# Modeling method for optimal scheduling of Park comprehensive energy source load storage and consumption considering customer portrait

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**Abstract:** Aiming at the problems of energy consumption optimization of park integrated energy source load storage system in power grid dispatching, a modeling method of park integrated energy consumption optimization dispatching considering user portrait is proposed. Firstly, an improved k-means portrait method is proposed for park users; Secondly, on the premise of considering the constraints of equipment operation in the park, cluster users in the park, and establish an energy consumption optimization scheduling model with the objective function of user satisfaction, net income of wind power consumption and equipment operation cost; Finally, SAPSO algorithm and fuzzy theory are used for decision-making. The example simulation shows that the proposed model is correct and effective, which is more precise and objective than the traditional model.

## 1. INTRODUCTION

In the context of the 14th Five-Year Plan and the "carbon neutrality and peak carbon emissions", there are higher requirements for IES'energy optimization and energy conservation and emission reduction [1-2],the collaborative optimization of users, power grids, and IES is becoming increasingly complex.By establishing a multi-objective optimization scheduling

model[3-4] between various energy subsystems, power grids, and users, it is an effective means to achieve coordinated and optimized operation of IES and improve the efficiency of user energy optimization. Therefore, it is necessary to conduct research on modeling the integrated energy optimization scheduling for a region.

IES includes the multi-energy coupling between cold, heat, electricity, and gas systems. Currently, the research on modeling energy optimization and scheduling for IES mainly focuses on multi-energy coupling systems and wind and solar power consumption.In literature [5], a multi-regional IES scheduling model is established considering the quantitative storage of heat and the coupling of electricity and heat.In literature [6], an optimization scheduling model is established for the electric-thermal-gas coupled IES through the unified energy path theory.In literature [7], a two-level optimization scheduling model is proposed for the electric-gas coupled IES to effectively absorb wind power.In literature [8], an economic optimization model is proposed for the thermal-electric coupled IES to prioritize the solution of wind power absorption.In literature [9], a collaborative optimization model for the electric-thermal-gas three-grid and transmission and distribution grids is established layer by layer based on the multi-energy coupling characteristics of the electric-gas-thermal IES.In literature [10], a multi-dimensional heterogeneity is established for the electric-thermal-gas coupled IES multi-energy system, considering the differentiated energy inertia of the hot gas pipeline, and an optimization model is established.In literature [11], a system economic optimization model is established for the electric-gas coupled IES, taking into account the dynamic characteristics of natural gas.The above research mainly focuses on establishing models from the perspective of multi-energy coupling and clean energy consumption in IES. In fact, the influence of users on IES scheduling is also very important during the process of participating in power grid scheduling. Establishing models from the perspective of energy alone has certain limitations.

There are also studies that take user factors into account in IES optimization scheduling modeling. Literature [12] focuses on analyzing the impact of user behavior and user satisfaction on the electric-gas coupling P2G-IES system and establishes a multi-objective optimization model.Literature [13] introduces user satisfaction for the thermal-electric-gas coupling IES and establishes a multi-objective optimization model that maximizes user satisfaction.Literature [14] focuses on the electric-gas-thermal coupling IES and considers the impact of user behavior on load, establishing an economic scheduling model.Literature [15]-[16] focuses

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on analyzing user heating behavior for the electric-thermal-gas coupling IES and establishes a dual-objective optimization model for the system.The above studies establish IES scheduling models taking into account user factors. On the one hand, they only consider user factors as a single constraint condition, and on the other hand, they only consider user load power as the only indicator of user satisfaction. This cannot reflect the coordinated interaction between IES users and the power grid, and cannot achieve user energy optimization, which has great limitations.

