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Electricity Sales Package Decision Making Using Two-Stage Density Clustering and Minimum Adjustment Distance Consensus

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Abstract: In the decision making of electricity sales packages, it is usually the specific situation of similar customers that provides the basis of a decision-making plan for target customer package selection, so it is particularly important to integrate the opinions of similar customers. Therefore, a multi-attribute group decision-making method for an electricity sales package is proposed, which is based on two-stage density clustering (TSDC) and minimum adjustment distance consensus. Firstly, in order to provide support for identifying similar customers among target customers, a sample customer set clustering method is proposed, which is based on a customer portrait label system and TSDC. Secondly, based on the entropy method, the attribute weight of the electricity sales package is determined. Based on the weight and the multi-attribute group decision-making consensus process, the minimum adjustment distance consensus of the sample customers' fuzzy evaluation matrix for the electricity sales package is proposed. Then, a full-ranking decision method for an electricity sales package based on target customer satisfaction is proposed. Finally, customers in a certain area of China are selected as an example. This example is used to verify the accuracy and effectiveness of the decision-making method of electricity sales package proposed in this paper.

Keywords: electricity sales package; customer portrait; TSDC; minimum adjustment distance consensus; multiple attribute group decision making

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1. Introduction

With the further development of power market reform, the power industry is gradually transforming and upgrading towards greening and low-carbonization. Under such a background, accelerating the establishment of a green power market is essential. By improving the mechanism of electricity sales in the electricity market, utilizing the role of the market, and stimulating the potential of both supply and demand, the development of green energy can be promoted. Electricity sales companies need to enrich the content of electricity sales services, innovate the service mode, and improve service quality to enhance market competitiveness and customer satisfaction and to adapt to the new trend of upgrading energy consumption. The electricity sales package, as an innovative approach to electricity sales services, represents a significant strategy. It allows electricity sales companies to attract new customers and enhance the loyalty of existing customers. In addition, customers also expect to reduce the cost of electricity consumption through appropriate electricity sales packages. However, the number of existing electricity sales packages is relatively large. For example, there are about 9000 electricity sales packages in the German electricity market [1] and more than 1800 electricity sales packages in Texas, U.S.A. [2]. There exist great differences in the perceptions of electricity sales packages for different customers. How the electricity sales companies make a decision on the

appropriate electricity sales package based on the evaluation information of customers is a key to increase the market share.

At present, the existing group decision-making methods for electricity sales packages include direct methods and indirect methods. The direct group decision-making methods are simple and easy to implement, such as iSelect [3], Power to Choose [4], Energy Made Easy [5], Check24 [6], Eprimo [7], Entega [8], and other online recommendation platforms for electricity packages. However, the direct methods only consider customers' cost and ignore the diversity of information about customers' evaluation of electricity sales packages. The indirect group decision-making methods for electricity sales packages involve offering group decision-making solutions for customers. These are based on electricity consumption characteristics, evaluation information, and electricity preferences. Techniques such as statistical analysis and mathematical modeling are used. For example, a hierarchical clustering algorithm for group decision-making methods based on the differences in the characteristics of customers' electricity consumption was proposed in [9]. A personalized electricity sales package group decision-making system based on residential customers' smart-meter electricity consumption characteristics was designed in [10]. Additionally, the collaborative filtering algorithm [11] is commonly utilized as an indirect method for electricity sales package group decision making. For example, a collaborative filtering algorithm for electricity sales package group decision making, based on the customers' electricity consumption characteristics by mining the customers' electricity consumption characteristics, was proposed in [12]. Then, electricity sales packages for target customers were recommended based on the similarity of electricity consumption characteristics between historical customers and target customers using this method. A residential electricity sales package group decision-making system, based on a Bayesian hybrid collaborative filtering algorithm, was designed considering the electricity consumption characteristics of household appliances of ordinary residential customers in [13]. In contrast with direct group decision-making methods, the characteristics of the customers' electricity consumption behavior were taken into account by the collaborative filtering algorithm. This improved the accuracy of group decision-making outcomes for electricity sales packages to a certain extent and provided ideas for package recommendations. However, different customers' evaluations and cognition of electricity sales packages are different. The above indirect decision-making method only considers a situation where customers are familiar with all the attributes of electricity sales packages and ignores the hesitant and ambiguous state of customers' evaluations [14], that is, the hesitant and ambiguous feature of customers' electricity sales package evaluation information [15]. Moreover, there exists significant variance in the evaluation feedback provided by different customers regarding the same electricity sales package. Even among customers with similar electricity consumption characteristics, substantial differences emerge in their evaluations of identical packages. Therefore, in order to minimize the errors of the group decision-making results for electricity sales packages, it is necessary to consider the consensus-reaching process during group decision making on electricity sales packages [16,17]. In the consensus-reaching process, it is crucial to minimize the differences between customers' original and adjusted evaluation information [18–20]. Therefore, it is important to consider the hesitant fuzzy characteristics of customers' evaluation information for electricity sales packages. Based on the consensus rule of minimum adjustment distance, studying the multi-attribute group decision-making method can improve the accuracy of package recommendations and enhance customer satisfaction.

In addition, customer clustering also plays an important role in the accuracy of electricity sales package group decision making. The electricity sales company can match target customers with historical similar customers based on the electricity consumption characteristics of the target customers. By leveraging the group decision-making results of historically similar customers, the company can recommend electricity sales packages to the target customers. The density clustering algorithm is a commonly used clustering algorithm that does not require the use of distance as a metric but determines the cluster

structure based on the closeness of the sample distribution. Ordering points to identify the clustering structure (OPTICS) was proposed as a clustering method based on any radius and threshold in [21]. It generated a cluster-ordered reachable graph with implicitly included parameters, leaving it up to users to select the clustering result as needed. This process often resulted in significant inconvenience for users. Then, a method for enhancing the density computation called the residual error-based density peak clustering algorithm (REDPC) was proposed in [22], which utilized the residuals of neighborhood data points to compute local density. This algorithm aimed to enhance the variability in density peaks. However, this method encountered the issue of collateral misclustering. Based on the above density clustering algorithm research, this paper will propose TSDC, which improves the customer clustering accuracy.

In total, a multi-attribute group decision-making method for electricity sales packages based on TSDC and minimum adjustment distance consensus will be proposed in this paper. The main contributions of the paper are listed as follows:

(1) A sample customer clustering method is proposed, the TSDC algorithm, avoiding the randomness, subjectivity, and associated errors existing in the current density clustering algorithm, which can improve the accuracy of identifying similar customers to the target customer.

(2) Considering the hesitant and fuzzy characteristics of customers' evaluation information on electricity sales packages, a multi-attribute group decision-making method for electricity sales packages is proposed based on the minimum adjustment distance consensus, realizing the transformation between the customers' evaluation information and the collective evaluation information, which can improve the accuracy of the group decision making on electricity sales packages.

Based on the customer portrait labeling system and TSDC, a method for clustering a sample customer set is proposed in Section 2. Based on the entropy method and minimum adjustment distance consensus-reaching process, a method for evaluating electricity sales packages is proposed in Section 3. Based on customers' satisfaction, the full-ranking decision method for electricity sales packages is proposed in Section 4. Finally, a concrete example is provided in Section 5.

2. Sample Customer Clustering Based on TSDC

2.1. Customer Portrait Label System Construction

There are differences in the electricity consumption and consumption habits of each customer. In order to identify similar customers among target customers, the monthly load data $P = \{P_{U_1}, P_{U_2}, \cdots, P_{U_i}, \cdots, P_{U_I}\}$ of the sample customer set $U = \{U_1, U_2, \cdots, U_i, \cdots, U_I\}$ are employed. In this paper, an electricity customer's portrait is constructed in five labels. The labels include (1) monthly load factor, (2) monthly minimum load factor, (3) monthly peak load utilization hours, (4) average peak/valley/flat load factor, and (5) average peak/valley/flat minimum load factor. Here, U_i represents the i-th customer, and P_{U_i} represents the load data $P_{U_i} = \{P_{U_i,1}, P_{U_i,2}, \cdots, P_{U_i,r}, \cdots, P_{U_i,R}\}$ of the i-th customer U_i in a month. $P_{U_i,r}$ is the load of customer U_i in the r-th period of a month. R is the total number of monthly periods, where the unit of a single period is half an hour. The physical meaning and definition of each portrait label are shown in Table 1. The specific meanings can be found in Appendix A.

Table 1. Portrait label system of customers.

Label	Physical Meaning	Definition
Monthly load factor	Fluctuation of monthly load	$g_{U_i,l} = \frac{P_{U_i,av}}{P_{U_i,\max}}$
Monthly minimum load factor	Stability of customers' electricity consumption	$g_{U_i,ml} = \frac{P_{U_i,\min}}{P_{U_i,\max}}$

Table 1. *Cont.*

Label	Physical Meaning	Definition
Monthly peak load utilization hours	Monthly load time utilization efficiency	$g_{U_i,lh} = \frac{Q_{U_i}}{P_{U_i,\max}}$
Average peak load factor	Load fluctuation in peak period (8:30–11:30; 18:00–23:00)	$g_{U_i,pl} = \frac{P_{U_i,av.pl}}{P_{U_i,\max.pl}} = \frac{1}{G}\sum_{t=1}^{G}\left(P_{t,(U_i,av.pl)}/P_{t,(U_i,\max.pl)}\right)$
Average valley load factor	Power consumption stability of customers during peak period	$g_{U_i,pml} = \frac{P_{U_i,\min.pl}}{P_{U_i,\max.pl}} = \frac{1}{G}\sum_{t=1}^{G}\left(P_{t,(U_i,\min.pl)}/P_{t,(U_i,\max.pl)}\right)$
Average flat load factor	Load fluctuation in valley period (23:00–24:00; 0:00–7:00)	$g_{U_i,vl} = \frac{P_{U_i,av.vl}}{P_{U_i,\max.vl}} = \frac{1}{G}\sum_{t=1}^{G}\left(P_{t,(U_i,av.vl)}/P_{t,(U_i,\max.vl)}\right)$
Average peak minimum load factor	Power consumption stability of customers during valley period	$g_{U_i,vml} = \frac{P_{U_i,\min.vl}}{P_{U_i,\max.vl}} = \frac{1}{G}\sum_{t=1}^{G}\left(P_{t,(U_i,\min.vl)}/P_{t,(U_i,\max.vl)}\right)$
Average valley minimum load factor	Load fluctuation in flat period (7:00–08:30; 11:30–18:00)	$g_{U_i,fl} = \frac{P_{U_i,av.fl}}{P_{U_i,\max.fl}} = \frac{1}{G}\sum_{t=1}^{G}\left(P_{t,(U_i,av.fl)}/P_{t,(U_i,\max.fl)}\right)$
Average flat minimum load factor	Power consumption stability of customers during flat period	$g_{U_i,fml} = \frac{P_{U_i,\min.fl}}{P_{U_i,\max.fl}} = \frac{1}{G}\sum_{t=1}^{G}\left(P_{t,(U_i,\min.fl)}/P_{t,(U_i,\max.fl)}\right)$

