IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 5 May 2024, accepted 22 May 2024, date of publication 31 May 2024, date of current version 10 June 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3407726

RESEARCH ARTICLE

Multimodal Renewable Energy Hybrid Supply Optimization Model Based on Heterogeneous Cloud Wireless Access

FENG TIAN[1], HONGJIANG WANG[1], HE JIANG[2], AND BAIDA ZHAO[3]

[1]College of Information, Shenyang Institute of Engineering, Shenyang 110036, China
[2]School of Renewable Energy, Shenyang Institute of Engineering, Shenyang 110036, China
[3]Innovation and Entrepreneurship Education Center, Shenyang Institute of Engineering, Shenyang 110036, China

Corresponding author: Feng Tian (yukytian1978@sina.com)

This work was supported in part by the Department of Education of Liaoning Province 2023 Basic Scientific Research Projects of Universities: ''Research on Key Technologies for Coordinated Regulation of Multi Load and Clean Energy Based on Deep Learning'' under Grant JYTMS20230313.

ABSTRACT With the increasing emphasis on environmental issues, the utilization of renewable energy has been recognized as a feasible solution to address the energy crisis and reduce environmental pollution. In view of this, this article proposes a multi-modal renewable energy hybrid power supply optimization model based on heterogeneous cloud wireless access. The model innovatively combines heterogeneous cloud wireless access technology and various intelligent optimization algorithms, including k-clustering algorithm, particle swarm optimization algorithm, and whale optimization algorithm, forming a hybrid optimization algorithm. In order to comprehensively evaluate the actual performance of the model, this study recruited 20 experts to provide detailed ratings on four core dimensions: cost-benefit ratio, reliability, robustness, and user satisfaction. The results showed that the model scored 95.1, 96.4, 95.6, and 96.2 in the four dimensions of cost-benefit ratio, reliability indicators, robustness, and user satisfaction, respectively. This series of significant data not only confirms the theoretical superiority of the model, but also demonstrates its strong potential and practical value in practical applications. In summary, this study provides a promising and innovative solution for the field of renewable energy supply.

INDEX TERMS K-clustering algorithm, heterogeneous cloud radio access, particle swarm optimization algorithm, WOA algorithm, energy supply optimization.

I. INTRODUCTION

With the growing global energy demand and the rapid development of renewable energy (RE), multimodal renewable energy hybrid supply (MREHS) systems have become a potential and attractive solution. Such systems combine multiple RE sources (e.g., solar, wind, hydro, etc.) to meet the energy demand, and achieve a balanced and optimized supply of energy through energy storage and energy conversion technologies. However, MREHS systems face some challenges [1]. First, energy production and consumption in these systems is characterized by uncertainty and time-varying nature, such as changes in weather conditions and volatility of energy supply. Second, different energy types and equipment have different characteristics and technical requirements, e.g., the availability of solar and wind energy is limited by seasonal, weather and geographical conditions. In addition, the cost and efficiency of energy storage and energy conversion devices are also factors to be considered [2], [3]. And the traditional methods often can only find the local optimal solution because they rely on fixed search strategies or heuristic rules and cannot fully explore the solution space of the problem. To solve the above problems, the researchers proposed a new hybrid energy supply model. The model combines cloud computing and wireless communication technologies to intelligently schedule energy production and consumption. In contrast, the new model can adaptively adjust parameters and search strategies to

The associate editor coordinating the review of this manuscript and approving it for publication was Gaetano Zizzo.

optimize according to the characteristics of the problem or the progress of the search process. This allows the algorithm to have better performance on different problems and better complex problem solving. However, in practical applications, how to choose the right learner and how to carry out the combination of predicted results is the challenge facing the current research. Researchers need to choose the right learner according to the characteristics of the data, the complexity of the model, and the cost of computing resources. The overfitting problem can be avoided by reducing the complexity of the model, regularization, feature selection, cross-validation and other methods. In view of this, the study uses K-clustering algorithm (KCA) based on heterogeneous cloud radio access (H-CRA) to divide the nodes into different clusters, and the nodes within each cluster possess similar characteristics. Then, particle swarm optimization (PSO) and whale optimization algorithm (WOA) are applied to optimize the nodes within each cluster, and by adjusting the node's parameters such as energy output, energy consumption, etc., a hybrid K-WOA-PSO optimization algorithm driven by heterogeneous cloud access is finally designed. In hybrid optimization models, each optimization algorithm plays an indispensable role. The KCA algorithm effectively groups nodes with similar characteristics in the energy supply system by clustering them, providing a foundation for subsequent optimization. The Particle Swarm Optimization (PSO) algorithm, with its global search capability, helps the algorithm quickly locate possible optimal solution regions. The Whale Optimization Algorithm (WOA) uses its local fine search ability to conduct deep searches in specific regions, accelerating the convergence speed of the algorithm. Through the organic combination of these three algorithms, the hybrid model not only improves search efficiency, but also enhances the ability to solve complex problems, achieving global optimization of the energy supply system. The study provides important theoretical support and practical guidance for promoting the development and application of RE. The article consists of four main components. A review of the state of the art in the field of MREHS population optimization methods and H-CRA research is presented in the second section. The third part establishes the MREHS optimization model of the heterogeneous cloud access-driven K-WOA-PSO hybrid optimization algorithm. In the fourth section, an applicability analysis is conducted and the algorithmic performance of the model is compared with experiments.

The innovation of this study is mainly reflected in the following aspects. First of all, the H-CRA technology is combined with a multimodal renewable energy hybrid power supply system, utilizing its distributed architecture and dynamic resource management capabilities to improve the system's adaptability to environmental changes and flexibility in energy supply. A novel hybrid optimization algorithm (K-WOA-PSO) was proposed by combining k-clustering algorithm (KCA), particle swarm optimization algorithm (PSO), and whale optimization algorithm (WOA). This fusion not only improves the search efficiency of the algorithm, but also enhances its global and local search capabilities, thereby more effectively finding the global optimal solution. The research utilizes H-CRA technology for intelligent scheduling, achieving real-time monitoring and optimization of energy production and consumption. This intelligent management strategy helps to improve energy utilization efficiency, reduce waste, and enhance system reliability and user satisfaction.

The main contributions of this study can be summarized as follows: a multi-modal renewable energy hybrid power supply optimization model based on heterogeneous cloud wireless access (H-CRA) is proposed. This model provides a new perspective and solution for the effective management and optimization of renewable energy by combining advanced communication technology and multi-agent algorithms. A hybrid optimization algorithm (K-WOA-PSO) has been studied and designed, which effectively improves the performance of energy supply systems. The fusion of this algorithm not only improves search efficiency, but also enhances the ability to solve complex problems. The research results contribute to promoting the efficient utilization of renewable energy, reducing environmental pollution, and promoting sustainable development of energy supply. This is of great significance for addressing the global energy crisis and environmental protection. The abbreviations and full names in the article are shown in Table 1.

