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ARTICLE

Assessment and Scheduling Priority of Industrial Load Regulation Capability for Demand Response in New-Type Power Systems

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ABSTRACT: Driven by the "Carbon Peak and Carbon Neutrality" strategic goals, high penetration of renewable energy poses severe challenges to power system flexibility. Unlocking the adjustable potential of demand-side industrial loads has become a critical pathway for constructing new-type power systems. To address the limitations of existing research, including single-dimensional characterisation of adjustable potential, insufficient consideration of both best and worst solutions in evaluation methods, and a lack of cluster coordination perspectives, this paper proposes a multi-dimensional adjustable potential assessment and priority ranking method for industrial loads. Firstly, based on the Affinity Propagation (AP) and k-means secondary clustering algorithms, interruptible and transferable regulation behaviour patterns are identified from massive historical load data, and multi-dimensional characteristic indicators covering capacity, time, and rate are extracted. Secondly, a comprehensive weight determination model integrating Best-Worst Method (BWM), improved CRITIC method, and game theory combination weighting is constructed, and the Set Pair Analysis-Variable Fuzzy Set (SPA-VFS) theory is introduced to establish a comprehensive assessment method for industrial users' adjustable potential. Finally, empirical analysis is conducted taking industrial users in a typical region as an example. The results demonstrate that the proposed method can effectively distinguish the regulation capability differences among different users. The comprehensive adjustable potential value of User 1 reaches 0.833, which is significantly superior to other industrial users, and the ranking results show better consistency and discrimination compared with TOPSIS and linear weighting methods. Meanwhile, the introduction of "time" and "rate" dimensions has a significant impact on the evaluation results. After removing these dimensions, the ranking of User 5 and User 6 is reversed, verifying the necessity of multi-dimensional feature characterisation. This study provides theoretical support and decision-making basis for industrial loads to participate in multi-time-scale dispatching of power systems.

KEYWORDS: Industrial load 1; adjustable potential 2; combination weighting 3; SPA-VFS 4; priority ranking 5

1 Introduction

1.1 Motivation

Under the systemic drive of the "Carbon Peak and Carbon Neutrality" strategic goals, China's energy structure is undergoing a profound and rapid green transformation [1]. A core hallmark of this shift is the historic crossover of renewable energy from a supplementary role to a dominant one in the power mix. As of the end of June 2025, the national installed capacity for renewable power generation has surpassed a historic milestone of 2.159 billion kilowatts, accounting for 59.2% of the country's total power generation capacity and solidifying its dominant position. Within this, the combined installed capacity of the more variable wind and solar power reached approximately 1.673 billion kilowatts, constituting a significant 45.9% share of the total capacity. According to the 2024 Energy Work Guidance Opinion, the proportion of new energy in total electricity generation must further increase to over 20% by 2027. However, while the explosive growth in renewable installed capacity contributes substantial green power, its inherent strong randomness, volatility, and intermittency fundamentally reshape the real-time power balance of the electricity system, posing unprecedented and severe challenges to system flexibility.

Traditionally, the responsibility for balancing and regulating the power system has primarily fallen on the generation side. Measures such as flexibility retrofits of coal-fired power plants, and the construction of pumped-storage hydropower and new energy storage systems have played a crucial foundational role [2]. Yet, as renewable penetration reaches high levels, the systemic shortcomings of relying solely on generation-side regulation have become increasingly apparent, manifesting in three core contradictions. First is the inertia of the regulation paradigm. The traditional unidirectional, passive "generation-follows-load" mode struggles to adapt to the new normal of "source-load interaction" under high renewable penetration. Second is the spatio-temporal mismatch of resources. High-quality flexible resources, such as flexible coal power and pumped-storage, are geographically concentrated in regions with limited overlap with renewable-rich areas like Northern, Northeastern, and Northwestern China, leading to severe local shortages in regulation capacity and exacerbating curtailment pressures [3]. Third is the lack of market-based incentives. In operational modes still influenced by planned dispatch, the fixed generation schedules of conventional power plants can conflict with the fluctuating output of renewables in both time and space, potentially crowding out renewable generation during periods of high renewable availability. These contradictions have had tangible impacts in practice. For instance, the wind and solar curtailment observed in several provinces during the peak summer load period in 2024 serves as a factual case illustrating the bottleneck faced by generation-side regulation.

Consequently, against the backdrop of insufficient generation-side regulation potential, shifting the focus to unlocking flexibility resources on the demand side has become an imperative for building a new-type power system. The 2024 Energy Work Guidance Opinion for the first time set a mandatory target for demand-side response capacity to reach above 5% of the maximum load by 2027. This marks the official elevation of demand-side resources from emergency backup and marginal supplements for grid security to a strategic pillar supporting the energy transition. Compared to the generation side, demand-side flexibility resources offer distinct advantages, including distributed deployment, fast response, near-zero marginal carbon emissions, and relatively lower investment costs. Among various demand-side resources, industrial users stand out as the most promising and practically feasible core target due to their large load magnitude, predictable consumption patterns, high automation levels, and concentrated adjustable capacity. Surveys indicate that industrial electricity consumption has long constituted over 65% of total societal electricity use. Within this, energy-intensive industries such as steel, chemicals, non-ferrous metals, and building materials possess significant individual production lines or enterprises with maximum loads reaching tens to hundreds of megawatts, representing immense regulation potential [4,5]. Therefore, harnessing the flexible regulation capability of industrial loads to achieve source-load coordination and interaction holds significant theoretical and practical importance for ensuring secure and stable grid operation, promoting efficient renewable energy integration, and reducing the overall societal cost of the energy transition.

1.2 Literature Review

In this process, demand-side resources, particularly industrial loads which dominate total societal electricity consumption, are transforming from passive energy consumers into active regulators supporting grid security and stability. Therefore, conducting accurate and reliable assessments of the adjustable potential of industrial loads is a critical prerequisite and scientific foundation for unlocking demand-side flexibility and realizing source-load coordination and optimization. This section aims to systematically review the state of research on adjustable potential assessment in terms of both characterization metrics and evaluation methods, comment on the contributions and limitations of existing work, and thereby clarify the positioning and innovative direction of this study.

