A Decomposition and Reconstruction-based Approach to Power User Demand Analysis

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Abstract. To address issues such as the continuously expanding electricity demand and worsening environmental conditions, extensive research on demand-side management methods has emerged, aiming to optimize the allocation of electricity resources by leveraging demand-side factors. However, in the context of the internet environment, demand information from electricity users exhibits characteristics of complexity, dynamism, and big data, thereby placing higher demands on the capability of power companies in demand processing and analysis. Consequently, this paper proposes a demand analysis method based on decomposition and reconstruction. By establishing rules for demand decomposition, demand ontology models, and mapping relationships between demand and actual engineering characteristics, it establishes the importance ranking of electricity user demands and response engineering characteristics. This assists decision-makers in formulating electricity scheduling schemes to ensure timely and orderly demand response and electricity supply.

Keywords: demand analysis; decomposition; reconstruction; emergency respons

1 Introduction

Analysis of electricity user demand is a crucial foundation for power grid to conduct power resource dispatch and utilize electricity resources rationally. Scientific analysis methods and accurate analysis results have significant implications for the stable operation of the power system. Different types of users (industrial, commercial, residential, etc.) have varying electricity demand and behavioral patterns. The electricity demand of a large and diverse set of users typically constitutes a massive amount of unstructured data, within which noise and duplicate data abound, affecting the quality and usability of the data. Additionally, electricity demand dynamically adjusts with factors such as weather, holidays, and economic activities, hence demand information possesses strong real-time and dynamic characteristics. These factors collectively make demand analysis and data utilization challenging.

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In addressing the myriad issues faced during the analysis of electricity user demand for the power grid, including diverse objects, varied attributes, multidimensional perspectives, low efficiency of manual analysis, and difficulties in analyzing different indicators, research is conducted. On one hand, this research can enhance customer service and satisfaction. On the other hand, understanding the changes in users' electricity demand enables the rational arrangement of power supply to ensure the stable operation of the power grid.

At present, the analysis of electricity demand mainly focuses on demand forecasting[1,2] and demand response[3-5]. In terms of demand forecasting, Wang Yueqiang et al. [1] used regression analysis, time series analysis model and forest analysis model to conduct data statistics and processing, analyze the change trend in the long period and predict the change of power demand. Tang Ming et al.[2] used LSTM neural network modeling to predict user behavior and verified it with numerical examples. In terms of demand response, Arana et al.[3] used Johansen co-integration test and error correction model to control the influence of power resources on power users' consumption and thus on power demand. Su Meng[4] analyzed the modeling method of user demand response model under four types of peak-valley TOU price, and studied the parameter estimation method of user response model using the least square principle. Cheng Shan[5] proposed a two-layer optimal allocation method of distributed renewable energy that takes into account flexible regulation of demand response, which can ensure the minimum loss of active power network and determine the optimal allocation scheme of renewable energy. In the aspect of power user demand analysis, Li Zhihui[6] analyzed the influencing factors and their change characteristics of power customer demand from four dimensions: season, temperature, time period, event and user attributes.

Based on the above analysis, conducting analysis on electricity demand allows for the understanding or prediction of changes in user demand, thereby enabling the rational arrangement of electricity supply to ensure both customer satisfaction for the power grid company and the stable operation of the power grid. However, current analyses regarding electricity demand primarily focus on demand forecasting and response, neglecting the emphasis on the demand ontology itself, namely the electricity users. Analysis methods for electricity users still rely on manual processing and analysis of collected data, which is time-consuming and prone to errors.

To address the issues of increasingly diverse sources of demand, varied structures of demand information, and low efficiency in manual analysis, this paper proposes a multi-source demand decomposition and reconstruction method. This method decomposes different types of demand information into demand units and then reconstructs a multi-source demand set based on ontology. The decomposed demand units are prioritized using the Analytic Hierarchy Process (AHP), and then transformed into corresponding engineering characteristics through Quality Function Deployment (QFD) to obtain the priority of the respective engineering characteristics.

The specific framework is illustrated in Figure 1.

