Multicriteria Decision-Making Framework for Supplier Selection: A Customer Community-Driven Approach

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Abstract—Supplier selection is the core of enterprise supply chain management. It involves a systematic evaluation of potential supply partners. Customer expectations for products and services are rarely considered when selecting suppliers. Considering customer factors in supplier selection faces many problems, including customer segmentation, importance ranking for customer requirements, and answering how customer requirements guide the supplier selection. For the above, a multicriteria supplier selection framework driven by customer communities is proposed. It includes three stages. In the first stage, a customer segmentation method is used to discover customer communities. In the second stage, the weighted interval rough number method quantitatively analyzes the customer requirements in each community, and then expert knowledge is integrated to determine the importance of supplier selection indicators. In the third stage, a genetic algorithm based on a stochastic tournament model is used to search for the optimal suppliers. A practical case study of a household refrigerator was conducted to illustrate the performance of our framework. A simulation experiment was designed to verify that our framework could update the supplier selection scheme according to changes in customer requirements in a dynamic scenario.

Index Terms—Customer community division, customer requirement, genetic algorithms, multicriteria decision-making, supplier selection.

I. INTRODUCTION

SUPPLY chain is the foundation for the development of most modern enterprises. As one of the most important problems in the supply chain, supplier selection is of great concern [1], [2].

In recent years, the following basic framework has been popular in solving the supplier selection problem. First, the supplier criteria (SCs) are formulated from multiple dimensions; then, multiple-criteria decision-making (MCDM) models or computational intelligence methods [3]–[6] are adopted to obtain the weights of SCs. Finally, the suppliers are sorted based on the supplier's score on SCs and the weights of SCs, and the best one or multiple suppliers are chosen.

An increasing number of industries have shifted from being driven by product capacity to being driven by customer requirements (CRs). In particular, the platform economy represented by the consumer Internet has shown that only customer centricity can help survive in a fiercely competitive environment. This requires enterprises to organically integrate CRs with supply chain planning in the process of product and service supply. Specifically, for supplier selection, it is necessary to shift from the traditional expert experience-based evaluation to a comprehensive evaluation that fully considers CRs. Given the above considerations, this article advocates that CRs should be fully considered in supplier selection. To this end, the decision-maker (DM) should elaborate the items of questionnaires that can effectively respond to CRs (i.e., CR items) and obtain CR data (CRD) to understand the customers' expectations of products and services. Then, the collected CRD is mapped to the supplier selection process. In our article, we found that if CRs are to be introduced in supplier selection, the issues and corresponding technical difficulties in Table I will be encountered.

Issue 1 emphasizes that understanding CRs is the primary task of a company in its supplier selection. Customer community division helps DMs segment customer markets and select suitable supplier partners in a targeted manner. The main idea of segmentation or community division is to group similar customers. A community can be described as a set of customers who have similar characteristics of demography, behaviors, values, etc. [7]. Issue 2 focuses on how to quantitatively characterize the importance of each CR item for different customer communities in order to achieve refined modeling of different types of customer groups and thus support the establishment of models for supplier selection. For Issue 3, the mapping relationship between SCs and CRs is studied. This allows the CR information to be used directly in the supplier selection process. Issue 4 advocates establishing an overall CR-oriented supplier selection framework that can output a ranking of multiple alternative suppliers or a set of feasible supplier selection schemes.

TABLE I
KEY ISSUES AND TECHNICAL DIFFICULTIES ENCOUNTERED IF CRs ARE
CONSIDERED IN SUPPLIER SELECTION

Issue	Technical difficulty	Our solution
(1) What types of customer communities exist in the market?	Segment customer communities accurately	Gaussian Peaking Clustering
(2) How to quantitatively analyze the ambiguous CRD in each customer community to obtain the relative importance rating of each CR item?	Assign importance weights to each CR item for fuzzy CRD	Weighted rough number method
(3) How to perform supplier selection with CR knowledge gained from CRD?	Establish the mapping relationship between CR items and SCs	Combine CR and expert knowledge mapping into SCs
(4) How to select suppliers?	Construct an appropriate supplier selection model	Stochastic tournament model based genetic algorithm

In this article, based on the analysis of the above issues, a customer community-driven multicriteria decision-making framework for supplier selection is proposed. It includes three stages. The first stage is the customer community division. To obtain high-quality customer community division results that can accurately reflect CRs, a novel customer segmentation method is used, called Gaussian peaking clustering (GPC), to qualitatively analyze what types of customer communities exist in the market. The second stage consists of using the weighted interval rough number method to quantitatively analyze CRs in each community for products and services, and then expert knowledge is combined to determine the importance of the SCs. The third stage consists of a stochastic tournament model-based genetic algorithm (GA) to perform supplier selection. The framework proposed in this article combines CRD with expert knowledge, takes CRs as an important factor in supplier selection, and outputs a group of suppliers that satisfy the CRs to the greatest extent. To the best of our knowledge, this is the first article to explore supplier selection considering CRs by a customer community-driven method. Experiments illustrated that our framework could support the adjustment of supplier selection schemes under dynamic changes in CRs.

In summary, the technical solutions of this article are presented in the third column of Table I, and they can be summarized as follows.

1) To get a high-quality customer community division result, a new type of customer segmentation method is used, called GPC, which is a heuristic clustering method. It helps the DM accurately understand customer expectations for products and services.

2) To deal with the ambiguity of CRD, a weighted interval rough number method is implemented to determine the relative importance rating (RIR) of CR items in different divided communities.

3) To determine the importance weights of SCs, a mapping relationship between CR items and SCs as established by experts and the RIR of each CR item in each community are combined. This enables the knowledge about the CRs obtained from CRD to be applied to the supplier selection process.

4) The stochastic tournament model-based GA is used in the supplier selection process and can output a CR-oriented supplier selection scheme.

The rest of this article is organized as follows. Section II reviews literature and related methodologies of supplier selection. In Section III, the customer community division technique and the determination process of RIR to CR item are described. In Section IV, the approach to establish the mapping relationship between CR items and SCs and the GA-based supplier selection algorithm is elaborated. In Section V, a practical case study of a household refrigerator from a home appliance enterprise is shown to validate the proposed framework. To verify the potential capability of the proposed framework in a dynamic scenario, a simulation experiment is illustrated in Section VI. Finally, Section VII conclude the article.

II. LITERATURE REVIEW

A. Techniques for Supplier Selection

In recent article, decision-making theories and techniques are widely used in solving supplier selection problems. These technologies help the DM establish the decision-making model of supplier selection. Decision-making techniques can be roughly divided into three categories, MCDM, mathematical programming (MP), and data mining and AI (DMAI).

1) MCDM Techniques: MCDM technique focuses on coordination between decision-making goals when multiple goals conflict with each other. There are three main types of MCDM technique, including multiattribute utility methods (MAUMs), outranking methods, and compromise methods.

a) MAUMs: MAUMs expresses the personal preference for each alternative through a utility function and provides quantitative analysis. AHP and its extended version ANP are typical representative methods of MAUMs. Beikkhakhian *et al.* [8] combined AHP and the technique for order preference by similarity to an ideal solution (TOPSIS) to rank suppliers. Azadnia *et al.* [9] introduced the fuzzy set theory into AHP and proposed an integrated approach of the rule-based weighted fuzzy method, fuzzy AHP, and multiobjective mathematical programming for sustainable supplier selection and order allocation problems. Awasthi *et al.* [10] presented an integrated fuzzy AHP-VIKOR approach-based framework for sustainable global supplier selection. Hashemi *et al.* [11] utilized ANP and the improved gray relation analysis (GRA) to evaluate the green supplier. More cases of using AHP/ANP to solve supplier selection problems can be found in [12]–[15].

b) Outranking methods: On the premise of known DMs' preference and evaluation values of suppliers, the outranking method utilizes binary relation, such as "as least as" and "as good as", to compare suppliers. ELECTRE and PROMETHEE [2], [16] are two popular methods of outranking methods. Among many outranking methods, PROMETHEE has received more attention in recent years, and some recent studies of it can be found in [17] and [18].

c) Compromise methods: TOPSIS and VIKOR are well-known compromise methods. Their application in supplier selection can be found in [19] and [20], respectively. Due to its

TABLE II
SUMMARIZATION OF MP AND DMAI TECHNIQUES APPLIED IN SUPPLIER SELECTION

Technique (Abbreviation)	Literature(s)	Description
Mathematical programming (MP) techniques		
A. Basic MP techniques		
Data envelopment analysis (DEA)	[29]	Independent usage of DEA
	[30]	Independent usage of DEA
Linear programming (LP)	[31]	Integration of fuzzy DEA and LP
Stochastic programming (SP)	[32]	Integration of AHP and SP
	[33]	Integrated QFD and SP
Goal programming (GP)	[34]	Integration of fuzzy ANP and GP
Multi-objective programming (MOP)	[35]	Integration of AHP, weighted sum model and fuzzy MOP
B. Mixed integer programming methods		
Mixed integer linear programming (MILP)	[36]	Independent usage of MILP
	[37]	Independent usage of MILP
	[38]	Usage of MILP with considering risk factor
Mixed integer nonlinear programming (MINLP)	[39]	Independent usage of MINLP
	[40]	Independent usage of MINLP
Data mining and artificial intelligence (DMAI) techniques		
A. Classification methods		
Neural network (NN)	[41]	Usage of adaptive neuro fuzzy inference system
Bayesian network (BN)	[5]	Usage of BN with considering risk factor
Support vector machine (SVM)	[42]	Integration of cooperative coevolution and kernel clustering with SVM
Decision tree (DT)	[43]	Integration of DT and BN
Rough set theory (RST)	[44]	A believable rough set approach
B. Clustering methods		
k-means	[45]	Integration of SP and k-means
k-medoids	[46]	PROCLUS (a k-medoids-like cluster method)
C. Other DMAI methods		
Grey system theory (GST)	[47]	Integration of GST and uncertainty theory

simple principles and formulas, TOPSIS is more popular than VIKOR.

d) Other MCDM methods: There are some other MCDM methods, including decision-making trial and evaluation laboratory (DEMATEL), simple multiattribute rating technique (SMART), and best-worst method (BWM). DEMATEL is a method combining the graph theory and matrix tools to analyze the complex relationship between multiple criteria. For example, Abdollahi *et al.* [21] combined ANP and DEMATEL for supplier portfolio selection problems. Besides, to improve the ability of DEMATEL to handle uncertain information, some DEMATEL methods based on gray logic or fuzzy logic have been proposed, which can be found in [3], [22]–[26]. Some scholars applied SMART and BWM to supplier selection, which can be found in [27] and [28].

2) MP and DMAI techniques: Mathematical programming (MP) and data mining & AI (DMAI) techniques have also been widely used in supplier selection. Since MP and DMAI techniques contain a large number of methods, we refer to two review articles [2], [16], which reviewed the application of DM techniques in the field of supplier selection from 2008 to 2018. According to [2], [16], MP techniques can be divided into two types: basic MP techniques and mixed-integer programming; DMAI techniques can be divided into three types: classification methods, clustering methods, and other DMAI methods. Table II sorts out the representative methods included in the MP and DMAI techniques in supplier selection [29]–[47].

B. Customer-Based Supplier Selection Process

In recent years, although supplier selection has been widely investigated, there was not much literature on integrating CRs into the supplier selection process. Customer-based supplier selection is an emerging topic that needs to be studied in depth.

Liu *et al.* [48] proposed a fuzzy three-stage integrated multicriteria decision-making approach to select the most qualified suppliers of new energy vehicle parts. Yadavalli *et al.* [49] developed an analytical model for the manufacturing firm to select suppliers based on customers' expectations. The customers' environmental and social expectations are translated in terms of the retailer's expectation level of the supplier's performance. In their method, they introduced the complex mathematical processes that are obscure for DMs, such as fuzzy set operations and fuzzy-TOPSIS technique using Z numbers (Z-TOPSIS). It limits their application in practical scenarios. Therefore, it is necessary to propose a supplier selection model that is easier for DMs to understand.