Quantifying adjustable potential first requires establishing a set of metrics that can comprehensively and accurately characterize its properties. Existing research has explored this aspect from multiple dimensions. One strand of studies focuses on defining potential from the perspectives of macro-aggregate volume and user classification. For instance, Xu et al. directly screened users with adjustment potential and estimated their adjustable load capacity by analyzing different load patterns, providing an initial aggregate perspective for potential assessment [6]. Sun et al. proposed an innovative industrial load classification framework, categorizing them into continuously adjustable and stepwise adjustable types, and established a generalized adjustment response model capturing their production characteristics and transient behavior. This reveals the differences in the internal adjustment mechanisms of different industrial load types, laying the groundwork for refined modeling [7]. Another strand of research expands the connotation of potential from the level of system integration and resource aggregation. Ammasaikutti et al. explored methods combining energy storage systems with the adjustable curtailment of distributed photovoltaic generation, reflecting the idea of enhancing overall regulation capability through multi-resource coordination [8]. Similarly, Liu et al. proposed a method to virtualize distributed switches and dynamically adjust their configuration [9]. These efforts are dedicated to solving the problem of unified characterization and aggregation of distributed, heterogeneous resources, enabling the large-scale manifestation of regulation capabilities from massive small-scale loads. Furthermore, in-depth mining of specific load types is also an important direction. He et al., targeting electric bus fleets, established a multi-period load analytical model integrating historical data and physical mechanisms, achieving precise assessment of mobile energy storage potential [10]. Yao et al. highlighted the significant regulation potential of public building air conditioning systems [11]. Such research underscores the necessity of potential assessment based on the physical characteristics and operational constraints of loads.

Corresponding to different characterization dimensions, scholars have developed diverse potential evaluation methods, which can be broadly categorized into the following three types. The first category is data-driven and pattern recognition-based methods. Their core is to automatically discover users' electricity consumption patterns and adjustable features by analyzing historical load data. For example, Zhang et al., addressing scenarios with limited data, constructed feature extraction and prediction models based on data mining [12]. These methods do not rely on complex physical modeling and are suitable for scenarios with a solid data foundation. However, their evaluation accuracy is heavily dependent on data quality and completeness, and their interpretability is often weak. The second category is multi-criteria comprehensive evaluation and ranking methods. This approach aims to comprehensively quantify multiple evaluation metrics to determine the priority of different users or resources in terms of their regulation value [13]. Xie et al. noted that accurate power load forecasting is crucial for grid stability and market efficiency, and conducted an empirical evaluation of PJM's hourly load forecasting [14]; Yang et al. employed the linear weighting method to calculate comprehensive evaluation values [15]. These methods provide direct decision support for grid dispatchers to optimize resource dispatch sequences. Nevertheless, their effectiveness highly depends on the scientificity of the metric system and the rationality of weight allocation. Existing methods often fail to fully consider the global relationship between evaluation indicators and both the ideal optimal and ideal worst solutions when determining weights, which may lead to distorted evaluation results or insensitivity to extreme values. The third category is mechanism modeling methods oriented towards specific constraints and precise calculation. These methods are closely integrated with the physical constraints of specific industrial processes or equipment. Yan et al., considering the "vibration prohibition zone" constraints of hydroelectric units, proposed a calculation method for precisely evaluating their regulation flexibility [16]. Such research offers high evaluation accuracy but suffers from poor model generalizability and is difficult to directly apply to other types of loads.

In summary, the research field on the assessment of adjustable potential in industrial loads has accumulated a rich body of knowledge, demonstrating significant progress in the classification and aggregation for potential characterization, as well as in data-driven and comprehensive evaluation methodologies. Nevertheless, several critical limitations persist in the current literature. (1) Potential characterization often exhibits limited dimensionality. Existing indicator systems primarily emphasize capacity, lacking adequate characterization of dynamic dimensions—such as adjustment rate and sustainable duration—and their inter-coupling relationships. Consequently, these systems struggle to provide comprehensive support for multi-timescale dispatch decision-making. (2) There are notable constraints in the prevailing evaluation methods. Techniques for determining indicator weights in comprehensive assessments frequently fail to sufficiently account for a solution's proximity to the ideal benchmark. Moreover, the evaluation process remains largely static, lacking in-depth analysis of the correlations and distinctions in adjustable potential across different users. (3) A cluster-coordination perspective is notably absent. The predominant approach terminates at single-user assessment, without advancing to a comparative analysis or an exploration of complementary potential among users from a system-level, cluster-optimization standpoint.

1.3 Our Contributions

To address the aforementioned research gaps, this study introduces innovations focused on three principal aspects. (1) It constructs a multi-dimensional and quantifiable comprehensive indicator system for evaluating load adjustable potential. Departing from the conventional capacity-centric framework, this paper innovatively develops an indicator system founded on three core dimensions: capacity, time, and rate. This approach enables a more refined and operationally relevant characterization of load regulation capability, thereby establishing a robust foundation for subsequent precise assessment and optimal scheduling. (2) It proposes an enhanced comprehensive evaluation model and deepens the comparative analysis of potential among users. Methodologically, this paper incorporates an advanced evaluation model capable of concurrently measuring a solution's closeness to the optimal solution and its distance from the worst-case solution. This effectively mitigates the issue of result distortion inherent in traditional methods that disregard the relationship with the worst-case scenario. (3) It completes the cycle from theory to application through empirical validation and priority ranking. Utilizing load data from nine actual industrial users, this paper empirically validates the proposed indicator system and evaluation model. The computational results yield not only the comprehensive adjustable potential value for each user but also a clearly defined user priority ranking.

1.4 Organization of This Paper

The structure of the remaining chapters of this paper is as follows. Section 2 describes the characteristic analysis and extraction methodology for industrial load regulation potential. Section 3 proposes the assessment methodology for adjustable potential of industrial users' load. Section 4 presents an empirical analysis, revealing the actual adjustable potential of typical industrial users in a region.

2 Characteristic Analysis and Extraction Method of Industrial Load Regulation Potential

2.1 Multi-Dimensional Feature Composition of Load Adjustable Potential

Load adjustable potential refers to the power load with flexible regulation capability that can adjust electricity consumption behavior and pattern, and increase or decrease power consumption according to the operational requirements of the power system [17]. According to the Special Action Implementation Plan for Power System Regulation Capacity Optimization (2025–2027), in-depth exploitation of load-side resource regulation potential requires optimizing provincial load layout, guiding adjustable loads with qualified conditions to participate in power system operation regulation through market-oriented approaches, clarifying the schemes for standardized, large-scale, normalized, and market-oriented participation in system regulation through virtual power plants and smart microgrids, and improving the dispatching operation mechanism and market trading mechanism of load-side response resources to achieve observability, measurability, adjustability, and controllability. In this context, as important adjustable resources on the load side, the refined assessment of industrial users' load regulation capability has become a crucial foundation for supporting the operation of new-type power systems. This assessment should not only be reflected in the adjustability of electricity consumption capacity, but also consider the temporal flexibility of regulation, response rate, regulation pattern, and coordination with system peak load. Specific characteristics are shown in Table 1.

Table 1: Multi-dimensional feature composition of load adjustable potential.