The portrait of customer U_i as $\vec{G}_{U_i} = [g_{U_i,l}, g_{U_i,ml}, g_{U_i,lh}, g_{U_i,pl}, g_{U_i,pml}, g_{U_i,vl}, g_{U_i,vml}, g_{U_i,fl}, g_{U_i,fml}]$ is built based on Table 1. The portrait reflects the electricity consumption habits of customer U_i. And it provides support for judging the similarity between the target customer and sample customers, where $g_{U_i,l}$, $g_{U_i,ml}$, $g_{U_i,lh}$, $g_{U_i,pl}$, $g_{U_i,pml}$, $g_{U_i,vl}$, $g_{U_i,vml}$, $g_{U_i,fl}$, and $g_{U_i,fml}$ respectively represent the monthly load rate, monthly minimum load coefficient, monthly maximum load utilization hours, peak period load rate mean, peak period minimum load coefficient mean, valley period load rate mean, valley period minimum load coefficient mean, normal period load rate mean, and normal period minimum load coefficient mean of the customer U_i.

2.2. Sample Customer Clustering Based on TSDC Algorithm

It is necessary to cluster the sample customers based on the constructed customer portraits. The portraits of the same type of power customers are often similar, while the portraits of different types are often quite different. And the portraits exhibit a dense intragroup and sparse intergroup structure. So, it is suitable to use a density clustering algorithm to cluster the sample customers. At the same time, considering the subjectivity and randomness of the traditional density clustering algorithm, the density values of the sample customer sets with different input orders are also different. And this will bring problems such as inconsistent clustering results and incorrect clustering results. By using density sorting and an adaptive search, this problem can be solved. In addition, the traditional density clustering algorithm is often unsatisfactory for the processing of individual discrete points. Therefore, the TSDC algorithm is proposed is this paper. TSDC is divided into two stages. The first stage is the recursive search in neighborhood (RSN), which clusters all the identified high-density customers. Through two-stage processing, the accurate and reasonable clustering of high-density customers, low-density customers, and discrete customers can be achieved.

Firstly, in order to identify high-density customers and cluster them, the sample customer set U is clustered based on density ranking and a self-adaptive search, that is, RSN. In order to quantify the density of customers in each sample set, the distance between customer U_i and another customer is calculated based on the constructed customer portraits. In addition, based on the distance, these customers are sorted in ascending order, which is recorded as $dist$. The distance between customer U_i and customer U_j is d_{ij}:

$$d_{ij} = \sqrt{\sum_{k=1}^{K} \left(g_{U_i,k} - g_{U_j,k}\right)^2} \tag{1}$$

where $g_{U_i,k}$ and $g_{U_j,k}$ respectively represent the k-th portrait labels of customer U_i and customer U_j.

Based on Euclidean distance d_{ij}, the similarity $s_\rho(U_i, U_j)$ between customer U_i and customer U_j is as follows:

$$s_\rho(U_i, U_j) = \frac{1}{1 + d_{ij}}. \tag{2}$$

Based on the distance d_{ij}, the density $\rho(U_i)$ of customer U_i is calculated, which is the number of customers in the neighborhood ε of customer U_i:

$$\rho(U_i) = \sum_j \eta(d_{ij} - \varepsilon), \tag{3}$$

where $\eta(x)$ is a 0-1 function; when $x < 0$, $\eta(x) = 1$, and when $x \geq 0$, $\eta(x) = 0$.

Secondly, in order to solve the randomness problem of clustering and improve the stability of clustering, each customer is arranged in descending order according to the density. Based on this method, a new sort under the density sorting strategy is obtained, which is denoted as SN. After the new ranking is obtained, customers can be clustered in order from high to low. This method can avoid the randomness of clustering results caused by the randomness of customer ranking order.

Then, in order to clarify the boundary between high-density customers and low-density customers, a density threshold (DT) is introduced. The density $\rho(U_i)$ of customer U_i with the minimum sum of relative density differences is defined as DT. The sum of the relative density difference of customer U_i is $\sum_{j=1}^{I} d_{ij}$.

In order to record the current number of clusters, the variable cn is introduced, and the initial value is 0. Whenever a new cluster is created, $cn = cn + 1$. When there are high-density customers in SN, that is, $\exists \rho(SN(i)) \geq DT$, a new cluster C_{cn} is created with $SN(1)$ and stored in the cluster output matrix C. Correspondingly, a cumulative number of clustered customers E_{cn} is created. And it is stored in the cumulative number of the clustered customer matrix E. E serves to record the number of customers in each cluster. The customer $SN(1)$ is used to create a new cluster. And this customer is also recorded as the center of the cluster and stored in the cluster center matrix ZX. Then, let the high-density customer $HU = SN(1)$, and $SN(1)$ is removed from SN, where $SN(1)$ denotes the number one customer in SN. The associated customers (direct density-reachable customers, density-reachable customers, density-connected customers) of $SN(1)$ are found in the remaining SN.

Note that when customer U_i is a high-density customer, if customer U_j is in the neighborhood ε of customer U_i, customer U_j is called the direct density-reachable customer of customer U_i.

That is, if $\rho(U_i) \geq DT, d_{ij} \leq \varepsilon$, then U_j is the direct density-reachable customer of customer U_i.

If customer U_j is a high-density customer and at the same time is the direct density-reachable customer of customer U_i, then customer U_k is the direct density-reachable customer of customer U_j. At this time, if customer U_k is a high-density customer, then customer

U_k is called the density-reachable customer of customer U_i; otherwise, customer U_k is the density-connected customer of customer U_i.

That is, $\rho(U_i) \geq DT, d_{ij} \leq \varepsilon, \rho(U_j) \geq DT, d_{jk} \leq \varepsilon$. What is more, if $\rho(U_k) \geq DT$, then U_k is the density-reachable customer of customer U_i, Otherwise, if $\rho(U_k) < DT$, then U_k is the density-connected customer of customer U_i.

The found customers are classified into the cluster of $SN(1)$ in turn. For each classified customer, the corresponding C_{cn} and E_{cn} are updated once, and the customer is deleted from SN. When all the associated customers of HU are classified into the same cluster, $HU = SN(1)$, and the previous operation is repeated until there is no high-density customer in SN, that is, $\forall\rho(SN(i)) < DT$, and the end of the RSN.

Then, considering the possibility of low-density customers remaining after the RSN is completed, we cluster the remaining customers using density sorting, nearest-neighbor allocation, and adaptive search. This process is known as search the nearest neighbor in cluster (SNNC).

In order to find the nearest neighbor of the cluster of low-density customers in the remaining SN for the customer $SN(i)$, the point pair set $A(i)$ is formed with it is first found in $dist$, where $A(i,j)$ represents the j-th customer in $dist$ that can form a point pair with $SN(i)$. Since $dist$ is arranged in ascending order of distance, the point pair set $A(i)$ is also arranged in ascending order of distance. That is, the larger j is, the farther $A(i,j)$ is from $SN(i)$. The cluster nearest neighbors of the customer $SN(i)$ are found in all $A(i)$. The cluster nearest neighbor refers to the following: if customer U_i is not in the cluster output matrix, and customers U_j and U_k are in the cluster output matrix, then for all customers U_k, the distance from customer U_j to customer U_i is less than the distance from customer U_k to customer U_i. In this case, U_j is called the cluster nearest neighbor of U_i. It satisfies the following formulas:

$$U_i \in \overline{C}, U_j \in C, \text{for } \forall U_k \in C, \exists d_{ik} - d_{ij} > 0$$

After selecting the cluster nearest neighbor of customer $SN(i)$, further distance discrimination of the cluster nearest neighbor is needed to confirm the attribution of customer $SN(i)$. If the distance between $SN(i)$ and its cluster nearest neighbor is less than or equal to the neighborhood ε, then $SN(i)$ is directly classified into the cluster where the cluster nearest neighbor is located. If the distance between $SN(i)$ and its cluster nearest neighbor is farther than the neighborhood ε and there are multiple clusters at this time, that is, $cn > 1$, then $SN(i)$ is also classified into the cluster where the cluster nearest neighbor is located. If there is only one cluster at this time, that is, $cn = 1$, then a new cluster C_{cn+1} is created with $SN(i)$. What is more, the customer $SN(i)$ is stored in the cluster center matrix ZX. When the customer $SN(i)$ completes the clustering, the clustering output matrix C, E, and cn are updated. According to this, the remaining SN is clustered in turn until all customers complete the clustering, and outputs C, E, and cn are obtained.

In total, the steps of sample customer clustering based on the TSDC algorithm can be summarized as follows.

Step 1: According to the monthly load data Q of the customer set U, the customer portrait label and the distance d_{ij} between each customer are calculated. And the distance sorted in ascending order, recorded as $dist$. Then, the customer density $\rho(U_i)$ is calculated and sorted in descending order, denoted as SN.

Step 2: The sum of the relative density differences between each customer is calculated, and the customer density with the minimum value is selected as the DT.

Step 3: All high-density customers and their associated customers are clustered in order of density ranking. C, E, and cn are updated. And the first customer of each cluster is set as the clustering center until there is no high-density customer in the neighborhood.

Step 4: It is determined whether the remaining customers include low-density customers. Proceed to step 5 if they do; otherwise go to step 8.

Step 5: It is determined whether the customer $SN(i)$ is in the neighborhood of the nearest neighbor of the cluster. If so, it is classified into the cluster where the nearest neighbor of the cluster is located; otherwise go to step 6.