Asadabadi *et al.* [50] was a recently published literature, in which the motivation is similar to our research. This article used the Markov chain to identify CRs and uses the ANP-QFD method to connect CRs and product requirements (PRs) and to connect PRs and SCs. Finally, the alternative suppliers are ranked and the best suppliers are selected. The introduction of the Markov chain allows [50] not only to identify CRs but also to track the dynamic changes in CRs. This is conducive to improving the enterprise response speed in the face of market emergencies and making its customer-oriented product service system more robust. However, in the process of CRs identification, the Markov chain modeling method has many inherent flaws.

1) It is assumed that the probability of state change is fixed.
2) For those events with continuous changes, such as the change of CRs, the former state will greatly affect the poststate. Such an event is difficult to meet the statistical independence required by the Markov chain.

3) The complex state transition matrix in the Markov chain model is difficult for DMs to understand.

Despite the limitations, Asadabadi *et al.* [50] still inspired our research work to focus on the dynamics of changes in CRs. We realize that in the real world, CR changes over time are dynamic, and the changing degree and speed are often unpredictable. After CRs change, only those enterprises that actively respond to changes in requirements on time will have the opportunity to survive.

Based on the above discussion, we believe that a customer-oriented supplier selection framework not only requires the feasibility of inner methods but also should have the ability to handle dynamic changes in CRs. To this end, after introducing the basic methods and framework in Sections III–IV, our proposed framework was applied to a practical case study from a real enterprise to verify the feasibility and effectiveness in Section V. Next, in Section VI, a simulation experiment was designed to verify the performance of our proposed framework in dynamic scenarios.

III. Customer Community Division and RIR of CR Item Determination

A. Customer Community Division: GPC Method

Customer community division is the basis of our proposed supplier selection. Clustering methods, such as typical k-means, are often used to solve customer community division problems. However, due to the randomness of the initial conditions of clustering, the clustering performance and algorithm stability fluctuate substantially. Therefore, this article proposes a heuristic information-based k-means method, which combines the heuristic information mined from CRD with k-means. Compared with the typical k-means, our method has better clustering performance and algorithm stability.

1) Acquisition of CRD

In this article, CRD is obtained by sending questionnaires to target customers. The questionnaire consists of multiple product-service features (i.e., CR items). Customers are required to use integers from 0–10 to score each CR item to express their personal preference. During the questionnaire filling process, customers are allowed to flexibly use crisp values or interval values to express their preferences for the CR items, which helps customers better express their subjectivity and ambiguity for each CR item.

2) Data Preprocessing: Data Cleaning and Transformation

Data Cleaning: CRD with interval values effectively reflects customer preferences. However, interval data exacerbate the ambiguity of the data, which brings challenges to customer community division. Therefore, it is necessary to perform data cleaning to delete those neutral CRD that fail to reflect customer intentions. Suppose the scores of one customer with k CR items is a vector $x = [x_1, x_2, \ldots, x_i, \ldots, x_n]^T$, where $x_i = [l_i, u_i]^T$. l_i and u_i represent the lower bound and upper bound of the customer score on the ith CR item, respectively. The entropy value of each score vector x is calculated using (1) to characterize whether the corresponding CRD has obvious requirement intentions on several CR items. For convenience, the mean value

of each interval (i.e., $\overline{x}_i = (l_i + u_i)/2$) is taken to calculate the entropy

$$H(x) = -\sum_{i=1}^{n} P(\overline{x}_i) \log_2 P(\overline{x}_i). \tag{1}$$

$P(\overline{x}_i) = \overline{x}_i / \sum_{i=1}^{n} \overline{x}_i$ represents the score percentage of the ith CR item to the total n CR items. The larger the entropy value, the lower is the CR intention.

After calculating and sorting the entropy values of all CRD, the expert is asked to analyze the current CRD and set the entropy threshold ε. The CRD with an entropy value greater than ε is deemed by the expert as this data with no obvious CR intentions (i.e., neutral CRD). Then, those CRD with no obvious CR intentions will be deleted.

To determine the entropy threshold efficiently, the dichotomy search method is adopted. The specific method is as follows.

In the actual process of selecting the entropy threshold, seven experts with business experience were invited to select the entropy threshold. These experts independently observed the entropy values of CRD. During the observation process, the dichotomy search method is used, which means that each time an intermediate value was selected from the CRD that had been sorted based on the entropy values. Then, this intermediate entropy value was evaluated to determine whether the corresponding CRD is fuzzy or not. If this CRD was judged to be fuzzy data, half of the data with lower entropy values were selected to continue the dichotomy search. If this CRD was judged to have nonfuzzy data, half of the data with higher entropy values were selected to continue the dichotomy search. This process eventually converged to a certain entropy value, which was used as the entropy threshold of one expert. Dichotomy search considerably improves the efficiency of expert evaluation for CRD. Taking 300 CRD as an example, the number of evaluations will not exceed nine times.

After the entropy threshold selection of all experts, the entropy thresholds of experts are sorted. To mitigate the effects of errors by experts, the highest and lowest entropy thresholds are removed. Experts then discuss and select the final entropy threshold. In the actual experiment process, the entropy thresholds of multiple experts obtained by using the dichotomy search will not differ greatly. Therefore, the choice of the entropy threshold has little effect on the supplier selection process.

Data Transformation: The processed CRD is modeled by the Gaussian distribution. The general form of the $(n$-1)-dimensional Gaussian distribution is as follows:

$$N(x, \mu, \Sigma) = \sqrt{\frac{1}{(2\pi)^{n-1} det(\Sigma)}} e^{(-\frac{1}{2}(x-\mu)^T \Sigma^{-1}(x-\mu))} \tag{2}$$

x is a $n-1$ dimensional vector; $\Sigma = \text{dig}(\sigma_1, \ldots, \sigma_{n-1})$ is the covariance matrix; $\mu = (\mu_1, \ldots, \mu_{n-1})^T$ is the mean value vector.

The Gaussian model requires the mean value μ and covariance matrix Σ. To calculate the covariance matrix, the interval values in CRD should be discretized. The specific operations are given in the following examples. Suppose the score of one customer

TABLE III
INSTANCE OF DISCRETIZED CRD

Original	Discretized interval	σ	Σ		
[3,4]	(3.00, 3.10, ..., 3.90,4.00)	0.33	0.33	0	0
[5,5]	(4.75, 4.85, ..., 5.15,5.25)	0.62	0	0.62	0
[10,10]	(9.75, 9.85, 9.95, 10.00)	0.11	0	0	0.11

with three CR items is a vector $x = [x_1, x_2, x_3]^T$. Each dimension of μ can be taken as the middle value of each interval, that is, $\mu = [\overline{x}_1, \overline{x}_2, \overline{x}_3]^T$. For Σ, discretize the interval values of each dimension at intervals of 0.1. When the interval length on the ith dimension in CRD is 0 (i.e., $x_i = [l_i, u_i]^T; l_i = u_i$), the interval length needs to be enlarged for discretization. The enlarged length is generally set to be the half value of the minimum length of the nonzero interval among all of the CR items. If the data interval is an edge interval (such as [0,0] or [10,10]), remove the interval out of [0,10] after interval enlarging. Taking $x = [[3,4], [5,5], [10,10]]^T$ as an example, Table III shows its discretization results and corresponding covariance matrix.

Given μ and Σ, each CRD can be transformed into a Gaussian function, termed customer requirement function (CRF). CRF reflects the distribution of the requirement intentions of one customer. However, the coefficients of $\sqrt{1/(2\pi)^{n-1} det(\Sigma)}$ in different CRFs are different due to Σ. The peak values of different CRFs are different. Therefore, it is meaningless to directly compare the levels of requirement intentions between different CRFs. To eliminate this phenomenon, all CRFs should be standardized. The method used in this article is to set the coefficient as 1.

The form of the standardized Gaussian distribution is as follows:

$$N_S(x, \mu, \Sigma) = 1 \times e^{(-\frac{1}{2}(x-\mu)^T \Sigma^{-1}(x-\mu))}. \quad (3)$$

Then, each CRF is accumulated according to (4) to obtain the customer requirement sum function (CRSF)

$$\text{CRSF} = \sum_{i=1}^{M} N_S^i \quad (4)$$

where M is the number of customers.

3) Implement GPC for Customer Community Division
Step 1: NGA for Searching Peak Points of CRSF

The modeled CRSF is a typical multimodal function, in which peak points are scattered in R^n. Fig. 1 shows a schematic diagram of a CRSF composed of many three-dimensional (3-D) CRFs. The CRD corresponding to each CRF has two CR items, namely "Price" and "Quality". It is worth noting that although the peak value of each CRF has been standardized, there are differences in the peak values of the CRSF in different regions because some CRFs are concentrated in certain areas, whereas some CRFs are relatively sparse in other certain areas. According to this characteristic, if the peak points of CRSF are found, the spatial distribution information of all CRFs can be obtained by judging their peak values. Then, the spatial distribution of CRD is obtained indirectly. The higher the peak value of the peak point, the more CRFs are gathered nearby. By searching for the peak points with high values in CRSF, the customer-gathering relationship hidden in CRD can be discovered.
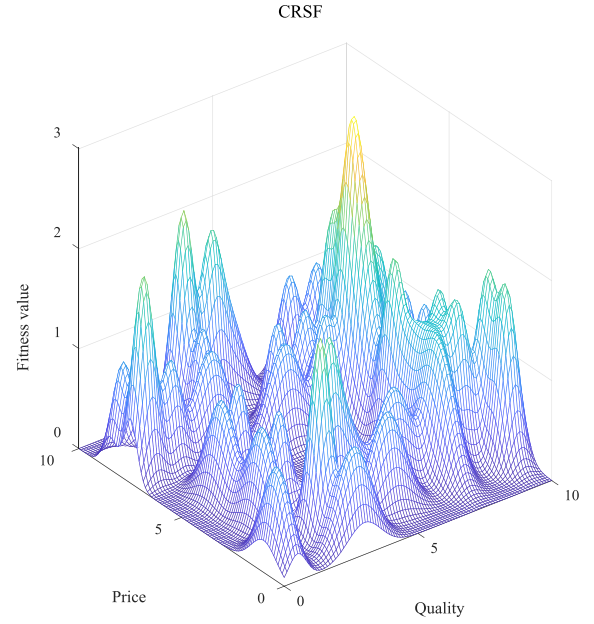

Fig. 1. Schematic diagram of one CRSF.

To search for as many diversified peak points as possible, a niching genetic algorithm (NGA) is used to search for the peak points in CRSF. Due to the random nature of the evolutionary algorithm, NGA is recommended to be executed multiple times to ensure that all peak points are searched as far as possible. Then, the fitness threshold δ is set to filter points with low fitness values. After running NGA multiple times, a peak point set containing a large number of peak points is obtained. Then, the duplicate points in the peak point set are deleted.

A small value for δ is recommended to prevent filtering out valuable peak points. In the actual operation process, the peak points obtained by running NGA multiple times are sorted according to the fitness value; then, δ can be used to filter out the peak points with lower fitness values.

Step 2: Obtain CRD Centroid

The peak point set implies the distribution information of CRFs, and it can be utilized to guide customer community division.

First, the data points in the peak point set are compared pairwise. If the Euclidean distance between the points in a pair is less than the distance threshold τ, the two data points will be combined into one group. τ is often set to a small value to ensure that each peak point group contains highly similar data. Then, agglomerative nesting (AGNES) is performed to combine the similar peak point groups.

τ is suggested to be set as one-tenth of the niching radius in NGA. If the distance is greater than τ, the two points will not be merged. A small τ ensures each *peak point group* contains highly similar data. Then, AGNES is performed to combine the similar *peak point groups*. Suppose the target cluster number of AGNES is K. K clusters will be obtained by executing AGNES.

