Dynamic Sensing and Collaborative Optimization Algorithm for Adjustable Resources on the Power User Side Combining Edge Computing and Internet of Things

Jiang Du[1], Xinlei Cai[2], Tingzhe Pan[3], Jiale Liu[2], Zhangying Cheng[2], Xin Jin[3]
[1]China Southern Power Grid Company Limited, Guangzhou 510663, Guangdong, China
[2]Electric Power Dispatching Control Center of Guangdong Power Grid Co., Ltd., Guangzhou 510000, Guangdong, China
[3]Electric Power Research Institute, CSG, Guangzhou 510663, Guangdong, China

Corresponding author: Jiang Du (e-mail: psce_sn2@163.com)

ABSTRACT To address the decentralized and dynamic characteristics of adjustable resources on the power user side, as well as the high sensing delay and low collaborative efficiency of traditional centralized architectures, this paper proposes a dynamic sensing and collaborative optimization algorithm combining edge computing with the Energy Internet of Things. An edge-terminal two-level sensing architecture is first constructed. Smart terminals collect electrical quantity, state quantity, and behavioral feature data on the user side, while edge nodes perform local real-time processing and preliminary data analysis. A dynamic sensing model based on two-dimensional clustering is then designed by integrating K-medoids and DBSCAN to jointly identify user behaviors and resource regulation capabilities. Finally, a multi-objective collaborative optimization model is established, and an improved particle swarm optimization algorithm is adopted to solve the Pareto optimal solution considering economy, stability, and environmental protection. Simulation results show that the algorithm reduces sensing delay to less than 55 ms for user scales up to 500 households, decreases the peak-valley load difference rate by 28.6%, and increases the renewable energy consumption rate by 11.3%, improving real-time regulation accuracy in distributed electromagnetic energy systems.

INDEX TERMS edge computing, energy internet of things, adjustable resources, dynamic sensing, electromagnetic systems

I. INTRODUCTION

A. RESEARCH BACKGROUND

ACCORDING to the BP World Energy Outlook Report released in 2023 [1], two-thirds of the global growth in electricity demand over the past decade has come from China. In the next few years, the growth of global electricity demand will accelerate further; however, driven by the "dual carbon" goals (carbon peaking and carbon neutrality), the increment of electricity consumption in China over the next decade will decline moderately compared with the previous decade. The construction of a new-type power system with new energy as the main body [2] is an indispensable path to achieve the "dual carbon" goals [3]. With the continuous increase in the proportion of renewable energy connected to the grid, the pressure of renewable energy consumption and power supply-demand balance has also increased accordingly. Therefore, organizing diversified and flexible adjustable resources, such as the thermal and mechanical loads available, to participate in aggregated regulation has become increasingly important for enhancing the regulatory capacity of the power system.

With the development of the Power Internet of Things (PIOT), the new-type power system will witness a surge in multi-source heterogeneous data, as information from diverse sources, including operational data from the industry, is integrated into the grid environment. Meanwhile, the demand for diversified and ecological power business applications derived from data value is constantly increasing, which will pose severe challenges to the existing power automation technology system. Driven by the goal of building a digital power grid, the digital and intelligent transformation of distribution stations (as the edge management and control units of the power grid) has been gradually implemented in recent years [4]. Distribution stations based on PIOT edge computing technology have become one of the key technical paths for constructing new-type distribution automation systems [5]. With the in-depth application of the Internet of Things (IoT) technology in distribution stations, the demand for massive data processing and diversified business services at the distribution edge will change dynamically and grow continuously over time. The edge computing capabilities of traditional distribution terminals face challenges in aspects such as terminal architecture design, flexible and efficient operation and maintenance, elastic function expansion [6], and business application ecology [7]. There is an urgent need for innovation to better support the transformation and upgrading of distribution automation systems [8]. To improve the development status of adjustable resources in the power system, in-depth research has been conducted at home and abroad on the grid connection of random power sources from the generation side, grid side, and user side. In particular, the generation side has formed a distributed energy bundling and consumption model in the form of microgrids and virtual power plants, and remarkable achievements have been made in practical applications. However, due to the inherent characteristic of real-time balance between power supply and demand, if only the generation side is considered when studying the dynamic changes of adjustable resources, the applicability of the research results will be limited. Moreover, as large end consumers of electricity, studying the dynamic sensing and collaborative optimization algorithms for adjustable resources in energy-intensive sectors like manufacturing plays a crucial role in improving the real-time performance and accuracy of resource regulation on the user side.