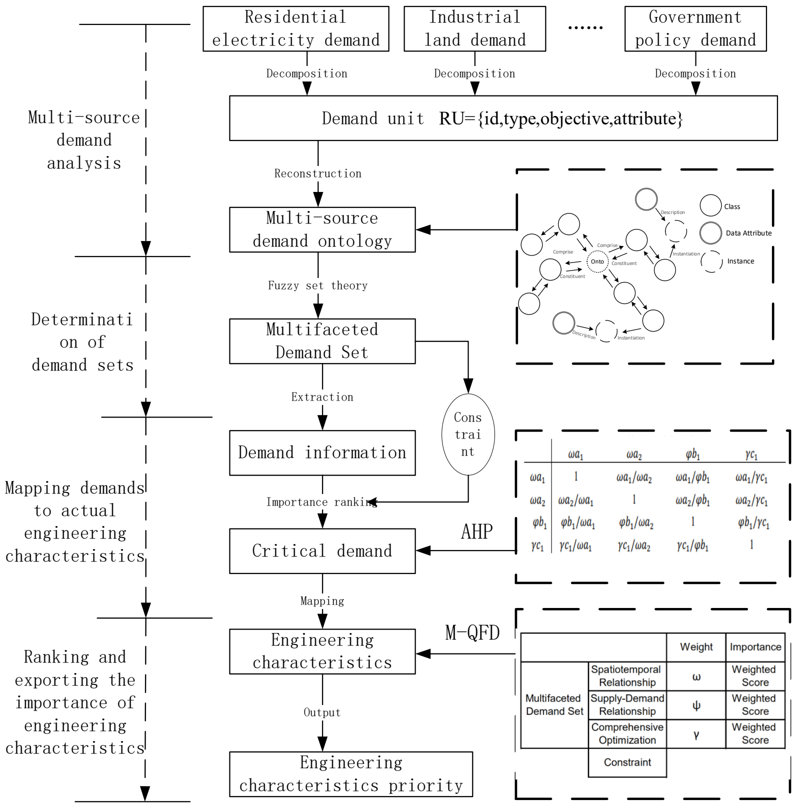

Fig. 1. Design framework of scheduling scheme based on multi-source demand.

2 Related Research

2.1 Decomposition and Refactoring Methods

Decomposition and reconstruction represent an innovative approach. In the process of analyzing multi-source demands, it is necessary to break down demand information with multiple meanings and objects to obtain sub-demands with singular and accurate content. Apart from differing sources, these pieces of information also exhibit non-standard and unstructured characteristics, making the decomposition of demands a standardized process.

Demands can be hierarchically decomposed, and the smaller the granularity of the decomposition, the greater the creativity involved, thus leading to a more complex demand decomposition model. This paper illustrates a four-layer decomposition model, as depicted in Figure 2.

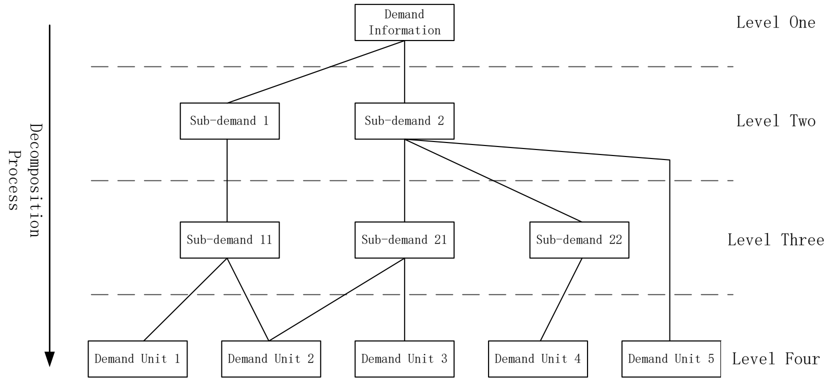

Fig. 2. Hierarchical model of requirements decomposition.

The first layer consists of the initial demand information, which may encompass multiple objects and characteristics. There are various criteria for decomposition, such as splitting based on target objects or according to linguistic logic.

The second layer involves the initial classification of information, resulting in sub-demands with relatively reduced information volume.

The third layer entails further subdivision of demand information, with each sub-demand containing objects and characteristics that are approaching singularity.

The fourth layer represents the final step of the decomposition process, where demands exist in the form of demand units. These demand units should adhere to the decomposition rules proposed in this section, being independent of each other. Similar demand units may require fusion.

The decomposition of demand information serves as the prerequisite and foundation for demand reconstruction, and demand units containing minimal information are also more easily transformed into corresponding engineering characteristics.

2.2 Ontology

Ontology is a standardized specification of knowledge in a specific domain through a set of concepts, properties, and relationships[7]. Originating from the field of philosophy, ontology enables knowledge sharing within a domain and facilitates the coordination of various data models, making it suitable for integrating heterogeneous data[8]. This paper establishes a flow-based multi-source demand ontology, integrating multi-source demand information based on classifications such as temporal-spatial relationships, supply-demand relationships, and comprehensive optimization. When multi-source demand information is ambiguous, the ontology's reasoning engine can assist in refining demand information.