Step 6: It is determined whether there is only one cluster in the current cluster number. If so, a new cluster is created with the customer, and the customer is set as the center of the cluster; otherwise they are classified into the cluster where the nearest neighbor of the cluster is located.

Step 7: The clustering output matrix C, E, and cn is updated, and it is determined whether there are low-density customers that are not clustered. If there are, go to step 5; otherwise go to step 8.

Step 8: Clustering results are output.

The flowchart of the customer set clustering method based on TSDC is shown in Appendix B.

3. Evaluation of Electricity Sales Packages Based on Minimum Adjustment Distance Consensus

3.1. Consensus-Reaching Process of Multi-Attribute Group Decision Making Based on Hesitant Fuzzy Linguistic Term Set

The customer set $U = \{U_1, U_2, \cdots, U_i, \cdots, U_I\}$ is clustered into the M-class customer $U = \{UT_1,\ UT_2, \cdots, UT_m, \cdots, UT_M\}$ after clustering, where $UT_m = \{UT_{m,1}, UT_{m,2}, \cdots, UT_{m,n}, \cdots, UT_{m,N}\}$, and $UT_{m,n}$ represents the n-th customer in the m-th class. Customer $UT_{m,n}$ evaluates the attribute set $CE = \{CE_1, CE_2, \cdots, CE_k, \cdots, CE_K\}$ of the electricity sales packages $X = \{X_1,\ X_2, \cdots, X_j, \cdots, X_J\}$.

Considering that customers' understanding of electricity sales packages is relatively limited, they often show a hesitant fuzzy state of 'either this or that' in the evaluation. Therefore, this paper introduces a hesitant fuzzy linguistic term set to describe the customers' evaluation information.

Let L language evaluations exist for each customer, where L is an odd number. L language evaluations are arranged in order and are respectively represented as $O_1, O_2, \cdots, O_l, \cdots, O_L$. If $l > x$, then $O_l \succ O_x$, which represents that the evaluation of O_l is better than that of O_x, and $\succ$ indicates that it is better.

Based on their own understanding of the electricity sales packages, the customer $UT_{m,n}$ makes an initial evaluation of the attributes of the electricity sales packages. The evaluation matrix is $A_0^{m,n} = \left(a_{m,n,0,j,k}\right)_{J\times K}$, where $a_{m,n,0,j,k}$ represents the initial evaluation of the k-th attribute of the j-th electricity sales package by the n-th customer in the m-th class. In addition, due to the hesitant fuzzy state of customer evaluation, $a_{m,n,0,j,k}$ contains no more than β language evaluations, that is,

$$\begin{array}{l} I(a_{m,n,0,j,k}{}^{+}) - I(a_{m,n,0,j,k}{}^{-}) + 1 \le \beta \\ j = 1, \cdots, J; k = 1, \cdots, K; m = 1, \cdots, M; n = 1, \cdots, N \end{array}, \quad (4)$$

where $a_{m,n,0,j,k}{}^{+}$ represents the highest amount of language evaluation of personal decision $a_{m,n,0,j,k}$. $a_{m,n,0,j,k}{}^{-}$ represents the lowest amount of language evaluation of personal decision $a_{m,n,0,j,k}$. $I(a)$ represents the serial number corresponding to the language evaluation quantity a, like $I(O_l) = l$.

Although the electricity profiles of customers within the same type are relatively similar, each customer's preferences for different electricity sales packages still vary. Additionally, their focus on the various attributes of the electricity sales packages differs. Therefore, for each type of customer, it is very important to achieve a relatively high consensus level through multi-attribute group decision making. This can not only offer target customers a more reliable reference but also can reduce the difficulty of calculation when making decisions for target customers.

Firstly, it is necessary to synthesize the individual decision matrix of each customer to obtain the collective decision matrix $A_{m,s}^{c} = \left(a_{m,s,j,k}^{c}\right)_{J\times K}$ based on the individual decision

matrix. In this process, for the collective decision matrix obtained, it is necessary to ensure that the difference between the individual decision matrices is as small as possible. This difference is the objective function, where we have

$$\min_{A^c_{m,s}} \max_{UT_{m,n} \in UT_m} \sum_{j=1}^{J} \sum_{k=1}^{K} \varsigma(a_{m,n,s,j,k}, a^c_{m,s,j,k}), \tag{5}$$

where $a_{m,n,s,j,k}$ represents the s-th evaluation of the k-th attribute of the j-th electricity sales package by the n-th customer in the m-th class. $a^c_{m,s,j,k}$ represents the s-th collective evaluation of the k-th attribute of the j-th electricity sales package by the m-th-class customer. $\varsigma(a_1, a_2)$ indicates the difference between evaluation a_1 and evaluation a_2.

$$\begin{cases} \min\limits_{A^c_{m,s}} \max\limits_{UT_{m,n} \in UT_m} \sum\limits_{j=1}^{J} \sum\limits_{k=1}^{K} \varsigma(a_{m,n,s,j,k}, a^c_{m,s,j,k}) \\ s.t. \left\{ I({a^c_{m,s,j,k}}^{+}) - I({a^c_{m,s,j,k}}^{-}) + 1 \leq \beta, j = 1, \cdots, J; k = 1, \cdots, K \right. \end{cases}. \tag{6}$$

In addition, for the collective decision matrix, it is important to ensure that the number of linguistic evaluation sets for each attribute of the package is less than the threshold β. The above process of obtaining a collective decision matrix based on individual decision matrix is called a minimum distance adjustment model (MDAM). The formulas in *s.t.* are to describe and limit the degree of the customers' hesitant fuzzy evaluation. And the detailed calculation model of MDAM is shown in Appendix C.

After obtaining the collective decision matrix, it is essential to assess whether the matrix accurately represents the opinions of individuals. Specifically, it is important to determine if the consensus level meets the required standards. In order to characterize the consensus level, the variable $CL^s_{m,n}$ is introduced to represent the consensus level between the n-th customer in the m-th class and the s-th collective decision. Among them, the consensus level is defined as follows:

$$CL^s_{m,n} = 1 - \frac{1}{JKL} \sum_{j=1}^{J} \sum_{k=1}^{K} \varsigma(a_{m,n,s,j,k}, a^c_{m,s,j,k}). \tag{7}$$

When the consensus level of the same category of customers reaches the consensus threshold α, it shows that the collective decision matrix can allow the category of customers to reach a higher consensus level. What is more, it can represent the opinions of the category of customers through the collective decision matrix. Otherwise, customers in this category need to adjust their personal opinions according to the collective decision matrix and then calculate whether the consensus level reaches the consensus threshold α until all customers in this category reach the consensus threshold α.

The above-mentioned adjustment process for individual opinions is called the minimum adjustment distance consensus rule (MADCR). In order to retain the original preference information as much as possible, we hope to minimize the adjustment distance between a customer's original evaluation and the adjusted personal evaluation, that is, the adjustment distance between the customer's original evaluation and the adjusted personal evaluation:

$$\min \sum_{n=1}^{N} \sum_{j=1}^{J} \sum_{k=1}^{K} \varsigma(a_{m,n,s,j,k}, \overline{a_{m,n,s,j,k}}). \tag{8}$$

Similarly, for the adjusted individual decision matrix, it is also necessary to ensure that the number of language evaluations for each sales package attribute is within β. The detailed calculation model of MADCR is shown in Appendix D.

When the consensus level of all customers reaches the consensus threshold α, it shows that the collective decision matrix can better reflect the opinions of all individuals. At this

time, the consensus process of multi-attribute group decision making is completed. And the final collective decision matrix A_m^c can be output, $A_m^c = A_{m,s}^c$.

3.2. Determination of Weight of Electricity Sales Package Attributes Based on Entropy Method

Considering the different preferences of each type of customer, the importance of the electricity sales package attributes is also different. Therefore, applying equal weights to the attributes of each electricity sales package is not feasible. It is essential to determine the weights based on customers' evaluation information of the electricity sales package attributes. If there is a significant difference in customers' evaluations of a package attribute, it implies a greater impact of the attribute on the comprehensive evaluation, necessitating a higher weight. Instead, if the difference in evaluations for a package attribute is minimal or identical across all customers, it indicates little to no effect in the comprehensive evaluation, allowing for a reduced or even zero weight for the attribute. Therefore, this paper applies the entropy method to determine the weight of each attribute $\varpi_m = [\varpi_{m,1}, \varpi_{m,2}, \cdots, \varpi_{m,k}, \cdots, \varpi_{m,K}]$, where $\varpi_{m,k}$ represents the evaluation weight of the m-th customer for the k-th package attribute. To prevent meaningless logarithms in the calculation of entropy values, data preprocessing is necessary.

$$a_{m,j,k}^{c'} = \frac{a_{m,j,k}^c - \min(a_{m,1,k}^c, \cdots, a_{m,N,k}^c)}{\max(a_{m,1,k}^c, \cdots, a_{m,N,k}^c) - \min(a_{m,1,k}^c, \cdots, a_{m,N,k}^c)} + 1, \tag{9}$$

where $a_{m,j,k}^{c'}$ is the index after treatment, $A_m^{c'} = \left(a_{m,j,k}^{c'}\right)_{J \times K}$.

Then the proportion of the j-th electricity sales package to the attribute $\theta_{m,j,k}$ under the k-th attribute in the m-th customer is calculated:

$$\theta_{m,j,k} = \frac{a_{m,j,k}^{c'}}{\sum_{j=1}^{J} a_{m,j,k}^{c'}} \quad (k = 1, 2, \cdots, K). \tag{10}$$

According to the proportion, the entropy value $\sigma_{m,k}$ of the k-th attribute in the m-th customer is obtained:

$$\sigma_{m,k} = -\frac{1}{\ln(K)} \sum_{j=1}^{J} \theta_{m,j,k} \log(\theta_{m,j,k}) \ (k = 1, 2, \cdots, K). \tag{11}$$

Finally, according to the entropy value, the weight $\varpi_{m,k}$ of each attribute is

$$\varpi_{m,k} = \frac{1 - \sigma_{m,k}}{\sum_{k=1}^{K} (1 - \sigma_{m,k})} \quad (k = 1, 2, \cdots, K). \tag{12}$$

4. Full-Ordering Decision Making on Electricity Sales Packages Based on Customer Satisfaction

The decision-making process of electricity sales companies regarding their packages must prioritize customer satisfaction, as it significantly impacts the likelihood of successful outcomes. Consequently, this paper proposes a comprehensive decision-making framework for electricity sales packages, focused on maximizing customer satisfaction. Firstly, the method involves identifying similar customers to the target customers from historical customers. Secondly, satisfaction levels regarding electricity sales package are evaluated. Finally, by integrating the similarities between target customers and similar customers, the satisfaction level towards electricity sales packages for target customers can be accurately assessed.