II. RELATED WORKS

The creation of energy optimization models has received an increasing amount of attention due to the quick development of wireless communication and cloud computing technologies as well as the rising popularity of renewable energy. For 5G and future wireless networks with high data rates, low energy consumption, and low latency, Moosavi et al. propose an orthogonal frequency division multiple access (OFDMA) and non-orthogonal multiple access (NOMA)-based heterogeneous cloud radio access network (H-CRAN) architecture. The findings showed that, with less complexity than the ideal solution, the suggested algorithm accomplishes a fair balance between energy efficiency and delay in terms of EC and EEE [4]. Pérez et al. developed a strategy in a shared backhaul fiber-optic wireless (FiWi)-enhanced H-CRAN with multi-access edge computing and offloading to fulfill the arithmetic complexity requirements of 5G+ network services and applications. According to the data, the approach works better than the traditional way in terms of energy usage and average latency, with an 80% improvement in average latency under heavy load [5]. Zhang et al. addressed the complex interference problem caused by the separation of the control and broadcast functions from the baseband processing unit (BBU) pool in H-CRAN by proposing a joint channel matrix sparsity and normalized water injection resource allocation algorithm, which reduces the computational complexity by reducing the cooperative transmission. The technique can successfully lower baseband energy consumption and raise system energy efficiency, according to simulation results [6].

TABLE 1. Article abbreviations.

Abbreviation	Full name
RE	Renewable Energy
MREHS	Multi-Modal Renewable Energy Hybrid Supply System
H-CRA	Heterogeneous Cloud Radio Access
PSO	Particle Swarm Optimization
WOA	Whale Optimization Algorithm
KCA	K-Clustering Algorithm
EEE	Energy Efficiency
NOMA	Non-Orthogonal Multiple Access
FiW	Fiber-Wireless
BBU	Baseband Unit
RPF	Regularized Particle Filter
KDE	Kernel Density Estimation
S-k-means	mproved Swarm-based K-means
loT	Internet of Things
QEA	Quantum Evolution Algorithm
DWOA	Dynamic Whale Optimization Algorithm
NWFSSP	No-Wait Flow Shop Scheduling Problem
ACO	mproved Ant Colony Optimization
K++	An Improved K-means Algorithm
ESO	Energy Supply Optimization
IACO	mproved Ant Colony Optimization

Aiming at the problems of real-time applications demanding high data rates, increasing number of connected devices, and limited spectrum and energy resources in 5G networks, Odwa et al. proposed an efficient wireless resource allocation scheme based on Regularized Particle Filtering (RPF) and state estimation using Monte Carlo Markov chain. The results revealed that the average throughput was improved by 5.94%-52.98% compared to the SISR method, proving the effectiveness of the RPF scheme [7]. Zhu et al. proposed an improved soft k-means (IS-k-means) clustering algorithm that combines fast search and peak density clusters (CFSFDPs) with kernel density estimation (KDE) to optimize the selection of the initial clustering centers in order to address the complex energy-load-balancing problem in functional systems. Comparing the approach to various techniques published in the literature, simulation results showed that for small-scale WSNs with single-hop transmission, the algorithm can, on average, delay the time of first node death, half node death, and last node death [8]. For continuous monitoring applications in wireless sensor networks, Sathyamoorthy et al. suggested an efficient clustering and load balancing technique based on Q-learning. This technique uses an enhanced K-Means algorithm for sensor node deployment and Q-learning for cluster head election. According to the findings, the technique shortens the network lifetime by 3.34%, boosts throughput by 2.34%, lowers end-to-end latency by 8.23%, and raises packet delivery rate by 1.56% [9].

Currently, PSO is widely used in many fields by virtue of its simplicity and ease of implementation. For example, Abualigah et al. proposed the Grasshopper Optimization Algorithm, which was modified, hybridized, and extended to binary, chaotic, and multi-objective scenarios, to explore optimization problems in various fields. The results revealed that the algorithm is effective and verified in several application examples. The conclusion proves the superiority and applicability of the algorithm [10]. Ning et al. constructed a three-layer offloading framework in the Intelligent Internet of Vehicles (IoV) to minimize the overall energy consumption of the energy supply system and satisfy the user delay constraints, and combined it with a population intelligence algorithm to decompose it into two parts. The effectiveness of the suggested approach was demonstrated by experimental results, which showed that the performance evaluation based on the real trajectories of taxis in Shanghai, China, and that the average energy consumption was decreased by almost 60% when compared with the baseline algorithm [11]. Ning et al. proposed a three-objective gate allocation model based on improved quantum evolutionary algorithm (QEA) and PSO to address the problem of tight gate resources due to the continuous growth of air traffic demand. The method shown great optimization ability and practical utility for airport managers' decision-making. Experimental results showed that the system can effectively solve the passenger walking distance, robustness, and cost problems in airport management [12]. Srinivasan et al. proposed a static synchronous compensator (STATCOM) controller for effective management of low-frequency electrochemical oscillation damping problems in power systems, using a hybrid algorithm based on the Dragonfly Algorithm (DA) and WOA. By comparing the major performance analysis of the suggested DWOA model with the state-of-the-art model at the moment, the experimental results demonstrated that the efficacy of the model had been significantly enhanced [13]. For the No-Wait Flow Shop Scheduling Problem (NWFSSP), Zhang et al. proposed a Discrete Whale Optimization Algorithm (DWOA) with the goal of minimizing the completion time as the optimization objective. The algorithm was combined with Nearest Neighbor (NN) and Standard Deviation Heuristic (SDH) to obtain the initial population solution, and a dynamic transformation mechanism was added to balance the algorithm's exploration and exploitation capabilities. According to the experimental data, DWOA performs better than other algorithms and the improvement process is effective [14]. Li et al. proposed a hybrid intelligent algorithm called DWOA, which combines the benefits of WOA and differential evolution and balances exploration and exploitation in order to find the global optimal solution, in order to address the issue of the high complexity of inter-regional power plant energy supply planning. The findings showed that the successive reconfiguration model is simpler to solve and that, in comparison to WOA, DE, and DE-WOA, DWOA obtains a satisfactory solution with better accuracy and stability, deviating from the theoretical results by only 1.61% [15]. This is anticipated to encourage the thorough optimization of compressor stations.

In summary, H-CRA techniques and population optimization algorithms have a wide range of application prospects in the field of MREHS optimization, and the further development of energy mixing supply provides an important theoretical foundation. However, few studies have been conducted to combine population intelligence algorithms with H-CRA techniques for energy mixing energy supply optimization (ESO). Therefore, the study aims to investigate an ESO model based on combining group intelligence algorithm with H-CRA technology for more efficient and reliable energy supply.

III. COMBINING ENERGY SUPPLY OPTIMIZATION MODEL BASED ON HETEROGENEOUS CLOUD RADIO ACCESS WITH POPULATION OPTIMIZATION ALGORITHM

There are three primary subsections in this chapter. The first one deals with modeling the use of H-CRA modeling in the energy supply industry. The initial creation of algorithms like KCA and Group Intelligence Algorithm is the subject of the second subsection. The third subsection is to integrate H-CRA with KCA and group intelligence algorithms and make a series of improvements.