Ontology is an abstract conceptual model derived from the objective world, describing individuals and their relationships within a domain. An ontology typically comprises elements such as concepts, relationships, properties, and instances. Languages like RDF and OWL are used to describe ontologies. However, constructing domain ontologies is a time-consuming task involving repetitive manual operations.

To address these issues, Stanford University has developed an ontology editing tool called Protégé, which semi-automates the construction of domain ontologies. It can convert established ontologies into RDF, OWL, and other ontology languages, and supports modifications using ontology languages. Additionally, Stanford University has proposed a method for constructing ontologies known as the seven-step method, with the specific process illustrated in Figure 3.

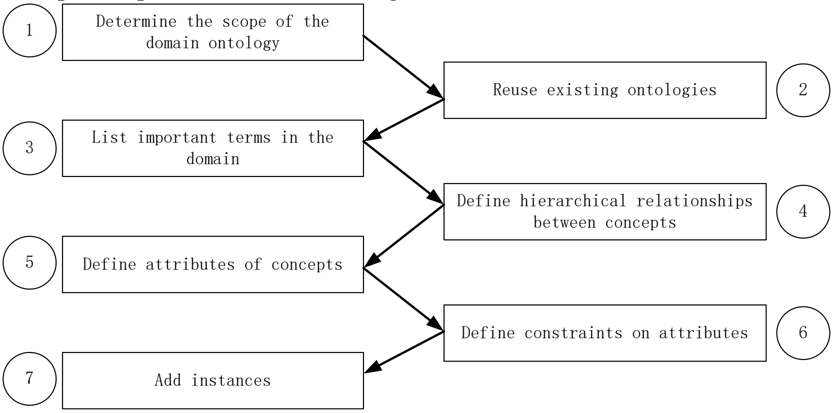

Fig. 3. Seven-step approach to ontology construction.

2.3 Fuzzy Set Theory

A multi-source demand set is a collection formed by demand units, further analyzed and integrated based on the multi-source demand ontology. User demands typically exist in natural language form, with descriptions of target objects being ambiguous, such as "too loud" or "not stable enough." Therefore, the multi-source demand set contains two types of demand: one with accurate descriptions and the other with uncertain concepts and fuzzy expressions.

The fuzzy set theory proposed by American control theorist Zadeh provides effective tools for handling such imprecise fuzzy information. Common methods for determining membership functions include:

1) Intuition-based method: Designers assess membership based on their design experience and disciplinary knowledge, typically used when data collection is challenging.

2) Comparative method: Membership is determined through pairwise comparisons of elements, often established through expert scoring.

3) Statistical method: Membership is calculated based on the proportion of elements in the set, using statistical techniques.

The most commonly used types of membership functions include rectangular functions, trapezoidal functions, and Gaussian functions, categorized as skewed large, middle, and skewed small functions based on different fuzzy sets.

2.4 Quality Function Deployment

Quality Function Deployment (QFD) is a planning tool used to enhance design quality by converting qualitative user requirements into quantitative engineering characteristics. It finds extensive applications in various fields such as manufacturing, healthcare, and construction, as it is rooted in the analysis of user needs to develop new products, earning it the moniker "the voice of the customer." QFD encompasses mapping matrices in four stages: design, detailed design, process, and production, with its core component known as the House of Quality (HOQ). The structure of the HOQ is depicted in Figure4.

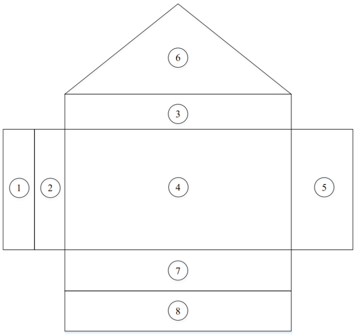

Fig. 4. Schematic diagram of House of Quality (HOQ).

Among these components:

1. User requirements: Characteristics desired by users for the product.
2. Importance ranking of requirements: Prioritization of requirements based on Analytic Hierarchy Process (AHP) or other scoring methods.
3. Engineering characteristics: Functional attributes designed or improved for the product.
4. Relationship matrix between requirements and engineering characteristics: Analysis of the correlation between requirements and engineering characteristics.
5. Market competitiveness: Evaluation of competing products in terms of their satisfaction of user requirements.
6. Relationship matrix of characteristics: Strength of relationships between technical improvement items.
7. Target values for engineering characteristics: Evaluation of the extent to which product improvements meet requirements.
8. Importance of engineering characteristics: Relationship between engineering measures and requirements.