No.	Performance Characteristic	Specific Content
1	Regulation pattern dimension	Including two typical regulation patterns: interruptible load and transferable load. Interruptible load is applicable to emergency dispatch scenarios, emphasizing rapid response capability; transferable load is applicable to peak-valley regulation scenarios, emphasizing temporal shifting capability.
2	Regulation capability dimension	Including indicators such as regulation capacity, regulation duration, response rate, and recovery rate, reflecting the regulation depth and regulation efficiency that users can achieve per unit time.
3	Regulation coordination dimension	Including indicators such as the matching degree between user load curve and system peak load curve, and peak-time electricity consumption concentration, reflecting the supporting capability of user regulation behavior to system regulation objectives.

2.2 Extraction Method of Load Regulation Potential

2.2.1 Primary Clustering: Identification of Interruptible Regulation Characteristics

Firstly, the Affinity Propagation (AP) clustering algorithm is employed to conduct primary clustering on users' historical daily load curves, identifying their normal production patterns and interruptible regulation patterns. Through differential analysis between interruptible pattern curves and normal pattern curves, users' interruptible regulation behavior characteristics are extracted, including indicators such as interruptible capacity, interruption duration, interruption rate, and recovery rate, thereby quantifying users' rapid response capability under emergency conditions.

2.2.2 Secondary Clustering: Identification of Transferable Regulation Characteristics

For load curves with transferable characteristics identified in the primary clustering, the k-means algorithm is adopted for secondary clustering, combined with the Dynamic Time Warping (DTW) algorithm to determine the similarity and repeatability of their transferable behaviors. By analyzing load variation patterns within transferable intervals, users' transferable regulation characteristics are extracted, including indicators such as transferable capacity, transferable duration, peak-time electricity consumption proportion, and time difference between user peak load and system peak load, thereby quantifying users' flexibility and coordination in peak-valley regulation.

2.3 Assessment Index System of Adjustable Potential Based on Extraction Results

To support the formulation of industrial load dispatching strategies, an assessment index system for industrial users' load adjustable potential oriented to dispatching requirements is designed based on the feature extraction results of load adjustable potential through secondary clustering, covering three dimensions: interruptible potential, transferable potential, and production characteristics.

2.3.1 Interruptible Potential Indicators

The interruptible potential indicators aim to assess industrial users' capability to respond rapidly and interrupt load when facing emergency dispatch instructions [18]. These indicators encompass four indices: interruptible capacity, interruptible duration, interruption response rate, and interruption recovery rate.

(1) Interruptible capacity refers to the maximum load amount that industrial users can safely curtail under emergency conditions. It is obtained through weighted averaging of multiple interruptible curves acquired from primary clustering, as shown in the following equation:

$$P_{\text{int}} = \alpha_1 P_{11} + \alpha_2 P_{12} + \ldots + \alpha_c P_{ic} \tag{1}$$

where, P_{int} is the interruptible capacity.

(2) Interruptible duration refers to the time length that industrial users maintain the interruption state. It is obtained through weighted averaging of durations under different interruption modes, as shown in the following equation.

$$t_{\text{int}} = \alpha_1 t_1 + \alpha_2 t_2 + \ldots + \alpha_c t_c \tag{2}$$

where, t_{int} is the interruptible duration.

(3) Interruption rate refers to the speed of load reduction when industrial users switch from normal operation state to interruption state. It is calculated through weighted averaging of interruption rates under various interruption modes, as shown in the following equation:

$$K_{\text{int}} = \alpha_1 K_{11} + \alpha_2 K_{12} + \ldots + \alpha_c K_{1c} \tag{3}$$

where, K_{int} is the interruption rate.

(4) Recovery rate after interruption refers to the speed of load increase when industrial users restore normal operation from interruption state. It is calculated through weighted averaging of recovery rates under various interruption modes, as shown in the following equation:

$$K_{re} = \alpha_1 K_{21} + \alpha_2 K_{22} + \ldots + \alpha_c K_{2c} \tag{4}$$

where, K_{re} is the recovery rate after interruption.

2.3.2 Transferable Potential Indicators

The transferable potential indicators aim to assess industrial users' capability to flexibly shift electricity load from peak periods to other valley periods without affecting total electricity consumption. These indicators encompass four indices [19]: transferable capacity, transferable duration, time difference between peaks, and peak-time electricity consumption proportion.

(1) Transferable Capacity

Transferable capacity refers to the load amount that industrial users can shift from electricity peak periods to other periods. Based on the secondary clustering results of adjustable potential mentioned above, it is obtained by respectively calculating the difference between power at each point and the minimum power within the transferable interval for two transferable curves, and taking the average value.

(2) Transferable Duration

Transferable duration refers to the time length that the load shifting process can sustain. Based on the secondary clustering results of adjustable potential mentioned above, it is calculated through the peak value difference between two transferable curves, as shown in the following equation:

$$T_{trans} = T_1 - T_2 \tag{5}$$

where, T_{trans} is the transferable duration; T_1, T_2 are the peak values of the transferable curves, respectively.

(3) Peak-to-Peak Time Interval

The peak-to-peak time interval refers to the temporal difference between the electricity consumption peak of industrial users and the system-wide electricity consumption peak.

(4) Peak Period Consumption Ratio

The peak period consumption ratio denotes the proportion of electricity consumption by industrial users during system peak hours relative to their total daily electricity consumption, calculated as follows:

$$G_t = \frac{W_p}{W_d} \tag{6}$$

where, G_t is defined as the peak period consumption ratio; W_p denotes the electricity consumption of industrial users during system peak hours; and W_d represents the total daily electricity consumption.

2.3.3 Production Indicators

Production indicators are designed to evaluate the value and willingness of industrial users to participate in demand response programs from the perspective of their own production and operational attributes. This category encompasses two sub-indicators: energy consumption per unit output value and electricity consumption scale.

(1) Energy Consumption per Unit Output Value

Energy consumption per unit output value refers to the total energy consumption required by industrial users to generate a unit of output value, expressed as follows:

$$M = \frac{E}{V} \tag{7}$$

where, M denotes the energy consumption per unit output value; E represents the comprehensive energy consumption of industrial users; and V indicates the gross industrial output value.

(2) Electricity Consumption Scale

Electricity consumption scale refers to the overall magnitude of electricity usage by industrial users, typically quantified by annual total electricity consumption or annual electricity expenditure.

3 Method for Assessing the Adjustable Potential of Industrial User Load

3.1 Assessment Methodology for Adjustable Potential of Individual Industrial Users

(1) BWM Method

The Best-Worst Method (BWM) was proposed by Dutch scholar Jafar Rezaei in 2015 and has been widely applied across various domains [20]. The computational procedure is as follows:

Step 1: Determine the set of criteria, expressed as:

$$U = \{U_1, U_2, \ldots, U_n\} \tag{8}$$

where, n denotes the total number of adjustable potential evaluation criteria for industrial users.