Therefore, in order to fully reflect the utility of users in IES energy optimization and dispatch, this paper establishes a model for IES energy optimization and dispatch in the park considering user personas.Taking the cold-heat-electricity-gas IES in the park as the research object, considering the two indicators of energy storage user responsiveness and energy storage user interactive benefits, clustering and characterizing the energy storage users based on the improved K-means algorithm, establishing a mathematical model for energy storage user satisfaction in the park;and establishing an optimization dispatch model with the objectives of maximizing energy storage user satisfaction in the park, maximizing net wind power consumption benefits in the park, and minimizing operating costs in the park. Finally, in the example, the SAPSO algorithm and fuzzy theory are used to optimize the model for decision-making, and the accuracy of the model is verified by comparing the scheme without considering the user persona factor.

## 2. MODELING OF MAIN EQUIPMENT FOR SOURCE LOAD STORAGE IN INDUSTRIAL PARK

The source-load-storage system in the industrial park includes power equipment (wind power, distribution network, natural gas network [17]), energy storage equipment (electric energy storage, thermal energy storage, gas energy storage), load equipment (electric load, thermal load, cold load), and other energy-using equipment. The basic architecture is shown in Figure 1 [18].

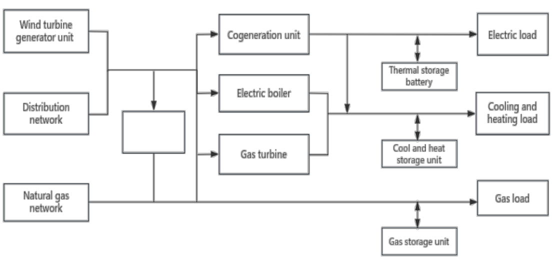


**Figure 1** Framework of the source load storage system in the industrial park

### 2.1 Wind power stochastic fuzzy output model

At present, using the Weibull distribution to describe the characteristics of wind speed probability distribution is a common method, and its wind speed Weibull probability density function can be expressed as:

$$\varphi(v)=\frac{k}{c}\left(\frac{v-\gamma}{c}\right)^{k-1}\exp\left[-\left(\frac{v-\gamma}{c}\right)^{k}\right] \tag{1}$$

Formula:γ $\gamma$ for the location parameter, c for the scale parameter, and k for the shape parameter.

However, the traditional Weibull model cannot simultaneously reflect the randomness and ambiguity of wind power output. Therefore, the shape parameter k and scale parameter c in the Weibull distribution are randomly and vaguely processed, and their membership functions are mined. The membership functions of shape parameter k and scale parameter c can be expressed as [19]:

$$u(k)=\begin{cases}(k-\xi_k^1)/(\xi_k^2-\xi_k^1) & \xi_k^1\le k\le\xi_k^2\\ (\xi_k^3-k)/(\xi_k^3-\xi_k^2) & \xi_k^2\le k\le\xi_k^3\\ 0 & k<\xi_k^1\ or\ k\ge\xi_k^3\end{cases} \tag{2}$$

$$\mathrm{u(c)}=\begin{cases}(\mathrm{c}-\xi_\mathrm{c}^1)/(\xi_\mathrm{c}^2-\xi_\mathrm{c}^1) & \xi_\mathrm{c}^1\le \mathrm{c}<\xi_\mathrm{c}^2\\ 1 & \xi_\mathrm{c}^2\le \mathrm{c}<\xi_\mathrm{c}^3\\ (\xi_\mathrm{c}^4-\mathrm{c})/(\xi_\mathrm{c}^4-\xi_\mathrm{c}^3) & \xi_\mathrm{c}^3\le \mathrm{c}<\xi_\mathrm{c}^4\\ 0 & \mathrm{c}<\xi_\mathrm{c}^1\ \text{or}\ \mathrm{c}\ge\xi_\mathrm{c}^4\end{cases} \tag{3}$$

Formula: $\xi_k^i(i=1,2,3)$ represents the triangular fuzzy variable of shape parameter k , $\xi_k^j(j=1,2,3,4)$ represents the trapezoidal fuzzy variable of the scale parameter c.