The data centroids of these clusters can be regarded as possible customer community centroids. The obtained K centroids provide high-quality heuristic information for the subsequent CRD clustering process (i.e., customer community division).

Step 3: CRD Clustering

Here, k-means algorithm is used for the CRD clustering. Set K possible centroids output by AGNES and K as the initial cluster centroids and the target cluster number of k-means, respectively. Possible customer community centroid can be considered as heuristic information that could improve the clustering performance of k-means. Considering that each datum in CRD is an interval value, take the average value of the interval as the input of k-means. After k-means with heuristic information is executed, K clusters of CRD will be output.

Since the actual number of customer communities cannot be known in advance, the selection of K needs to be slightly larger. Therefore, there are still clusters with the same CR intention among the different clusters output by k-means with heuristic information. It is necessary to further merge these clusters to obtain the final result of the customer community division.

B. RIRs of CR Items Determination

To deeply understand CR intention in each community, the weighted rough number method is implemented to quantitatively analyze the CRD to determine the RIR of each CR item in the corresponding community.

1) Definition of Interval Rough Number: The fundamental theories and previous work of the interval rough number method can be found in [51]–[53].

Assume U is the universe containing every object and Y is an arbitrary object of U. $R = \{I_1^*, I_2^*, \ldots, I_m^*\}$ is defined in U, where I_i^* is presented in an interval; that is, $I_i^* = [I_{li}^*, I_{ui}^*]$; $I_{li}^*, I_{ui}^* \in R$. I_{li}^* and I_{ui}^* stand for the lower boundary and the upper boundary of I_i^*, respectively.

If both lower and upper boundaries are ordered in the manner of $I_{l1}^* < I_{l2}^* < \ldots < I_{lm}^*$ and $I_{u1}^* < I_{u2}^* < \ldots < I_{um}^*$, then the set of the lower class $R_l = \{I_{l1}^*, I_{l2}^*, \ldots, I_{lm}^*\}$ and the set of the upper class $R_u = \{I_{u1}^*, I_{u2}^*, \ldots, I_{um}^*\}$ can be defined.

For any $I_{li}^* \in R_l$ and $I_{ui}^* \in R_u$ ($1 \le i \le m$), the lower approximations of I_{li}^* and I_{ui}^* are defined as

$$\underline{Apr}(I_{li}^*) = \cup\{Y \in U/R_l(Y) \le I_{li}^*\} \tag{5}$$

$$\underline{Apr}(I_{ui}^*) = \cup\{Y \in U/R_u(Y) \le I_{ui}^*\}. \tag{6}$$

In addition, the upper approximations of I_{li}^* and I_{ui}^* are defined as

$$\overline{Apr}(I_{li}^*) = \cup\{Y \in U/R_l(Y) \ge I_{li}^*\} \tag{7}$$

$$\overline{Apr}(I_{ui}^*) = \cup\{Y \in U/R_u(Y) \ge I_{ui}^*\}. \tag{8}$$

Thus, the lower class I_{li}^* and upper class I_{ui}^* can be expressed by the corresponding lower limitations $\underline{Lim}(I_{li}^*)$, $\underline{Lim}(I_{ui}^*)$ and upper limitations $\overline{Lim}(I_{li}^*)$, $\overline{Lim}(I_{ui}^*)$, respectively

$$\underline{Lim}(I_{li}^*) = \frac{1}{M_L}\sum R_l(Y)|Y \in \underline{Apr}(I_{li}^*) \tag{9}$$

$$\underline{Lim}(I_{ui}^*) = \frac{1}{M_L^*}\sum R_u(Y)|Y \in \underline{Apr}(I_{ui}^*). \tag{10}$$

M_L and M_L^* are the numbers of objects contained in $\underline{Apr}(I_{li}^*)$ and $\underline{Apr}(I_{ui}^*)$, respectively

$$\overline{Lim}(I_{li}^*) = \frac{1}{M_U}\sum R_l(Y)|Y \in \overline{Apr}(I_{li}^*) \tag{11}$$

$$\overline{Lim}(I_{ui}^*) = \frac{1}{M_U^*}\sum R_u(Y)|Y \in \overline{Apr}(I_{ui}^*). \tag{12}$$

M_U and M_U^* are the numbers of objects contained in $\overline{Apr}(I_{li}^*)$ and $\overline{Apr}(I_{ui}^*)$, respectively.

The interval between $\overline{Lim}(I_{li}^*)$ and $\underline{Lim}(I_{li}^*)$ is considered as the rough boundary interval of I_{li}^*, which is denoted as $RB(I_{li}^*)$

$$RB(I_{li}^*) = \overline{Lim}(I_{li}^*) - \underline{Lim}(I_{li}^*). \tag{13}$$

For I_{ui}^*, $RB(I_{ui}^*)$ can be calculated as follows:

$$RB(I_{ui}^*) = \overline{Lim}(I_{ui}^*) - \underline{Lim}(I_{ui}^*). \tag{14}$$

Accordingly, the vague classes I_{li}^* and I_{ui}^* can be represented by their corresponding rough number comprising the lower limitation and upper limitation. The rough numbers of I_{li}^* and I_{ui}^* are denoted as $RN(I_{li}^*)$ and $RN(I_{ui}^*)$, respectively

$$RN(I_{li}^*) = [\![\underline{Lim}(I_{li}^*), \overline{Lim}(I_{li}^*)]\!]. \tag{15}$$

For I_{ui}^*, $RB(I_{ui}^*)$ can be calculated as follows:

$$RN(I_{ui}^*) = [\![\underline{Lim}(I_{ui}^*), \overline{Lim}(I_{ui}^*)]\!]. \tag{16}$$

Finally, the interval rough number I_i^* can be represented as follows:

$$IRN(I_i^*) = [RN(I_{li}^*), RN(I_{ui}^*)]. \tag{17}$$

2) Customers' Weight Assignment: In the weighted interval rough number method, the importance of each customer can be considered. If the customers from whom data are collected differ in importance, then each CRD may be given a certain weight that characterizes the importance degree of the customer when determining the RIR of each CR item.

Suppose one community consisting of n customers (i.e., n CRD). The sum of the weights w of each CRD in this community should satisfy the following formula:

$$\sum_{i=1}^n w_i = 1. \tag{18}$$

3) Procedures for Determining the RIR of CR Item: Taking a community with three customers as an example, the process of determining the RIR of one CR item is explained. Suppose the score of three customers in terms of one CR item is $R = \{[2,3], [1,3], [5,6]\}$.

Step 1: Determine the customer's weight

DM assigns weights to represent the different values from the three customers. In this example, each customer is given the same weight, that is, the weight of each customer is 1/3.

Step 2: Quantification analysis using interval rough number

The lower approximations of the first customer's lower and upper classes are calculated as follows:

$$\underline{Apr}(I_{l1}^*) = \underline{Apr}(2) = \{1,2\}$$
$$\underline{Apr}(I_{u1}^*) = \underline{Apr}(3) = \{3,3\}.$$

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The upper approximations of the first customer's lower and upper classes are calculated as follows:

$$\overline{Apr}(I_{l1}^*) = \overline{Apr}(2) = \{2, 5\}$$

$$\overline{Apr}(I_{u1}^*) = \overline{Apr}(3) = \{3, 3, 6\}.$$

According to (9)–(12), the lower limitations and upper limitations are equal to

$$\underline{Lim}(I_{l1}^*) = \underline{Lim}(2) = (1 + 2)/2 = 1.5$$

$$\underline{Lim}(I_{u1}^*) = \underline{Lim}(3) = (3 + 3)/2 = 3$$

$$\overline{Lim}(I_{l1}^*) = \overline{Lim}(2) = (2 + 5)/2 = 3.5$$

$$\overline{Lim}(I_{u1}^*) = \overline{Lim}(3) = (3 + 3 + 6)/2 = 4.$$

Then, the interval rough numbers of the first customer can be represented by the rough numbers of I_{l1}^* and I_{u1}^*

$$RN(I_{l1}^*) = [\![\underline{Lim}(I_{l1}^*), \overline{Lim}(I_{l1}^*)]\!] = [\![1.5, 3.5]\!]$$

$$RN(I_{u1}^*) = [\![\underline{Lim}(I_{u1}^*), \overline{Lim}(I_{u1}^*)]\!] = [\![3, 4]\!].$$

The rough numbers of other customer ratings are shown as follows:

$$RN(I_{l2}^*) = [\![1, 8/3]\!], RN(I_{u2}^*) = [\![3, 4]\!]$$

$$RN(I_{l3}^*) = [\![8/3, 5]\!], RN(I_{u3}^*) = [\![4, 6]\!].$$

According to [51], the overall average upper and lower importance rating of the ith CR item can be calculated as follows:

$$AIR(CR_i) = \sum_{j=1}^{n} w_j RN(Ct_j(CR_i)). \tag{19}$$

$AIR(CR_i)$ stands for the average importance rating of CR_i (i.e., ith CR item); n is the number of customers in the community. w_j stands for the weight of the jth customer; $RN(Ct_j(CR_i))$ stands for the rough number of the rating of the ith CR item provided by the jth customer.

Based on (19) and the weights of the three customers, the lower class' average importance rating of R is

$$AIR_l(R) = \frac{1}{3} \times [\![1.5, 3.5]\!] + \frac{1}{3} \times [\![1, 8/3]\!] + \frac{1}{3}$$

$$\times [\![8/3, 5]\!] = \left[\frac{31}{18}, \frac{67}{18}\right].$$

The upper class' average importance rating of R is

$$AIR_u(R) = \frac{1}{3} \times [\![3, 4]\!] + \frac{1}{3} \times [\![3, 4]\!] + \frac{1}{3} \times [\![4, 6]\!]$$

$$= \left[\frac{10}{3}, \frac{14}{3}\right].$$
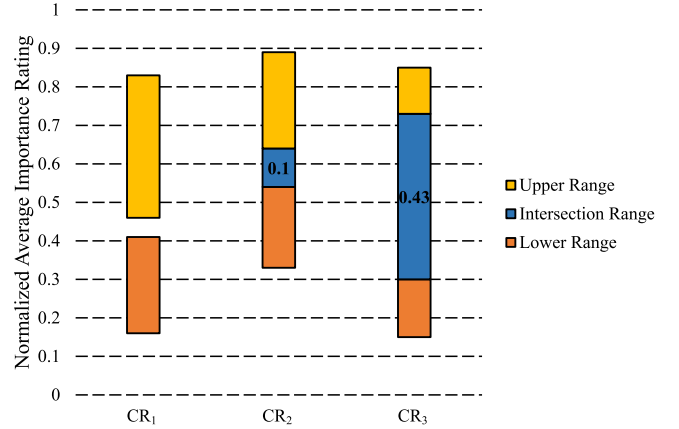
Step 3: Effectiveness verification

Fig. 2. Bar graph of normalized average importance ratings of CR items.

In this step, the average importance rating of each CR item (including lower and upper classes' average importance rating) is normalized and then depicted in a bar graph.

Fig. 2 illustrates an example that shows the average importance rating of three CR items. The "Upper Range", which is the yellow bar, corresponds to the upper class's average importance rating of one CR item, and the "Lower Range", which is the orange bar, corresponds to the lower class's average importance rating of one CR item. The blue bar in Fig. 2 is denoted as the "Intersection Range", which is the overlap part between the lower and upper classes' average importance rating of one CR item. The longer the length of the "Intersection Range", the more contradictory are the intentions for CR items from customers. In Fig. 2, the lengths of the "Intersection Range" of CR_2 and CR_3 are 0.10 and 0.43, respectively.