A. HETEROGENEOUS CLOUD RADIO ACCESS MODELING

In the modeling process of heterogeneous cloud wireless access networks, it is crucial to conduct detailed analysis and optimization of multi-mode renewable energy hybrid supply systems. The core of this work lies in identifying and defining key decision variables that affect system performance, and improving overall operational efficiency and energy supply stability through reasonable configuration and management. When defining decision variables, the first thing to consider is the quantity, scale, and configuration of various types of renewable energy equipment; The type and capacity of energy storage equipment, each with its specific capacity efficiency and environmental adaptability. In addition to the energy equipment itself, the type and capacity of energy storage equipment are also important components of decision variables. For example, battery energy storage systems, pumped storage, or compressed air storage. The selection of energy conversion equipment and its parameter settings are also important decision-making points that cannot be ignored. Through intelligent scheduling and network optimization, energy loss can be effectively reduced and energy utilization efficiency can be improved. With the above basis, it is necessary to establish constraint conditions next. These constraints come from multiple aspects, such as the uncertainty and time-varying nature of renewable energy supply; Technical and cost limitations of equipment; The volatility and prediction errors of energy demand; And requirements for environmental protection and sustainable development. From this, energy supply constraints and technological constraints can be obtained as shown in equation (1).

$$\begin{cases} S(t) \geq D(t) + \delta \\ P_{\min} \leq P_i(t) \leq P_{\max} \end{cases} \tag{1}$$

In equation (1), $S(t)$ represents the total energy supply at time tt, $D(t)$ represents the energy demand at time tt, δ is a positive threshold representing the minimum reserve of the system. $P_i(t)$ represents the production capacity of the second type of energy equipment at time t, $P_{\min}$ And $P_{\max}$ Represent the minimum and maximum production capacity of the device, respectively. Firstly, from the perspective of optimization algorithms, mixed optimization analysis may involve the combination of multiple algorithms, such as linear programming, nonlinear programming, dynamic programming, heuristic algorithms, etc. These algorithms each have their own advantages and disadvantages, and need to be selected and adjusted according to the specific characteristics of the problem. Secondly, from the perspective of system modeling, hybrid optimization analysis needs to consider multiple aspects such as the overall architecture, energy flow, and information transmission of the system, which involves knowledge from multiple disciplines such as systems engineering, control theory, and information science. Therefore, the H-CRA technique was used, in the H-CRA-based MREHS optimization model, the role of H-CRA is reflected in several key aspects [16], [17]. Compared to cloud services such as Google Cloud and Amazon SageMaker, the characteristics of H-CRAN are mainly reflected in its powerful data processing and transmission capabilities. It provides computing and storage resources for the base stations in different geographical locations through cloud resource pools, realizing efficient communication and flexible network management. In addition, H-CRAN enables a distributed architecture and multimodal access capabilities for multiple wireless communication standards and frequency bands, enhancing network compatibility and diversity. At the same time, H-CRAN can dynamically manage network resources, optimize energy utilization and reduce the dependence on the traditional power grid through intelligent scheduling and prediction technology. Finally, H-CRAN combines artificial intelligence and machine learning technologies to realize intelligent and autonomous energy management, and ensure the stable and efficient operation of the network under changing environments and energy conditions. First, its distributed architecture provides strong support for flexible deployment of base stations and integration of RE sources. This architecture not only adapts to different environments and energy conditions, but is also easily scalable to meet growing communication demands. Second, H-CRA is able to dynamically manage network resources. By monitoring energy changes and network demand in real time, as well as predicting the availability of RE, resource allocation is adaptively adjusted to ensure efficient network operation [18], [19]. In addition, its multimodal access capability enhances the compatibility and diversity of the network, supporting a wide range of wireless communication standards and frequency bands, while providing greater flexibility for hybrid energy supply strategies with multimodal RE sources. Through load balancing technology, H-CRA effectively disperses network traffic and optimizes energy consumption in conjunction with RE strategies, thereby reducing dependence on the traditional power grid. The optimization of backhaul links further improves the data transmission efficiency and energy management effectiveness, which helps to enhance the performance of the entire RE power supply system [20], [21]. Finally, with the help of artificial intelligence and machine learning technologies, H-CRA realizes intelligent and autonomous energy management, enabling the network to make intelligent decisions based on real-time data and historical information, and to adapt itself to changing environmental and energy conditions to ensure stable and efficient network operation. Together, these features reflect the central role of H-CRA in the MREHS-based optimization model, as shown in Fig. 1.

MREHS refers to the utilization of many different types of RE sources, which together provide the required energy for a system or application through rational configuration and management [22], [23]. The goal of this hybrid energy supply is to achieve efficient, steady, and sustainable energy use by combining the benefits of many RE sources. Renewable energy sources that are multimodal include biomass, geothermal, hydro, sun, and wind [24], [25]. These energy sources have different characteristics and applicable conditions, for example, solar and wind energy are affected by geographic location and climatic conditions, while hydroelectric energy depends on water resources, and geothermal energy is related to underground heat sources. By combining and configuring these energy sources in a reasonable way, the deficiency of a single energy source can be compensated and the stability and reliability of energy supply can be improved. Hybrid energy supply systems usually include components such as energy conversion equipment, storage equipment, and control systems. Energy conversion equipment converts RE into electricity or other forms of energy, storage equipment is used to balance the difference between energy supply and demand, and the control system monitors and schedules the entire system to ensure the efficient use of energy, the structure of which is shown in Fig. 2.

In this system there is a Cloud Resource Pool which provides resources such as storage, computation and network for supporting data storage and processing. Below the Cloud Resource Pool are multiple Base Stations, which are distributed in different geographical locations and communicate with the nodes through different wireless communication technologies (Wi-Fi, 4G, 5G, etc.). The Base Station is responsible for transmitting the data from the nodes to the Cloud Resource Pool and getting the processed data from the Cloud Resource Pool back to the nodes. Below the base station are multiple nodes (Nodes), which are the core nodes in the energy supply system, e.g., energy generators, energy consuming devices, etc. Every node connects wirelessly to the matching base station and uploads the data it has gathered to the cloud resource pool so it may be processed and analyzed. Below the nodes are multiple Sensor Nodes, which are responsible for collecting environmental data, energy data, etc. and transmitting the data to the nodes. Below the nodes are multiple Actuator Nodes, which are responsible for executing corresponding operations, such as controlling the output of energy generating devices, controlling the switch of energy consuming devices, etc., according to the commands received from the cloud resource pool. The whole system realizes flexible communication support between nodes and efficient data transmission capability through H-CRA, so that the nodes, sensor nodes and Actuator Nodes in the energy supply system can realize data transmission, communication and control, thus realizing intelligent management and optimization of the energy supply system. Through the integration of H-CRA, K-clustering (K-means clustering), and PSO algorithms, the MREHS system may be optimized to enhance energy use efficiency and sustainability.

B. DESIGN OF MODEL-ASSISTED ALGORITHMS FOR ENERGY SUPPLY OPTIMIZATION

1) THE BASIC FLOW OF THE KCA CLUSTERING

The K-clustering algorithm is a popular unsupervised learning technique that groups n items into k clusters ($k \leqslant n$) with the goal of maximizing object similarity within a cluster and maximizing object difference between clusters. In energy supply systems, K-clustering can group nodes based on their energy output, energy consumption, and other characteristics [26], [27]. The energy heating feature clustering model based on K-clustering is an effective method for analyzing and understanding the underlying structure and characteristics of energy heating data. The model reveals the intrinsic laws of the data by gathering similar data points together in a series of steps to form clusters with similar characteristics. And Fig. 3 depicts the clustering process.