Step 2: Determine the best evaluation criterion U_b and the worst evaluation criterion U_w.

Step 3: Calculate the preference weights of the best criterion over all other criteria, as follows:

$$A_b = (a_{b1}, a_{b2}, \ldots, a_{bn}) \tag{9}$$

Step 4: Calculate the preference weights of all other criteria over the worst criterion, as follows:

$$A_w = (a_{1w}, a_{2w}, \ldots, a_{nw}) \tag{10}$$

Step 5: Using the planning model, find the minimum solution that achieves the maximum value for $\frac{w_b}{w_j}\Big| a_{bj}$ and $\frac{w_j}{w_w}\Big| a_{jw}$ types with respect to all $j \in \{1, 2, 3, \ldots, n\}$ cases, and obtain the optimal weight $(w_1, w_2, \ldots, w_n)$.

(2) Improved CRITIC Method

The CRITIC (Criteria Importance Through Intercriteria Correlation) method is an objective weighting approach based on data contrast intensity and intercriteria correlation. To fully account for the correlations among evaluation criteria and the dispersion degree of criterion data in assessing the adjustable potential of industrial users, the entropy method is introduced to modify the CRITIC method to a certain extent. The computational procedure is as follows:

Step 1: Calculate the proportion of each criterion value to be evaluated under each alternative and criterion, as follows:

$$\begin{cases} P_{ij} = \dfrac{x'_{ij}}{\sum\limits_{i=1}^{n} x'_{ij}} \\ \sum P_{ij} = 1 \end{cases} \tag{11}$$

where, x'_{ij} denotes the standardized data.

Step 2: Calculate the information entropy of the adjustable potential indicators for industrial users, as follows:

$$\begin{cases} e_j = -\xi \sum_{i=1}^{m} P_{ij} \cdot \ln P_{ij} \\ \xi = \dfrac{1}{\ln n} \end{cases} \tag{12}$$

where, ξ ensures that the information entropy is meaningful.

Step 3: Calculate the weights of the improved CRITIC method, as follows:

$$B_j = \frac{\left(e_j + S_j\right) \sum_{i=1}^{n} \left(1 - \left|l_{ij}\right|\right)}{\sum_{j=1}^{m} \left(e_j + S_j\right) \sum_{i=1}^{n} \left(1 - \left|l_{ij}\right|\right)} \tag{13}$$

where, l_{ij} denotes the element in the i-th row and j-th column of the conflict matrix.

(3) Game Theory Combination Weighting

Adopting the concept of game theory, the subjective and objective weights are treated as two players in a game. The combination coefficients are determined by minimizing the sum of deviations between the final combined weights and both subjective and objective weights, thereby forming a comprehensive weight that integrates the advantages of subjective and objective weighting approaches. The computational procedure is as follows:

Step 1: Calculate the criterion weights using S methods to construct the weight vector set of evaluation criteria $W_k = \left\{W_{k1}, W_{k2}, \ldots, W_{kn}\right\}, (k = 1, 2, 3, \ldots, S)$. Given that n represents the number of adjustable potential evaluation criteria for industrial users, the arbitrary linear combination of S vectors is expressed as follows:

$$W_\beta = \sum_{k=1}^{S} \lambda_k W_k^T, \lambda_k > 0 \tag{14}$$

where, W_β denotes a possible weight vector; λ_k represents the linear combination coefficients.

Step 2: The optimal combination coefficients are derived by balancing multiple weighting methods. Assuming a most satisfactory linear combination coefficient λ^* that minimizes the deviation between W_β and W_k, equilibrium among S weight vectors is achieved through the following optimization function:

$$\min \left\| \sum_{k=1}^{S} \lambda_k W_k^T - W_k \right\| \tag{15}$$

where, by solving the above equation, the optimal combination coefficient, namely $\lambda^* = (\lambda_1, \lambda_2, \ldots, \lambda_L)$.

$$\lambda^* = \frac{\lambda_k}{\sum_{k=1}^{S} \lambda_k} \tag{16}$$

The optimal integrated weights are calculated as follows:

$$Q = \sum_{k=1}^{S} \lambda^* W_k^T \left(k = 1, 2, \ldots, S\right) \tag{17}$$

Additionally, the comprehensive evaluation values of industrial users' adjustable potential are sorted; a lower value signifies superior performance in the corresponding dimension.

3.2 Comprehensive Assessment Method for Adjustable Potential of Industrial Users

The SPA-VFS evaluation method is an integrated comprehensive evaluation approach combining Set Pair Analysis (SPA) and Variable Fuzzy Set (VFS) theory. It is primarily employed to address system assessment problems characterized by uncertainty, fuzziness, and complexity. This study adopts the SPA-VFS method to evaluate the comprehensive adjustable potential of industrial users' load, thereby establishing a load dispatch priority ranking. The specific steps are as follows:

Step 1: The threshold for the g-th level is C_g, and the threshold for the g-th level of the evaluation index for the adjustable potential of industrial user load in the j-th level is C_{jg}. Transform the matrix $T = (T_{\text{int}}, T_{trans}, T_{act})$ into a matrix $T' = \left(T'_{\text{int}}, T'_{trans}, T'_{act}\right)$ where larger values indicate better performance.

Step 2: Calculate the single-item correlation degree between T' and grade g. The single-item correlation degree between the j-th potential indicator of user i and grade g is as follows:

$$\mu_{ijg} = \begin{cases} 1 - 2\left|\dfrac{C_{j,g-1} - T'_{ij}}{C_{j,g-1} - C_{j,g-2}}\right|, & T'_{ij} \in grad\,(g-1) \\ 1, & T'_{ij} \in grad\,(g) \\ 1 - 2\left|\dfrac{C_{jg} - T'_{ij}}{C_{jg} - C_{j,g+1}}\right|, & T'_{ij} \in grad\,(g+1) \\ -1 & other \end{cases} \tag{18}$$

where, $grad\,(g)$ denotes grade g.