3 Methods of Analysis

3.1 Multisource Requirements Decomposition

This paper refers to the concept of demand units proposed by Sheng et al.[9], where demands are decomposed into the smallest units that cannot be further subdivided. The decomposition of multi-source demands can be represented as follows:

$$\mathrm{RS}=\{\mathrm{RU}_1,\mathrm{RU}_2,\mathrm{RU}_3,\cdots,\mathrm{RU}_n\} \tag{1}$$

Among them, RU represents a demand unit, and RS represents a demand set composed of demand units. In order to effectively utilize demand information in subsequent mapping processes, demand units are standardizedly represented as:

$$RU=\{id,type,objective,attribute\} \tag{2}$$

In this context, "id" represents the index number of the demand unit, "type" denotes the type of the demand unit, "object" signifies the object of demand information, and "attribute" specifies the specific technical attributes. The formulation of the RU decomposition rules draws on the independence axiom and information axiom of the AD theory, and is further improved based on the practical characteristics of electricity resource scheduling. The specific rules for demand decomposition are outlined in Table 1:

Table 1. Decomposition rules for demand units.

Name	Content of the rules
Principles of Independence	The information carried between demand units should be mutually independent without interference.
Principle of Minimization of Information	Demands should be divided into the smallest units that cannot be further subdivided, i.e., containing the minimum amount of information.
Principle of Similarity Integration	Similar demand units should be merged
Principle of Semantic Consistency	Demand units should correspond to the original requirements and be semantically consistent with the demands

In this section, we will further investigate the decomposition rules of demands based on the previous section, proposing a flow-based demand information decomposition rule. The concept of flow originates from the functional modeling stage in the design process, where the overall function is hierarchically decomposed to obtain singular sub-functions. These sub-functions are interconnected through temporal-spatial relationships, supply-demand relationships, and comprehensive optimization. This concept bears similarity to the aforementioned definition of demand units in this paper. In the process of decomposing user demands, demands are also required to be decomposed into indivisible minimal units. Additionally, demands contain detailed information regarding electricity needs, serving as an idealized description of electricity resource scheduling. Therefore, this paper formulates flow-based demand decomposition rules (Figure 5).

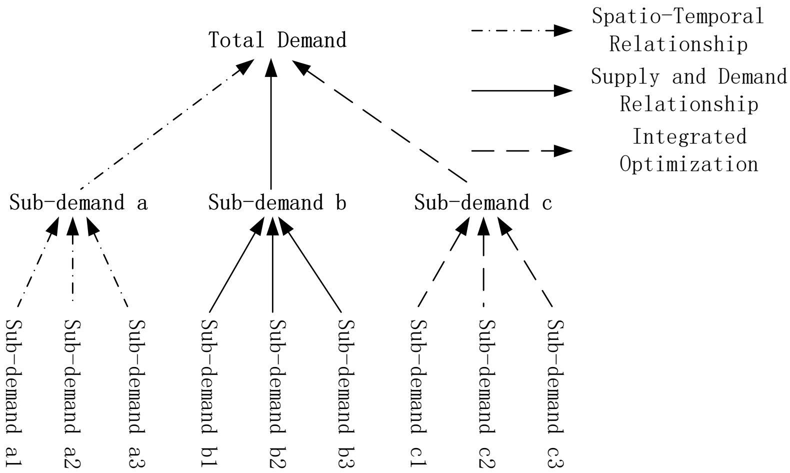

Fig. 5. Flow-based requirements decomposition process.

Temporal-spatial relationships refer to the mutual influence and intertwining of electricity resource scheduling demands in time and space. Both the load and energy supply of the power system fluctuate with time, and there are differences in energy demand among different regions. Therefore, effective coordination and balance of electricity resource scheduling demands are required at different time periods and geographical locations to meet the requirements of electricity supply and demand.

Supply-demand relationships denote the interactive relationship between resource supply and load demand in the power system. The power system needs to schedule rationally based on real-time load conditions and available resources to ensure a balance between electricity supply and demand. When the electricity load exceeds the supply capacity, adjustments to the output of generation resources or purchasing additional electricity are required. Conversely, when the electricity load is low, generation capacity can be appropriately reduced to improve energy utilization efficiency.