First, careful data preparation is required to ensure the accuracy and effectiveness of clustering. This includes selecting those features that best reflect the energy characteristics of the nodes, such as output volume, consumption volume, and duration of use, and normalizing the data of these features to eliminate the effects due to differences in the quantiles. Next, selecting the appropriate k-value and initializing the center of mass are the key steps. k-value selection should be based on the understanding of the heating system and actual needs. For example, if it is desired to identify several major energy usage patterns, then the k-value can be set to a value similar to the expected number of patterns. And although the selection of the initial center of mass has some influence on the final result, the K-means algorithm can usually converge to a better solution through several iterations. During the clustering process, each node is assigned to the cluster where its nearest center of mass is located. This step reflects the similarity between the nodes and the different

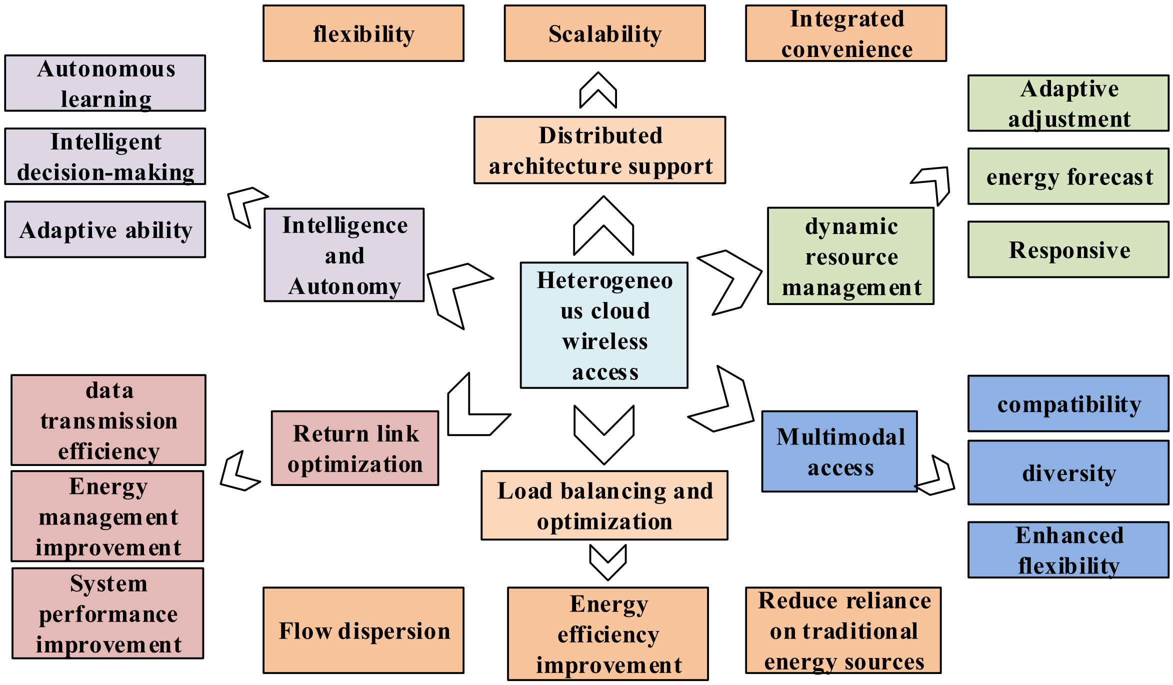


FIGURE 1. The multifaceted effects of heterogeneous cloud wireless access.

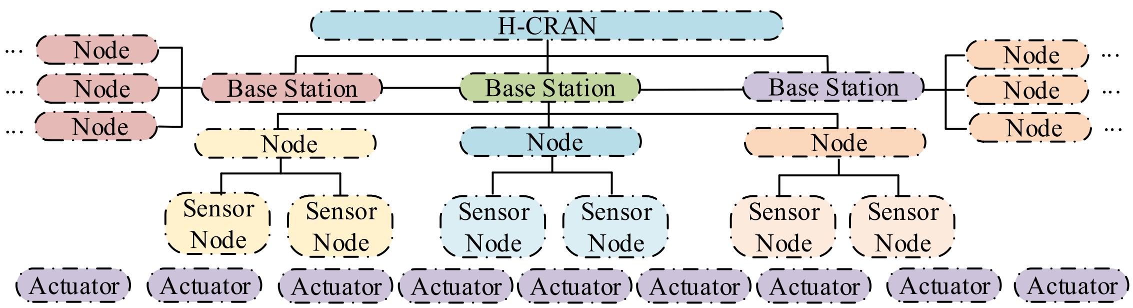


FIGURE 2. Schematic diagram of heterogeneous cloud wireless access technology institutions.

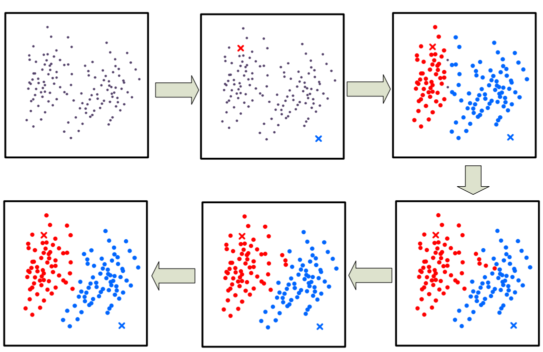


FIGURE 3. Schematic diagram of K-means clustering algorithm clustering process.

energy usage patterns. As the iteration proceeds, the nodes within the clusters become more and more similar, while the differences between the clusters become more and more obvious, as shown in Fig. 4.

The next step is the initialization step, which includes selecting an appropriate number of clusters (k values) and randomly selecting k objects as the centroids of the initial clusters. The selection of k value should be based on practical needs or experience, and the selection of initial centroids has a certain impact on clustering results, but usually better results can be obtained through multiple iterations. During the clustering and grouping process, the KCA algorithm is used to cluster the previously extracted feature data, with the aim of reasonably dividing the nodes in the network into K clustering sets. Choose cosine similarity as the standard to measure the similarity between data points, ensuring that nodes within the same cluster have a high degree of similarity in energy output and consumption characteristics. The K value, as the core parameter of clustering, plays a crucial role in the clustering effect. In order to find the optimal K value, the contour coefficient is introduced as an evaluation index, which can effectively reflect the compactness and

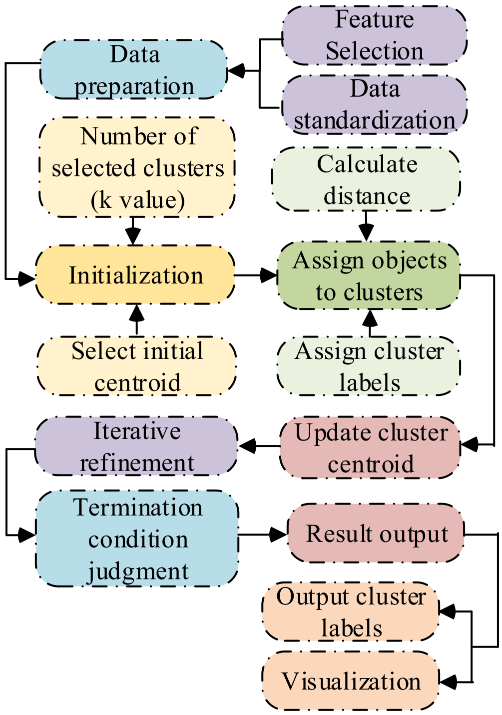


FIGURE 4. Schematic diagram of the clustering model structure for energy heating characteristics based on K-clustering.