Experts are required to specify a threshold to determine whether the currently analyzed CRD has consistent attitudes toward each CR item. If the length of the "Intersection Range" in the ith CR item is less than the threshold, then it is considered that the currently analyzed CRD has an acceptable conflict of requirements for the ith CR item; if not, it is necessary to collect data again and investigate the ith CR item again.

Step 4: Define the relative importance range of CR items

After Step 3, the relative customer importance range of the ith CR item is defined, which can be calculated as follows:

$$Range(CR_i)$$

$$= \begin{bmatrix} \min\{\min(AIR_u(CR_i), \max(AIR_l(CR_i))\} \\ \max\{\min(AIR_u(CR_i), \max(AIR_l(CR_i))\} \end{bmatrix}. \tag{20}$$

Thus, the relative customer importance range of R is

$$Range(R) = \left[\frac{10}{3}, \frac{67}{18}\right].$$

Step 5: Determine the RIR of each CR item

Finally, based on the above mathematical process, the RIR of the ith CR item can be defined as follows:

$$RIR(CR_i) = \lambda_i Range_L(CR_i) + (1 - \lambda_i)Range_U(CR_i). \tag{21}$$

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$Range_L(CR_i)$ and $Range_U(CR_i)$ stand for the lower and upper boundary of $Range(CR_i)$, respectively. λ_i is determined by the average rough boundary of lower and upper classes' average importance rating of the ith CR item, which can be calculated as follows:

$$\lambda_i = \frac{RB(AIR_u(CR_i))}{RB(AIR_u(CR_i)) + RB(AIR_l(CR_i))}. \tag{22}$$

Thus, the RIR of R can be calculated as follows:

$$\lambda_R = \frac{RB(AIR_u(R))}{RB(AIR_u(R)) + RB(AIR_l(R))}$$
$$= \frac{4/3}{4/3 + 36/18} = \frac{2}{5},$$

$$RIR(R) = \lambda_R Range_L(R) + (1 - \lambda_R) Range_U(R)$$
$$= \frac{2}{5} \times \frac{10}{3} + (1 - \frac{2}{5}) \times \frac{67}{18} = \frac{107}{30}.$$

By repeating the above five steps, DM can determine the RIR of each CR item for each customer community.

C. Insight of GPC and Weighted Interval Rough Number Method

By deploying GPC, the originally chaotic CRD are divided into multiple communities and then each community contains customers with similar requirement characteristics. For different communities, the characteristics of CRs are quite different, which helps the DMs to understand the distribution of CRs existing in the current market.

GPC mines the information about CRs hiding in CRD and obtains a high-quality community division result. To further guide the selection of suppliers based on CRs, the weighted interval rough number method is then used to determine the RIR of each CR item in each community. Through this method, the degree of requirement for each CR item in each community can be quantitatively described.

In [51], all CRD are used as the input of the weighted interval rough number method, and finally, a comprehensive ranking of the importance of CR items is obtained. In our method, the weighted interval rough number method is executed multiple times to analyze the RIR of CR items, which reduces the possibility of failure of the weighted interval rough number method due to the ambiguity of CRD and ensures the reliability of the output results. Besides, by introducing the concept of customer community, companies can more intuitively understand the different requirements from different customer communities, which provides an intuitive reference for DMs to plan targeted marketing strategies with limited resources.

IV. Mapping From CR Items to SCs and the Supplier Selection Method

A. Mapping From CR Items to SCs

To integrate CRs into the supplier selection process, the experts are required to establish the mapping matrix from CR items to SCs. The process of establishing the mapping from CR items to SCs is a process of establishing the relationship between CRs and technical requirements, which can be regarded as an expert evaluation process. It is not the core content of this article. The following only gives the commonly used methods for reference. It is well known that the house of quality (HOQ) [54] can be used by enterprises to solve this problem. Besides, classic methods such as AHP, GRA, and TOPSIS [8]–[19] can also be used for establishing this mapping.

B. GA-Based Supplier Selection

To transform supplier selection into the problem that can be solved by GA, the following defines chromosome coding; selection, crossover, and mutation operation; and fitness function.

1) Chromosome Coding: Assume t suppliers should be selected from r alternative suppliers. The binary coding is used to transform a supplier selection solution to a $chromosome$, where 1 represents that the supplier is selected, and 0 represents the supplier is not selected.

2) Selection, Crossover, and Mutation Operation: The selection and crossover operation adopts the tournament selection mechanism [55] and the one-point crossover mechanism [56], respectively. For the mutation operation, randomly select two bits of a $chromosome$ that are 1 and 0, and turn them into 0 and 1. Besides, the elite mechanism [57] is also adopted for enhancing the convergence of the GA.

3) Fitness Function: The fitness function is used to characterize the quality of the viable supplier selection solution. It can be defined as follows:

$$Maximize\ Fitness$$

$$Fitness =$$

$$\left(\sum_{i=1}^{c} \alpha_i^T W_{com}^i \sum_{j=1}^{r} \sum_{k=1}^{m} \beta_j^T X_{jk} \sum_{h=1}^{n} W_{CR-SC}^{kh} RIR_i(CR_h) \right)$$

$$- \gamma_s \sum_{j=1}^{r} S^2(\beta_j^T X_j)$$

$$\text{s.t.} \sum_{i=1}^{c} \alpha_i^T W_{com}^i = 1. \tag{23}$$

The parameters and decision variables considered in the model are as follows.

Parameters:
c: The number of customer communities.
r: The total number of alternative suppliers.
m: The number of SCs.
n: The number of CR items.
Decision variables:
W_{com}^i: The weight of the ith community.
α_i: $0-1$ variable. It is 1 if the ith community is identified as the target community, which means that the enterprise believes it is necessary to meet its requirements, and it is 0 otherwise.
$RIR_i(CR_h)$: The RIR of the hth CR item in the ith community.
W_{CR-SC}^{kh}: The mapping weight from the kth SC to the hth CR item.

β_j: $0-1$ variable in the *chromosome*. It is 1 if the jth supplier is selected and 0 if not.

X_{jk}: The score of the jth supplier on the k SC obtained by expert experience.

$S^2(\alpha_j X_j)$: The sample variance of the score of the jth selected supplier in m SCs.

For simplicity, the fitness function can be represented also in the form of matrix operations

$Maximize\ Fitness$

$Fitness =$

$$\sum [\alpha^T W_{com} W_{CR-SC} RIR(CR) \beta^T X - \gamma_s S^2(\beta^T X)]$$

$$\text{s.t.} \sum \alpha^T W_{com} = 1. \tag{24}$$

The fitness function has three characteristics.

1) The concept of customer community is embedded in the supplier selection process. α is a 0–1 vector, which is used to represent whether the corresponding community is identified as a target community. For the communities containing fewer customers, α may be set to 0 by the DM. W_{com} is the weight vector of different communities, W_{com}^i is the weight of the ith community, W_{com}^i is calculated as follows:

$$W_{com}^i = \frac{Num_i}{\sum \alpha Num}. \tag{25}$$

Num is the vector consisting of the customer number in all communities. Num_i is the customer number in the ith community.

2) CRs are considered in the supplier selection process. $W_{CR-SC} RIR(CR)$ represents the weight matrix of SCs, which considers RIR of all CR items in different communities. $RIR(CR)$ contains the RIR of n CR items of all target communities. W_{CR-SC} is the mapping matrix obtained by expert experience and is used to map n CR items to m SCs. β^T is a 0–1 vector used to represent whether the corresponding supplier is selected (i.e., *chromosome*). X is the score matrix containing the scores of r alternative suppliers in m SCs.

3) The fitness function contains a penalty. To enhance the robustness of the supplier selection scheme, a penalty is added to the fitness function. $S^2(\beta^T X)$ is the sample variance vector that stands for the sample variance of the scores of the selected suppliers on m SCs. It means that the optimization goal is to output a robust supplier selection scheme that can fully meet the requirements of target communities. γ_s is the penalty coefficient. γ_s is taken as 1 in this article.

V. CASE STUDY

A. Background

Home appliances are typical products of manufacturing, and they are consumed by almost the entire family. Satisfying the individual requirements of different customers in the same community is a problem faced by the home appliance industry. A practical case from a large international home appliance enterprise can be used to prove the feasibility and effectiveness of our proposed supplier selection framework. Their representative product is the household refrigerator. The DM of this enterprise is seeking a systematic supplier selection method based on the PRs of their target customers. Currently, 50 alternative refrigerator suppliers are monitored by this enterprise, and they are all willing to provide this enterprise with the necessary supply information for supplier evaluation. The enterprise plans to select 15 suppliers from these 50 alternative suppliers to deepen supply partnerships. The supplier selection framework driven by the customer community in this article can be applied to provide the DM with the best supplier selection scheme.

B. Identification of the CR Items and SCs

After expert discussion and market research, the home appliance enterprise formulated seven CR items and five SCs. The details are as follows.

CR items:

CR_1: The desire for the refrigerator to keep fresh, refrigerate, and freeze at the same time.

CR_2: The desire for the refrigerator to support time-of-use electricity pricing.

CR_3: The desire for the refrigerator to be controlled remotely.

CR_4: The desire for the refrigerator to customize the storage volume of each part.

CR_5: The desire for the refrigerator to manage food information.

CR_6: The desire for the refrigerator to protect the privacy of users' food information.

CR_7: The desire for the refrigerator to book maintenance service.

SCs:

SC_1: Technology.

SC_2: Quality of service.

SC_3: Variety of business.

SC_4: Cost.

SC_5: Response speed.

According to the quarterly customer service report from this enterprise, 203, 173, and 192 customer feedback questionnaires in three months were collected, respectively. After sorting out these questionnaires, 568 CRD were obtained. Experts scored the performance of 50 alternative suppliers from the perspective of five SCs. Due to the ambiguity of CRs, the customers' expectations for CR items were scored in intervals. Since experts have management experience, to accurately evaluate the SCs of alternative suppliers, crisp values were used to score each supplier.

Data Cleaning: According to (1), 568 CRD entropy values are calculated. Then, sort the 568 CRD in ascending order by their entropy values, as shown in Table IV. After expert discussion, the entropy threshold ε is set to 2.683. The deleted CRD are bolded in Table IV. After data cleaning, 512 CRD are left.

Data Transformation: According to (3) and (4), 512 CRD is transformed into 512 CRFs. Then, the CRSF can be further obtained.