By randomly blurring the shape parameter k and scale parameter c in the Weibull distribution using equations (2) and (3), and describing wind speed using a random fuzzy variable distribution, the uncertain wind power output is given by [20]:

$$\mathrm{P_w}=\begin{cases}0 & \mathrm{v_{in}>v_t\ or\ v_t>v_{out}}\\ 0.5\rho\mathrm{AC_r v_t^3} & \mathrm{v_{in}<v_t<v_{out}}\\ \mathrm{P_N} & \mathrm{v_N<v_t<v_{out}}\end{cases} \tag{4}$$

Formula: $\rho$ for the air density, A for the blade area, $C_r$ for the wind energy utilization coefficient, $P_N$ for active rated value of fan, $v_t$ for Randomly fuzzy wind speed, $v_{in}$ for cut-in wind speed, $v_{out}$ for cut-out wind speed, $v_N$ for rated wind speed.

### 2.2 Operation model of energy storage equipment in industrial park

The comprehensive energy storage equipment in industrial parks includes energy storage batteries, thermal storage tanks, and gas storage tanks. Their operating models are not only related to their initial storage capacity, but also to their charging and discharging status, charging and discharging efficiency, mechanical loss, and other factors. Thermal and gas storage are also affected by factors such as pressure and volume.

Among them, the operation model of energy storage battery is:

$$E(t) = E(t_0) + \delta_{oc} \frac{E_N}{\eta_{oc}} \Delta t \quad (5)$$

Formula: $E(t)$ and $E(t_0)$ are the power of the energy storage battery at time t and $t_0$; $\delta_{oc}$ for the charging and discharging state, taking the value of 1/-1, indicating the charging and discharging state; $E_N$ for rated charging and discharging power of the energy storage battery; $\eta_{oc}$ for the charging and discharging efficiency of the energy storage battery.

The operation model of the heat storage tank is:

$$Q(t) = Q(t_0) - \mu_{LOSS} Q(t_0) + \delta_{HS} \frac{Q(\Delta t)}{\eta_{HS}} \quad (6)$$

Formula: $Q(t)$ and $Q(t_0)$ are the heat storage capacity of the thermal storage tank at time t and t0; $\mu_{LOSS}$ for the heat dissipation rate; $\delta_{HS}$ is the heat storage state, taking the value of 1/-1, indicating the heat storage state; $Q(\Delta t)$ for the heat storagef form time t0 to time t; $\eta_{oc}$ for the thermal efficiency of storage

Gas storage tank operation model:

$$V(t) = V(t_0) + \delta_{GS} V(\Delta t) \frac{p_{high} - p_{low}}{p_0} \quad (7)$$

Formula: $V(t)$ 、 $V(t_0)$ are the gas storage volumes at time t and $t_0$ of the gas storage tank; $\delta_{GS}$ is the gas storage state of the gas storage tank, 1 is the gas storage state, and -1 is the gas discharge state; $V(\Delta t)$ is the volume of stored gasat time t and t0; $p_{hing}$ 、 $p_{low}$ are the absolute air pressure under high and low working conditions; $p_0$ for the standard pressure.

### 2.3 Load response model of industrial park

The comprehensive energy load of the industrial park includes cold, heat, electricity, and gas loads. In order to effectively reflect the physical operating characteristics of the load in the park, this article models load reduction, interruptible load, and load transfer.

Among them, the mathematical model of load reduction in the park can be expressed as:

$$P_{cut}(t) = (1 - \xi) P_{cut}(t-1) \quad (8)$$

Formula: $P_{cut}(t)$ 、 $P_{cut}(t-1)$ are the load powers before and after load reduction, $\xi$ is the allowable load reduction ratio.

The mathematical model of interruptible load in industrial parks can be expressed as follows:

$$P_{off}(t) = s(0,1) P_{off}(t-1) \quad (9)$$

Formula: $P_{off}(t)$ 、 $P_{off}(t-1)$ are the load powers before and after the load interruption.