Comprehensive optimization relationships entail the comprehensive optimization of electricity resource scheduling demands across multiple aspects. Power system managers need to consider various factors such as fluctuations in electricity load, availability of renewable energy, constraints of transmission lines, generation costs, as well as meeting requirements for environmental protection and sustainable development.

3.2 Source Requirements Aggregation Construction

The specific construction of the multi-source demand ontology can be represented in the form of quadruples: $Onto = \{C_{RI}, O_{RI}, D_{RI}, I_{RI}\}$, where $Onto$ represents the multi-source demand ontology, CRI represents the set of concepts and classes within the multi-source demand ontology, ORI denotes object properties, representing relationships between individuals, DRI signifies data properties used to define the attributes and attribute values of individuals themselves, and IRI represents instances created based on types. The relationships between these constituent elements are illustrated in Figure 6.

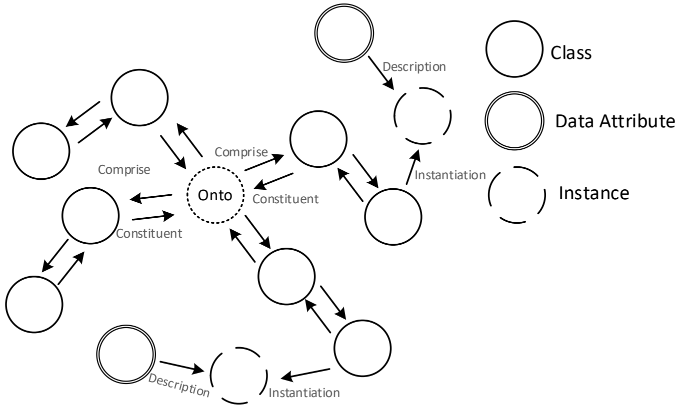

Fig. 6. Relationship between elements in the ontology.

In establishing the multi-source demand ontology, this paper initially defines three fundamental classes: energy, material, and signal. On one hand, this facilitates the reintegration of user demands, while on the other hand, it clarifies the classification boundaries of demand information. The multi-source demand ontology is built on the basis of the three fundamental classes: temporal-spatial relationships, supply-demand relationships, and comprehensive optimization. Other demand units are classified according to these three major categories, constituting various subclasses of the ontology. There exist various relationships between classes, such as relevance, irrelevance, subordination, and influence. Object properties in the ontology represent relationships, focusing on the correlation between two classes. Additionally, relationships between two classes can exhibit transitivity and reflexivity. Data properties describe the attributes of classes themselves. For example, if a user desires a power of 600 kW for a supply vehicle, then the power of 600 kW is one of the data properties of that vehicle.

In accurately expressing elements in ordinary sets, characteristic functions are used to describe the relationship between elements and sets, denoted by χA for set A's characteristic function:

$$\chi_A(x) = \begin{cases} 0, x \notin A \\ 1, x \in A \end{cases} \quad (3)$$

Indeed, in fuzzy set theory, the relationship between elements and sets is measured using membership functions to quantify the degree of association between them. The function's value extends from 0 and 1 to the interval [0,1], namely:

$$\psi_U(x) \in [0,1] \tag{4}$$

In the equation, ψ represents the membership function, U denotes the fuzzy set, and xx signifies the element. The degree of membership of each element relative to the set represents the extent to which the element belongs to the set. For demand units decomposed according to a hierarchical structure, the rationality of classification can be assessed by calculating the degree of membership between the unit and its superiors.

Next, let's analyze the multi-source demand set using a middle-type trapezoidal function, which can be expressed as:

$$\psi_U(x) = \begin{cases} \left(\frac{x-a}{b-a}\right)^k & ,a \le x < b \\ 1 & ,b \le x < c \\ \left(\frac{d-x}{d-c}\right)^k & ,c \le x < d \\ 0 & ,x < a \ or \ d < x \end{cases} \tag{5}$$

In this equation, aa, bb, cc, and dd respectively represent the critical boundaries of the set. The relationship between element x and set U is established only when the degree of membership of element x to set U reaches a certain confidence level. The graphical representation of the function is illustrated in Figure 7.