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TABLE IV
568 CRD WITH ENTROPY VALUES IN ASCENDING ORDER

Order	Entropy value									
1-10	1.977	1.986	1.995	2.095	2.110	2.113	2.132	2.135	2.139	2.166
11-20	2.176	2.182	2.188	2.201	2.206	2.209	2.211	2.218	2.229	2.235
21-30	2.240	2.244	2.254	2.255	2.262	2.272	2.274	2.285	2.288	2.296
...	...	...	...	...	...	...	...	...	...	...
501-510	2.675	2.675	2.675	2.676	2.677	2.678	2.678	2.678	2.680	2.680
511-520	2.683	2.683	**2.685**	**2.685**	**2.689**	**2.690**	**2.692**	**2.693**	**2.695**	**2.695**
521-530	**2.695**	**2.696**	**2.698**	**2.698**	**2.699**	**2.701**	**2.701**	**2.701**	**2.702**	**2.702**
531-540	**2.703**	**2.703**	**2.703**	**2.704**	**2.706**	**2.706**	**2.709**	**2.711**	**2.712**	**2.715**
541-550	**2.718**	**2.725**	**2.725**	**2.727**	**2.727**	**2.727**	**2.728**	**2.729**	**2.731**	**2.735**
551-560	**2.736**	**2.737**	**2.737**	**2.740**	**2.742**	**2.743**	**2.747**	**2.748**	**2.748**	**2.749**
561-568	**2.753**	**2.754**	**2.757**	**2.758**	**2.758**	**2.762**	**2.770**	**2.783**		

TABLE V
PARAMETER SETTING IN GPC

Parameter	Value	Description
M	100	The times of NGA running
I_GPC	500	Iteration times of NGA in single running
N_GPC	40	The number of populations
E_GPC	15	The number of elite populations
Pc_GPC	0.95	Crossover probability
Pm_GPC	0.10	Mutation probability
L	4	Niching radius
δ	0.05	Fitness threshold
τ	0.30	Distance threshold
K	20	The number of communities predicted by experts

TABLE VI
ANALYSIS RESULT OF THE OUTPUT 20 CLUSTERS

Cluster	CR item						
	CR_1	CR_2	CR_3	CR_4	CR_5	CR_6	CR_7
Cluster 1		◎				◎	◎
Cluster 2	◎	◎	◎			◎	◎
Cluster 3		◎	◎	◎	◎		◎
Cluster 4		◎	◎	◎	◎		◎
Cluster 5		◎				◎	◎
Cluster 6	◎	◎	◎	◎		◎	◎
Cluster 7		◎	◎				
Cluster 8	◎		◎				
Cluster 9	◎		◎				
Cluster 10		◎	◎				
Cluster 11			◎	◎	◎		
Cluster 12		◎	◎				
Cluster 13	◎	◎	◎				
Cluster 14	◎	◎	◎				
Cluster 15	◎	◎	◎				
Cluster 16	◎			◎	◎		
Cluster 17	◎		◎		◎		
Cluster 18		◎	◎				
Cluster 19	◎		◎				
Cluster 20		◎	◎	◎		◎	

TABLE VII
RESULT OF CUSTOMER COMMUNITY DIVISION

Community	Cluster(s)	The number of customers
Community 1	Cluster 1 and 5	89
Community 2	Cluster 2	33
Community 3	Cluster 3 and 4	19
Community 4	Cluster 6	2
Community 5	Cluster 7, 10, 12, and 18;	42
Community 6	Cluster 8, 9, and 19	88
Community 7	Cluster 11	8
Community 8	Cluster 13, 14, and 15	67
Community 9	Cluster 16	67
Community 10	Cluster 17	63
Community 11	Cluster 20	34

C. Stage 1: Implement GPC for Customer Community Division

After data preprocessing, GPC is executed. The parameter settings are in Table V. The details of GPC are in the following steps.

1) Step 1: Apply NGA for Peak Points Searching: Run NGA 100 times. Then, a peak point set containing a large number of data points is obtained. Next, duplicate data points are removed.

2) Step 2: Data Aggregation: First, the data points in the peak point set are aggregated according to distance threshold τ. Then, 1392 peak point groups are obtained. Next, AGNES is used to cluster 1392 peak point groups into 20 clusters. The data centroids of each cluster (the possible centroids of customer communities) are obtained.

3) Step 3: k-means-Based Clustering and Community Division: The mean value of each dimension of 512 CRD is used to represent the original interval data as the data input of k-means. Twenty possible centroids (i.e., heuristic information) are used as 20 initial cluster centroids of k-means. The boxplot of clusters output by heuristic k-means is shown in Fig. 3.

The distribution of each box in each boxplot is almost separate; that is to say, CRD in the same cluster has the same characteristics. For example, in Cluster 1, the scores of the CR items on the second, sixth, and seventh are significantly bigger than those of other CR items. It means that customers in Cluster 1 have an obvious requirement intention for those CR items on the second, sixth, and seventh. According to the above analysis process, the analysis results of each cluster are shown in Table VI, where ◎ represents a CR item that the customer cares about.

From Table VI, it can be seen that there are customers in some clusters that have the same requirement intention for refrigerators, such as Cluster 1 and Cluster 5. Such clusters should be merged to form the same customer community. The result of the customer community division is presented in Table VII.

It can be seen in Table VII that there are only two customers in Community 4, which correspond to Cluster 6. Observing the boxplot of Cluster 6 (see Fig. 3), these two customers score very low on the fifth CR item. The scores of the remaining CR items are relatively balanced and concentrated around $4-6$ points. After discussion with DMs, Community 4 should not be considered in the following process. After Community 4 is abandoned, the remaining 10 communities are identified as the target communities.

D. Stage 2: Determine the RIR of All CR Items for Each Community

After the customer community division, the weighted interval rough number method is used to determine the RIR of each CR item in each target community. Assume that all customers in each community have the same weight. That is, for each community, the weight of CRD [see (19)] takes the same weight.

The RIR of each CR item in each target community is shown in Table VIII.
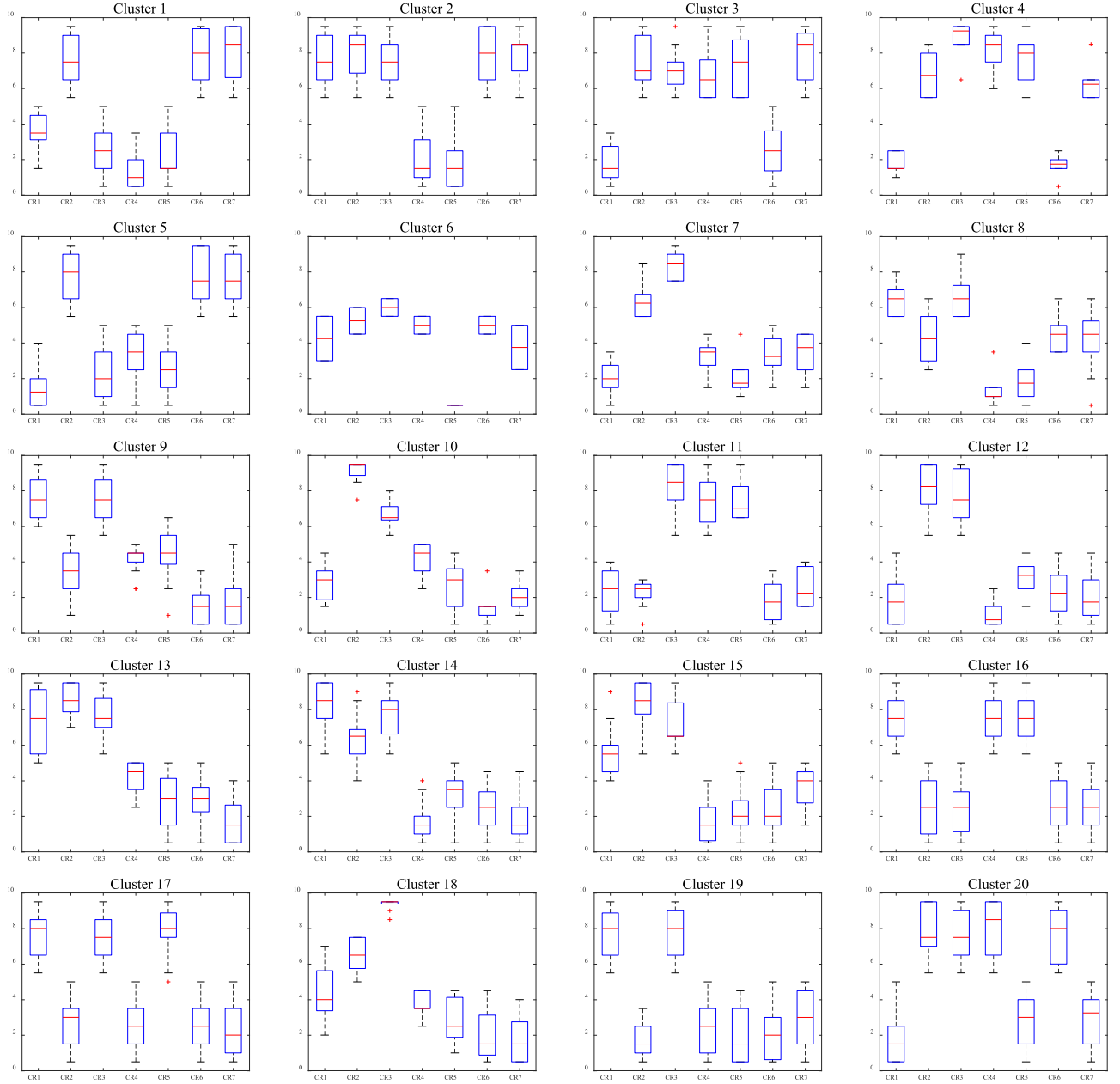
Fig. 3. Boxplot of 20 clusters output by our heuristic k-means.

E. Stage 3: Supplier Selection Scheme Generation

1) Mapping From CR Items to SCs: According to Section IV-A, there are many methods to determine the mapping relationship between CR items and SCs. In this case, the enterprise provides us with the mapping matrix, as shown in Table IX. It uses a crisp value between 0–1 to represent the relationship between the CR item and SC. The closer the value is to 1, the greater is the correlation between CR items and SCs.

2) Supplier Selection: GA-based supplier selection is implemented to provide the DM with an optimal supplier selection scheme. The parameter settings of GA are shown in Table X.

Based on the above process, each matrix or vector in (24) is obtained, following which the fitness function can be constructed.

Table XI summarizes the matrices and vectors involved in the fitness function.

Finally, the optimal supplier selection scheme output by GA is shown in Table XII.

F. Data Perturbation Experiment

Robustness is an important issue for the proposed framework. To investigate the robustness of our methodology, data perturbation experiments are conducted on W_{CR-SC} and $RIR(CR)$, which are the core inputs of the model. For each perturbation experiment on W_{CR-SC} (or $RIR(CR)$), a random value in $(-\Delta, \Delta)$ is applied to each data of W_{CR-SC} (or $RIR(CR)$). Considering that the data scales in W_{CR-SC} and $RIR(CR)$ are

TABLE VIII
CALCULATION RESULT OF THE RIR FOR CR ITEMS IN EACH TARGET COMMUNITY

Target community	CR item						
	CR_1	CR_2	CR_3	CR_4	CR_5	CR_6	CR_7
Community 1	2.33	7.79	2.38	2.42	2.45	7.83	7.72
Community 2	7.71	7.86	7.67	2.17	1.80	7.89	7.98
Community 3	2.01	7.25	7.50	7.28	7.40	2.24	7.48
Community 5	2.64	7.70	7.98	2.63	2.77	2.23	2.26
Community 6	7.59	2.62	7.56	2.72	2.68	2.34	2.75
Community 7	2.24	2.06	8.20	7.49	7.44	1.79	2.44
Community 8	7.11	7.80	7.49	2.44	2.72	2.43	2.38
Community 9	7.60	2.57	2.39	7.66	7.56	2.57	2.39
Community 10	7.64	2.62	7.52	2.42	7.97	2.56	2.30
Community 11	1.75	7.77	7.64	8.02	2.70	7.59	2.90

TABLE IX
MAPPING MATRIX BETWEEN CR ITEMS AND SCS

	SC_1	SC_2	SC_3	SC_4	SC_5
CR_1	0.77	0.11	0.27	0.91	0.08
CR_2	0.77	0.13	0.55	0.20	0.15
CR_3	0.85	0.30	0.10	0.19	0.15
CR_4	0.33	0.21	0.22	0.66	0.93
CR_5	0.69	0.85	0.73	0.13	0.19
CR_6	0.73	0.23	0.83	0.10	0.12
CR_7	0.10	0.97	0.14	0.33	0.86

TABLE X
PARAMETER SETTING IN GA

Parameter	Value	Description
I_GA	200	Iteration times of GA
N_GA	20	The number of populations
E_GA	1	The number of elite populations
Pc_GA	0.90	Crossover probability
Pm_GA	0.10	Mutation probability

TABLE XI
SUMMARY OF MATRIX OR VECTOR USED IN FITNESS FUNCTION

Matrix/Vector	Description	Access approach
α	0-1 vector; obtained in Section V-C	GPC and DMs' decision
W_{com}	Community weight vector; can be calculated according to Table VII and (25)	GPC and (25)
W_{CR-SC}	Mapping matrix between CR items and SCs; obtained in Table IX	HOQ, AHP and TOP-SIS etc.
$RIR(CR)$	RIR matrix; obtained in Table VIII (Need to convert the data scale to 0-1)	Weighted interval rough number method
X	Score matrix; obtained in Section V-B	Expert evaluation according multiple SCs

TABLE XII
GENERATED SUPPLIER SELECTION SCHEME

	The selected suppliers							
Supplier ID	4	9	10	11	13	17	21	26
	27	31	36	40	41	42	45	

both 0–1, Δ takes 0.01 as the initial value and gradually increases to 0.50. Perturbation experiments are repeated 20 times for each Δ.