S(0,1) is the load interruptible state, 0 indicates interruptible, and 1 indicates non-interruptible.

The mathematical model of the transferable load of the industrial park is:

$$P_{tr}(t) = (1 - \varsigma) P_{tr}(t-1) \quad (10)$$

Formula: $P_{tr}(t)$ 、 $P_{tr}(t-1)$ are the load powers before and after load reduction, $\varsigma$ is the allowable load transfer ratio.

### 2.4 Other equipment operation models in industrial parks

Other equipment in the park includes electricity-to-gas equipment, combined heat and power units, gas turbines, and electric boilers, whose operating models and physical characteristics are related to factors such as energy conversion efficiency. For specific expressions, refer to reference [21].

## 3. PORTRAIT METHOD BASED ON IMPROVED K-MEANS

Clustering power users by using clustering analysis is an effective method for user profiling.To overcome the shortcomings of traditional K-means clustering algorithm[22], which randomly selects the clustering center, this paper proposes an improved K-means algorithm for user profiling clustering.

If the user indicator data to be clustered is represented by the set $P = \{p_1, p_2, .., p_N\}$, then it is necessary to perform portrait clustering on P. The steps are as follows:

First determine the population number K and initial clustering center $p_i(x_i, y_i)$; Secondly, for the next K-1 cluster centers, calculate the shortest distance between each point in the P set and $P_i$, and sum the distance of each point $sum(D(x))$ [23]:

$$D(x) = \sqrt{(x - x_i^2) + (y - y_i^2)} \quad (11)$$

$$\begin{cases} R_1(D(x)) = random(D(x)) \\ R_{i+1}(D(x)) = R_i(D(x)) - D(x) \end{cases} \quad (12)$$

Formula: $random(D(x))$ is a random value representing 0 to $sum(D(x))$ 、 $R_1(D(x))$ 、 $R_{i+1}(D(x))$ respectively representing the first and the (i+1)th iteration values.

Finally, we iterate through formula (10), and when $R_{i+1}(D(x)) \le 0$, the P corresponding to $D(x)$ is the next cluster center.

This article proposes two indicators for user satisfaction with energy use in the objective function: energy storage user responsiveness and energy storage user interactive benefits. It uses K-means clustering to improve the portrait, and determines the weight values of the two indicators based on different combinations of clustering portrait categories, in order to dynamically solve the model.

# 4. MULTI-OBJECTIVE OPTIMIZATION SCHEDULING MODEL FOR INDUSTRIAL PARK SOURCE LOAD STORAGE CONSIDERING USER PERSONAS

## 4.1 Objective function

Based on the collaborative optimization decision-making problem of comprehensive energy source-load-storage in industrial parks, this paper establishes a multi-objective optimization scheduling model for source-load-storage in industrial parks considering user profiles, with the objectives of maximizing user satisfaction with energy use, maximizing net benefits from wind power consumption, and minimizing operating costs of source-load-storage equipment in industrial parks.

Among them, user satisfaction is expressed by energy storage user responsiveness $\varphi_1$ and energy storage user interaction benefit $\varphi_2$, with the specific expressions as follows:

$$\begin{cases} F_1 = a_1\varphi_1 + a_2\varphi_2 \\ \varphi_1 = (\sum_{N=1}^{N}\sum_{t=1}^{T}\frac{P_E(t)}{E(t)})/N \\ \varphi_2 = 1 + \sum_{N=1}^{N}\sum_{t=1}^{T}\frac{P_{out}(t)c_{out}(t) - P_{in}(t)c_{in}(t)}{E(t_0)c_{in}(t_0)} \end{cases} \quad (13)$$

Formula:Nis the number of energy storage equipment in the industrial park; $P_E(t)$ is the actual power consumption of the energy storage user at timet; $c_{out}$ 、 $c_{in}$ are the response prices for discharging and charging energy storage devices; $E(t)$ 、$E(t_0)$ are the storage amounts at the time of energy storage t and t0.