separation of clustering. After determining the optimal K value, execute the clustering algorithm and analyze the obtained clustering results. For example, certain clusters may represent high-energy consuming devices within an organization due to their high energy consumption characteristics. And other clusters may be identified as high energy efficiency devices due to efficient energy conversion. This analysis helps to gain a deeper understanding of the energy consumption patterns of devices or nodes, providing data support for subsequent optimization measures. Iterative optimization refers to the process of assigning objects and repeatedly updating the centroid step size until specific termination conditions are met, such as when the maximum number of iterations is reached or the change in centroid is less than a threshold. This process is the core of clustering algorithms, which improves the accuracy of clustering by constantly changing the centroid and object attribution. The process terminates and reports the cluster label of each object once the termination conditions are met. In addition, tools such as scatter plots can be used to visualize the distribution of various clusters, providing a more intuitive representation of clustering results. KCA is also useful for clustering nodes with similar energy characteristics together, which is very helpful for optimizing MREHS systems. Its coefficient of variation is shown in equation (1).

$$CVp = |\frac{Sp}{Ap}| = |\frac{\sqrt{\sum_{i=1}^{n}(x_{i,p} - \frac{\sum_{i=1}^{n} x_{i,p}}{n})^2}}{\frac{\sum_{i=1}^{n} x_{i,p}}{n}}| \tag{2}$$

In equation (1), Sp represents the standard deviation, Ap represents the mean, and$p$ represents the dimension. Equation (3) provides the formula for determining the importance coefficient.

$$Wp = \frac{CVp}{CV_1 + CV_2 + CV_3} \tag{3}$$

The choice of the beginning center of mass has a significant impact on the KMA, and various initial centers of mass may produce various clustering outcomes. By running the K-mean algorithm several times, several different clustering results can be obtained, and then these results are integrated by integration, which improves the stability of the clustering results. Integrated learning can reduce the local optimum problem caused by improper selection of the initial center of mass and make the clustering results more reliable. Therefore, the study designs the IK-means algorithm by randomly selecting the initial center of mass by running the K-means algorithm several times with different initial centers of mass obtained by initialization each time, drawing on the implementation of integrated learning. In order to evaluate the clustering results of each run, some common metrics for evaluating the clustering effect can be used, such as contour coefficient and Davies-Bouldin index. The contour coefficient, which takes a value between [−1,1] to represent the tightness and separation of the clusters, indicates how well the clustering is done. The closer the value is to 1, the better. The tightness and separation of the clustering results are balanced by the Davies-Bouldin index; the smaller the value, the better the clustering.

2) THE BASIC FLOW OF THE PSO ALGORITHM

The PSO algorithm is a heuristic optimization method that draws inspiration from the foraging habits of birds. Finally multiple clustering results are selected for integration and results are fused using voting. The research sets the parameter of Particle Swarm Optimization (PSO) as: population size n = 10, which means that there are 10 particles searching simultaneously in the solution space. Each particle moves in a D = 3-dimensional space, indicating that each solution consists of three variables. The algorithm will perform a maximum of N = 50 iterations to ensure that particles are given enough time to find the optimal solution. The inertia weight w is set to 0.9, which determines the tendency of particles to maintain their original velocity. The self-learning factor c and group learning factor c are both set to 1.1, which affect the speed at which particles approach their own historical best and global best solutions, respectively.PSO algorithm is characterized by strong global search capability, easy implementation and fast convergence speed, and it is suitable for multi-dimensional continuous optimization problems, and the basic steps of its algorithm are shown in Fig. 5.

3) THE BASIC FLOW OF THE WOA ALGORITHM

The benefits of WOA include its ease of use, low number of parameters to tweak, ability to break out of the local optimum,

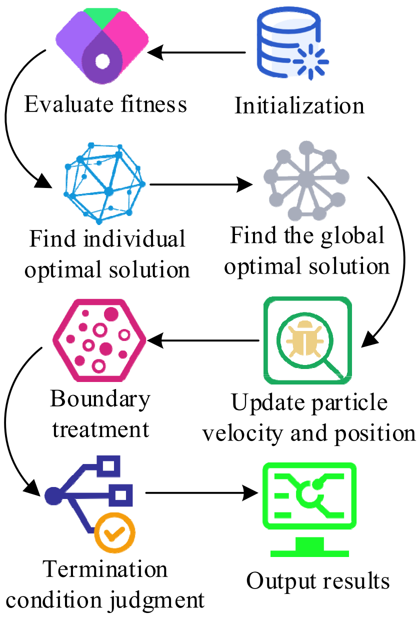


FIGURE 5. Algorithm flowchart of PSO.

speed in locating the optimal solution, and effectiveness in resolving a variety of optimization issues. It also has relatively good convergence and stability for basic problems. Assuming that in the d-dimensional space, assuming that X_k^* denotes the current optimal whale position and r_1 and r_2 are random numbers between [0,1], the formula for its optimization search is illustrated in equation (4).

$$\begin{cases} X_k^{T+1} = X_k^* - \overline{A} \times D_k \\ D_k = \left|\overline{C} \times X_k^* - X_k^T\right| \\ \overline{A} = 2a \times r_1 - a \\ \overline{C} = 2r_2 \\ a = 2 - \dfrac{2T}{T_{\max}} \end{cases} \tag{4}$$

In equation (4), T denotes the current iteration number, $\bar{A}$ and a represent the coefficient vectors, and B denotes the linear decrease from 2 to 0 with the increase of iteration number. Assuming that r denotes the logarithmic spiral shape parameter, the expression form for simulating the whale spiral feeding behavior is shown in equation (5).

$$\begin{cases} X_k^{T+1} = \overline{D}_k \times e^{rq} \times \cos(2\pi q) + X_k^* \\ \overline{D}_k = \left|X_k^* - X_k^T\right| \end{cases} \tag{5}$$

In equation (5), r denotes the logarithmic spiral shape parameter, q denotes the random number between [−1,1], and $\overline{D}_k$ denotes the distance between the searching individual and the prey. X_k^{i+1} denotes the kth component of the spatial coordinate X^{i+1} and the specific expression form is shown in equation (6).

$$X_k^{T+1} = \begin{cases} X_k^* - \overline{A} \times D_k, & P < 0.5 \\ X_k^* + D_k \times e^{rc} \times \cos(2\pi c), & P \geq 0.5 \end{cases} \tag{6}$$

In equation (6), P denotes the probability, and assuming that X_k^{rand} denotes a random individual whale, the search-and-prey mathematical model is shown in equation (7).

$$\begin{cases} X_k^{T+1} = X_k^{rand} - \overline{A} \times D_k \\ D_k = \left|\overline{C} \times X_k^{rand} - X_k^T\right| \end{cases} \tag{7}$$

The specific algorithm flow of WOA is shown in Fig. 6.