The supplier selection scheme obtained in each perturbation experiment is compared with the original supplier selection scheme (that is, the previous scheme in Table XII) and calculates the average change ratio (%) under each Δ.

The experimental results are shown in Fig. 4. The abscissa of the line graph is the value of Δ, and the ordinate of the line graph is the average change ratio of the supplier selection scheme.

As shown in Fig. 4, when $\Delta = 0.20$, if the perturbation is applied to W_{CR-SC}, then 2.25 suppliers on average will be changed; if the perturbation is applied to $RIR(CR)$, then 0.6 suppliers on average will be changed. Our method shows strong robustness, especially when the perturbation range is approximately $(-0.10, 0.10)$.

VI. SIMULATION EXPERIMENT

A. Background

Table VI shows that most customer communities in the current market share a common requirement for the third CR item.

With the development of the ecosystem of smart home appliances, an increasing number of customers hope to be able to control various home appliances anytime and anywhere to promote the lifetime efficiency of the appliance. It is easy to understand this tendency. However, as Internet technology continues to be integrated into daily life, various types of personal and private information, such as health information, food information, and so on, are uploaded to enterprise servers. With the introduction of data privacy protection in various countries and regions (such as GDPR in Europe), increasing attention has been paid by customers to the protection of privacy data by enterprises.

Considering the industrial background, three sets of CRD in chronological order (termed CRD4, CRD5, and CRD6) were manually designed. The real 568 CRD from three months (203, 173, and 192 CRD, respectively), which were used in the case study of Section VI, were taken as the starting three sets of CRD, termed CRD1, CRD2, CRD3. Assume that CRD4, CRD5, and CRD6 were new CRD that the enterprise obtained after one month, two months, and three months. Assume that {CRD1, CRD2, CRD3, CRD4, CRD5, CRD6} is a time series sample of CRs. Assume a user-data leakage event occurs, and the public continues to pay more attention to the issue of privacy data protection. Then, this appeal will be reflected in the requirements of the customers with respect to the products. At this point, the number of customers with an obvious requirement for privacy data protection (that is, CR_6) increases over time, but the requirement for the other CR items does not change.

Based on the above assumptions, a simulation experiment is performed to study whether our customer community-based supplier selection framework can provide an updated supplier selection scheme for DMs according to the dynamic changes of the market requirement. The algorithm procedures and parameter settings are consistent with Section V.

Besides, CRD4, CRD5, and CRD6 contain 150 CRD, respectively. Tables VIII, XIV, and XV give basic information on CRD4, CRD5, and CRD6, which will be introduced in the following.

B. Principle of Data Generation

The design of CRD4–CRD6 is based on CRD1–CRD3. CRD1–CRD3 represents the data of three groups (three months)
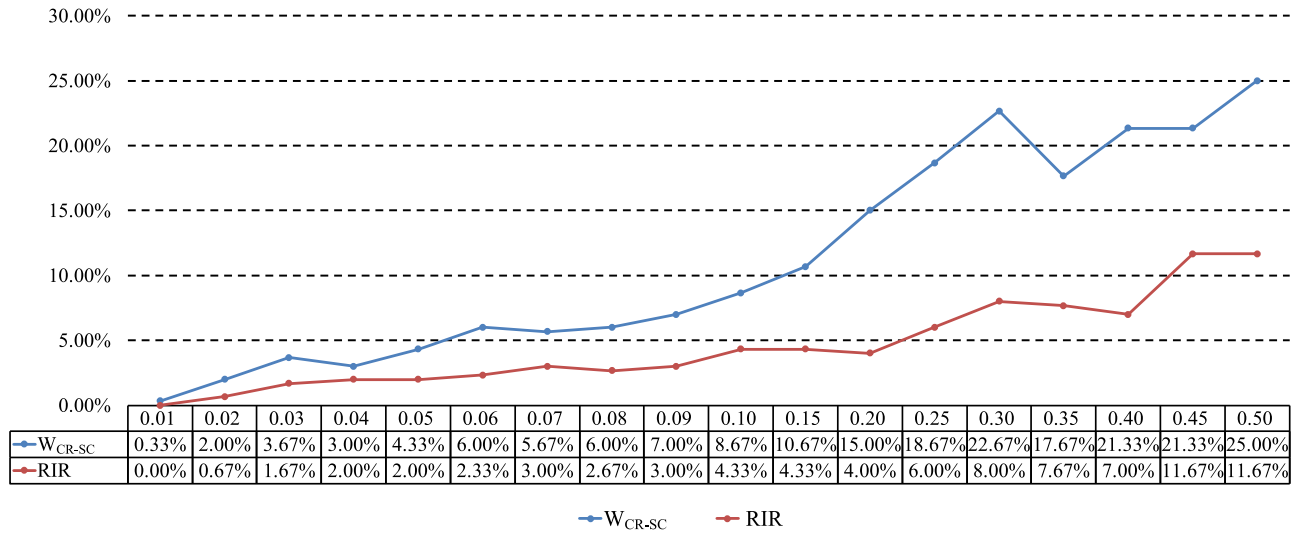
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Data perturbation experiment

	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50
$W_{CR\text{-}SC}$	0.33%	2.00%	3.67%	3.00%	4.33%	6.00%	5.67%	6.00%	7.00%	8.67%	10.67%	15.00%	18.67%	22.67%	17.67%	21.33%	21.33%	25.00%
RIR	0.00%	0.67%	1.67%	2.00%	2.00%	2.33%	3.00%	2.67%	3.00%	4.33%	4.33%	4.00%	6.00%	8.00%	7.67%	7.00%	11.67%	11.67%

Fig. 4.   Experiments of data perturbation.

TABLE XIII
SUMMARY OF CRD IN CRD4

Community	CR item							Number of customers
	CR_1	CR_2	CR_3	CR_4	CR_5	CR_6	CR_7	
Community 1		⊙				⊙	⊙	26
Community 2	⊙	⊙	⊙			⊙	⊙	9
Community 3		⊙	⊙	⊙		⊙	⊙	7
Community 4		⊙	⊙			⊙		12
Community 5	⊙		⊙					25
Community 6			⊙	⊙	⊙			5
Community 7	⊙	⊙	⊙					15
Community 8	⊙			⊙	⊙			21
Community 9	⊙		⊙		⊙			18
Community 10		⊙	⊙	⊙		⊙		12

TABLE XV
SUMMARY OF CRD IN CRD6

Community	CR item							Number of customers
	CR_1	CR_2	CR_3	CR_4	CR_5	CR_6	CR_7	
Community 1		⊙				⊙	⊙	25
Community 2	⊙	⊙	⊙			⊙	⊙	10
Community 3		⊙	⊙	⊙		⊙	⊙	9
Community 4		⊙	⊙			⊙		14
Community 5	⊙		⊙			⊙		23
Community 6			⊙	⊙	⊙	⊙		7
Community 7	⊙	⊙	⊙			⊙		11
Community 8	⊙			⊙	⊙	⊙		18
Community 9	⊙		⊙		⊙	⊙		20
Community 10		⊙	⊙	⊙		⊙		13

TABLE XIV
SUMMARY OF CRD IN CRD5

Community	CR item							Number of customers
	CR_1	CR_2	CR_3	CR_4	CR_5	CR_6	CR_7	
Community 1		⊙				⊙	⊙	21
Community 2	⊙	⊙	⊙			⊙	⊙	13
Community 3		⊙	⊙	⊙		⊙	⊙	5
Community 4		⊙	⊙			⊙		11
Community 5	⊙		⊙					23
Community 6			⊙	⊙	⊙			6
Community 7	⊙	⊙	⊙			⊙		16
Community 8	⊙			⊙	⊙			20
Community 9	⊙		⊙		⊙	⊙		21
Community 10		⊙	⊙	⊙		⊙		14

before the occurrence of this user-data leakage event. These can be understood as relatively fixed static CRs.

Taking the data generation of CRD4 as an example, we generated a set of CRD containing ten communities. As CRD4 can be considered, the data obtained by the enterprise one month after the user-data leakage event, the CRs in the market will not change much. Therefore, when designing CRD4, it not only needs to reflect the overall increase in the requirement of CR_6 in CRD, but also ensure that the characteristics of customer groups in CRD4 are the same as those in the previous three months. The data generation of CRD5 and CRD6 is similar to that of CRD4. In general, the data generation of CRD4–CRD6 is to increase new CRD with a preference for CR_6 under the premise that the characteristics of the customer community remain unchanged.

C. Phase 1: One Month Later

There are ten customer communities in CRD4. The detailed information is shown in Table XIII. Comparing Tables VI and XIII, it can be found that in CRD1, CR_6 is slightly increasing. For example, Community 5 in Table VI has the CR intention combination of CR_2 and CR_3. Then, after a month, CR_2, CR_3, and CR_6 constitute a new CR intention combination (see Community 4 in Table XIII).

Input $\{CRD2, CRD3, CRD4\}$ as input data for the supplier selection framework. According to the technical process described in Section VI, the final supplier selection scheme is obtained, as shown in the second row of Table XIV.

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TABLE XVI
SUPPLIER SELECTION SOLUTION OF FOUR PHASES

	The selected suppliers														
Previous scheme	4	9	10	11	13	17	21	26	27	31	36	40	41	42	45
Phase 1	4	9	10	11	13	17	21	26	27	31	35	36	40	41	45
Phase 2	4	9	10	11	13	17	22	26	27	31	35	36	40	41	45
Phase 3	4	9	10	11	13	17	22	26	31	35	36	40	41	45	46

TABLE XVII
SCORE OF SUPPLIERS WITH SUPERIOR PERFORMANCE IN SC_1 AND SC_3

	Supplier 11	Supplier 22	Supplier 35	Supplier 46
SC_1	8.50	8.95	8.83	8.42
SC_2	1.33	1.10	1.00	1.57
SC_3	7.35	8.97	7.69	9.62
SC_4	2.12	1.33	1.28	1.28
SC_5	3.92	1.67	1.46	1.30

D. Phase 2: Two Months Later

There are nine customer communities in CRD5. The detailed information is shown in Table XIV. It can be seen that more and more customers are beginning to pay attention to the protection of private data. CR_6 has become a public CR item that customers in seven communities care about.

Input $\{CRD3, CRD4, CRD5\}$ as input data for the supplier selection framework. According to the technical process described in Section VI, the final supplier selection scheme is obtained, as shown in the third row of Table XVI.

E. Phase 3: Three Months Later

There are 11 customer communities in CRD6. The detailed information is shown in Table XV. As the impact of the user-data leakage event continues to increase, it has become a general public requirement for enterprises to make efforts to protect customers' private data. As shown in Table XV, CR_6 is valued by customers in all communities.

Input $\{CRD4, CRD5, CRD6\}$ as input data for the supplier selection framework. According to the technical process described in Section VI, the final supplier selection scheme is obtained, as shown in the fourth row of Table XV.

F. Result Analysis

Based on the assumptions of this experiment, due to the occurrence of the user-data leakage event, the number of customers who value CR_6 continues to increase over time. According to the mapping matrix in Table IX, CR_6 is relatively related to SC_1 and SC_3. Therefore, for different phases, the suppliers with higher scores on SC_1 and SC_3 would gradually be valued by the enterprise and be selected as cooperative suppliers. Table XVII shows the suppliers with higher scores on SC_1 and SC_3 among the 50 alternative suppliers.