Based on the customer clustering results obtained in Section 2.2, similar historical customers to the target customer can be identified. The target customer is set to $U' = \{U'_1, U'_2, \cdots, U'_i, \cdots U'_I\}$, where U'_i is the i-th target customer, and I is the total number of tar-

get customers. Based on the portrait $\overrightarrow{G}_{U'_i} = [g_{U'_i,l}, g_{U'_i,ml}, g_{U'_i,lh}, g_{U'_i,pl}, g_{U'_i,pml}, g_{U'_i,vl}, g_{U'_i,vml}, g_{U'_i,sl}, g_{U'_i,sml}]$ of the target customer U'_i, the distance between the cluster center of the M-class customer and the $\overrightarrow{G}_{U'_i}$ is calculated respectively. The customer in the corresponding class with the smallest distance is determined to be a similar customer to the target customer U'_i, which is recorded as $UT_m = \{UT_{m,1}, UT_{m,2}, \cdots, UT_{m,n} \cdots, UT_{m,N}\}$, where N is the total number of similar customers to target customer U'_i. $UT_{m,n}$ is the n-th customer similar to the target customer U'_i. Then, the similarity matrix between target customer U'_i and similar customers is expressed as $S = (s'_\rho(U'_I, UT_{m,n}))_{I \times N}$. It should be noted that the monthly load data of target customers are unknown and must be predicted using the load forecasting method.

Based on the evaluation information of similar customers' electricity sales packages obtained in Section 3, the evaluation information of customers is expected. And the satisfaction matrix $W_{UT,X} = (w_{UT_{m,n},X_j})_{N \times J}$ of similar customers' electricity sales packages is obtained. Where $w_{UT_{m,n},X_j}$ is the n-th customer of similar customers' satisfaction with the electricity sales package X_j, we obtain

$$w_{UT_{m,n},X_j} = CL_{UT_{m,n}} \times \sum_{k=1}^{K} (A_{j,k}^{UT_{m,n}} \times \omega_{UT_m,k}). \tag{13}$$

The satisfaction of m-th-type customer UT_m with electricity sales package X_j is

$$w_{UT_m,X_j} = \frac{1}{N} \sum_{n=1}^{N} [CL_{UT_{m,n}} \times \sum_{k=1}^{K} (A_{j,k}^{UT_{m,n}} \times \omega_{UT_m,k})]. \tag{14}$$

The satisfaction matrix of electricity sales packages for each type of customer is

$$V_{UT,X} = (w_{UT_m,X_j})_{M \times J}. \tag{15}$$

The satisfaction of the target customer's electricity package depends on the satisfaction of the similar customer's package and the similarity between the target customer and the similar customer. The satisfaction $w_{U'_i,X_j}$ of the target customer U'_i with the electricity package X_j is

$$w_{U'_i,X_j} = \frac{1}{N} \sum_{n=1}^{N} [S_{UT_{m,n}} \times CL_{UT_{m,n}} \times \sum_{k=1}^{K} (A_{j,k}^{UT_{m,n}} \times \omega_{UT_m,k})] \tag{16}$$

Based on the quantitative results of target customer satisfaction, this paper proposes a full-ranking method for electricity sales packages. That is, based on the satisfaction of target customers, the electricity retailers will sort each package and make decisions on all packages and corresponding sorting results from target customers for customers to choose and purchase.

In order to measure the effect of the proposed full-ranking decision method, based on the ranking results, the root mean square error (RMSE) is calculated. In this paper, we use φ_i to represent the RMSE. The RMSE for the decision-making result of the electricity package for a target customer is as follows:

$$\varphi_i = \sqrt{\frac{\sum_{j=1}^{J} (P_{ij} - P_{ij}^*)^2}{J}}. \tag{17}$$

where P_{nj} and P_{nj}^* are the actual sorting results of the target customer U'_i for the package X_j, and the sorting results obtained by the algorithm. The smaller the RMSE of the electricity sales package decision is, the better the decision effect of the proposed algorithm is.

In summary, the proposed package and decision-making method can be divided into two stages: the construction of a sample customer set evaluation information database and the decision making for target customers' electricity sales packages. The decision-making process for electricity sales packages based on TSDC and the minimum adjustment distance consensus is shown in Figure 1.

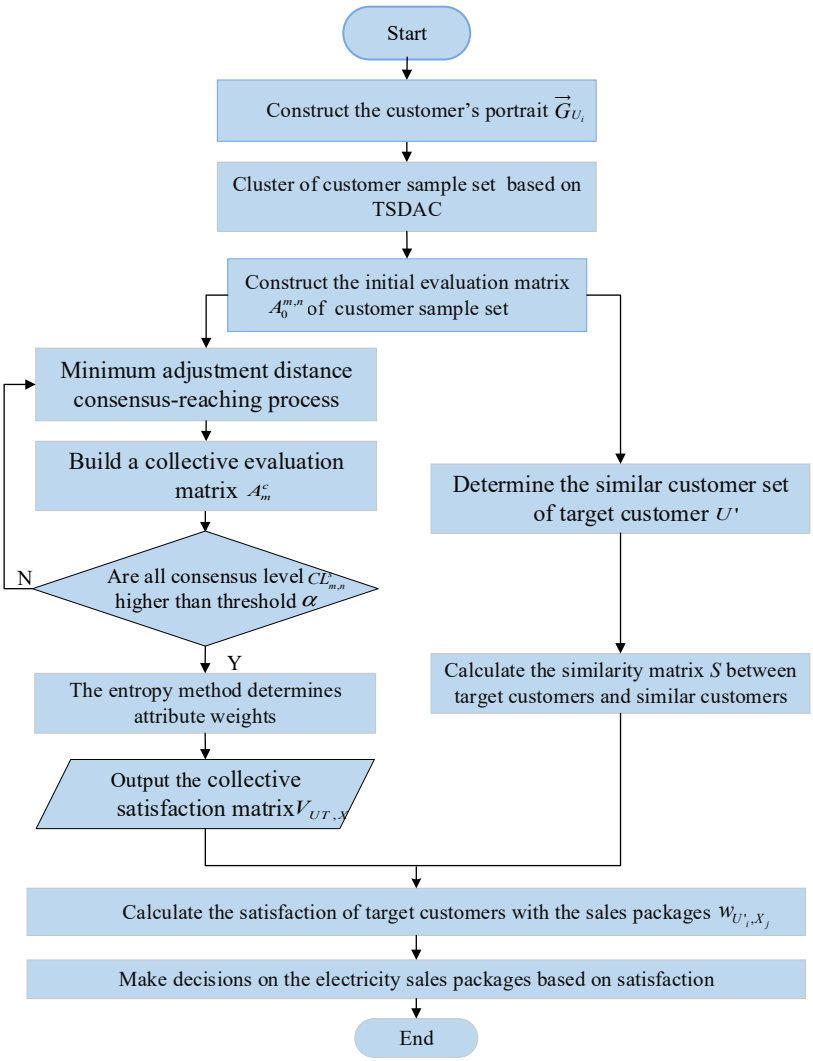


Figure 1. Flowchart of electricity sales package decision making using TSDC and minimum adjustment distance consensus.

5. Case Studies

5.1. Background

Using a particular region in China as a case study, this paper validates and analyzes the proposed decision-making method for electricity sales packages. Utilizing load data gathered from 300 typical customers $U = \{U_1, U_2, \cdots, U_{300}\}$ between 1 April 2020 and 30 April 2020, the leave-one-out cross-validation method is applied to validate the proposed approach. This involves selecting one customer at a time as the target customer, while the remaining 299 customers serve as the sample set.

Referring to data from the provincial trading center and actual customer usage, the electricity sales company offers package set $X = \{X_1, X_2, X_3, X_4\}$ to customers. The detailed attribute information is provided in Appendix E. Given that the primary focus of this section is to examine electricity sales package decision-making methods, the load

data collected from the 300 customers above are directly analyzed as the monthly load of target customers.

5.2. Analysis of Group Decision Making on Electricity Sales Packages

5.2.1. Sample Customer Clustering

Based on the proposed TSDC algorithm, the sample customers are clustered. The clustering results are shown in Figures 2–4, which are peak-flat type, late-peak type, and peak-avoidance type. Based on the clustering results of sample customers, the distances between the portraits of target customers and the clustering centers of the peak-flat type, late-peak type, and peak-avoiding type are 0.6392, 0.0650, and 0.3270, respectively. Therefore, the similar customer to the target customer U_8 is the late-peak customer.

From Figures 2–4, it can be seen that the sample set customers can be clustered into three categories: late-peak type, peak-flat type, and peak-avoidance type. Among them, the late-peak type is dominated by residents' electricity load, working during the day and at home at night. The peak-flat type is mainly based on office space such as commercial and office buildings. The peak-avoidance type is mostly KTV, bars, and other night places.

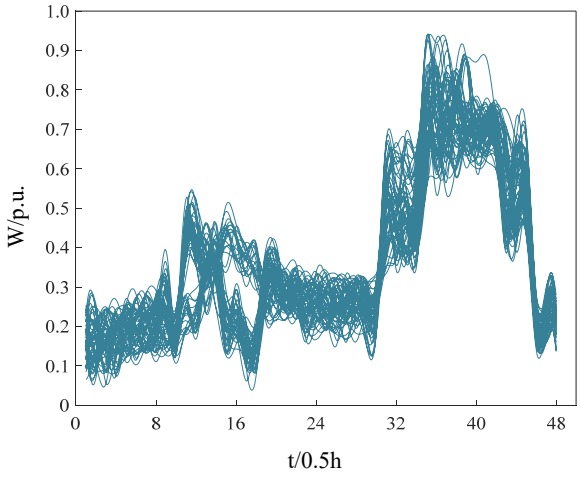


Figure 2. Sample set customer clustering results (late-peak type).