B. RESEARCH STATUS

In practical engineering applications, due to the development of new energy technologies and the existence of certain objective factors, traditional single models often fail to meet the prediction requirements under complex conditions. In recent years, with the deepening of research, hybrid modeling strategies have emerged [9] and gradually become a research focus. Hybrid models aim to integrate the advantages of different single models to improve modeling accuracy and computational efficiency. Reference [10] combines Long Short- Term Memory (LSTM) with reinforcement learning to predict the daily electricity consumption of two building complexes in a certain block, achieving favorable results. Reference [11] adopts a hybrid prediction method combining Convolutional Neural Network and Long Short-Term Memory (CNN-LSTM) to determine the hourly thermal load of a specific area, realizing more accurate load prediction to meet the needs of actual production. In recent years, driven by the digital transformation tasks of power grid enterprises and relevant national policies on distribution network construction [12], the scale of distribution networks has become increasingly large and complex, and the number of connected devices has increased significantly. This poses challenges to the data information processing capability and power business service capability of distribution automation systems [13,14]. To address this, the digital and intelligent transformation of distribution stations (as edge management and control units of the power grid) is being gradually implemented [15], laying a solid foundation for the construction of a new-type distribution automation system with high reliability and full coverage. In this process, to better foster and develop new competitive industries, and provide more powerful information resource support and efficient information processing capabilities, emerging cutting-edge technologies such as the Energy Internet of Things (IoE) and edge computing have been widely applied to the distribution side, and gradually become key technical means for building new-type distribution automation systems [16]. On the premise of acquiring device-level data through IoT technology, some studies have conducted in-depth analysis of the electricity consumption characteristics and response rules of end-users, proposed a method for evaluating the price elasticity of electricity demand based on device electricity consumption characteristics, and on this basis, put forward a guiding recommendation method for electricity tariff packages and a realtime demand response transaction decision-making method.

The participation of user-side resources in power transactions is an inevitable trend to ensure the safe and reliable operation of power systems and promote the mature development of power markets. Against the background of large-scale integration of renewable energy into the power grid, user-side resources with rapid response capabilities have become an important means for power system dispatching and operation to balance power supply and demand [17]. The participation of user-side dynamic sensing in market transactions is a key way for these resources to play a role in power regulation, while promoting price discovery in the spot market and mitigating price fluctuations [18]. The real-time market has more stringent reliability requirements for user-side resources participating in transactions, including many constraints such as response capacity, response duration, start-up time, and deviation range. Therefore, at this stage, the entry threshold for market entities participating in transactions is relatively high. Typical transaction participants are industrial users with large-scale adjustable loads. Chios proposed an optimal scheduling strategy for participating in the day-ahead and real-time markets; by complementing the advantages of day-ahead scheduling and real-time balance, the market revenue of industrial users with energy storage systems participating in demand response transactions was increased [19]. Ahmed Abdulaal proposed four two-stage discrete-continuous multi-objective load optimization methods for industrial users; considering multiple constraints such as user utility, price, and climate, the Pareto optimal strategy for users to participate in demand response transactions was solved [20].

However, current research has many shortcomings: most studies classify users based on static load data or single behavior labels. For example, the K-means algorithm is used for clustering and identification of industrial loads, but the dynamic evolution characteristics of user behaviors changing with time and environment are ignored. As a potential solution, edge computing enables servers deployed at the network edge to provide computing services for users with low latency; however, limited computing resources and high dynamics of mobile users bring many challenges to the effective scheduling of computing tasks. Although the combination of mixed-integer programming and genetic algorithms can solve multi-objective optimization problems, their convergence speed is slow in high-dimensional resource scheduling scenarios, limiting their practicality. This paper intends to conduct research on the dynamic sensing and collaborative optimization of adjustable resources on the industrial power user side, including the flexible loads of manufacturing, by combining edge computing and the Internet of Things, so as to realize the accurate identification of users with high regulation potential and establish a multi-objective collaborative optimization model.

II. DESIGN OF SENSING ARCHITECTURE FOR INTEGRATION OF EDGE COMPUTING AND POWER INTERNET OF THINGS (PIOT)

A. OVERALL ARCHITECTURE DESIGN

This paper constructs a three-level architecture of "terminal sensing - edge processing - cloud collaboration". The terminal layer deploys devices such as smart electricity meters, temperature sensors, and photovoltaic inverters, which serve as edge nodes to collect multi-dimensional data on the user side. The edge layer realizes local data storage, preprocessing, and preliminary analysis through edge gateways, and executes real-time regulation instructions. The cloud layer is responsible for global optimization decision-making, historical data storage, and algorithm model training, and issues optimization objectives and constraint conditions to the edge layer. In this architecture, edge nodes act as the core of data processing, with integrated functions of computing, storage, and communication. They support multiple network connection methods such as RJ-45 interface and Fiber Distributed Data Interface (FDDI), and adapt to the differentiated needs of urban users and industrial scenarios. Edge nodes and terminal devices adopt wired/wireless dual-channel heterogeneous networking technology to improve communication reliability and fault tolerance, ensuring the stability of data transmission.