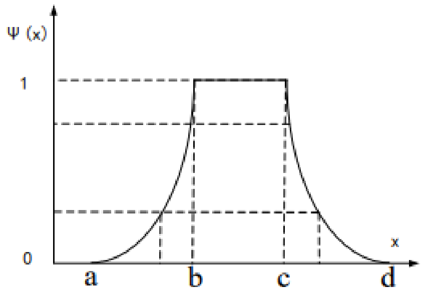

Fig. 7. Image of trapezoidal subordinate function.

n the hierarchical decomposition of demands, at the lowest level, the constituent elements are demand units with singular objects and attributes. However, in the intermediate part of the hierarchical structure composed of sub-demands, elements may contain multiple objects or attributes. In such cases, classification is conducted based on the maximum membership degree principle. Assuming there are nn subsets $u1$, $u2$, … un, in the multi-source demand set UU, for any sub-demand x0x0 in the multi-source demand set, where$i \in \{1,2, \dots, \mathrm{n}\}$, if it satisfies:

$$\psi_i(x_0) = V_{j=1}^{n} \psi_i(x_0) \tag{6}$$

In this case, sub-demand $x0$ should belong to subset ui, where ψ represents the membership function, and V denotes the inner product operation of vectors. After processing with fuzzy theory based on the multi-source demand ontology, the multi-source demand set U can be represented in vector form:

$$U = (R_b, R_s, \cdots, R_{sn}, R_u) \tag{7}$$

In this context, Rb represents the three basic subclasses of multi-source demand: temporal-spatial, supply-demand, and comprehensive optimization. Rs represents the split lower-level sub-demands, where Rsn denotes the nth-level sub-demand, and Ru represents the demand units defined in this paper.

3.3 Requirements to Engineering Feature Mapping

In the context of multi-source demand in this paper, traditional Quality Function Deployment (QFD) tools cannot complete the mapping process from requirements to functions. Therefore, this section proposes an improvement to the QFD tool, introducing the MHOQ (Multi-source House of Quality), to accomplish the mapping process from multi-source demands to functions. On the left side of the MHOQ, the left wall composed of user demands is replaced by a group formed by the multi-source demand set. In the demands, there exist constraint information that imposes restrictions, such as the continuous power supply time of a supply vehicle should be greater than 3 hours, denoted as a constraint condition: T>3h. Consequently, in the subsequent solution generation phase, supply vehicles with power supply times less than 3 hours will not be recommended. Based on this concept, this paper enhances the left wall of the MHOQ, as shown in Figure 8.

		Weight	Importance
Multifaceted Demand Set	Spatiotemporal Relationship	ω	Weighted Score
	Supply-Demand Relationship	ψ	Weighted Score
	Comprehensive Optimization	γ	Weighted Score
	Constraint		

Fig. 8. Improved left wall of the mass house.

In the improved left wall of the House of Quality, temporal-spatial relationships, supply-demand relationships, and comprehensive optimization are assigned corresponding weights to meet the requirements of different environments. To evaluate the relative importance of different demands, we use the Analytic Hierarchy Process (AHP) to score various types of demands in the multi-source demand set. The core idea of AHP is to pairwise compare the demands to be evaluated. After satisfying consistency conditions, the importance of each demand is then calculated using methods such as the eigenvalue method. In the improved House of Quality, since demands are weighted, the format of the modified AHP comparison matrix is as shown in Figure 9.

	ωa_1	ωa_2	φb_1	γc_1
ωa_1	1	$\omega a_1/\omega a_2$	$\omega a_1/\varphi b_1$	$\omega a_1/\gamma c_1$
ωa_2	$\omega a_2/\omega a_1$	1	$\omega a_2/\varphi b_1$	$\omega a_2/\gamma c_1$
φb_1	$\varphi b_1/\omega a_1$	$\varphi b_1/\omega a_2$	1	$\varphi b_1/\gamma c_1$
γc_1	$\gamma c_1/\omega a_1$	$\gamma c_1/\omega a_2$	$\gamma c_1/\varphi b_1$	1

Fig. 9. Improved comparison matrix.

The calculation method for the Consistency Index (CI) of the comparison matrix remains unchanged, and the formula for CI calculation is as follows:

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{8}$$

Where λmax represents the maximum eigenvalue of the comparison matrix, and n denotes the number of demands. The Consistency Ratio is defined as:

$$CR = \frac{CI}{RI} \tag{9}$$

Where the Random Index (RI) for consistency can be obtained through table lookup. If the Consistency Ratio is within an acceptable range, the test passes. Given a comparison matrix A, the relative importance of each demand can be calculated by solving the following equation:

$$A\omega = \lambda\omega \tag{10}$$

Once technical personnel have determined the importance of multi-source demands, they need to establish corresponding engineering characteristics based on their design experience, i.e., realizing the functional attributes of demands. The relationship between demands and engineering characteristics is not simply a one-to-one correspondence. Some engineering characteristics can fulfill multiple demands, while some demands may require multiple engineering characteristics for implementation. Therefore, further analysis of the correlation between demands and engineering characteristics is necessary to optimize scheduling plans. The relationship matrix between multi-source demands and engineering characteristics is used to evaluate the degree of correlation, as shown in Figure 10, and the strength of the correlation can be expressed as 1, 3, 5, or 7, with a larger number indicating a stronger correlation between the two indicators.