Step 3: The comprehensive connection degree between user i and level g is calculated as:

$$\mu_{ig} = \sum_{j=1}^{r} \omega'_j \mu_{ijg} \tag{19}$$

Step 4: The variable fuzzy set theory is introduced to calculate the relative membership degree δ_{ig} between user i and level g. To avoid distortion caused by the maximum membership principle, the relative membership degree δ_{ig} is processed by the characteristic value h_{ig} and sorted to form the priority.

$$\delta_{ig} = \left(1 + \mu_{ig}\right)/2 \tag{20}$$

$$h_i = \sum_{g=1}^{G} C_g \delta_{ig} / \sum_{g=1}^{G} \delta_{ig} \tag{21}$$

3.3 Comprehensive Assessment Procedure for Adjustable Potential of Industrial Users

Regarding the constructed evaluation index system for industrial users' adjustable potential—including interruptible, transferable, and production potentials—subjective weights are derived using BWM, objective weights are obtained through improved CRITIC, and optimal fusion is realized via game-theoretic combination weighting to obtain the assessment results of the three single potentials. Subsequently, an SPA-VFS-based comprehensive evaluation model is established, wherein the three single potentials serve as evaluation criteria to determine the comprehensive adjustable potential value and formulate load dispatch priorities, as depicted in Fig. 1.

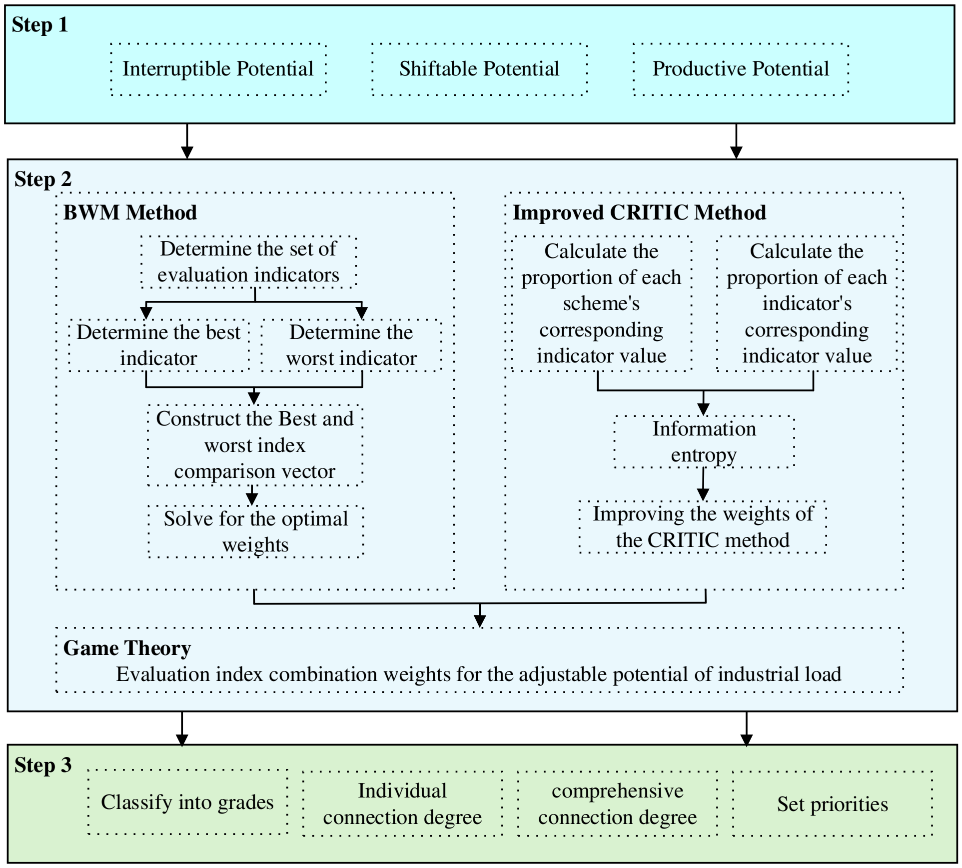

Figure 1: Flowchart of the proposed calculation procedure.

4 Case Analysis

4.1 Basic Data Information

Industrial users from a representative regional grid are selected for case study to verify the proposed method and indicator system. The target user operates multiple production lines with significant power demand. Typical daily load profiles for 2024 were collected and cleansed, yielding three clusters through primary clustering: normal production, interruptible, and transferable load curves (Fig. 2). Primary clustering identifies an interruptible capacity of 6.56 MW, duration of 6.24 h, ramp rate of 2.76 MW/h, and recovery rate of 2.18 MW/h. Transferable potential is further analyzed using Intervals 1 and 3, yielding transferable capacity of 4.23 MW, duration of 2.69 h, peak-to-peak interval of 0.4 h, and peak consumption ratio of 32.1% (Fig. 3). Energy intensity and consumption scale are derived from survey data. Initial indicator values for Users 1, 5, and 6 are shown in Fig. 4.

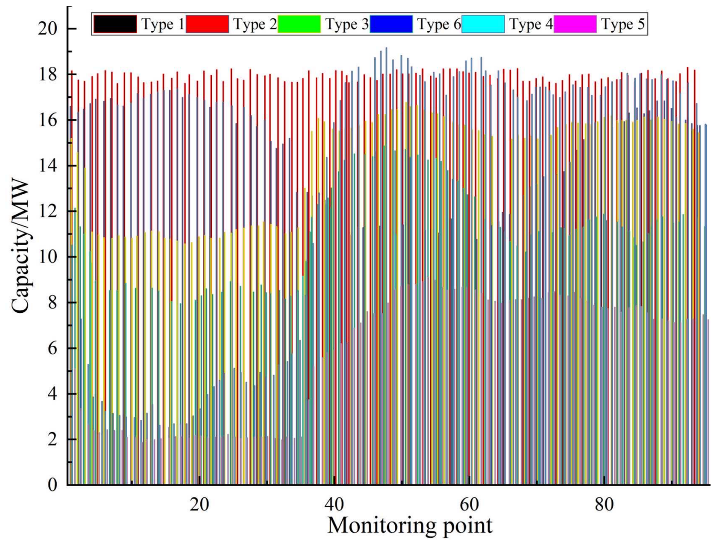

Figure 2: Extraction results of primary clustering.

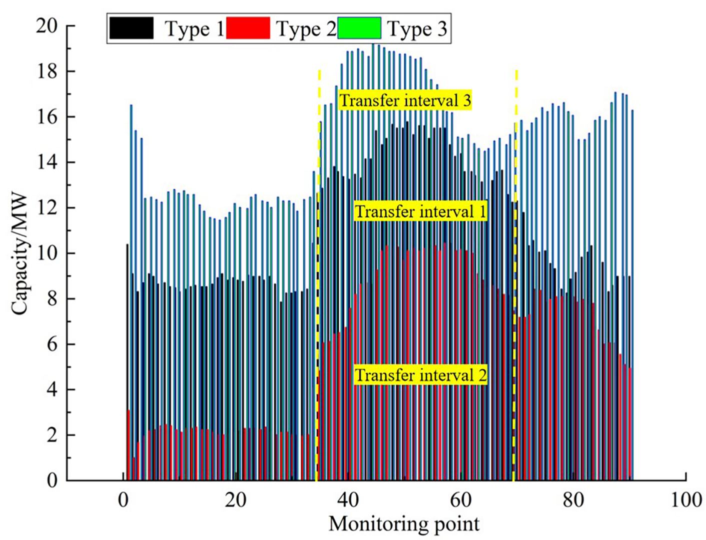

Figure 3: Extraction results of secondary clustering.