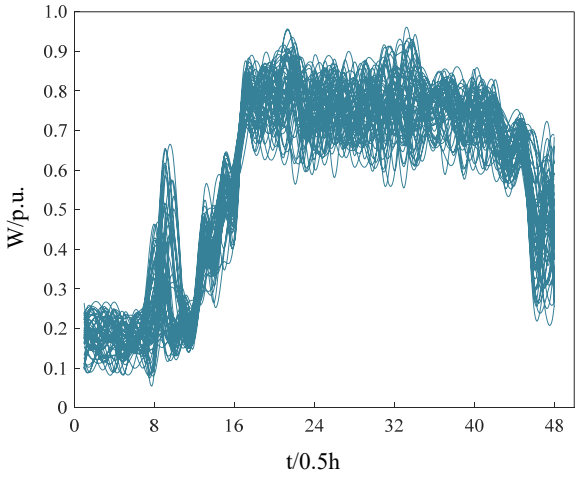


Figure 3. Sample set customer clustering results (peak-flat type).

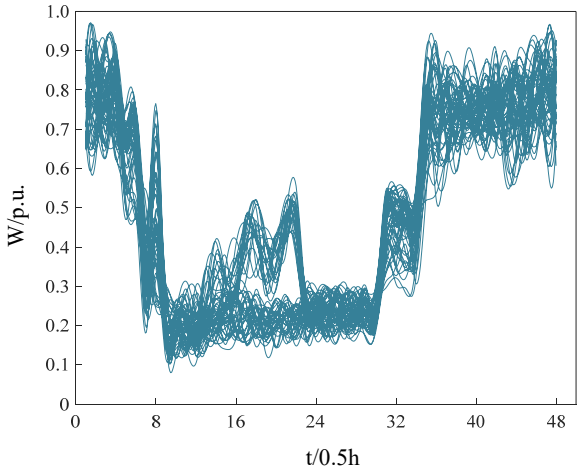


Figure 4. Sample set customer clustering results (peak-avoidance type).

5.2.2. Sample Customer Clustering

Based on the satisfaction of similar customers' electricity sales packages and the similarity between target customers and similar customers, for which the details can be seen in Appendix F, the normalized results for the satisfaction of target customers with the electricity sales packages are obtained, as shown in Table 2.

Table 2. Normalization results of the satisfaction of target customers with electricity retail plans.

Electricity Sales Packages	X_1	X_2	X_3	X_4
Target customer satisfaction	0.6913	0.3796	1.0000	0.8690

It can be seen from Table 2 that target customer U_8 has the highest satisfaction with X_3. In practice, this customer leads a commuter lifestyle, spending daytime hours at work and evenings at home. His electricity consumption peaks between 18:00 and 23:00 upon returning from work, with a heightened emphasis on cost considerations. Because U_8 is a residential customer, compared with high-quality electricity demand, this type of customer has a greater demand for energy conservation, which is consistent with the satisfaction results of the late-peak sample customer set package. It can be seen that the results obtained in this paper are consistent with the theoretical analysis, which also shows the accuracy of the proposed customer satisfaction quantification method.

Based on the above results, the electricity sales package and ranking results provided by the electricity sales company to target customer are shown in Table 3.

Table 3. Recommended ranking results and simulated actual ranking results.

Electricity Sales Packages	**Recommendation Ranking of This Paper**	**Actual Ordering of Simulations**
X_1	3	3
X_2	4	4
X_3	1	1
X_4	2	2

Considering that the actual ranking results of each package are difficult to obtain, this paper makes the following hypothesis for the selection mode to simulate the actual selection:

Option 1: Customers with high total power consumption are more inclined to choose a tiered price package.
Option 2: Customers with high non-peak power consumption are more inclined to choose time-of-use tariff packages.
Option 3: In the case of the same price of the electricity sales package, customers with high sensitivity to power quality disturbances are more inclined to choose power quality-improvement services.
Option 4: When the prices of the electricity sales packages are equivalent, customers are more inclined to choose cost-saving incentive policies.
Option 5: When the prices of the electricity sales packages are equivalent, customers are more inclined to choose the electricity sales package with a high proportion of new energy.
Option 6: In the case of the same price of the electricity sales package, customers are more inclined to choose the electricity sales package without the package exit fee.

Based on the above simulation assumptions and the actual load characteristics of the customer, each electricity sales package is associated with the customer to simulate the actual sorting result. And the target customer U_8 simulates the actual sorting result, as shown in Table 3. It should be noted that in the actual situation, customers may also have different selection modes. But this does not affect the implementation of the decision-making method for electricity sales packages mentioned in this paper.

From Table 3, it can be seen that for customer U_8, the ordering of packages obtained by this method is the same as the simulation results, and the RMSE is 0. It should be noted that not all the RMSEs of customers are 0. There are some target customers with RMSEs of 0.707 or other values. Because the RMSE is small, it can still show that the results of the package ranking obtained by the method in this paper are in line with the actual situation. Similarly, other customers can be randomly selected as target customers, and the evaluation results of each target customer's package satisfaction can be found in Appendix F.

5.2.3. Sample Customer Clustering

In order to further verify the rationality and feasibility of the decision-making method proposed in this paper, the decision-making method in this paper is compared with the following two decision-making methods. And the decision-making results for each decision-making method are calculated, as shown in Figure 2.

Method 1: Without clustering customers. The decision-making arrangement of electricity sales packages will be based on two aspects, that is, the satisfaction of sample set customers and the similarity between target customers and sample set customers.

Method 2: The evaluation attribute of the electricity sales package only considers the cost and ignores other attributes. Based on TSDC and the minimum adjustment distance consensus, the electricity sales package group decision-making method is reached.

We assess the accuracy of the different methods by calculating the average RMSE of all customers of the same type, ϕ. We find that $\phi = \frac{\sum_{i=1}^{N} \varphi_i}{N}$, where N represents the number of customers of a particular type.

As can be seen from Figure 5, the ϕ of the proposed method is less than 1, while the ϕs of method 1 and method 2 are larger than that of the proposed method. ϕ represents the difference between the results obtained by this method and the simulated actual selection results. And the larger ϕ is, the larger the deviation is and the worse the method is. On the contrary, the smaller ϕ is, the smaller the deviation is and the better the method is. Therefore, compared with method 1 and method 2, the method proposed in this paper is more effective.

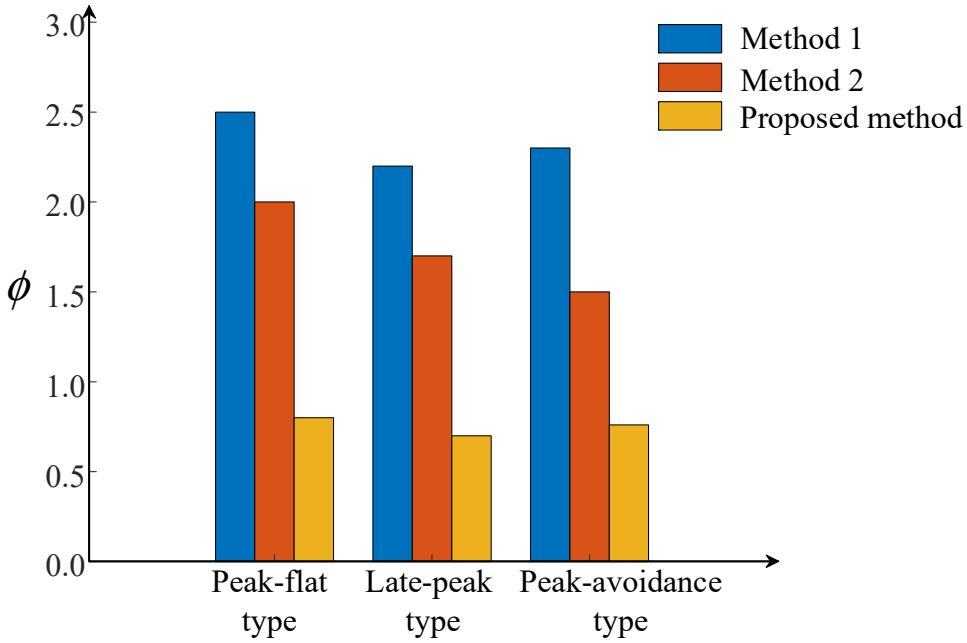


Figure 5. The ϕ of the ordering results of electricity sales package decisions under different methods.

The result of method 1 without customer clustering is the largest, and the ϕ is 2.429. This shows that without performing customer clustering, the exceptional characteristics of individual customers within the sample set can have a significant influence on the target customers. This can result in a larger overall decision-making error, as the decision making does not account for the diversity of the target customer base.

The result of method 2 that only considers the cost is the second largest, and the maximum ϕ is 1.975. This shows that by solely focusing on cost and neglecting other important factors, the decision making for electricity sales packages will fail to capture the nuanced and varied requirements of different customer types. This situation can lead to inferior decision results.

6. Conclusions

This paper proposes an electricity sales package decision-making method based on TSDC and minimum adjustment distance consensus. This method has the following characteristics:

(1) The proposed sample customer set partitioning method based on the TSDC algorithm avoids the problems of randomness, subjectivity, and associated errors in the current density clustering algorithm, and improves the accuracy of sample customer set partitioning.

(2) A minimum adjustment distance consensus-reaching process considering the hesitant fuzzy characteristics of customer evaluation information is proposed. The feedback mechanism in this process helps to effectively integrate the customers' personal views into a collective evaluation, which plays a vital role in the decision-making process for electricity sales packages.

It should be noted that this paper only conducts preliminary research on the decision-making method for electricity sales packages based on the hesitation and ambiguity of customer evaluation information. After piloting the decision-making method on a larger scale, it is essential to explore the integration of subjective scoring and objective evaluation indicators for quantifying customer satisfaction. Additionally, research is needed on the decision-making process regarding electricity sales packages, taking into account the market price linkage and market share dynamics of electricity sales companies.

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Conflicts of Interest: The authors declare no conflict of interest.