In Phase 1, the number of customers who valued CR_6 increased slightly compared to the previous. In the supplier selection scheme of Phase 1, a new supplier "#35" was selected as a cooperative supplier instead of supplier "#42". As shown in the second column of Table XVII, the score of supplier "#35" on SC_1 and SC_3 was high. It could meet the CR for privacy data protection.

TABLE XVIII
EXPERT OPTIONS ON THE IMPORTANCE OF CR ITEMS

CR items	EX.1	EX.2	EX.3
CR_1	H	H	H
CR_2	VH	H	H
CR_3	VH	H	VH
CR_4	M	M	M
CR_5	L	L	VL
CR_6	M	L	L
CR_7	M	M	M

TABLE XIX
EXPERT OPTIONS ON THE MAPPING RELATIONSHIP BETWEEN CR AND SC

		CR_1	CR_2	CR_3	CR_4	CR_5	CR_6	CR_7
SC_1	EX.1	H	VH	VH	M	H	H	L
	EX.2	H	H	VH	L	VH	H	L
	EX.3	VH	H	H	M	VH	H	L
SC_2	EX.1	L	L	L	M	H	L	VH
	EX.2	L	VL	L	L	VH	L	VH
	EX.3	VL	L	L	M	VH	M	H
SC_3	EX.1	L	M	L	M	H	VH	L
	EX.2	VL	M	VL	L	H	VH	M
	EX.3	L	M	VL	M	VH	H	L
SC_4	EX.1	VH	VL	VL	H	VL	L	M
	EX.2	VH	L	VL	H	L	L	M
	EX.3	VH	VL	L	M	VL	L	L
SC_5	EX.1	VL	L	VL	VH	VL	L	H
	EX.2	VL	VL	L	VH	L	L	VH
	EX.3	VL	VL	VL	VH	L	L	H

In Phase 2, compared to Phase 1, an increasing number of customers expressed an obvious requirement for CR_6. A new supplier "#22" was selected as a cooperative supplier instead of supplier "#21". As shown in the second column of Table XVII, the score of supplier "#22" on SC_1 and SC_3 was high. It could meet the CR for privacy data protection.

In Phase 3, it was a common public requirement for an enterprise to make efforts to protect customers' private data. Therefore, all of the suppliers with high scores in SC_1 and SC_3 in Table XVII were selected.

The above experiment illustrates that our customer community-based supplier selection framework could update the supplier selection scheme according to the dynamic changes of CR, thus enabling enterprises to adjust the supplier network in time and respond to market changes.

VII. COMPARISON

To better demonstrate the characteristics of our proposed framework, a typical fuzzy QFD method for supplier selection was used for comparison [58].

Since the importance of CR items and the mapping relationship between CR and SC in the fuzzy QFD method are linguistic variables, three experts were invited to conduct the linguistic evaluation based on the list of linguistic meaning in [58]. Tables XVIII and XIX give expert opinions on the importance of CR items and the mapping relationship between CR and SC, respectively.

According to the technical description in prior work [58], triangular fuzzy numbers were used to handle the expert opinions in the HOQ.

TABLE XX
FUZZY WEIGHT OF EACH SC

	α	β	γ
SC_1	29.3333	41.0000	54.6667
SC_2	14.2857	23.9524	35.6190
SC_3	16.6349	26.3968	38.1587
SC_4	14.9841	23.9841	34.9841
SC_5	11.6825	20.4921	31.3016

TABLE XXI
COMPARISON OF FUZZY-QFD AND OUR METHOD

	The selected suppliers															
Fuzzy-1	4	9	10	**11**	13	17	21	26	27	31	36	40	41	42	45	
Fuzzy-2	4	9	10	**11**	13	17	21	26	37	31	**35**	36	40	41	45	
Previous scheme	4	9	10	**11**	13	17	21	26	27	31	36	40	41	42	45	
Phase1	4	9	10	**11**	13	17	21	26	27	31	**35**	36	40	41	45	
Phase2	4	9	10	**11**	13	17	**22**	26	27	31	**35**	36	40	41	45	
Phase3	4	9	10	**11**	13	17	**22**	26	31	**35**	36	40	41	45	**46**	

[1] Suppliers with high satisfaction in CR_6 are marked in bold.

Then, the fuzzy weight of each SC could be obtained, as shown in Table XX.

After obtaining the weight of each SC, the next step of the fuzzy-QFD approach processed each expert's opinions on the various suppliers with each SC. Then, all of the suppliers were ranked.

The number of potential suppliers in our case was 50. It is a very time-consuming task for three experts to evaluate each SC of all of the potential suppliers. Therefore, we could not strictly follow the fuzzy-QFD approach to complete supplier selection.

For experimental comparison, the supplier ranking could be established by

$$Maximize\ Fitness$$

$$Fitness = \sum \left[W_{HOQ}\beta^T X - \gamma_s S^2(\beta^T X) \right]. \tag{26}$$

The difference between the new equation and the original equation is that $[\alpha^T W_{com} W_{CR-SC} RIR(CR)]$ is replaced with W_{HOQ}. $[\alpha^T W_{com} W_{CR-SC} RIR(CR)]$ in the original equation can be regarded as the nominal weight vector of SC considering the customer community.

Therefore, we replaced the previous nominal weight vector of SC with W_{HOQ}. Since the weight vector of SC given by fuzzy QFD had three groups (see Table XX) but (26) only needs one group of the weight vector, the middle vector β was chosen as W_{HOQ}.

The scale of W_{HOQ} was converted into the same scale as the original $[\alpha^T W_{com} W_{CR-SC} RIR(CR)]$ before the selection of the supplier scheme. Our method unitizes the vector of W_{HOQ} and then multiplies each item of the unitized W_{HOQ} by $\sum([\alpha^T W_{com} W_{CR-SC} RIR(CR)])$.

After the GA operation, the final supplier selection scheme is shown in the row of "Fuzzy-1" in Table XXI.

Comparing "Fuzzy-1" with "Previous scheme", it can be found that the supplier selection scheme obtained by combining the fuzzy-QFD approach and the proposed framework in this article were consistent.

For further comparison, we changed the expert opinions results for CR_6 in Table XVIII from {M,L,L} to {H,H,H} to simulate the public's concern for privacy protection. The new supplier selection scheme is shown in the row of "Fuzzy-2" in Table XXI. As shown, "#35" was added to the supplier selection scheme. The new supplier selection scheme was consistent with our method. The comparison of the results shows that our method effectively described the requirements of customers for supplier selection in different phases.

However, due to the limitation of personnel costs, the activities of companies organizing experts to evaluate current market conditions cannot be updated in real time. It may be held once a quarter. Therefore, market research methods based on expert evaluation are often not flexible enough to deal with sensitive and changeable markets. Different from expert evaluation, our method mainly relies on CRD. The acquisition of CRD does not require many experts. Besides, CRD itself is dynamically acquired, which can better reflect the dynamic changes of the market. Therefore, our method has advantages in both the input costs of experts and the dynamic market perception.

VIII. CONCLUSION

Different from previous research, a systematic supplier selection method based on customer community was proposed in this article. It enabled the enterprise to provide products and services closer to CRs by selecting suitable suppliers. Customer community division divided the complex structure of the market into multiple communities according to the different characteristics of CRs. This helped companies better understand the expectations of different types of customers for products and services. Besides, the perspective of the community also helped companies understand the different priorities of customers' PRs and the distribution of those requirements in the market. This enabled companies to deploy marketing strategies more effectively and accurately with limited resources. In general, integrating CR into the supplier selection process helps increase customer satisfaction and build a stronger supplier partnership.

From the three stages in our framework, the summarized issues of the supplier selection process in Table I were studied. In the first stage, GPC was used to divide CRD into multiple communities to recognize customer communities that exist in the market (solving for Issue 1), which enables DMs to grasp the different requirements of customers in the market. In the second stage, the weighted interval rough number method and expert knowledge were used to determine the RIR of CR items in each community and the mapping relationship between CR items and SCs, respectively. In this stage, quantitative CR and SC were connected (solving for Issue 2 and Issue 3). In the third stage, the supplier selection model integrated with CRs was established. Then, the stochastic tournament model-based GA was used to perform the CR-based supplier selection problem (solving for Issue 4).

The feasibility and effectiveness of our proposed framework were verified by a practical refrigerator case from a home appliance enterprise. A simulation experiment was also designed to verify the performance of the proposed framework in a dynamic scenario. The experimental results demonstrated that our framework perceives the dynamic changes of the CRs in the

market and updates the supplier selection scheme dynamically according to the market changes.

The focus of this article was to establish a supplier selection framework by a customer community-driven approach. There is still much room for research on its details. Our supplier selection framework can capture changes in CRs caused by changes in market conditions and further provide DMs with an optimized supplier selection scheme. However, in the real world, since there is a time lag from the capture of CRD to supplier selection and then to product delivery, supplier selection based on CRD in the previous cycle may not fully meet the requirement of customers in the next cycle. The above situation may cause the updated supplier selection scheme to lag behind changes in CR. Therefore, forecasting methods need to be combined to alleviate the lag of model output to dynamic market changes. Second, the GA-based supplier selection model proposed in this article is a simplification of the actual scenario. In actual supplier selection, the goal pursued by the supplier selection scheme provided to DMs may not only satisfy CRs but there may also be some actual supplier selection constraints. It is necessary to employ our framework in more scenarios to expand its scope of application. Third, the customer community division proposed in this article mainly relies on clustering to divide customers into multiple communities based on different CR characteristics existing in the CRD. In practical applications, combining domain knowledge of different industries to explore more effective customer community division methods deserves further consideration. Finally, our framework requires experts to directly participate in the decision-making process of supplier selection, which inevitably makes the results of supplier selection affected by personal subjective preferences. In future work, effective methods to avoid or reduce the direct participation of experts in decision-making should be developed to further solve this problem.

REFERENCES

[1] S. Hendiani, A. Mahmoudi, and H. Liao, "A multi-stage multi-criteria hierarchical decision-making approach for sustainable supplier selection," *Appl. Soft Comput.*, vol. 94, 2020, Art. no. 106456.

[2] J. Chai, J. N. K. Liu, and E. W. T. Ngai, "Application of decision-making techniques in supplier selection: A systematic review of literature," *Expert Syst. Appl.*, vol. 40, no. 10, pp. 3872–3885, 2013.

[3] Z. Chen, X. Ming, T. Zhou, and Y. Chang, "Sustainable supplier selection for smart supply chain considering internal and external uncertainty: An integrated rough-fuzzy approach," *Appl. Soft Comput.*, vol. 87, 2020, Art. no. 106004.

[4] S. Hendiani, H. Liao, R. Ren, and B. Lev, "A likelihood-based multi-criteria sustainable supplier selection approach with complex preference information," *Inf. Sci.*, vol. 536, pp. 135–155, 2020.

[5] S. Hosseini and K. Barker, "A Bayesian network model for resilience-based supplier selection," *Int. J. Prod. Econ.*, vol. 180, pp. 68–87, 2016.

[6] P. K. Medhi and S. Mondal, "A neural feature extraction model for classification of firms and prediction of outsourcing success: Advantage of using relational sources of information for new suppliers," *Int. J. Prod. Res.*, vol. 54, no. 20, pp. 6071–6081, 2016.

[7] A. Hiziroglu, "Soft computing applications in customer segmentation: State-of-art review and critique," *Expert Syst. Appl.*, vol. 40, no. 16, pp. 6491–6507, 2013.

[8] Y. Beikkhakhian, M. Javanmardi, M. Karbasian, and B. Khayambashi, "The application of ISM model in evaluating agile suppliers selection criteria and ranking suppliers using fuzzy TOPSIS-AHP methods," *Expert Syst. Appl.*, vol. 42, no. 15/16, pp. 6224–6236, 2015.

