. That means: t = 4, q_{i5} = 4. Product throughput (PT) refers to partner's Make-to-Order competency, whose membership is described by pieces per month. Product development competency (PDC) refers to partner's competency on old product improvement in the need of core enterprise, whose membership is qualitatively described by the gather {very poor, poor, neutral, strong, and very strong}. It can be mapped to {1, 2, 3, 4, 5}. Time in dealing with production emergency (TPE) refers to days needed to resume normal production from interruption when exception production accident emerges. Its membership can be described through average days used. Compatibility of corporation cultures (CCC) refers to whether obvious conflict exists or not between core enterprise of the supply chain and cooperation partners. Its membership can be qualitatively described by the gather {conflict, consistent, and same}. It can be mapped to {1, 2, 3}

(6) Assume that the five experts have already participated in the approach of production partner selection one times, based on which multi-experts weighting carries on. If there are more than one times the expert has participated, his weight is computed by average value of each individual experience.

(7) Consensus-based similarity and case-based similarity take equal importance in the case application, i.e. b=0.5. Hamming distance is employed, i.e. h=1.

(8) Feature weights are ignored, which do not have essential impact on multi-experts weighting in CBR-based MES.

(9) If the situation of candidate-partners' feature value is bigger than that of the virtual benchmark emerges, let the former be replaced by the latter.

Corresponding relationship between the R^6 model and partner selection task in supply chain and value of parameters can be shown in Fig. 6.

Virtual benchmarks drawn out by the five experts are shown in Table 1. And feature values of candidate-partners above threshold are shown in Table 2. Standardized virtual benchmarks based on each individual expert's knowledge and multi-experts' consensus preferences on virtual benchmark are shown in Table 3. While, standardized candidate-partners above threshold are shown in Table 4. The five experts' weights computed by weighting founded on consensus-based similarity and case-based similarity, and integrated weights are shown in Table 5.

In this application, the five experts are all experienced ones and familiar with the problem of supplier selection. Their decision experiences are so similar. So, their decision accuracies differ a little, as a result of which, their weights computed by similarity-based experts weighting differ a little. And from the application we can found that experts' weights computed by similarity-based expert weighting in CBR-based MES is directly influenced by experts' decision experiences. It is more objective and reasonable than supra-actor-based experts weighting, which is directly influenced by the supra-actor's preferences.