In Fig. 6, the WOA modeling first initializes the parameters and the position of the whale group, and then calculates and records the current position of the optimal whale individual. Then the value of each parameter is calculated, if $P < 0.5$ and $\left|\overline{A}\right| \leq 1$, the current whale individual approaches the optimal whale individual to encircle the prey by spiraling, otherwise, the current whale enters into the search and predation behavior. After calculating the values of each parameter, the algorithm will determine the behavior of individual whales based on these values. If the current whale is close to the optimal whale individual, it will gradually surround the prey in a spiral rotation, simulating the whale's predatory behavior to achieve precise search. Otherwise, the current whale will enter a wider range of search and predation behaviors to explore other regions in the solution space. After each iteration, the algorithm recalculates the fitness value of each whale and compares it with the previously recorded best whale position. If a better solution is found, update the optimal position. This process will continue until the maximum number of iterations N = 50 is reached, or until the optimal solution that meets the termination condition is found. The parameter b that controls the spiral shape is set to 1, which affects the behavior pattern of whale individuals when surrounding prey, making the search process more flexible and efficient. Ultimately, the algorithm will output the objective function value of the optimal individual whale, which is the optimal solution to the problem. However, WOA exists the problem of premature convergence and easy to fall into the local optimum, the study improves on the basis of WOA and designs IWOA. firstly, the chaotic sequences are generated using tent mapping in the initialization stage in order to make the initial solution uniformly distributed, the specific method is shown in equation (8).

$$x_{k+1} = \begin{cases} \mu x_k, & x_k < 0.5 \\ \mu(1 - x_k), & x_k \geq 0.5 \end{cases} \tag{8}$$

In equation (8), μ denotes the chaos parameter and x_k denotes the kth mapping function value. In order to dynamically adjust the whales' seining behavior, the study introduces adaptive probability balancing. When the whale approaches the prey, the adaptive probability increases and the whale performs a finer local search. When the whale moves away from the prey, the adaptive probability decreases and the whale performs a broader global search. This dynamic adjustment helps to improve the search efficiency of the algorithm, as described in equation (9).

$$\overline{P} = 1 - \log_{10}(1 + \frac{9T}{T_{\max}}) \tag{9}$$

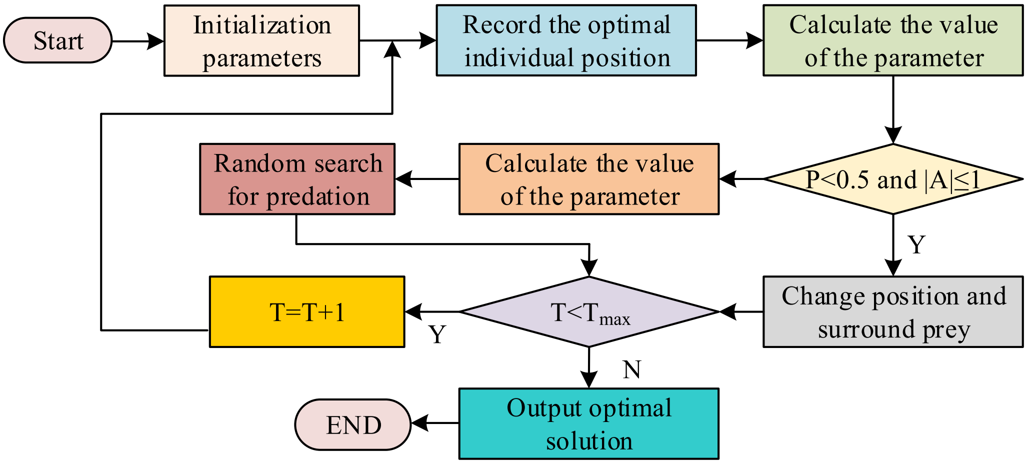


FIGURE 6. Specific process of WOA modeling.

C. H-CRAN ENERGY SUPPLY OPTIMIZATION MODEL COMBINING K-CLUSTERING WITH IWOA PSO

A single PSO algorithm or WOA algorithm may fall into a local optimum solution in some cases. By combining the two algorithms, the diversity of the algorithms can be increased and the risk of falling into local optimality can be reduced [28]. PSO algorithm and WOA algorithm have some complementarity in search mechanism.PSO algorithm is good at global search, while WOA algorithm is good at local fine search. By combining the two, one may completely take advantage of each's benefits and raise the algorithm's search efficiency and accuracy. The WOA algorithm's local search capability may conduct a detailed search within the region, speeding up the algorithm's convergence, while the PSO algorithm's global search capability can assist the algorithm in swiftly locating the possible optimal solution region. In Figure 7, the IWOA-PSO procedure is displayed.

First set the basic parameters of the particle swarm, such as size, dimension, velocity range, position range, and so on. At the same time, the initial position and velocity are randomly assigned to each particle in the particle swarm. Each particle is usually encoded as a multidimensional vector whose dimension corresponds to the number of variables of the optimization problem. In addition to the particle swarm size and dimension, PSO parameters such as learning factor and inertia weights, as well as spiral shape parameters and step size in the WOA algorithm need to be set. The second step is data collection, which utilizes H-CRA technology to collect data from various nodes in the energy supply system, including key features such as energy output and energy consumption. The third step is data preprocessing, where the collected raw data may require preprocessing operations such as cleaning, normalization, or normalization to eliminate noise and magnitude differences. Feature selection, from the preprocessed data, features that are closely related to energy supply performance are selected to reduce computational complexity and improve optimization. The third step is feature extraction, where key features related to energy supply

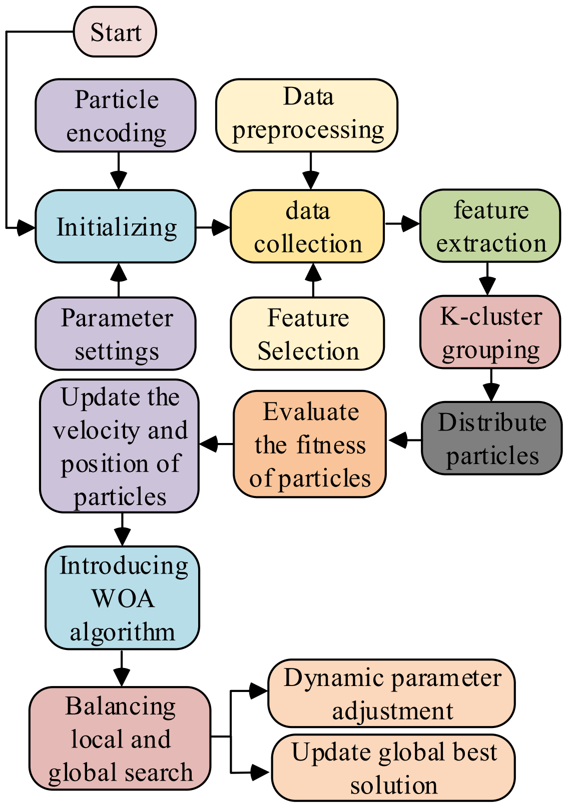


FIGURE 7. Schematic diagram of IWOA PSO structure.