	Engineering characteristics 1	Engineering characteristics 2	Engineering characteristics 3	Engineering characteristics 4	......
Demand unit 1	1	3	5	7	
Demand unit 2	5	3	3	7	
Demand unit 3	1	7	1	5	
Demand unit 4	7	1	1	1	
......					

Fig. 10. Relationship matrix between multi-source requirements and engineering characteristics.

3.4 Importance Ranking of Engineering Characteristics

Once the correlation between demands and engineering characteristics is determined, the respective importance of engineering characteristics can be obtained through calculation. The importance of engineering characteristics directly measures whether the technical features proposed by technical personnel contribute to the improvement of the scheduling plan. The formula for calculating the importance of engineering characteristics can be expressed as:

$$H_j = \frac{\sum_{i=1}^{m} K_i r_{ij}}{\sum_{i=1}^{m} K_i}, i = 1, 2, \cdots, m \tag{11}$$

Where: H_j represents the importance level of the engineering characteristic; K_i represents the importance level of the multi-source demand; r_{ij} represents the correlation between the demand and the engineering characteristic; m represents the number of demands.

Through the analysis of the correlation between demands and engineering characteristics, it is possible to filter out some irrelevant demand information. Finally, by determining the correlation between demands and engineering characteristics and the importance of engineering characteristics, the importance of engineering characteristics and their correlation with demands can be provided to the scheduling plan designers. They can then utilize their design knowledge and experience to determine the final scheduling plan.

4 Requirements Analysis Case

In the preceding chapters, a method for decomposing and reconstructing the demands of electricity users and mapping them to engineering characteristics was proposed. This chapter applies the aforementioned method to analyze the demands of electricity users during extreme high-temperature weather conditions in the summer.

4.1 Background

As the proportion of renewable energy sources such as hydro, wind and solar in the grid continues to increase, the strong correlation, randomness and uncertainty of weather will make it more challenging to connect distributed power sources (DGS) to the grid[10].When faced with extreme weather conditions caused by high temperatures leading to drought (hereafter referred to as extreme high-temperature weather causing drought), the power system often experiences significant impacts. Drought caused by high temperatures can affect the efficiency of hydroelectric power generation and cooling systems, making it difficult for the power generation system to maintain normal operation. Extreme weather events may also lead to a surge in electricity demand while constraining power production, exacerbating the tense situation in the power system. Therefore, when confronted with the impact of extreme weather, the power system needs to collect and analyze user demands from multiple aspects, implement flexible operation and emergency response mechanisms to minimize the impact on public life and economic activities to the greatest extent possible.

4.2 User Needs Analysis in Extreme Hot Weather

In response to the extreme high-temperature weather in Sichuan, China in 2022, user feedback was collected through the National Grid 95598 Intelligent Mutual Assistance website. The primary medium for collecting the demands was natural language, which was segmented into tuple tags through pre-processing with segmentation and part-of-speech tagging. Table 2 presents some of the user demands.

Table 2. Selected user requirements in extreme heat.

Source	Content (tuple tags)
User 1	<a neighborhood, evening, protection, ..., stable>
User 2	<a factory, daytime, environmental, ..., minimal>
User 3	<a nursing home, all day, ..., secure, stable>

Based on the concept of demand units proposed in this paper and the decomposition rules for multi-source demands, combined with the electricity resources in various regions, the decomposed demand units can be obtained and stored in the form of $RU = \{id, type, objective, attribute\}$. Some of the demand units are shown in Table 3 below:

Table 3. Electricity consumer demand units in extreme hot weather.