Nomenclature

U	Sample customer set
P	Monthly load data of the sample customer set
Q	Monthly load data
$\overrightarrow{G}_{U_i}$	Portrait of customer U_i
d_{ij}	Euclidean distance between customer U_i and customer U_j
$dist$	A customer set in which each customer is sorted in ascending order by distance
$s_\rho(U_i, U_j)$	Similarity between customer U_i and customer U_j
DT	Density threshold between high-density customers and low-density customers
cn	Current number of clusters
SN	A customer set in which each customer is sorted in descending order by density
C	Cluster output matrix
E_{cn}	Cumulative customer number of the cn-th cluster
ZX	Cluster center matrix
HU	High-density customer
$A(i)$	Point pair set
$A(i,j)$	The j-th customer in $dist$ that can form a point pair with $SN(i)$
$UT_{m,n}$	The n-th customer in the m-th class
CE	Attribute set of the electricity sales packages
X	Electricity sales package set
L	Maximum number of language evaluations; it is an odd number
O_l	The l-th language evaluation
β	Linguistic evaluation quantity threshold
α	Consensus threshold
$a_{m,n,s,j,k}$	The s-th evaluation of the k-th attribute of the j-th electricity sales package by the n-th customer in the m-th class
$a^c_{m,s,j,k}$	The s-th collective evaluation of the k-th attribute of the j-th electricity sales package by the m-th-class customer
$\varsigma(a_1, a_2)$	The difference between evaluation a_1 and evaluation a_2
$CL^s_{m,n}$	The consensus level between the n-th customer in the m-th class and the s-th collective decision
A^c_m	Final collective decision matrix
$\varpi_{m,k}$	The evaluation weight of the m-th customer for the k-th package attribute
$a^{c'}_{m,j,k}$	Index after treatment
$\theta_{m,j,k}$	The ratio of the j-th electricity sales package to the attribute under the k-th attribute of the m-th customer
$\sigma_{m,k}$	The entropy value of the k-th attribute for the m-th customer
$w_{UT_{m,n},X_j}$	The n-th customer of similar customers' satisfaction with the electricity sales package X_j
φ_i	The deviation of the decision-making result of the electricity package for target customer U'_i

Appendix A

Appendix A.1. Monthly Load Factor

The monthly load factor, which reflects the fluctuation in monthly load, is expressed as

$$g_{U_i,l} = \frac{P_{U_i,av}}{P_{U_i,\max}}. \tag{A1}$$

where $P_{U_i,av}$ represents the monthly average load of customer U_i. $P_{U_i,\max}$ represents the monthly maximum load of customer U_i.

Appendix A.2. Monthly Minimum Load Coefficient

The monthly minimum load coefficient, which reflects the stability of customers' electricity consumption, is expressed as

$$g_{U_i,ml} = \frac{P_{U_i,\min}}{P_{U_i,\max}}. \tag{A2}$$

where $P_{U_i,\min}$ represents the monthly minimum load of customer U_i. $P_{U_i,\max}$ represents the monthly maximum load of customer U_i.

Appendix A.3. Monthly Maximum Load Utilization Hours

The monthly maximum load utilization hours reflect the monthly load time utilization efficiency and are expressed as

$$g_{U_i,lh} = \frac{Q_{U_i}}{P_{U_i,\max}}. \tag{A3}$$

where Q_{U_i} represents the monthly total power of customer U_i. $P_{U_i,\max}$ represents the monthly maximum load of customer U_i.

Appendix A.4. Peak Period Load Rate Average Value

The peak period load rate average value, which reflects the load fluctuation in the peak period (8:30–11:30; 18:00–23:00), is expressed as

$$g_{U_i,pl} = \frac{P_{U_i,av.pl}}{P_{U_i,\max.pl}} = \frac{1}{G}\sum_{t=1}^{G}\left(P_{t,(U_i,av.pl)} / P_{t,(U_i,\max.pl)}\right). \tag{A4}$$

where $P_{U_i,av.pl}$ and $P_{U_i,\max.pl}$ respectively represent the monthly average load and monthly maximum load of the customer U_i during the peak period. $P_{t,(U_i,av.pl)}$ and $P_{t,(U_i,\max.pl)}$ respectively represent the average load and maximum load of the customer U_i during the peak period of the t-th day. G represents the total number of days per month.

Appendix A.5. Mean Value of the Minimum Load Coefficient in the Peak Period

The mean value of the minimum load coefficient in the peak period, which reflects the power consumption stability of customers during the peak period, is expressed as

$$g_{U_i,pml} = \frac{P_{U_i,\min.pl}}{P_{U_i,\max.pl}} = \frac{1}{G}\sum_{t=1}^{G}\left(P_{t,(U_i,\min.pl)} / P_{t,(U_i,\max.pl)}\right). \tag{A5}$$

where $P_{U_i,\min.pl}$ and $P_{U_i,\max.pl}$ respectively represent the monthly minimum load and monthly maximum load of the customer U_i during the peak period. $P_{t,(U_i,\min.pl)}$ and $P_{t,(U_i,\max.pl)}$ respectively represent the minimum load and maximum load of the customer U_i during the peak period of the t-th day. G represents the total number of days per month.

Appendix A.6. Valley Period Load Rate Average Value

The valley period load rate average value, which reflects the load fluctuation in the valley period (23:00–24:00; 0:00–7:00), is expressed as

$$g_{U_i,vl} = \frac{P_{U_i,av.vl}}{P_{U_i,\max.vl}} = \frac{1}{G}\sum_{t=1}^{G}\left(P_{t,(U_i,av.vl)} / P_{t,(U_i,\max.vl)}\right). \tag{A6}$$

where $P_{U_i,av.vl}$ and $P_{U_i,\max.vl}$ respectively represent the monthly average load and monthly maximum load of the customer U_i during the valley period. $P_{t,(U_i,av.vl)}$ and $P_{t,(U_i,\max.vl)}$ respectively represent the average load and maximum load of the customer U_i during the valley period of the t-th day. G represents the total number of days per month.

Appendix A.7. Mean Value of the Minimum Load Coefficient in the Valley Period

The mean value of the minimum load coefficient in the valley period reflects the power consumption stability of customers during the valley period and is expressed as

$$g_{U_i,vml} = \frac{P_{U_i,\min.vl}}{P_{U_i,\max.vl}} = \frac{1}{G}\sum_{t=1}^{G}\left(P_{t,(U_i,\min.vl)} / P_{t,(U_i,\max.vl)}\right). \tag{A7}$$

where $P_{U_i,\min.vl}$ and $P_{U_i,\max.vl}$ respectively represent the monthly minimum load and monthly maximum load of the customer U_i during the valley period. $P_{t,(U_i,\min.vl)}$ and $P_{t,(U_i,\max.vl)}$ respectively represent the minimum load and maximum load of the customer U_i during the valley period of the t-th day. G represents the total number of days per month.

Appendix A.8. Flat Period Load Rate Average Value

The flat period load rate average value, which reflects the load fluctuation in the flat period (7:00–08:30; 11:30–18:00), is expressed as

$$g_{U_i,fl} = \frac{P_{U_i,av.fl}}{P_{U_i,\max.fl}} = \frac{1}{G}\sum_{t=1}^{G}\left(P_{t,(U_i,av.fl)} / P_{t,(U_i,\max.fl)}\right). \tag{A8}$$

where $P_{U_i,av.fl}$ and $P_{U_i,\max.fl}$ respectively represent the monthly average load and monthly maximum load of the customer U_i during the flat period. $P_{t,(U_i,av.fl)}$ and $P_{t,(U_i,\max.fl)}$ respectively represent the average load and maximum load of the customer U_i during the flat period of the t-th day. G represents the total number of days per month.

Appendix A.9. Mean Value of the Minimum Load Coefficient in the Flat Period

The mean value of the minimum load coefficient in the flat period, which reflects the power consumption stability of customers during flat period, is expressed as

$$g_{U_i,fml} = \frac{P_{U_i,\min.fl}}{P_{U_i,\max.fl}} = \frac{1}{G}\sum_{t=1}^{G}\left(P_{t,(U_i,\min.fl)} / P_{t,(U_i,\max.fl)}\right). \tag{A9}$$

where $P_{U_i,\min.fl}$ and $P_{U_i,\max.fl}$ respectively represent the monthly minimum load and monthly maximum load of the customer U_i during the flat period. $P_{t,(U_i,\min.fl)}$ and $P_{t,(U_i,\max.fl)}$ respectively represent the minimum load and maximum load of the customer U_i during the flat period of the t-th day. G represents the total number of days per month.

Appendix B

The flowchart of the customer set segmentation method based on TSDC is shown below.

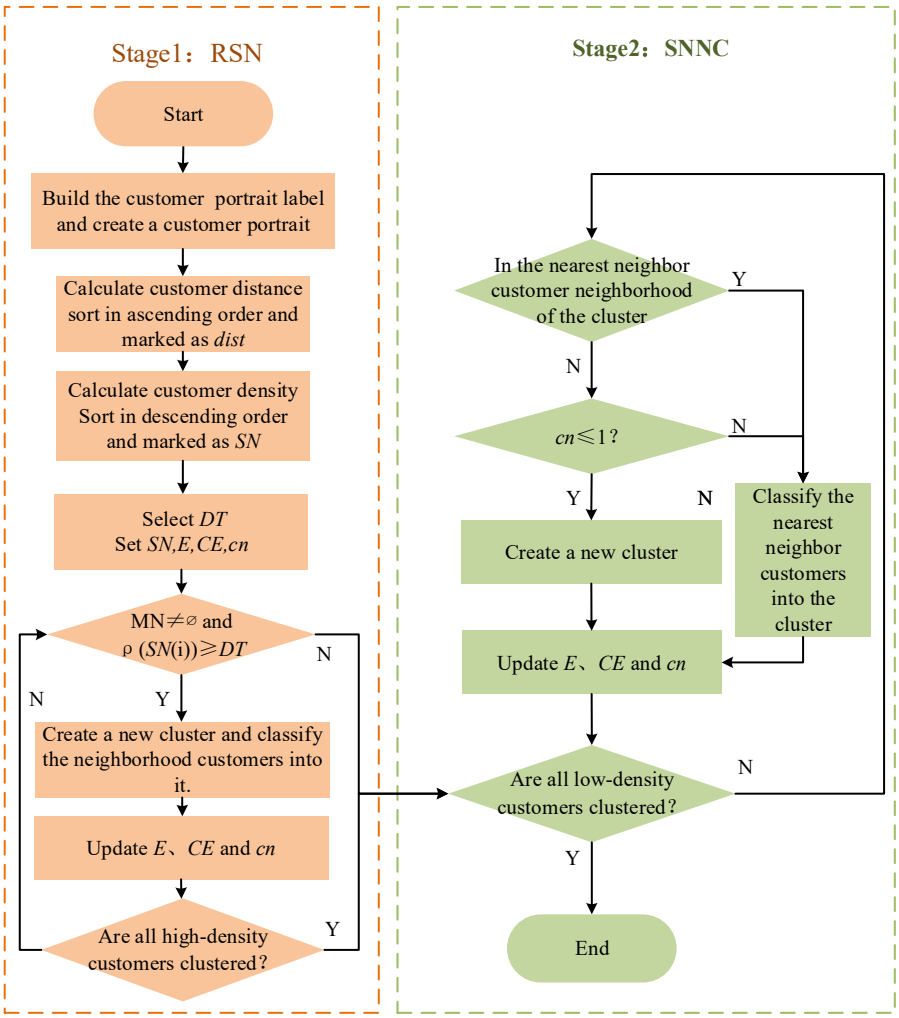


Figure A1. Flowchart of the customer set clustering method based on TSDC.