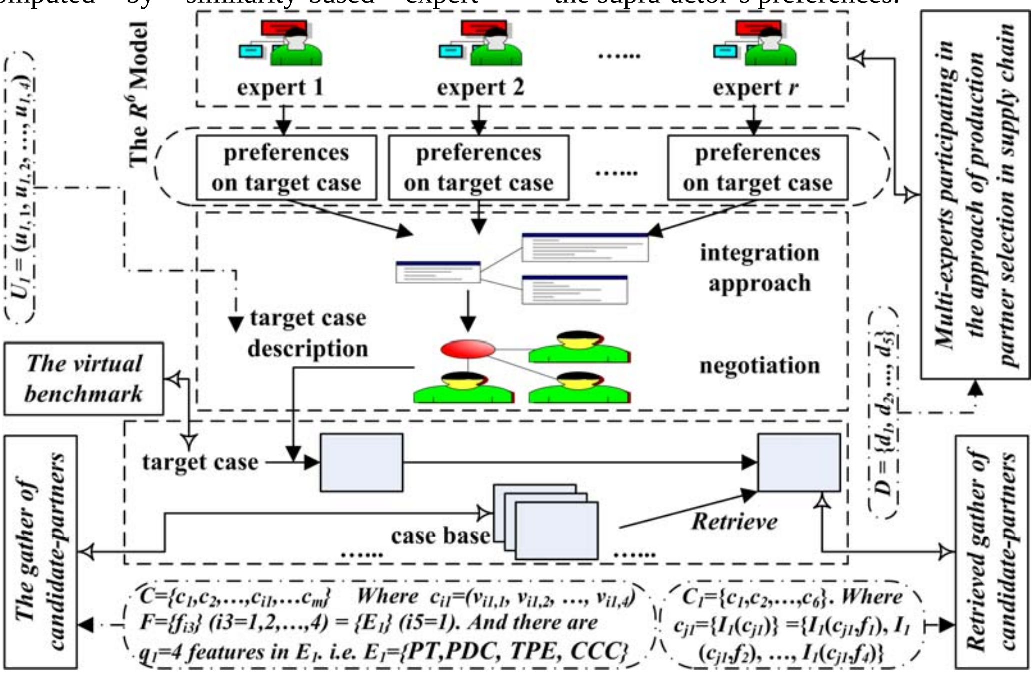

Fig. 6. Corresponding relationship between the R^6 model and supplier selection task

Table 1. Virtual benchmarks based on each individual expert's knowledge

Features Experts	PT (pieces/month)	PDC	TPE (days)	CCC
d_1	4200	Very Strong	1	Same
d_2	4200	Strong	0.5	Consistent
d_3	4400	Strong	1	Consistent
d_4	4400	Strong	1.5	Consistent
d_5	4300	Very Strong	1	Same

Table 3. Standardized virtual benchmarks based on each individual expert's knowledge and standardized consensus virtual benchmark of multi-experts

Features Experts	PT (pieces /month)	PDC	TPE (days)	CCC
d_1	0.9545	1	0.5	1
d_2	0.9545	0.8	0.75	0.6667
d_3	1	0.8	0.5	0.6667
d_4	1	0.8	0.25	0.6667
d_5	0.9773	1	0.5	1
Consensus	0.9756	0.8722	0.5245	0.7870

Table 2. Feature values of candidate-partners above threshold

Features Partners	PT (pieces/month)	PDC	TPE (days)	CCC
c_1	3900	Strong	1.5	Consistent
c_2	4000	Neutral	2	Consistent
c_3	3800	Strong	1	Consistent
c_4	4100	Neutral	1.5	Same
c_5	4200	Neutral	2	Conflict
c_6	4100	Strong	1	Same

Table 4. Standardized feature values of candidate-partners above threshold

Features Partners	PT (pieces /month)	PDC	TPE (days)	CCC
c_1	0.8864	0.8	0.25	0.6667
c_2	0.9091	0.6	0	0.6667
c_3	0.8636	0.8	0.5	0.6667
c_4	0.9318	0.6	0.25	0.7870(1)
c_5	0.9545	0.6	0	0.3333
c_6	0.9318	0.8	0.5	0.7870(1)

Table 5. The five experts' weights computed by weighting founded on consensus-based similarity and case-based similarity, and the final integrated weights of experts

Weights Experts	$Weicon(d_{i4})$	$Weicas(d_{i4})$	$Wei(d_{i4})$
d_1	0.1858	0.2032	0.1945
d_2	0.1875	0.1957	0.1916
d_3	0.2213	0.1972	0.2093
d_4	0.1815	0.1932	0.1874
d_5	0.2239	0.2107	0.2173

And that is a shortcoming that can not be overcome by supra-actor-based experts weighting methods, such as AHP, directly giving weights, Simos's procedure, etc.. With the time going on, experts' decision experiences are collected into the experience base. The more of the times an expert participates in supply partner selection approach, the more decision experience information of the expert is stored into experience base, and the more accurately his weight will be computed by the new similarity-based expert weighting method in CBR-based MES.

5 Conclusion

In the situation of global outsourcing of AM and application of CBR into this area, this research proposed the R^6 process-oriented model of CBR-based MES, based on which and some assumptions, a new similarity-based multi-experts weighting approach of CBR-based MES in outsourcing partner selection area of AM was proposed. The assumption of the new expert weighting is more reasonable than that of traditional supra-actor-based expert weighting methods. Finally, the new one was applied into supplier selection to compute multi-experts' weights. And this similarity-based experts weighting method can also be extended to some other inference mechanism based MES.

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