[9] A. H. Azadnia, M. Z. M. Saman, and K. Y. Wong, "Sustainable supplier selection and order lot-sizing: An integrated multi-objective decision-making process," *Int. J. Prod. Res.*, vol. 53, no. 2, pp. 383–408, 2015.

[10] A. Awasthi, K. Govindan, and S. Gold, "Multi-tier sustainable global supplier selection using a fuzzy AHP-VIKOR based approach," *Int. J. Prod. Econ.*, vol. 195, pp. 106–117, 2018.

[11] S. H. Hashemi, A. Karimi, and M. Tavana, "An integrated green supplier selection approach with analytic network process and improved Grey relational analysis," *Int. J. Prod. Econ.*, vol. 159, pp. 178–191, 2015.

[12] Q. Dong, K. Zhü, and O. Cooper, "Gaining consensus in a moderated group: A model with a twofold feedback mechanism," *Expert Syst. Appl.*, vol. 71, pp. 87–97, 2017.

[13] M. N. Kasirian and R. M. Yusuff, "An integration of a hybrid modified TOPSIS with a PGP model for the supplier selection with interdependent criteria," *Int. J. Prod. Res.*, vol. 51, no. 4, pp. 1037–1054, 2013.

[14] F. Dweiri, S. Kumar, S. A. Khan, and V. Jain, "Designing an integrated AHP based decision support system for supplier selection in automotive industry," *Expert Syst. Appl.*, vol. 62, pp. 273–283, 2016.

[15] S. Wan, G. Xu, and J. Dong, "Supplier selection using ANP and ELECTRE II in interval 2-tuple linguistic environment," *Inf. Sci.*, vol. 385, pp. 19–38, 2017.

[16] J. Chai and E. W. T. Ngai, "Decision-making techniques in supplier selection: Recent accomplishments and what lies ahead," *Expert Syst. Appl.*, vol. 140, 2020, Art. no. 112903.

[17] K. Govindan, M. Kadziński, and R. Sivakumar, "Application of a novel PROMETHEE-based method for construction of a group compromise ranking to prioritization of green suppliers in food supply chain," *Omega*, vol. 71, pp. 129–145, 2017.

[18] M. Segura and C. Maroto, "A multiple criteria supplier segmentation using outranking and value function methods," *Expert Syst. Appl.*, vol. 69, pp. 87–100, 2017.

[19] R. Khemiri, K. Elbedoui-Maktouf, B. Grabot, and B. Zouari, "A fuzzy multi-criteria decision-making approach for managing performance and risk in integrated procurement-production planning," *Int. J. Prod. Res.*, vol. 55, no. 18, pp. 5305–5329, 2017.

[20] X.-Y. You, J.-X. You, H.-C. Liu, and L. Zhen, "Group multi-criteria supplier selection using an extended VIKOR method with interval 2-tuple linguistic information," *Expert Syst. Appl.*, vol. 42, no. 4, pp. 1906–1916, 2015.

[21] M. Abdollahi, M. Arvan, and J. Razmi, "An integrated approach for supplier portfolio selection: Lean or agile," *Expert Syst. Appl.*, vol. 42, no. 1, pp. 679–690, 2015.

[22] G. A. Keskin, "Using integrated fuzzy DEMATEL and fuzzy C: Means algorithm for supplier evaluation and selection," *Int. J. Prod. Res.*, vol. 53, no. 12, pp. 3586–3602, 2015.

[23] K. Govindan, R. Khodaverdi, and A. Vafadarnikjoo, "Intuitionistic fuzzy based DEMATEL method for developing green practices and performances in a green supply chain," *Expert Syst. Appl.*, vol. 42, no. 20, pp. 7207–7220, 2015.

[24] C.-M. Su, D.-J. Horng, M.-L. Tseng, A. S. Chiu, K.-J. Wu, and H.-P. Chen, "Improving sustainable supply chain management using a novel hierarchical grey-DEMATEL approach," *J. Cleaner Prod.*, vol. 134, pp. 469–481, 2016.

[25] Z. Liu, X. Ming, and W. Song, "A framework integrating interval-valued hesitant fuzzy DEMATEL method to capture and evaluate co-creative value propositions for smart PSS," *J. Cleaner Prod.*, vol. 215, pp. 611–625, 2019.

[26] R.-J. Lin, "Using fuzzy DEMATEL to evaluate the green supply chain management practices," *J. Cleaner Prod.*, vol. 40, pp. 32–39, 2013.

[27] S.-Y. Chou, and Y.-H. Chang, "A decision support system for supplier selection based on a strategy-aligned fuzzy SMART approach," *Expert Syst. Appl.*, vol. 34, no. 4, pp. 2241–2253, 2008.

[28] J. Rezaei, "Best-worst multi-criteria decision-making method," *Omega*, vol. 53, pp. 49–57, 2015.

[29] S. Talluri, H. A. DeCampos, and G. T. M. Hult, "Supplier rationalization: A sourcing decision model," *Decis. Sci.*, vol. 44, no. 1, pp. 57–86, 2013.

[30] M. Mahdiloo, R. F. Saen, and K.-H. Lee, "Technical, environmental and eco-efficiency measurement for supplier selection: An extension and application of data envelopment analysis," *Int. J. Prod. Econ.*, vol. 168, pp. 279–289, 2015.

[31] M. Dotoli, N. Epicoco, and M. Falagario, "A fuzzy technique for supply chain network design with quantity discounts," *Int. J. Prod. Res.*, vol. 55, no. 7, pp. 1862–1884, 2017.

[32] D. Manerba, R. Mansini, and G. Perboli, "The capacitated supplier selection problem with total quantity discount policy and activation costs under uncertainty," *Int. J. Prod. Econ.*, vol. 198, pp. 119–132, 2018.

[33] J. Yoon, S. Talluri, H. Yildiz, and W. Ho, "Models for supplier selection and risk mitigation: A holistic approach," *Int. J. Prod. Res.*, vol. 56, no. 10, pp. 3636–3661, 2018.

[34] G. Bodaghi, F. Jolai, and M. Rabbani, "An integrated weighted fuzzy multi-objective model for supplier selection and order scheduling in a supply chain," *Int. J. Prod. Res.*, vol. 56, no. 10, pp. 3590–3614, 2018.

[35] Z. Babić and T. Perić, "Multiproduct vendor selection with volume discounts as the fuzzy multi-objective programming problem," *Int. J. Prod. Res.*, vol. 52, no. 14, pp. 4315–4331, 2014.

[36] A. L. Cunha, M. O. Santos, R. Morabito, and A. Barbosa-Povoa, "An integrated approach for production lot sizing and raw material purchasing," *Eur. J. Oper. Res.*, vol. 269, no. 3, pp. 923–938, 2018.

[37] C. Arampantzi, I. Minis, and G. Dikas, "A strategic model for exact supply chain network design and its application to a global manufacturer," *Int. J. Prod. Res.*, vol. 57, no. 5, pp. 1371–1397, 2019.

[38] M. Sali and E. Sahin, "Line feeding optimization for just in time assembly lines: An application to the automotive industry," *Int. J. Prod. Econ.*, vol. 174, pp. 54–67, 2016.

[39] H. Adeinat and J. A. Ventura, "Integrated pricing and supplier selection in a two-stage supply chain," *Int. J. Prod. Econ.*, vol. 201, pp. 193–202, 2018.

[40] A. Negahban and M. Dehghanimohammadabadi, "Optimizing the supply chain configuration and production-sales policies for new products over multiple planning horizons," *Int. J. Prod. Econ.*, vol. 196, pp. 150–162, 2018.

[41] M. Tavana, A. Fallahpour, D. D. Caprio, and F. J. Santos-Arteaga, "A hybrid intelligent fuzzy predictive model with simulation for supplier evaluation and selection," *Expert Syst. Appl.*, vol. 61, pp. 129–144, 2016.

[42] X. Guo, Z. Zhu, and J. Shi, "Integration of semi-fuzzy SVDD and CC-Rule method for supplier selection," *Expert Syst. Appl.*, vol. 41, no. 4, pp. 2083–2097, 2014.

[43] B. Nepal and O. P. Yadav, "Bayesian belief network-based framework for sourcing risk analysis during supplier selection," *Int. J. Prod. Res.*, vol. 53, no. 20, pp. 6114–6135, 2015.

[44] J. Chai and J. N. K. Liu, "A novel believable rough set approach for supplier selection," *Expert Syst. Appl.*, vol. 41, no. 1, pp. 92–104, 2014.

[45] A. Jabbarzadeh, B. Fahimnia, and F. Sabouhi, "Resilient and sustainable supply chain design: Sustainability analysis under disruption risks," *Int. J. Prod. Res.*, vol. 56, no. 17, pp. 5945–5968, 2018.

[46] A. Jula, Z. Othman, and E. Sundararajan, "Imperialist competitive algorithm with PROCLUS classifier for service time optimization in cloud computing service composition," *Expert Syst. Appl.*, vol. 42, no. 1, pp. 135–145, 2015.

[47] M. S. Memon, Y. H. Lee, and S. I. Mari, "Group multi-criteria supplier selection using combined grey systems theory and uncertainty theory," *Expert Syst. Appl.*, vol. 42, no. 21, pp. 7951–7959, 2015.

[48] A. Liu, Y. Xiao, H. Lu, S.-B. Tsai, and W. Song, "A fuzzy three-stage multi-attribute decision-making approach based on customer needs for sustainable supplier selection," *J. Cleaner Prod.*, vol. 239, 2019, Art. no. 118043.

[49] V. S. Yadavalli, J. D. Darbari, N. Bhayana, P. Jha, and V. Agarwal, "An integrated optimization model for selection of sustainable suppliers based on customers' expectations," *Operations Res. Perspectives*, vol. 6, 2019, Art. no. 100113.

[50] M. R. Asadabadi, "A customer based supplier selection process that combines quality function deployment, the analytic network process and a Markov chain," *Eur. J. Oper. Res.*, vol. 263, no. 3, pp. 1049–1062, 2017.

[51] P. Zheng, X. Xu, and S. Q. Xie, "A weighted interval rough number based method to determine relative importance ratings of customer requirements in QFD product planning," *J. Intell. Manuf.*, vol. 30, no. 1, pp. 3–16, 2019.

[52] L.-Y. Zhai, L.-P. Khoo, and Z.-W. Zhong, "A rough set enhanced fuzzy approach to quality function deployment," *Int. J. Adv. Manuf. Technol.*, vol. 37, no. 5-6, pp. 613–624, 2008.

[53] L.-Y. Zhai, L.-P. Khoo, and Z.-W. Zhong, "A rough set based QFD approach to the management of imprecise design information in product development," *Adv. Eng. Inform.*, vol. 23, no. 2, pp. 222–228, 2009.

[54] M. M. H. Chowdhury and M. A. Quaddus, "A multi-phased QFD based optimization approach to sustainable service design," *Int. J. Prod. Econ.*, vol. 171, pp. 165–178, 2016.

[55] H. Kiliç and U. Yüzgeç, "Improved antlion optimization algorithm via tournament selection and its application to parallel machine scheduling," *Comput. Ind. Eng.*, vol. 132, pp. 166–186, 2019.

[56] D. E. Goldberg, *Genetic Algorithm in Search, Optimization, and Machine Learning*. Boston, MA, USA: Addison-Wesley, 1989.

[57] H. Zhang, F. Liu, Y. Zhou, and Z. Zhang, "A hybrid method integrating an elite genetic algorithm with tabu search for the quadratic assignment problem," *Inf. Sci.*, vol. 539, pp. 347–374, 2020.

[58] M. Bevilacqua, F. Ciarapica, and G. Giacchetta, "A fuzzy-QFD approach to supplier selection," *J. Purchasing Supply Manage.*, vol. 12, no. 1, pp. 14–27, 2006.

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