B. DATA ACQUISITION MECHANISM OF THE TERMINAL LAYER

The terminal layer configures differentiated sensing devices according to user types (residential users, industrial users, commercial users), and the collected data is divided into three categories:

- Electrical quantity data: Including real-time power, voltage, current, energy consumption, etc. It is collected by smart electricity meters with a sampling cycle of 1 minute and an accuracy of Class 0.5.
- State quantity data: Covering equipment operating status (such as air conditioner on/off, EV charging status), interface compatibility, available duration, etc. Radio Frequency Identification (RFID) technology is used to realize automatic identification of equipment status.
- Environmental and behavioral data: Including indoor temperature, light intensity, user response willingness level, historical response frequency, etc. It is collected through temperature sensors and user interaction terminals.

All collected data is encapsulated in a standardized format and transmitted to edge nodes through a dedicated communication protocol for the Power Internet of Things, ensuring data consistency and interoperability.

C. LOCAL PROCESSING FLOW OF THE EDGE LAYER

After receiving terminal data, edge nodes execute the following processing flow:

- Data preprocessing: An outlier detection algorithm is used to eliminate abnormal data caused by sensor faults, and missing values are supplemented by interpolation to reduce data noise.
- Feature extraction: Features such as peak-valley difference, average load, and fluctuation coefficient are extracted from the electrical quantity time series, and a multi-dimensional feature matrix is constructed by combining state quantity and behavioral data.
- Local decision-making: Based on the pre-trained clustering model, users with high regulation potential are identified. For emergency scenarios (e.g., frequency deviation > 0.1Hz), local rapid regulation is executed without waiting for cloud instructions.
- Data upload: The preprocessed data and local decision results are uploaded to the cloud as needed, reducing redundant data transmission and lowering bandwidth occupation.

The edge layer and the cloud layer realize data synchronization through an encrypted communication channel. The cloud layer dynamically updates the decision parameters of edge nodes according to the global operating status, forming a regulation mode of "local rapid response + global optimized coordination". This architecture effectively supports diversified power business applications (including demand response, load scheduling, and renewable energy consumption optimization) by leveraging edge computing's low-latency processing capability and IoE's comprehensive perception advantage.

III. DYNAMIC SENSING ALGORITHM BASED ON TWO-DIMENSIONAL CLUSTERING

A. CONSTRUCTION OF FEATURE VECTORS

To achieve accurate sensing of adjustable resources, two types of indicator systems—behavioral feature vectors and resource feature vectors—are constructed:

1) Behavioral Feature Vectors

Behavioral feature vectors reflect the response reliability and dynamic change characteristics of users, including 5 dimensions:

- Response start delay: The time interval from receiving a regulation instruction to initiating the adjustment;
- Response duration: The effective duration of maintaining the adjusted state;
- Unit adjustable load capacity: The maximum load power that can be adjusted per unit time;
- Historical response frequency: The number of times a user has participated in regulation within the past 30 days;
- Response willingness level: A 0-5 level indicator evaluated based on user feedback and historical execution.

All behavioral feature data form a time-series matrix through a set sampling period, providing basic data support for clustering analysis.

2) Resource Feature Vectors

Resource feature vectors represent the physical regulation capabilities of user-side equipment, including 5 dimensions:

- Type of adjustable device: Such as temperature-controlled loads, electric vehicles (EVs), distributed energy storage, etc.;
- Response interface compatibility: The degree of adaptation between the device and the communication protocol of the regulation system;
- Device availability status: A binary status indicator for normal operation, standby, or fault;
- Maximum adjustable capacity: The total adjustable load of the device;
- Available duration: The maximum duration of maintaining the full-load adjustment state.

Resource feature items are input into the clustering algorithm in the form of a structured parameter matrix to ensure data computability.

3) Implementation of the Two-Dimensional Clustering Algorithm

A two-dimensional clustering strategy of "behavioral clustering - resource clustering - intersection screening" is adopted, with specific steps as follows:

4) Behavioral Dimension Clustering (K-medoids Algorithm)

The K-medoids algorithm based on a radius threshold is used for behavioral feature clustering, which has the advantage of being insensitive to outliers and achieving stronger clustering stability. Compared with K-means, K-medoids is selected primarily for its robustness to abnormal data points, which is critical for handling realworld user behavior data that may contain noise from sensor errors or irregular user activities. To address the dynamic evolution of user behaviors, the K-medoids clustering is integrated with a temporal weighting mechanism and a sliding window update strategy:

These enhancements enable the static K-medoids framework to capture dynamic behavioral changes, overcoming the limitation of traditional static clustering algorithms that ignore temporal evolution.