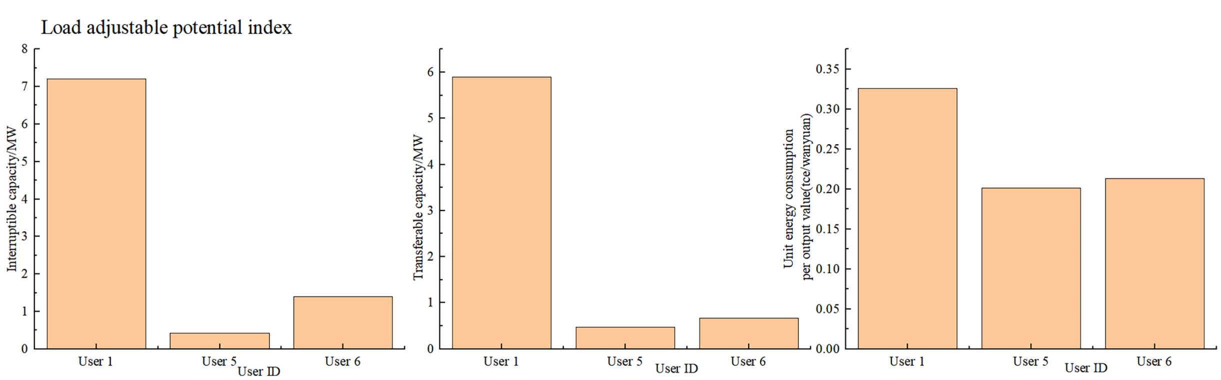

Figure 4: Initial indicator values of User 1, User 5, and User 6.

4.2 *Results Discussion and Analysis*

4.2.1 Analysis of Evaluation Results

(1) Analysis of Single-Indicator Potential Evaluation Results

The preprocessed results of single indicators and corresponding weights for transferable potential, interruptible potential, and production potential of each user are presented in Fig. 5.

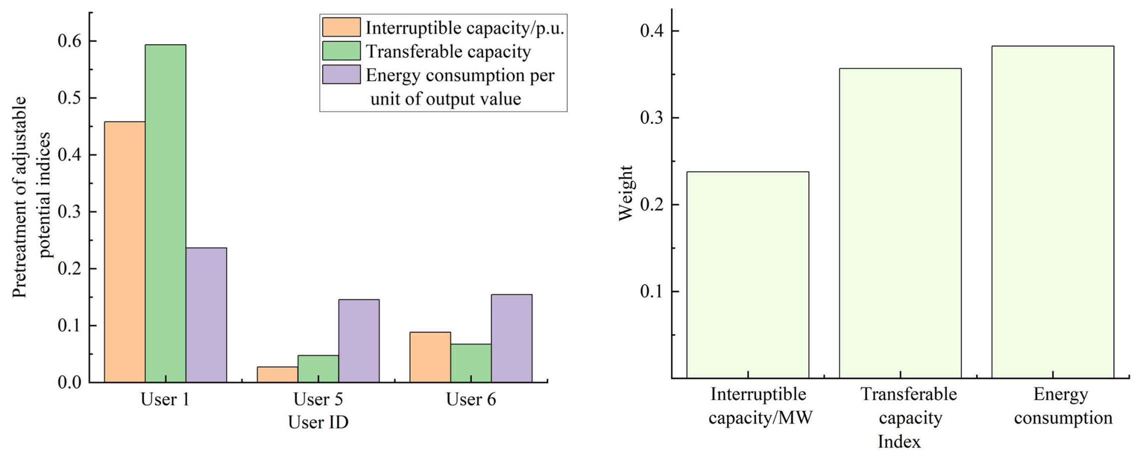

Figure 5: Adjustable potential indicator data.

The evaluation results of single indicators for adjustable potential are presented in Fig. 6.

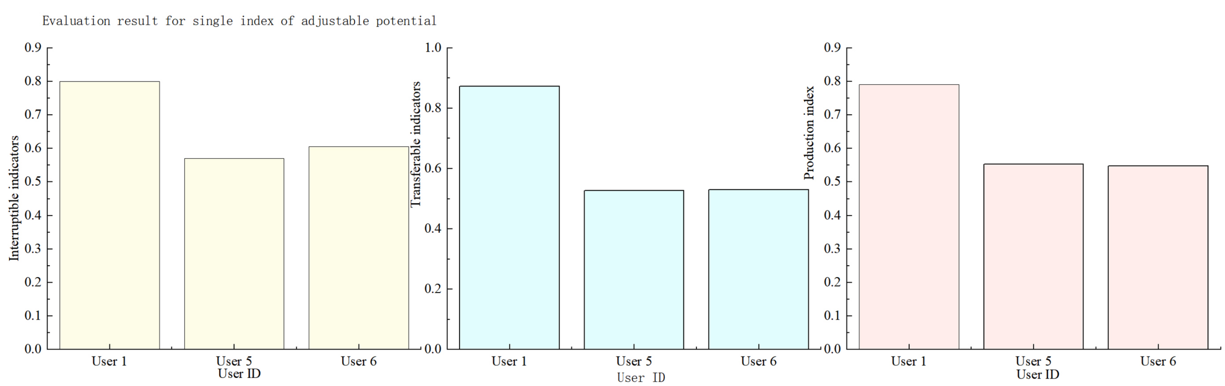

Figure 6: Evaluation results of single indicators for adjustable potential.

As illustrated in Fig. 6, the single-indicator evaluation results for adjustable potential of Users 1, 5, and 6 indicate that User 1 exhibits a higher dispatch priority, whereas Users 5 and 6 demonstrate relatively lower potential, necessitating further excavation or optimization of their electricity consumption patterns. Specifically, User 1 achieves an interruptible indicator of 0.792 (Rank 1), a transferable indicator of 0.566 (Rank 1), and a production indicator of 0.591 (Rank 1). This user demonstrates superior performance across all three dimensions with balanced and leading overall potential, categorizing it as a user with strong comprehensive regulation capability and suitable for prioritized dispatch. User 5 obtains an interruptible indicator of 0.772 (Rank 3), a transferable indicator of 0.521 (Rank 3), and a production indicator of 0.524 (Rank 3). All indicators of this user remain at relatively low levels, particularly the poorest transferable potential, indicating limited regulation capability and lower value for demand response participation. User

6 achieves an interruptible indicator of 0.788 (Rank 2), a transferable indicator of 0.538 (Rank 2), and a production indicator of 0.534 (Rank 2). Similar to User 5, all potential indicators of this user are at middle-to-lower levels, with particularly weak transferable and production potentials, resulting in insufficient overall adjustable potential.