$a_1$、 $a_2$ are the weight factors of the indicator portrait, which are set through an improved K-means clustering portrait method. Before each iteration, the response of energy storage users and the interactive benefits of energy storage users are classified through clustering portraits. The indicator portrait weight factors are set according to different indicator category combinations, and the model is dynamically solved in a rolling manner.The setting principles of the indicator portrait weight factors are as follows:

1) The sum of the two weight factors is 1;
2) If the energy storage user responsiveness and the energy storage user interaction benefit belong to the same category, then $a_1 = a_2 = 0.5$;
3) If the response of energy storage users and the category of energy storage user interaction benefits are the same, the principle of weight factor being greater for the higher category will be met.For example, if $a_1$ is one level higher than $a_2$ , then $a_1 = 0.6$、$a_2 = 0.4$; $a_1$ is two levels higher than $a_2$ , then $a_1 = 0.7$、 $a_2 = 0.3$.

To consider the impact of government subsidies on wind power consumption revenue, the objective function of wind power consumption net revenue can be expressed as:

$$F_2 = \sum_{t=1}^{T}((c_R + \frac{x(1+x)^t}{(1+x)^t - 1}c_t - c_R^{'})P_W(t)) \quad (14)$$

Formula: $c_R$ for the unit sales price of wind power; $x$ is the proportion of government subsidies for wind power; $c_R^{'}$ is the unit price of wind turbine maintenance cost.

The objective function of the operating cost of the industrial park mainly consists of the operating costs of electrical $C_{rl}$ and thermal loads (including transferable loads, interruptible loads, and curtailable loads) and the cost of combined heat and power units (CHP) $C_{chp}$ ,which is expressed as follows:

$$F_3 = C_{rl} + C_{chp} \quad (15)$$

$$C_{rl} = \sum_{l=1}^{D}\sum_{t=1}^{T}\rho_l P_{load,l}(t) \quad (16)$$

$$C_{chp} = \sum_{k=1}^{N_G}\sum_{t=1}^{T}\lambda P_{chp}(t)c_{chp}^{'} \quad (17)$$

Formula: $P_{load,l}$ for load power; D for the number of load types; $\rho_l$ is the operation price coefficient of load equipment; $\lambda$ for CHP efficiency; $N_G$ is the number of CHP in the park; $P_{chp}$ for CHP active power, $c_{chp}$ for the unit cost of CHP.

## 4.2 Constraint condition

### *4.2.1 Power balance constraint*

The power described in Formula(11) to Formula(15)must meet its power constraints, the specific form is:

$$P_{\max} \le P \le P_{\min} \quad (18)$$

Among them,*P* is the power described in Formula(11) to Formula(15), $P_{\max}$、$P_{\min}$ are the maximum and minimum values.

### *4.2.2 Static security constraints*[24]

$$f_{l,t} \le f_l^{\max}, l \in L, t \in T \quad (19)$$

Formula: $T$ for the period of time, L is the total number of transmission components, $f_{l,t}$ for transmission power, $f_l^{\max}$ for maximum transmission power.

# 5. MODEL SOLVING

## 5.1 Model solving process based on SAPSO algorithm

In the process of solving using traditional Particle Swarm Optimization (PSO), there are problems such as local search in the optimization process or oscillation during the optimization process [25]. Based on this, an improved adaptive particle swarm optimization algorithm (SAPSO) is proposed to solve the model, and adding the clustering portrait method proposed in Section 2 of this article to determine the weight factors of its indicator portraits can improve the computational solution results when iteratively optimizing the objective function $F_1$.The algorithm solving flowchart is shown below in Figure 2:

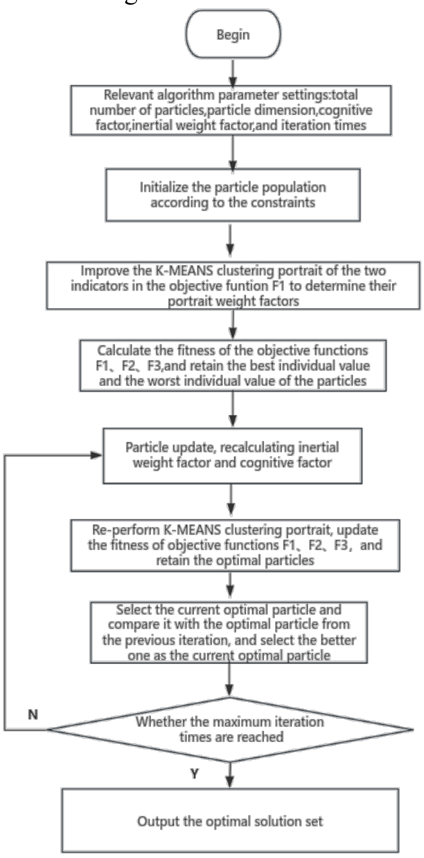


**Figure 2** Flowchart of model solving based on SAPSO algorithm

## 5.2 Selection of optimal compromise solution based on fuzzy theory

The multi-objective optimization often results in a set of optimal solutions. Using fuzzy theory, the optimal compromise solution can be selected, with the fuzzy membership function as follows[26]:

$$u_m = \begin{cases} 1 , & f_m \le f_{m\min} \\ \dfrac{f_{m\max} - f_m}{f_{m\max} - f_{m\min}} , & f_{m\min} \le f_m \le f_{m\max} \\ 0 , & f_{m\max} \le f_m \end{cases} \tag{20}$$

Standardize the satisfaction degree in formula (18) as follows:

$$\mu^k = \frac{\sum_{m=1}^{M} \mu_m^k}{\sum_{k=1}^{N} \sum_{m=1}^{M} \mu_m^k} \tag{21}$$

Formula: $u^k$ is the normalized satisfaction of the kth Pareto optimal solution, and N is the number of solution sets.The maximum normalized satisfaction is the optimal compromise solution.

# 6. NUMERICAL SIMULATION

## 6.1 Parameter Settings

Taking the comprehensive energy system of a certain park as an example, the operating parameters of the comprehensive energy storage equipment and other equipment are shown in Tables 1 and 2.The weight factors for the response of energy storage users and the interactive benefit indicators of energy storage users under the clustering of images are shown in Section 4.1. For the above model, the SAPSO algorithm is used for model solving. The algorithm settings are as follows: the number of iterations is 100, the number of particles is 100, the cognitive factors are 0.5 and 4, and the inertia weight factors are 0.4 and 0.9.

**Table 1** Parameters of energy storage equipment

| Parameters | value | Parameters | value |
|---|---|---|---|
| $P_{in,\max}$ | 200kW | $E_{\min}$ | $200kW \cdot h$ |
| $P_{out,\max}$ | 200kW | $\eta_{in}$ | 0.96 |
| $E_{\max}$ | $800kW \cdot h$ | $\eta_{out}$ | 0.96 |

**Table 2** Operating parameters of other equipment

| Parameters | value | Parameters | value |
|---|---|---|---|
| $v_{in}$ | 3m/s | $\rho_{cut}$ | 0.61¥/$kW \cdot h$ |
| $v_{out}$ | 25 m/s | $\rho_{tr}$ | 0.52¥/$kW \cdot h$ |
| $\lambda$ | 0.95 | $c_R$ | 1.2¥/$kW \cdot h$ |
| $\rho_{off}$ | 0.82¥/$kW \cdot h$ | $x$ | 0.8 |

## 6.2 Simulation analysis of calculation example

To verify the impact of considering user personas on the optimal scheduling model, two simulation scenarios are set up:

Scenario 1: Considering the user portrait method, before each iteration of the model, the response of energy storage users and the interactive benefit indicators of energy storage users are clustered and classified to determine the weight factors, and the rolling model is solved;

Scenario 2: Without considering the user portrait method, that is, the weight factor does not change with model iteration, it is set $a_1 = a_2 = 0.5$

For scenario 1, when using the SAPSO algorithm to solve the model, the initialized particles are used as the initial energy storage user response and energy storage user interaction benefit index clustering basis to determine the initial weight factors of the objective function. The clustering portrait results are shown in Figure 3 and Figure 4.