- Temporal weighting: Recent behavioral data (within the latest 7 days) is assigned a higher weight (0.7) while older data (8-30 days) is assigned a lower weight (0.3) to emphasize recent behavior patterns.
- Sliding window: As defined in Section 3.2.3, clustering parameters are updated every 24 hours to adapt to time-varying user behaviors.
- Data standardization: The Z-score standardization method is applied to process behavioral feature vectors to eliminate differences in dimensions;
- Initial cluster center selection: Initial cluster centers are selected based on a density method to ensure uniform distribution of samples within clusters;
- Similarity calculation: Euclidean distance is used as the similarity metric to calculate the distance between samples and cluster centers;
- Cluster division: According to a preset radius threshold, samples with distances less than the threshold are divided into the same cluster, forming multiple user groups with similar behavioral features.

5) Resource Dimension Clustering (DBSCAN Algorithm)

The DBSCAN (Density-Based Spatial Clustering of Applications with Noise) algorithm based on the density aggregation principle is adopted for resource feature clustering, which is suitable for identifying users with controllable resources distributed in high-density areas.

- Set control parameters: Define the neighborhood search radius $\epsilon = 0.3$ and the minimum number of neighborhood samples MinPts = 5;
- Core point identification: Traverse all samples and mark points with the number of samples in their neighborhood $\geq$ MinPts as core points;
- Cluster expansion: Take core points as the center, recursively merge adjacent core points and boundary points to form high-density clusters;
- Outlier elimination: Treat low-density isolated points as users with uncontrollable loads and exclude them from subsequent analysis.

6) Intersection Screening and Dynamic Update

The intersection of the behavioral clustering and resource clustering results is obtained to screen out users with high regulation potential who are "behaviorally reliable and resource-controllable". To adapt to the dynamic changes of user behavior, a sliding window mechanism is used to update clustering parameters, and clustering analysis is re-executed every 24 hours to ensure the timeliness of sensing results.

7) Performance Verification Indicators of the Sensing Algorithm

Three key indicators are defined to evaluate the performance of the dynamic sensing algorithm:

- Recognition accuracy: The ratio of the number of correctly identified users with high regulation potential to the actual total number of such users;
- Sensing delay: The total time consumed from data collection to the completion of user identification;
- Stability: The consistency coefficient of identification results for 7 consecutive days.

The above indicators are used to comprehensively measure the accuracy and real-time performance of the algorithm.

IV. MULTI-OBJECTIVE COLLABORATIVE OPTIMIZATION MODEL AND IMPROVED ALGORITHM

A. OPTIMIZATION OBJECTIVE FUNCTIONS

A multi-objective optimization function covering economy, stability, and environmental protection is con structed to achieve multi-dimensional optimal regulation.

1) Economic Objective (Minimizing Total Cost)

The total cost includes the user's electricity consumption cost and the power grid's regulation cost, and the objective function is as follows:

$$\min F_1 = \sum_{t=1}^{T} \sum_{i=1}^{N} (P_{i,t} \cdot c_t + C_{\mathrm{reg},i,t}) \tag{1}$$

Among them, T represents the scheduling cycle (unit: h), N denotes the number of users with adjustable resources, $P_{i,t}$ is the adjustment power of user i at time t, c_t stands for the time-of-use electricity price at time t, and $C_{\mathrm{reg},i,t}$ refers to the regulation cost of user i at time t.

2) Stability Objective (Minimizing Load Fluctuation)

With the goal of minimizing the peak-valley load difference rate, the operational stability of the power grid is improved. The objective is as follows:

$$\min F_2 = \frac{P_{\max} - P_{\min}}{P_{\mathrm{avg}}} \tag{2}$$

Among them, $P_{\max}$ is the maximum load power within the scheduling cycle, $P_{\min}$ is the minimum load power, and P_{avg} is the average load power.

3) Environmental Protection Objective (Minimizing Carbon Emissions)

Considering the difference in carbon emissions between renewable energy consumption and fossil energy consumption, the objective function is as follows:

$$\min F_3 = \sum_{t=1}^{T} P_{\mathrm{grid},t} \cdot \lambda_{\mathrm{grid}} - P_{\mathrm{ren},t} \cdot \lambda_{\mathrm{ren}} \tag{3}$$

Among them, $P_{\mathrm{grid},t}$ is the power supply power of the power grid at time t, λ_{grid} is the carbon emission coefficient of grid power supply, $P_{\mathrm{ren},t}$ is the renewable energy generation power at time t, and λ_{ren} is the carbon emission coefficient of renewable energy.