are extracted from the collected data to provide inputs for the subsequent K-clustering and optimization algorithms. In the fourth step K-clustering grouping, KCA is applied to cluster the extracted feature data and divide the nodes into K clusters. Nodes within each cluster have similar energy output and consumption characteristics. The fifth step allocates particles and assigns a certain number of particles to each cluster based on the clusters and the size of the particle population. These particles will be optimized on behalf of the nodes within that cluster. The sixth step evaluates the fitness of the particles and defines a fitness function for evaluating the performance of each particle. This function is usually based on the energy output and consumption of the nodes, as well as other possible constraints. The enhanced fitness function is displayed in equation (10). This is the seventh phase in the fitness function design process. The fitness function should be able to effectively reflect the energy supply system's performance, which often involves numerous aspects including energy output, consumption, efficiency, etc.

$$v(t+1) = \frac{w}{v(t)} + c1^{*}rand()^{*}(pBest - x(t)) + c2^{*}rand()^{*}(gBest - x(t)) \quad (10)$$

In equation (10), $v(t)$ represents the velocity at the current moment, w is the inertia weight, $rand()$ is the random function, and $pBest$ represents the individual's historical best position, whose position update formula is shown in equation (10).

$$\mathrm{x(t+1) = x(t) + v(t+1)} \quad (11)$$

In equation (10), x(t) denotes the position at the current moment and v(t+1) denotes the speed at the next moment. Since there are constraints in the system in energy, such as energy supply and demand balance, equipment capacity limitations, etc., they need to be handled accordingly in the adaptability function. Assuming that the energy gap is E_gap, the amount of equipment exceeding the limit is C_exceed, k2 is the coefficient of the penalty function, and the penalty function is shown in equation (12).

$$\mathrm{Penalization} = \mathrm{k1^{*}E\_gap + k2^{*}C\_exceed} \quad (12)$$

In equation (4), k1 is the coefficient of the penalty function, which is used to regulate the degree of punishment of the penalty function. The fitness value of the person who deviates from the energy supply and demand balance is decreased when the energy gap widens and the punishment function's value increases. In the eighth phase, each particle updates its position and velocity based on its own historical best position as well as the global best position, in accordance with the PSO algorithm's basic idea. The PSO algorithm's update formula, which often includes guidance in both directions of the individual's historical best and global best, is used to iterate the particle's velocity and location. The ninth step introduces the WOA algorithm, which is based on the PSO and introduces the WOA strategy. WOA simulates the predatory behavior of whales and updates the position of particles by moving spirally around the prey. The tenth step is to perform local and global search balance, combining the global search capability of PSO and the local fine search capability of WOA to achieve balance in the search process and avoid falling into the local optimal solution. Dynamic parameter adjustment, with the iteration, the parameters of PSO and WOA, such as learning factor and inertia weight, can be adjusted dynamically to realize the balance between global and local search. The dynamic adjustment formulas of learning factor and inertia weights are shown in equation (13), as shown at the bottom of the next page.

In equation (13), learning_factor_initial is the initial learning factor and inertia weight value, iteration denotes the current number of iterations, and max_iterations denotes the maximum number of iterations. The ability of local and global search can be balanced to increase the optimization algorithm's efficacy by dynamically modifying these parameters. Subsequently, the global optimal solution is updated, taking into account the fitness values of every particle in each iteration. Lastly, if additional termination circumstances are met or the predetermined number of iterations is reached, the process is checked. If satisfied, go to the next step, otherwise, return to step 7 to continue the iteration. The PSO-WOA-optimized node energy supply solutions within each cluster are fused to form the MREHS optimization solution for the whole energy supply system by considering the synergistic effect and overall performance among clusters. By fully utilizing WOA's local fine search capability and PSO's global search power, this method successfully keeps the algorithm from finding local optimal solutions and enhances the optimization effect. Finally, the system transfers the IPSO-WOA optimization results to each functional node efficiently through the H-CRAN framework proposed in the study, and realizes the overall optimization of the system through the actuators of each node, and the overall scheme of the MREHS optimization model based on H-CRA is shown in Fig. 8.

Effective optimization of MREHS can be achieved by integrating H-CRA, K-clustering and population group optimization algorithms. First, the flexible communication and efficient data transmission capabilities of H-CRA technology are utilized to connect the nodes in the energy supply system to ensure smooth data transmission and communication. Next, KCA is used to process the collected node data, cluster the nodes according to their energy output, energy consumption and other characteristics, and divide the nodes into different clusters, with nodes within each cluster possessing similar characteristics. Then, the PSO-WOA optimization algorithm is applied to optimize the nodes in each cluster, and the energy supply in each cluster is optimized by adjusting the nodes' energy output, energy consumption and other parameters. Finally, the optimized node energy supply schemes in each cluster are fused to form the MREHS optimization scheme for the whole energy supply system. This fusion method makes full use of the advantages of each algorithm, improves the energy utilization efficiency and energy supply quality, and realizes the intelligence and efficiency of the energy supply system. In order to implement the above framework, we will study the use of IoT communication protocol libraries such as MQTT and CoAP to achieve efficient communication of H-CRA. Scikit learn in Python is used to implement KCA clustering analysis, while Pyswarm optimization algorithm library is used to optimize PSO and WOA processes. When implementing the above architecture, microservices architecture may be used to ensure system scalability and maintainability. Various services can communicate through the message queue RabbitMQ to achieve real-time data transmission and processing. In addition, utilizing containerization technology Docker and to deploy and manage the entire system. During the process, tools such as Prometheus and Grafana were used for real-time monitoring and data analysis of the system.

IV. PERFORMANCE TESTING AND APPLICABILITY ANALYSIS OF MREHS OPTIMIZATION MODELS

This chapter is organized into two main subsections. The first subsection focuses on the performance testing and comparison experiments of each component as well as the ablation experiments of the study's proposed K-WOA-PSO model. The second subsection applies the algorithm to a real MREHS system for applicability analysis

A. TESTING OF MODEL PERFORMANCE AND COMPARATIVE EXPERIMENTS

Aiming at the problem that traditional ESO methods rely on heuristic rules or fixed search strategies, which are unable to comprehensively explore the solution space of the problem, the study designs a heterogeneous cloud access-driven hybrid optimization algorithm of K-WOA-PSO based on the heterogeneous cloud access, which combines the KCA with the WOA-PSO. To verify the applicability of the algorithm in the ESO problem, the study first conducts model ablation experiments. The experiments are conducted for the missing K-clustering module, the missing WOA module, and the PSO module, respectively. The convergence curves of the four models are computed by the Alike function and the generalized penalty function of the second kind, and the experimental results are shown in Fig. 9.

The convergence of the K-WOA-PSO hybrid optimization algorithm and its three variants (lack of WOA module, lack of K-clustering module, and lack of PSO module) in the second generalized penalty function can be clearly seen through an in-depth interpretation of Fig. 9(a). Among them, the K-WOA-PSO algorithm achieves convergence at about the 160th iteration, showing a relatively fast convergence rate. In contrast, the other three variants of the algorithm converged relatively slowly, reaching convergence at the 80th, 90th and 390th iterations, respectively. In terms of adaptation, the K-WOA-PSO algorithm reaches the lowest -15.1, which is significantly better than the other three variants, which all stay around -8.Turning to the Alic function analysis in Fig. 9(b), the K-WOA-PSO algorithm reaches convergence at the 71st iteration, again proving its efficient convergence performance. The other three variants of the algorithm, on the other hand, converge relatively slowly, at the 392nd, 190th and 20th iterations, respectively. In terms of fitness performance, the K-WOA-PSO algorithm achieves the lowest -12.5, while the fitness of the other three algorithms converges at -11.3, -11.6 and 1.3, respectively. This result shows that the K-WOA-PSO algorithm also demonstrates superior performance in algebras. In addition, Whale Optimization Algorithm-Genetic Algorithm (WOA-GA), Particle Swarm Optimization-Genetic Algorithm (PSO-GA) and Whale Optimization Algorithm-Ant Colony Optimization (WOA-ACO) for comparison experiments, the Breast Cancer dataset and the Iris dataset were used to train the four algorithms for 600 iterations respectively, and the results are shown in Fig. 10.