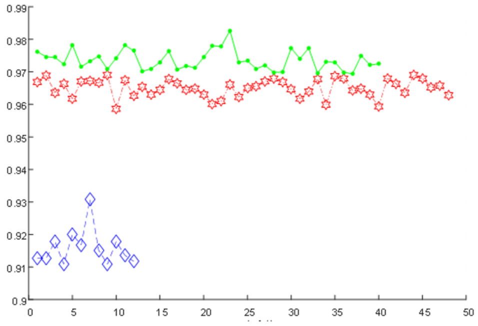

**Figure 3** Clustering division of energy storage user response portrait

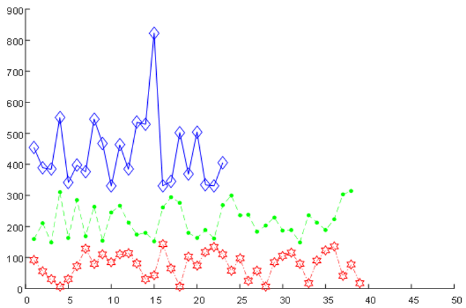

**Figure 4** Clustering division of energy storage user interaction benefit portrait

The results of Figure 3 and Figure 4 show that using the improved K-means algorithm for portrait clustering can divide the energy storage user responsiveness and energy storage user interaction benefit indicators into three categories, respectively. Based on different category combinations, their weight factors can be determined. The weight factor values of the energy storage user responsiveness and energy storage user interaction benefit indicators under the initial portrait clustering are shown in Figure 5 and Figure 6.

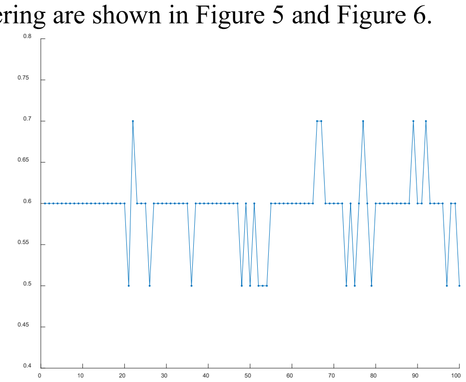

**Figure 5** Response weight index of energy storage users under initial portrait clustering

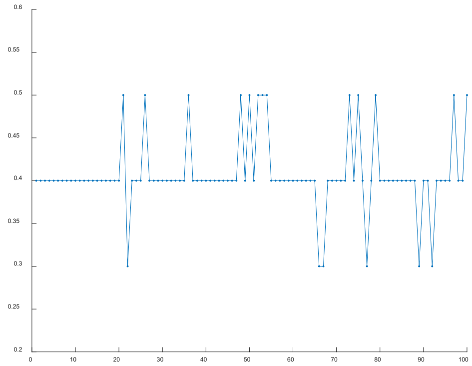

**Figure 6** Weight factors of interaction benefit indicators for energy storage users under initial portrait clustering

The results of Figures 5 and 6 show that the multi-objective optimization scheduling model for source-load-storage in the park considering user personas, the response of energy storage users and the weight factor of interactive revenue indicators for energy storage users in the model are dynamic factors with uncertainty, which will change with the number of iterative populations and iterations. This objectively demonstrates that the model constructed in this paper is accurate.

The algorithm proposed in Section 4.1 is used to iteratively optimize the model. However, the results of multi-objective optimization often yield a Pareto optimal solution set, as shown in Figure 7.The optimal compromise solution is selected using fuzzy theory, as shown in Table 3.