B. CONSTRAINT CONDITIONS

1) Power Balance Constraint

The power supply and power consumption at each moment within the scheduling cycle shall remain balanced, and the constraint is as follows:

$$P_{\mathrm{grid},t} + P_{\mathrm{ren},t} = \sum_{i=1}^{N} \left(P_{i,t}^{\mathrm{base}} + P_{i,t}\right) \tag{4}$$

Among them, $P_{i,t}^{\mathrm{base}}$ denotes the base load power of user i at time t.

2) Equipment Output Constraint

The adjustment power of the adjustable resources on the user side shall not exceed the maximum adjustable capacity of the equipment, and the constraint is as follows:

$$-P_{i,\max} \leq P_{i,t} \leq P_{i,\max} \tag{5}$$

Among them, $P_{i,\max}$ is the maximum adjustable power of user i.

3) User Comfort Constraint

For perceptual loads such as temperature-controlled loads, a temperature fluctuation range constraint is set:

$$T_{i,\min} \leq T_{i,t} \leq T_{i,\max} \tag{6}$$

where $T_{i,t}$ is the indoor temperature of user i at time t, and $T_{i,\min}$ and $T_{i,\max}$ are the minimum and maximum comfortable temperature thresholds, respectively.

4) Response Duration Constraint

The duration of a single adjustment shall not be less than the minimum response time to avoid equipment damage caused by frequent start-stop operations:

$$t_{i,\mathrm{on}} \geq t_{i,\min} \tag{7}$$

where $t_{i,\mathrm{on}}$ is the duration of a single adjustment for user i, and $t_{i,\min}$ is the minimum response time.

C. IMPROVED PARTICLE SWARM OPTIMIZATION (PSO) ALGORITHM

To address the problem of premature convergence in the traditional particle swarm optimization algorithm, dynamic inertia weight and adaptive learning factors are introduced, and the improved algorithm is as follows:

1) Dynamic Inertia Weight

A nonlinear inertia weight strategy is adopted to balance the global search and local search capabilities of the algorithm:

$$\omega(t) = \omega_{\max} - (\omega_{\max} - \omega_{\min}) \cdot \left(\frac{t}{T_{\max}}\right)^2 \quad (8)$$

where $\omega(t)$ is the inertia weight at iteration t, with $\omega_{\max} = 0.9$ and $\omega_{\min} = 0.4$, and $T_{\max}$ is the maximum number of iterations.

2) Adaptive Learning Factors

The learning factors are dynamically adjusted with the iteration process to improve the convergence speed of the algorithm:

$$\begin{aligned} c_1(t) &= c_{1,\max} - (c_{1,\max} - c_{1,\min}) \cdot \frac{t}{T_{\max}} \\ c_2(t) &= c_{2,\max} + (c_{2,\max} - c_{2,\min}) \cdot \frac{t}{T_{\max}} \end{aligned} \quad (9)$$

where $c_1(t)$ and $c_2(t)$ are the individual learning factor and social learning factor, respectively, with $c_{1,\max} = 2.5$, $c_{1,\min} = 1.0$, $c_{2,\max} = 2.5$, and $c_{2,\min} = 1.0$.

3) Algorithm Solution Process

- Initialize particle population: Set the population size to 50 and the particle dimension to $N \times T$, and randomly generate initial positions and velocities;
- Fitness calculation: Convert the multi-objective function into a single-objective fitness function using the weighted sum method, where the weight coefficients are determined by the Analytic Hierarchy Process (AHP);
- Update individual optimal and global optimal: Record the historical optimal position of each particle and the global optimal position of the population;
- Update particle position and velocity: Update the particle state based on the dynamic inertia weight and adaptive learning factors;
- Convergence judgment: If the maximum number of iterations is reached or the change in fitness value is less than the threshold (10^{-6}), stop the iteration and output the optimal solution.

V. SIMULATION EXPERIMENTS AND RESULT ANALYSIS

A. EXPERIMENTAL ENVIRONMENT AND PARAMETER SETTINGS

The simulation environment was built based on the Matlab 2023b platform, with hardware configuration including an Intel Core i7-12700H processor and 32GB of memory. The simulation scenario selected a lowvoltage distribution station in a certain city, covering 200 residential users, 30 commercial users, and 10 industrial users. The adjustable resources included air conditioners, electric vehicles (EVs), distributed photo voltaics (PV), and energy storage devices.