(2) Analysis of Comprehensive Evaluation Results for Adjustable Potential

The comprehensive evaluation results of adjustable potential for each user are presented in Fig. 7.

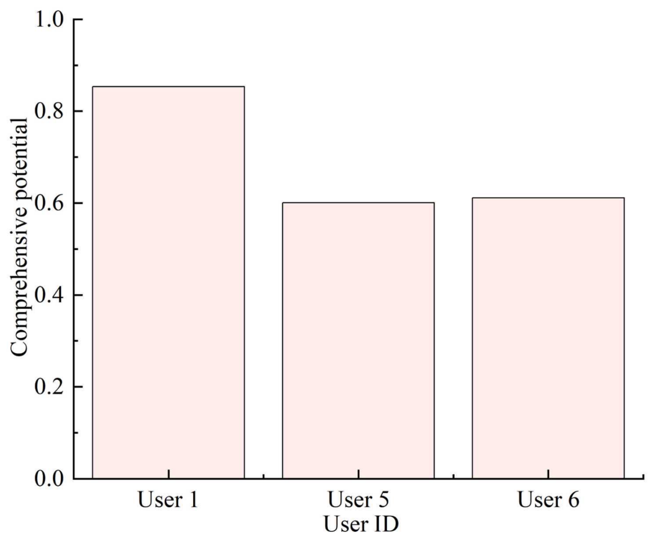

Figure 7: Comprehensive adjustable potential of load for each user.

As illustrated in Fig. 7, the comprehensive adjustable potential results for Users 1, 5, and 6 indicate that User 1 exhibits significantly superior regulation potential compared to Users 5 and 6, and should be prioritized in load dispatch; whereas Users 5 and 6 need to explore approaches to enhance their adjustable capability based on their respective production characteristics, or participate in demand response as supplementary regulation resources.

(3) Analysis of Adjustable Potential Evaluation Dimension Variation

When only a single dimension of adjustable potential evaluation indicators is considered, the comprehensive potential assessment results for industrial users also vary significantly, as illustrated in Fig. 8.

As illustrated in Fig. 8, the comprehensive potential and ranking of Users 1, 5, and 6 vary under different indicator systems. Under the complete system incorporating "time" and "rate" indicators, User 1 achieves a comprehensive potential of 0.833 (Rank 1); under the new system excluding these two dimensions, the comprehensive potential becomes 0.813 with Rank 1 maintained. User 1 demonstrates stable ranking across both systems, indicating that its regulation capability not only performs well in time and rate dimensions but also possesses balanced advantages in other indicator dimensions, rendering its ranking insensitive to system adjustments. User 5 obtains a comprehensive potential of 0.588 (Rank 3) under the complete system and 0.542 (Rank 2) under the new system. The slight ranking improvement primarily stems from the increased weighting of remaining indicators after excluding time and rate metrics, wherein User 5's relative performance in these indicators surpasses that of User 6, thereby achieving a ranking interchange. User 6 achieves a comprehensive potential of 0.592 (Rank 2) under the complete system and 0.536 (Rank 3) under the new system. Contrary to User 5, User 6 may possess certain advantages in time and rate dimensions; when these indicators are excluded, its comprehensive potential is substantially impacted, resulting in being surpassed by User 5. In summary, User 1 maintains stable assessment results across different indicator systems, demonstrating robust comprehensive regulation capability. The ranking variations of Users 5 and 6 further validate the significance of "time" and "rate" dimension indicators in adjustable potential evaluation. Excluding these indicators leads to biased assessment results, compromising accurate judgment of users' actual regulation capabilities.

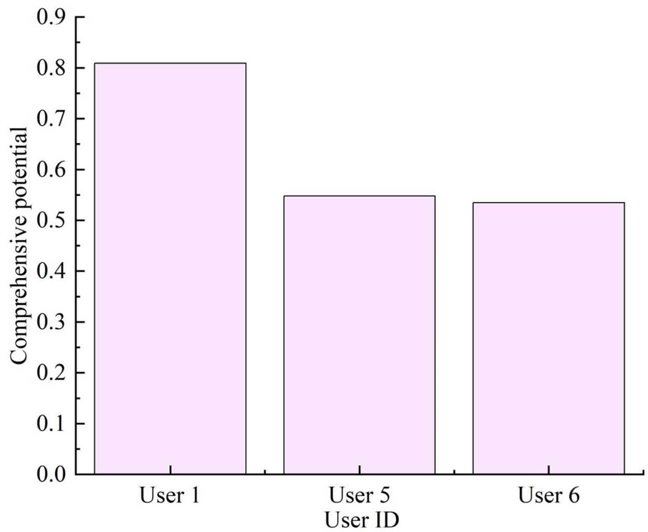

Figure 8: Comprehensive adjustable potential of load for each user.

4.2.2 Comparative Analysis of Evaluation Methods

(1) Comparative Analysis of Clustering Methods

The daily load curves of industrial users are influenced by multiple factors including production schedules, working days vs. rest days, and seasonal variations, exhibiting high complexity and stochasticity. Classifying massive daily load curves to group those with similar electricity consumption patterns, and automatically identifying normal full-load production states, partial equipment shutdown interruptible states, and production time-shifted transferable states in actual production processes, constitutes a significant challenge. The performance of different clustering methods also varies considerably. This section further analyzes the comparative performance of the proposed method against alternative approaches, as illustrated in Fig. 9.

As illustrated in Fig. 9, the proposed method demonstrates distinct advantages across three dimensions: functional coverage, clustering quality, and application support, enabling more comprehensive and accurate excavation of industrial users' load adjustable potential characteristics. Specific manifestations are observed in three aspects. ① From the perspective of functional integrity: The k-means clustering method can extract normal production curves and interruptible characteristic curves to calculate interruptible potential indicators, yet fails to extract transferable characteristic curves, resulting in inability to calculate transferable potential indicators with significant functional deficiency. The AP clustering method can extract transferable characteristic curves but cannot calculate transferable potential indicators based on its results, still exhibiting functional bottlenecks in implementation. The proposed method employs a two-stage clustering strategy, not only completely extracting three types of characteristic curves (normal, interruptible, and transferable), but also simultaneously calculating both interruptible and transferable potential indicators, achieving full-process coverage from feature extraction to indicator calculation with the most complete functionality.