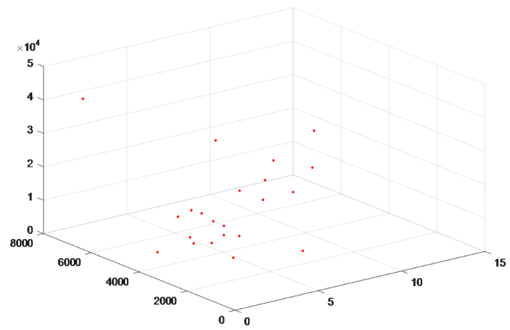

**Figure 7** Pareto Optimal Solution Set Considering User Profiles

**Table 3** Optimal compromise solution based on fuzzy theory

| | customer satisfaction | Net income /￥ | Operating costs/￥ |
|---|---|---|---|
| function value | 4.43 | 3160.2 | 1447 |

For scenario 2, without considering the user profile, it is believed that the weight factors of the energy storage user responsiveness and energy storage user interaction benefit indicators do not change with iteration during model optimization.The Pareto optimal solution set is shown in Figure 8, and the optimal compromise solution is selected using fuzzy theory, as shown in Table 4.

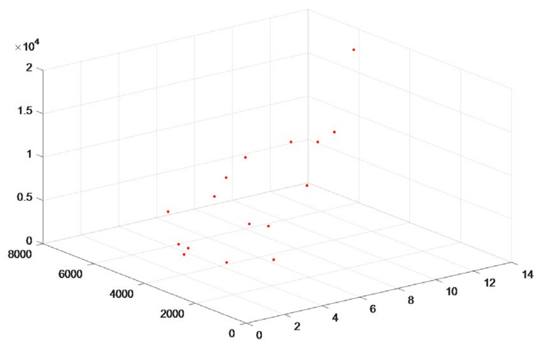

**Figure 8** Pareto Optimal Solution Set without Considering User Profiles

**Table 4** Optimal compromise solution based on fuzzy theory

| | customer satisfaction | Net income /￥ | Operating costs/￥ |
|---|---|---|---|
| function value | 3.50 | 1542.4 | 3791.2 |

Comparing the results in Table 3 and Table 4, it is clear that the results obtained by considering user personas are better, as reflected in the significant improvement in user satisfaction and net wind power consumption benefits. User satisfaction has increased from 3.5 to 4.43, an increase of 26.57%;net wind power benefits have doubled from 1542.4 yuan to 3160.2 yuan;and the operating costs of the park have also decreased significantly. Considering user personas, the operating costs of the park have decreased from 3791.2 yuan to 1447 yuan, a decrease of 61.73%. Therefore, the multi-objective optimization scheduling model for industrial park source-load-storage considering user personas can improve user satisfaction and wind power consumption, reduce operating costs of the industrial park, and achieve energy optimization for the industrial park.

## 7. Conclusion

This article aims to construct an optimal dispatching model for the comprehensive energy source-load-storage system in industrial parks, considering user profiles. Compared with the optimal dispatching model without considering user profiles, the conclusions are as follows:

The energy optimization scheduling model established in this article comprehensively considers user satisfaction, wind power consumption, and industrial park equipment operating costs, and uses user portrait technology to cluster users into categories. The simulation results show that introducing user portraits into the model for clustering and classification can improve user satisfaction, net benefits of wind power consumption, and reduce equipment operating costs in industrial parks. To a certain extent, the introduction of user portrait methods is more conducive to achieving comprehensive energy optimization in industrial parks, resulting in more economic and environmentally friendly decision-making outcomes.

## Acknowledgment

This project was supported by the Science and Technology Project of State Grid Corporation of China(5216A223000J) and the Energy Internet Supply and Demand Operation Hunan Provincial Key Laboratory Fund(2019tp1053)

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