The key parameter settings are as follows: scheduling cycle $T = 24$h, sampling interval of 15 minutes; renewable energy penetration rate of 30%, with PV output fitted using measured data; time-of-use electricity prices: peak periods (10:00–14:00, 18:00–22:00) at 1.2 CNY/kWh, flat periods (7:00–10:00, 14:00–18:00, 22:00–23:00) at 0.7 CNY/kWh, and valley periods (23:00–7:00 the next day) at 0.3 CNY/kWh; comfortable temperature range of 18–26 °C; maximum number of algorithm iterations $T_{\max} = 200$.

B. PERFORMANCE TESTING OF THE DYNAMIC SENSING ALGORITHM

1) Comparison of Recognition Accuracy

The two-dimensional clustering algorithm proposed in this paper was compared with the traditional K-means algorithm and the single DBSCAN algorithm. The test results are shown in Table 1.

TABLE 1. Comparison of Recognition Accuracy of Different Sensing Algorithms

Algorithm Type	Residential User Accuracy	Commercial User Accuracy	Industrial User Accuracy	Average Accuracy
K-means Algorithm	78.5%	82.3%	85.7%	82.2%
Single DBSCAN Algorithm	81.2%	84.6%	87.1%	84.3%
Two-Dimensional Clustering Algorithm in This Paper	92.3%	94.7%	96.2%	94.4%

As can be seen from Table 1, the recognition accuracy of the algorithm in this paper for all types of users is higher than that of traditional algorithms, with the average accuracy improved by 12.2%-10.1%. The reason is that the two-dimensional clustering considers both behavioral characteristics and resource capabilities, avoiding the one-sidedness of single-dimensional recognition.

2) Sensing Delay and Stability Tests

The sensing delay under different user scales was tested, and the results are shown in Table 2; the stability test results over 7 consecutive days are shown in Table 3.

TABLE 2. Sensing Delay Under Different User Scales

User Scale (Households)	K-means Algorithm (ms)	Single DBSCAN Algorithm (ms)	Two-Dimensional Clustering Algorithm in This Paper (ms)
100	128	115	42
200	213	197	45
300	305	286	48
500	487	452	53

Note: The proposed algorithm achieves a sensing delay of less than 50ms for user scales up to 300 households, and extends to 53ms for 500 households, which is still significantly lower than traditional algorithms.

TABLE 3. Stability Test of the Dynamic Sensing Algorithm

Test Day	Consistency Coefficient of Recognition Results	Number of Users with High Regulation Potential (Households)	Fluctuation Range (Households)
Day 1	1.000	86	-
Day 2	0.976	84	2
Day 3	0.982	85	1
Day 4	0.968	83	2
Day 5	0.973	85	2
Day 6	0.985	86	1
Day 7	0.979	85	1
Average Consistency Coefficient	0.978	-	1.57

C. PERFORMANCE TESTING OF THE COLLABORATIVE OPTIMIZATION ALGORITHM

1) Multi-Objective Optimization Results

The improved particle swarm optimization (PSO) algorithm proposed in this paper was compared with the traditional particle swarm optimization algorithm and genetic algorithm, and the optimization results are shown in Table 4.

TABLE 4. Multi-Objective Optimization Results of Different Optimization Algorithms

Algorithm Type	Total Cost Reduction Rate	Peak-Valley Load Difference Rate Reduction	Carbon Emission Reduction Rate	Convergent Iteration Count
Traditional PSO Algorithm	15.7%	18.3%	8.6%	142
Genetic Algorithm	17.2%	20.5%	9.8%	186
Improved PSO Algorithm in This Paper	23.5%	28.6%	11.3%	

As can be seen from Table 4, the improved algorithm in this paper outperforms the comparison algorithms in terms of total cost reduction rate, peak-valley load difference rate reduction, and carbon emission reduction rate. Meanwhile, the number of convergent iterations is reduced by 31.0%-47.3%. This is because the introduction of dynamic inertia weight and adaptive learning factors improves the search efficiency and optimization accuracy of the algorithm.

2) Optimization Effects Under Different Scenarios

The optimization effects of the algorithm under different renewable energy penetration rates were tested, and the results are shown in Table 5.

TABLE 5. Optimization Effects Under Different Renewable Energy Penetration Rates

Penetration Rate	Total Cost Reduction Rate	Peak-Valley Load Difference Rate	Renewable Energy Consumption Rate	User Comfort Satisfaction
20%	21.8%	26.3%	92.5%	93.7%
30%	23.5%	28.6%	94.8%	92.4%
40%	25.1%	31.2%	96.3%	91.8%
50%	26.7%	33.5%	97.1%	90.5%

As shown in Table 5, with the increase in renewable energy penetration rate, the improvement effects of total cost reduction rate and peak-valley load difference rate become more significant, and the renewable energy consumption rate continues to rise. However, the user comfort satisfaction only decreases slightly. This indicates that the algorithm can still achieve a multi-objective balance in scenarios with high penetration rates.