② From the practical application perspective: The k-means clustering method is sensitive to initial cluster numbers and unable to identify transferable characteristics, making it difficult to support quantitative assessment of transferable potential and limiting its applicability in load regulation capability analysis. Although the AP clustering method can discover transferable characteristic curves, its cluster centers are original data curves that cannot generate more representative transfer patterns, rendering transferable potential indicators ineffective for calculation. The proposed method integrates the adaptive clustering advantage of AP clustering with the center reconstruction capability of k-means, enabling automatic determination of cluster numbers while generating more representative transferable curves, providing a reliable foundation for precise quantification of transferable potential and enhancing the practicality and credibility of evaluation results.

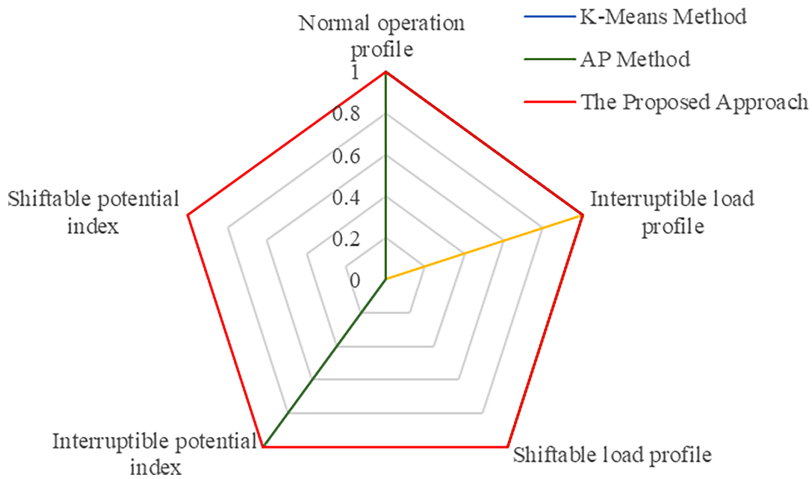

Figure 9: Comparative analysis of different clustering methods.

(2) Comparative Analysis of Potential Evaluation Methods

To validate the effectiveness of the proposed method, the evaluation results are horizontally compared with those obtained from the linear weighting method and the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS), as illustrated in Fig. 10.

As illustrated in Fig. 10, the comprehensive evaluation method proposed in this study—integrating BWM, improved CRITIC, and SPA-VFS—demonstrates superior discriminatory capability and rationality in handling marginal users. On one hand, the individual loss mechanism prevents simple compensation of inferior indicators by superior ones; on the other hand, the decision mechanism coefficient reconciles overall efficiency with individual equilibrium, enabling evaluation results to more authentically reflect users' actual adjustable potential. For users with stable rankings (e.g., User 1), the proposed method maintains consistency with mainstream approaches, verifying its overall reliability. For instance, User 1 achieves Rank 1 across all three evaluation methods, exhibiting high consistency. This indicates that regardless of the evaluation model employed, User 1's comprehensive regulation capability remains stably at middle-to-upper levels. While maintaining overall ranking stability, the proposed method yields more rational numerical distributions compared to alternative approaches: it neither exhibits the systematically low values characteristic of the linear weighting method, nor suffers from insufficient discrimination among certain users as observed in TOPSIS. This demonstrates the robustness and numerical interpretability of the evaluation results.

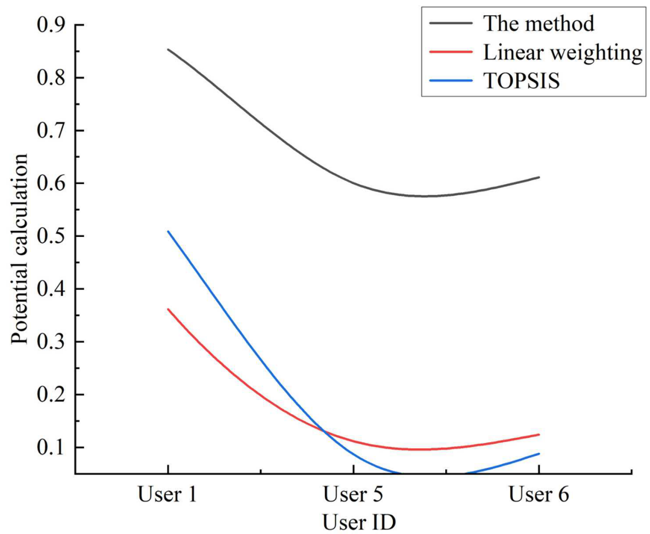

Figure 10: Comparative analysis of different evaluation methods.

5 Conclusion

This study addresses the imperative for excavating industrial load flexibility under high-penetration renewable energy integration, proposing an adjustable potential assessment methodology for industrial users based on two-stage clustering and SPA-VFS. The principal conclusions are as follows:

(1) The constructed multi-dimensional indicator system effectively characterizes the heterogeneity of industrial load regulation potential. Through the "two-stage clustering" strategy, three behavioral patterns—normal production, interruptible, and transferable—can be automatically identified from massive historical load data, extracting multi-dimensional features encompassing capacity, time, and rate dimensions, thereby establishing a data foundation for refined assessment. Empirical results indicate that User 1 achieves an interruptible capacity of 6.56 MW and transferable capacity of 4.23 MW, with interruption and recovery rates of 2.76 and 2.18 MW/h, respectively, demonstrating balanced regulation capability.

(2) The proposed comprehensive evaluation model integrating BWM, improved CRITIC, game theory combination weighting, and SPA-VFS overcomes the limitations of single methodologies, achieving optimal fusion of subjective and objective information. Comparative analysis with linear weighting and TOPSIS methods demonstrates that the proposed method maintains overall ranking stability while exhibiting superior discriminatory capability for marginal users. The consistent ranking results for Users 1, 5, and 6, coupled with more rational numerical distributions, validate the robustness of the evaluation mechanism.

(3) The incorporation of "time" and "rate" dimensions exerts significant influence on assessment outcomes. Sensitivity analysis reveals that exclusion of these dimensions leads to ranking interchange between Users 5 and 6, indicating that capacity-only indicators fail to accurately reflect users' actual regulation capability. Multi-timescale feature characterization holds substantial value for supporting refined dispatch in novel power systems.

(4) This methodology provides a complete solution for industrial load participation in demand response—from potential identification and feature extraction to priority ranking—facilitating virtual power plant operators in screening high-quality regulation resources and formulating differentiated dispatch

strategies. Future research may extend to synergistic regulation potential assessment under multi-energy system coupling scenarios, as well as dynamic game model construction incorporating market mechanisms and user willingness.

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

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