Number	Requirements module
1	{004, Zero-level load, Telecommunication Chengdu Hub Center, to ensure stable power supply for the entire hub throughout the day.}
2	{006, First-level load, West China Hospital of Sichuan University Main Campus, to ensure daytime power supply for outpatient and o perating rooms; continuous power supply for inpatient buildings and critical care units.}
3	{012, Second-level load, Chengdu Museum, to ensure power supply for security systems.}
4	{016, Third-level load, Jinxiu Garden Residential Community, to pr ovide power supply during late night and early morning hours.}

Then, we established a multi-source requirements ontology using the Protégé tool, with subclasses based on spatiotemporal, supply-demand, and comprehensive optimization. The requirements units were categorized and classified based on a stream-based approach. As the requirements ontology continued to expand, this paper defines that additional classes, relationships, and instances can be incorporated into the initial ontology to enhance the multi-source requirements ontology for extreme high-temperature conditions.

Refinement of unreasonable classifications was conducted through fuzzy set theory. For instance, the classification of different time periods at a specific location under the context of spatiotemporal relationships is refined using fuzzy set theory. Considering the collection of different time periods at a certain location, a membership function for working hours at that location is established (a=9, b=11, c=13, d=18), indicating a high membership degree for electricity demand during working hours from 9 AM to 6 PM. A membership threshold of 0.6 is set, and elements with membership degrees below 0.6 are excluded from the demand set during working hours in that area. This process eventually forms a multi-source demand set for electricity demand during extreme high-temperature weather conditions.

The Analytic Hierarchy Process (AHP) methodology, enhanced by improved AHP analysis and the Quality House (QH) method, is employed to assess the importance of demands. Initially, weights are assigned to spatiotemporal relationships, supply-demand relationships, and comprehensive optimization, with values of 0.3, 0.4, and 0.4, respectively. Subsequently, a judgment matrix is constructed, and after scoring, characteristic vectors for each demand unit are calculated, along with a maximum characteristic root of 5.1352. The Consistency Index (CI) is determined to be 0.0338, and with reference to the Random Index (RI) table, the corresponding value is found to be 1.11. Hence, the Consistency Ratio (CR) is calculated as 0.0305, which is less than 0.1, indicating the weights are reasonable and do not require modification.

Demand units with high importance are selected and transformed into corresponding engineering characteristics. Some of the transformation results are summarized in Table 4 below.

Table 4. Multi-source requirements and engineering characteristics.

Requirements module	Importance	Engineering Characteristics
Chengdu Telecommunication Hub Center providing uninterrupted power supply.	0.427	Dual power supply with backu p power provision.
Particular areas of West China Hospital o f Sichuan University Main Campus requir ing electricity.	0.382	Dual power supply with backu p power provision for two circu its.
Chengdu Museum requiring power for its security system.	0.343	Power supply via ring network configuration with backup gene rators.
Jinxiu Garden Residential Community re ceiving power during late night and early morning hours.	0.235	Power supply at 10kV voltage l evel with a single power source
Jinxiu Garden Residential Community re ceiving power during working hours.	0.089	Power supply at 10kV voltage l evel with a single power source

Based on the aforementioned demand analysis, amidst the plethora of noise, duplicate data, and unstructured user information, it has been deduced that the power demands of the communication hub and hospital hold greater significance. In cases of insufficient power supply, priority will be given to ensuring the electricity needs of areas with higher levels of importance, such as the communication hub and hospital.

By incorporating the prioritized information derived from multiple sources of demand and engineering characteristics, power dispatch personnel will find it easier to heed the voices of electricity users during the scheduling process. This will lead to the development of power scheduling arrangements that are more aligned with the needs of the users.

5 Conclusion

Through meticulous analysis of the user demand information, we employed various perspectives, including spatiotemporal relations, power resource supply-demand dynamics, and objective power resources. Initially, we decomposed these requirements into detailed components from three different flow directions. This step aided in a comprehensive understanding of the complexity of demands, breaking them down into smaller units for precise and actionable handling.

Subsequently, we systematically reconstructed these decomposed demand units. This process involved integrating relevant information, eliminating redundancy, ensuring the final demand units are clearer and more accurate.

To determine the importance of each demand unit, we utilized an enhanced Analytic Hierarchy Process (AHP). This method considered the interrelationships among the demand units and quantitatively determined their relative weights within the overall structure. This allowed us to strategically focus on the most impactful demand units and derive the importance of engineering characteristics through mapping demand to actual engineering features, ultimately facilitating the design of scheduling schemes for auxiliary power dispatchers.

Overall, this approach effectively analyzes user demand information, contributing to a better understanding of electrical power requirements. Simultaneously, it provides necessary data support for the efficient scheduling of power systems, ensuring systems can flexibly respond to diverse demands, thus better meeting users' electrical needs.

Acknowledgments

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