3) Experimental Conclusions

Simulation experiments show that the edge-terminal two-level sensing architecture constructed in this paper effectively reduces the sensing delay, and the average recognition accuracy of the two-dimensional clustering algorithm reaches 94.4%. The improved particle swarm optimization algorithm performs better in multi-objective optimization, achieving a 23.5% reduction in total cost, a 28.6% decrease in peak-valley load

difference rate, and an 11.3% reduction in carbon emissions. The algorithm exhibits good adaptability and stability under scenarios with different user scales and renewable energy penetration rates, and can meet the dynamic regulation needs of adjustable resources on the user side.

VI. CONCLUSIONS

Targeting the complex, adjustable resources on the industrial power user side, including the thermal and mechanical loads of the industry, this paper proposes a dynamic sensing and collaborative optimization algorithm combining edge computing and the Energy Internet of Things (IoE). Through architecture design, algorithm improvement, and simulation verification, the following conclusions are drawn:

1) The three-level sensing architecture integrating edge computing and the Energy Internet of Things (IoE) realizes the organic combination of data collection, local processing, and global collaboration. The sensing delay is reduced to less than 55ms for user scales up to 500 households, providing technical support for real-time regulation;

2) The behavior-resource two-dimensional clustering algorithm overcomes the limitations of single-dimensional recognition. With an average recognition accuracy of 94.4% and a stability coefficient of 0.978, it can accurately identify users with high regulation potential;

3) The improved particle swarm optimization algorithm based on dynamic inertia weight achieves a balance between economy, stability, and environmental protection in

multi-objective optimization, and its convergence speed and optimization accuracy are better than those of traditional algorithms.

AUTHOR CONTRIBUTIONS

Conceptualization –Jiang Du, Xinlei Cai, Tingzhe Pan, Jiale Liu, Zhangying Cheng and Xin Jin; methodology – Jiang Du, Xinlei Cai, Tingzhe Pan, Zhangying Cheng and Xin Jin; investigation – Jiang Du, Xinlei Cai, Tingzhe Pan, Jiale Liu, Zhangying Cheng and Xin Jin; writing-original draft preparation – Jiang Du, Xinlei Cai, Tingzhe Pan, Jiale Liu, Zhangying Cheng and Xin Jin. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

FUNDING

This research was supported by, 1,Supported by the Science and Technology Project of China Southern Power Grid Co., Ltd[036000KK52220005 (GDKJXM20220148)].

2,Supported by the National Key R&D Program of China for International S&T Cooperation Projects (2019YFE0118700) .

ACKNOWLEDGEMENTS

Not applicable.

REFERENCES

[1] H. Y. Li, M. Yu, Y. M. Zheng, X. D. Dai, and M. Z. Lin, "Scenario-based analysis of world energy supply and demand outlook by 2050-Based on BP World Energy Outlook (2023 Edition)," Natural Gas and Oil, vol. 41, no. 5, pp. 131-137, 2023.

[2] H. Gao, T. Jin, C. Feng, C. Li, Q. Chen, and C. Kang, "Review of virtual power plant operations: Resource coordination and multidimensional interaction," Applied Energy, vol. 357, 122284, 2024, doi: 10.1016/j.apenergy.2023.122284.

[3] C. Yu, S. Liang, L. Zhang, M. Gao, J. Huang, Y. Zhu, T. Liu, and X. Bian, "Low Carbon Economic Optimization Dispatching of Medium and Low Voltage Distribution Systems Based on Carbon Emission Flow," 2023 8th International Conference on Power and Renewable Energy (ICPRE), pp. 1433-1438, 2023, doi: 10.1109/ICPRE59655.2023.10353861.

[4] W. Di, W. Wei, W. Shaoqu, Y. Zhuofei, S. Houtao, and H. Dan, "Research and application of low-voltage flexible interconnection technology of distribution network," 2022 Asian Conference on Frontiers of Power and Energy (ACFPE), pp. 478-483, 2022, doi: 10.1109/ACFPE56003.2022.9952180.

[5] D. Kumar, R. K. Singh, R. Mishra, and S. Fosso Wamba, "Applications of the internet of things for optimizing warehousing and logistics operations: A systematic literature review and future research directions," Computers & Industrial Engineering, vol. 171, 108455, 2022, doi: 10.1016/j.cie.2022.108455.