Appendix C

To facilitate model solving, we equivalently transform the MDAM into a 0–1 linear programming model.

First, the difference $\varsigma(a_{m,n,s,j,k}, a^c_{m,s,j,k})$ between $a_{m,n,s,j,k}$ and $a^c_{m,s,j,k}$ is defined as $(\frac{1}{2}r_{m,n,s,j,k} + \frac{1}{2\sqrt{3}}t_{m,n,s,j,k})$,

where $r_{m,n,s,j,k} = \left| \sum_{l=0}^{L} l(b_{m,j,k,l} + c_{m,j,k,l}) - I({a_{m,n,s,j,k}}^{+}) - I({a_{m,n,s,j,k}}^{-}) \right|$,

$$t_{m,n,s,j,k} = \left| \sum_{l=0}^{L} l(b_{m,j,k,l} - c_{m,j,k,l}) - I({a_{m,n,s,j,k}}^{+}) + I({a_{m,n,s,j,k}}^{-}) \right|,$$

$$b_{m,j,k,l} = \begin{cases} 1 & {a^c_{m,s,j,k}}^{+} = O_l \\ 0 & {a^c_{m,s,j,k}}^{+} \neq O_l \end{cases}, l = 0, \cdots, L; j = 1, \cdots, J; k = 1, \cdots, K,$$

$$c_{m,j,k,l} = \begin{cases} 1 & {a^c_{m,s,j,k}}^{-} = O_l \\ 0 & {a^c_{m,s,j,k}}^{-} \neq O_l \end{cases}, l = 0, \cdots, L; j = 1, \cdots, J; k = 1, \cdots, K,$$

When solving for the minimum of the sum of customers' evaluation differences, $\sum_{j=1}^{J}\sum_{k=1}^{K}\varsigma(a_{m,n,s,j,k}, a^{c}_{m,s,j,k})$ is equal to finding the minimum of $\sum_{j=1}^{J}\sum_{k=1}^{K}(\frac{1}{2}r_{m,n,s,j,k}+\frac{1}{2\sqrt{3}}t_{m,n,s,j,k})$, that is, the minimum of h in the case where $\sum_{j=1}^{J}\sum_{k=1}^{K}(\frac{1}{2}r_{m,n,s,j,k}+\frac{1}{2\sqrt{3}}t_{m,n,s,j,k})-h\leq 0$.

Furthermore, the number of evaluation language terms must not exceed the set threshold β, which is $\sum_{l=0}^{L} l(b_{m,j,k,l}-c_{m,j,k,l})\leq \beta-1 \quad j=1,\cdots,J; k=1,\cdots,K$. Additionally, there must be at least one evaluation language term, which is $\sum_{l=0}^{L} l(b_{m,j,k,l}-c_{m,j,k,l})\geq 0$ $j=1,\cdots,J; k=1,\cdots,K$, where $b_{m,j,k,l}$ and $c_{m,j,k,l}$ are the 0–1 variables.

In addition, each customer has only one highest and lowest evaluation of each attribute of each electricity sales package, which is $\sum_{l=0}^{L} b_{m,j,k,l}=1 \quad j=1,\cdots,J; k=1,\cdots,K$, $\sum_{l=0}^{L} c_{m,j,k,l}=1 \quad j=1,\cdots,J; k=1,\cdots,K$.

Appendix D

To facilitate model solving, we equivalently transform the MADCR model into a 0–1 linear programming model.

First, we define the difference $\varsigma(a_{m,n,s,j,k}, \overline{a_{m,n,s,j,k}})$ between customers' pre-adjusted evaluations $a_{m,n,s,j,k}$ and customers' adjusted evaluations $\overline{a_{m,n,s,j,k}}$ as $(\frac{1}{2}u_{m,n,s,j,k}+\frac{1}{2\sqrt{3}}v_{m,n,s,j,k})$, where $u_{m,n,s,j,k}=\left|\sum_{l=0}^{L} l(x_{m,n,j,k,l}+y_{m,n,j,k,l})-I(a_{m,n,s,j,k}{}^{+})-I(a_{m,n,s,j,k}{}^{-})\right|$,

$$v_{m,n,s,j,k}=\left|\sum_{l=0}^{L} l(x_{m,n,j,k,l}-y_{m,n,j,k,l})-I(a_{m,n,s,j,k}{}^{+})+I(a_{m,n,s,j,k}{}^{-})\right|.$$

In addition, we respectively define $k_{m,n,s,j,k}$ and $z_{m,n,s,j,k}$ as

$$k_{m,n,s,j,k}=\left|\sum_{l=0}^{L} l(x_{m,n,j,k,l}+y_{m,n,j,k,l}-p^{c}_{m,j,k,l}-q^{c}_{m,j,k,l})\right|,$$

$$z_{m,n,s,j,k}=\left|\sum_{l=0}^{L} l(x_{m,n,j,k,l}-y_{m,n,j,k,l}-p^{c}_{m,j,k,l}+q^{c}_{m,j,k,l})\right|.$$

where $x_{m,n,j,k,l}=\begin{cases}1 & a_{m,n,s,j,k}{}^{+}=O_l\\ 0 & a_{m,n,s,j,k}{}^{+}\neq O_l\end{cases}, l=0,\cdots,L; j=1,\cdots,J; k=1,\cdots,K; n=1,\cdots,N,$

$y_{m,n,j,k,l}=\begin{cases}1 & a_{m,n,s,j,k}{}^{-}=O_l\\ 0 & a_{m,n,s,j,k}{}^{-}\neq O_l\end{cases}, l=0,\cdots,L; j=1,\cdots,J; k=1,\cdots,K; n=1,\cdots,N,$

$$p^{c}_{m,j,k,l}=\begin{cases}1 & \overline{a^{c}_{m,s,j,k}}^{+}=O_l\\ 0 & \overline{a^{c}_{m,s,j,k}}^{+}\neq O_l\end{cases}, l=0,\cdots,L; j=1,\cdots,J; k=1,\cdots,K,$$

$$q^{c}_{m,j,k,l}=\begin{cases}1 & \overline{a^{c}_{m,s,j,k}}^{-}=O_l\\ 0 & \overline{a^{c}_{m,s,j,k}}^{-}\neq O_l\end{cases}, l=0,\cdots,L; j=1,\cdots,J; k=1,\cdots,K,$$

$$I(\overline{a_{m,n,s,j,k}}^{+})=\sum_{l=0}^{L} l x_{m,n,j,k,l},$$

$$I(\overline{a_{m,n,s,j,k}}^{-}) = \sum_{l=0}^{L} l y_{m,n,j,k,l},$$

$$I(\overline{a_{m,s,j,k}^{c}}^{+}) = \sum_{l=0}^{L} l p_{m,j,k,l},$$

$$I(\overline{a_{m,s,j,k}^{c}}^{-}) = \sum_{l=0}^{L} l q_{m,j,k,l}.$$

Furthermore, the number of evaluation language terms must not exceed the set threshold β, which is $\sum_{l=0}^{L} l(p_{m,j,k,l}^{c} - q_{m,j,k,l}^{c}) \leq \beta - 1 \quad j = 1, \cdots, J; k = 1, \cdots, K$. Additionally, there must be at least one evaluation language term, which is $\sum_{l=0}^{L} l(p_{m,j,k,l}^{c} - q_{m,j,k,l}^{c}) \geq 0$ $j = 1, \cdots, J; k = 1, \cdots, K$, $\sum_{l=0}^{L} l(x_{m,n,j,k,l} - y_{m,n,j,k,l}) \geq 0 \quad j = 1, \cdots, J; k = 1, \cdots, K.$

where $p_{m,j,k,l}^{c}, q_{m,j,k,l}^{c}, x_{m,n,j,k,l}$ and $y_{m,n,j,k,l}$ are the 0–1 variables.

In addition, each customer and the collective have only one highest and lowest evaluation for each attribute of each electricity sales package, which is $\sum_{l=0}^{L} x_{m,n,j,k,l} = 1$ $n = 1, \cdots, N; j = 1, \cdots, J; k = 1, \cdots, K$, $\sum_{l=0}^{L} y_{m,n,j,k,l} = 1 n = 1, \cdots, N; j = 1, \cdots, J; k = 1,$ $\cdots, K$, $\sum_{l=0}^{L} p_{m,j,k,l}^{c} = 1 \quad j = 1, \cdots, J; k = 1, \cdots, K$, $\sum_{l=0}^{L} q_{m,j,k,l}^{c} = 1 \quad j = 1, \cdots, J; k = 1, \cdots, K.$

Appendix E

The set of electricity sales packages offered by the electricity sales company is shown in Table A1.

Table A1. The set of electricity sales packages.