[6] H. Gauttam, G. Nain, K. K. Pattanaik, and P. Mendes, "Edge-AI: A systematic review on architectures, applications, and challenges," Journal of Network and Computer Applications, vol. 245, 104375, 2026, doi: 10.1016/j.jnca.2025.104375.

[7] Y. Ai, M. Peng, and K. Zhang, "Edge computing technologies for Internet of Things: a primer," Digital Communications and Networks, vol. 4, no. 2, pp. 77-86, 2018, doi: 10.1016/j.dcan.2017.07.001.

[8] L. Liu, L. Chen, S. Xu, Y. Xu, and C. Shi, "Design and implementation of intelligent monitoring terminal for distribution room based on edge computing," Energy Reports, vol. 7, pp. 1131-1138, 2021, doi: 10.1016/j.egyr.2021.09.154.

[9] W. Zhang, J. Lian, C. Y. Chang, and K. Kalsi, "Aggregated Modeling and Control of Air Conditioning Loads for Demand Response," IEEE Transactions on Power Systems, vol. 28, no. 4, pp. 4655-4664, 2013, doi: 10.1109/TPWRS.2013.2266121.

[10] X. Zhou, W. Lin, R. Kumar, P. Cui, and Z. Ma, "A data-driven strategy using long short term memory models and reinforce ment learning to predict building electricity consumption," Applied Energy, vol. 306, 118078, 2022, doi: 10.1016/j.apenergy.2021.118078.

[11] J. Song, L. Zhang, G. Xue, Y. P. Ma, and Q. L. Jiang, "Predicting Hourly Heating Load in a District Heating System Based on a Hybrid CNN-LSTM Model," Energy and Buildings, vol. 243, no. 3, 110998, 2021, doi: 10.1016/j.enbuild.2021.110998.

[12] Y. W. Shang, L. M. Zhou, Z. Ma, and Y. H. Wang, "Preliminary exploration of digital active distribution systems," Proceedings of the CSEE, vol. 42, no. 5, pp. 13, 2022, doi: 10.13334/j.0258-8013.pcsee.210180.

[13] X. Z. Dong, Z. H. Hua, L. Shang, B. Wang, L. K. Chen, Q. P. Zhang, and Y. C. Huang, "Morphological characteristics and technology outlook of new distribution systems," High Voltage Engineering, vol. 47, no. 9, pp. 3021-3035, 2021, doi: 10.13336/j.1003-6520.hve.20211103.

[14] J. M. Cai, N. Xie, C. M. Wang, and M. T. Fan, "Digital technologies and modeling methods for distribution network planning-A review of research results from the 24th International Conference on Electricity Distribution (CIRED)," Power System Technology, vol. 43, no. 6, pp. 8, 2019, doi: 10.13335/j.1000-3673.pst.2018.2856.

[15] D. Q. Liu, X. J. Zeng, and Y. N. Wang, "Security situation assessment of intelligent distribution transformer terminals based on information entropy," Southern Power System Technology, vol. 14, no. 1, pp. 6, 2020, doi: 10.13648/j.cnki.issn1674-0629.2020.01.003.

[16] Y. Yang, Z. Q. Ao, J. Liu, R. Chen, and J. Jiang, "Edge computing data processing mechanism based on container technology for digital power grids," Southern Power System Technology, vol. 15, no. 5, pp. 6, 2021, doi: 10.13648/j.cnki.issn1674-0629.2021.05.012.

[17] D. K. Critz, S. Busche, and S. Connors, "Power systems balancing with high penetration renewables: The potential of demand response in Hawaii," Energy Conversion and Management, vol. 76, no. Dec., pp. 609-619, 2013, doi: 10.1016/j.enconman.2013.07.056.

[18] E. Heydarian-Forushani, M. P. Moghaddam, M. K. Sheikh-El-Eslami, M. Shafie-khah, and J. Catalao, "Risk constrained offering strategy of wind power producers considering Intraday Demand Response Exchange," 2016 IEEE/PES Transmission and Distribution Conference and Exposition (T&D), pp. 1-1, 2016, doi: 10.1109/TSTE.2014.2324035.

[19] S. Choi and S. W. Min, "Optimal Scheduling and Operation of the ESS for Prosumer Market Environment in Grid-Connected Industrial Complex," IEEE Transactions on Industry Applications, vol. 54, no. 3, pp. 1949-1957, 2018, doi: 10.1109/TIA.2018.2794330.

[20] A. Abdulaal, R. Moghaddass, and S. Asfour, "Two-stage discrete-continuous multi-objective load optimization: An industrial consumer utility approach to demand response," Applied Energy, vol. 206, pp. 206-221, 2017, doi: 10.1016/j.apenergy.2017.08.053.