	Unit Price/(Yuan·(kW·h)$^{-1}$)	Percentage of Renewable Energy/%	Value-Added Service	Incentive Policy	Package Exit Fee
X_1	0.51 (<500 kW·h) 0.63 (500–1000 kW·h) 0.82 (>1000 kW·h)	15	Power quality-improvement services	On-time settlement of electricity discount 8%	$160
X_2	0.58 (<500 kW·h) 0.6 (500–1000 kW·h) 0.86 (>1000 kW·h)	20	Energy-saving management	Reward power ratio of 9%	$170
X_3	0.87 (peak: 10:00–12:00, 13:00–19:00) 0.60 (flat: 06:00–10:00, 12:00–13:00, 19:00-22:00) 0.31 (valley: 22:00–morrow 06:00)	10	Energy-saving management	On-time settlement of electricity discount 8%	none
X_4	0.82 (peak: 08:00–15:00, 17:00–21:00) 0.64 (flat: 6:00–08:00, 15:00–17:00, 21:00-22:00) 0.33 (valley: 22:00–morrow 06:00)	15	Power quality-improvement services	Reward power ratio of 9%	none

The evaluation was based on seven linguistic evaluation scales. Among them are O_1-VP, O_2-P, O_3-SP, O_4-F, O_5-SG, O_6-G, and O_7-VG, where the meanings of each linguistic evaluation scale are as follows: O_1 means very poor (VP), O_2 means poor (P), O_3 means slightly poor (SP), O_4 means fair (F), O_5 means slightly good (SG), O_6 means good (G), O_7 means very good (VG).

Appendix F

Taking late-peak customer A_8 as an example, their satisfaction with each electricity sales package is shown in Figure A2.

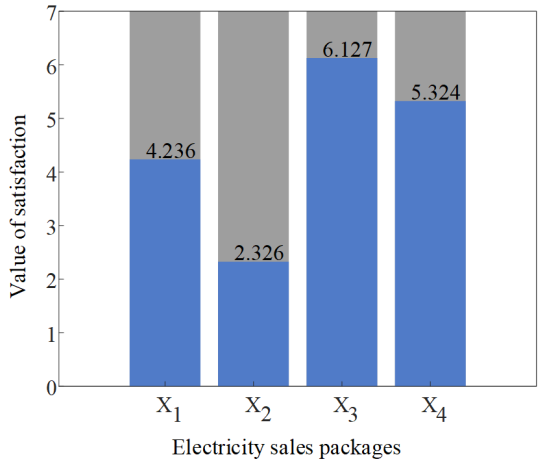


Figure A2. Customer A_8's satisfaction with each electricity sales package.

According to Figure A2, the customer's satisfaction with the electricity sales package X_3 is the highest, at 6.127, indicating that the customer's satisfaction with the electricity sales package is between 'G' and 'VG'.

Statistics on the satisfaction of customers in other late-peak sample sets with electricity sales packages and the customer proportion in each language evaluation level corresponding to each electricity sales package are shown in Figure A3.

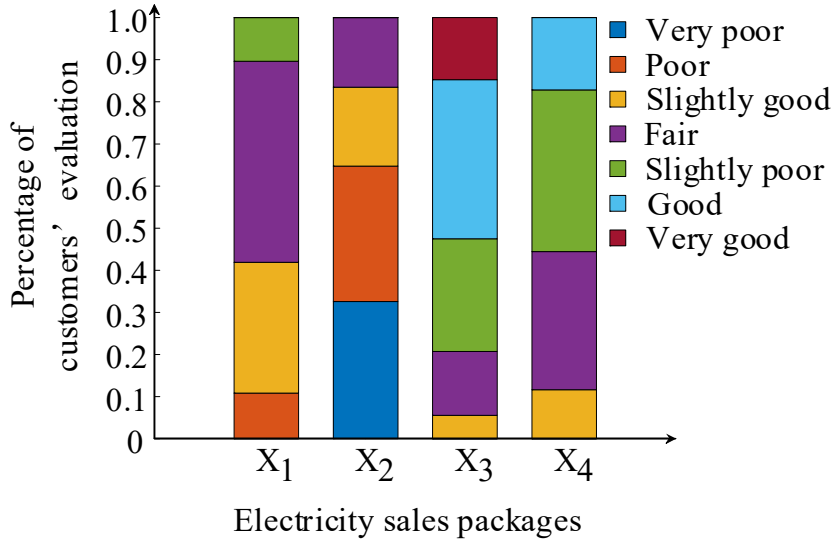


Figure A3. The number distribution of late-peak-type customers in each language evaluation level range.

From Figure A2, it can be seen that the customers' evaluation results for each electricity sales package are quite different. The customers' evaluation level for the electricity sales

package X_3 is higher, and most of the evaluation levels are between 'SG' and 'VG'. The satisfaction with the electricity sales package X_2 is low, and most of the levels are between 'VP' and 'SP'. The results are consistent with the satisfaction of customer A_8 in Figure A3.

Further, the similarity between the target customer and each customer in the late-peak sample set is calculated using Equation (2), as shown in Figure A4.

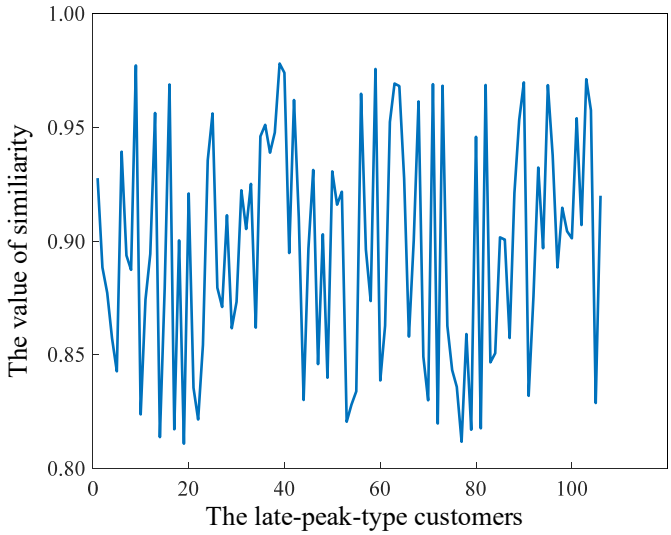


Figure A4. Similarity between target customers and customers of the late-peak-type sample customer set.

It can be seen from Figure A4 that the similarity between target customers and each customer in the late-peak-type sample set is more than 80%. It can be seen that the TSDC algorithm proposed in this paper can effectively classify customers with similar portraits into one category.

The quantitative results of satisfaction of other types of customers are shown in Figures A5–A7. A line of one color represents a customer.

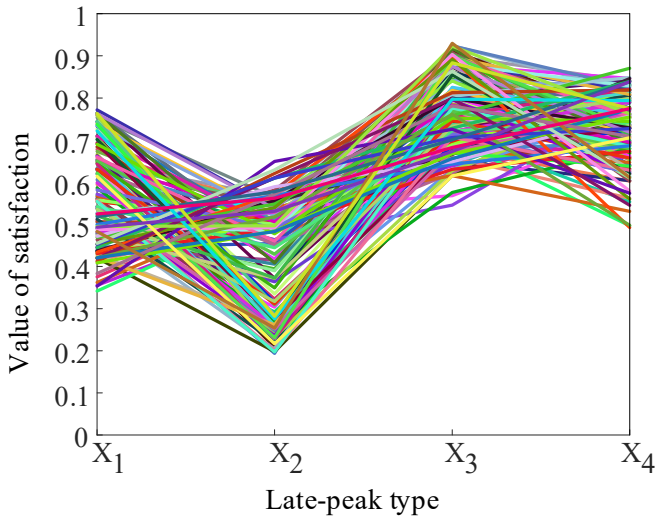


Figure A5. The quantitative results of the satisfaction of the customers of the late-peak type with the electricity sales packages.

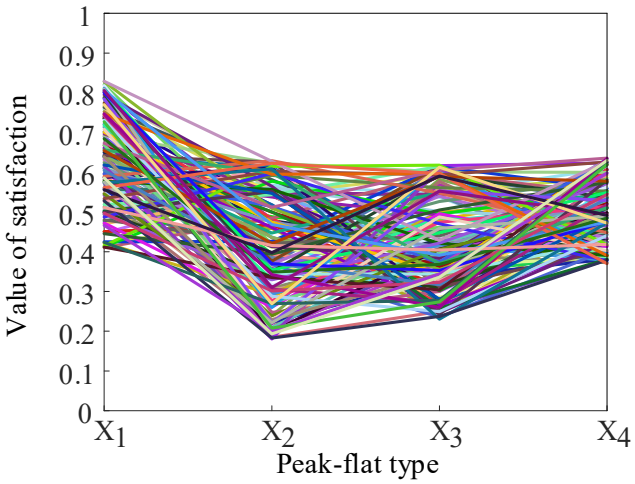


Figure A6. The quantitative results of the satisfaction of the customers of the peak-flat type with the electricity sales packages.

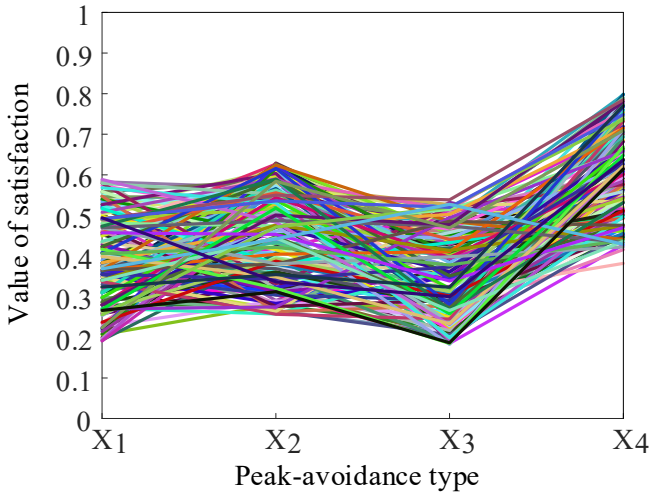


Figure A7. The quantitative results of the satisfaction of the customers of the peak-avoidance type with the electricity sales packages.

Figures A5–A7 show that customers of the same type exhibit similar overall satisfaction trends with each electricity sales package. In contrast, different types of target customers have varying ranking results for each electricity sales package.

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