According to the results in Fig. 10(a), the WOA-PSO model shows excellent performance. After only 150 iterations, the model achieves 95.1% accuracy in problem solving, exceeding the performance of other models. In Fig. 10(b), the accuracy of all algorithmic models varies when using the Breast Cancer dataset. However, the WOA-PSO model has a relatively stable change in accuracy, showing only a slight 0.5% decrease. In contrast, the WOA-ACO model had the largest change in accuracy, with a significant 14.8% increase in accuracy at convergence, eventually converging to 90.9% accuracy. These findings demonstrate the high problem-solving performance of the WOA-PSO model and the critical importance of selecting the right algorithmic model for the Breast Cancer dataset in order to maintain accuracy and convergence. In order to build an experimental environment to implement KCA to process the node data and perform the clustering analysis of energy output and consumption characteristics, the experiments are simulated using the scikit-learn library in Python. The experiment results are displayed in Fig. 11. Scikit-learn is a potent machine learning toolkit that offers a range of widely used clustering techniques, including K-means clustering algorithms.

In Fig. 11(a), the traditional KCA produces seven categories when processing the data, which are relatively centralized, showing that the algorithm is able to capture the intrinsic structure of the data to a certain extent. However, due to things like the intricacy of the data distribution and the choice of the starting clustering center, using this conventional clustering method might also result in unstable clustering outcomes. In Fig. 11(b), the improved integrated KCA produces 10 clusters when processing the same data. Compared with the traditional KCA, the integrated KCA obtains a more detailed and accurate clustering delineation by integrating the results of multiple runs. This means that integrated KCA is better able to capture the subtle differences and local structure of the data, providing more comprehensive and accurate clustering information. To fully verify the algorithm's superiority, the experiment compares the three algorithms to process the data with varying numbers of

$$\begin{cases} \text{learning\_factor} = \text{learning\_factor\_initial}^{*}(1 - \text{iteration} / \text{max\_iterations}) \\ \text{inertia\_weight} = \text{inertia\_weight\_initial}^{*}(1 - \text{iteration} / \text{max\_iterations}) \end{cases} \tag{13}$$

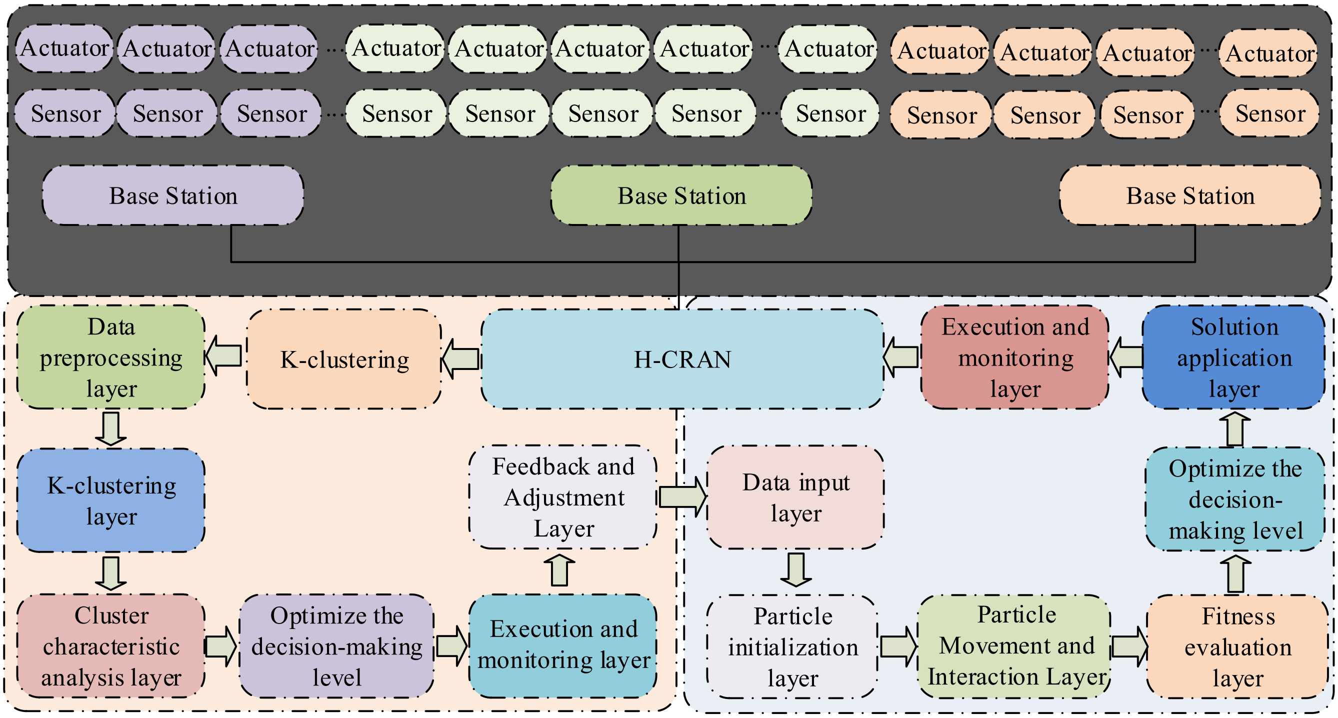


FIGURE 8. Overall scheme of multimodal renewable energy hybrid energy supply optimization model based on heterogeneous cloud wireless access.

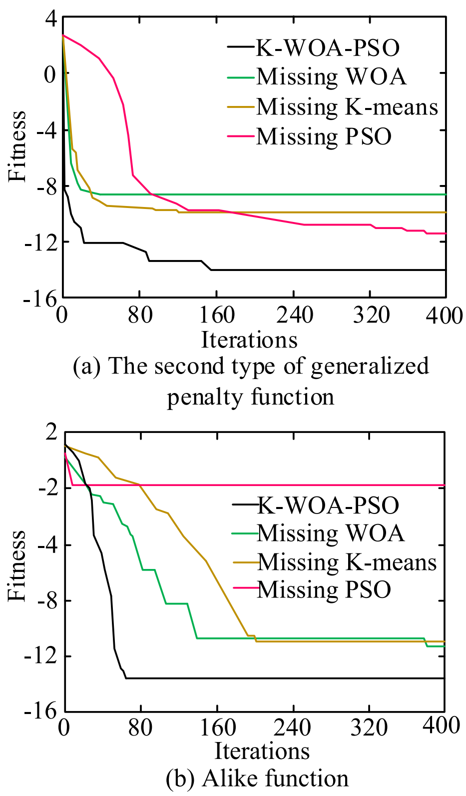


FIGURE 9. Performance of four algorithms in two functions.

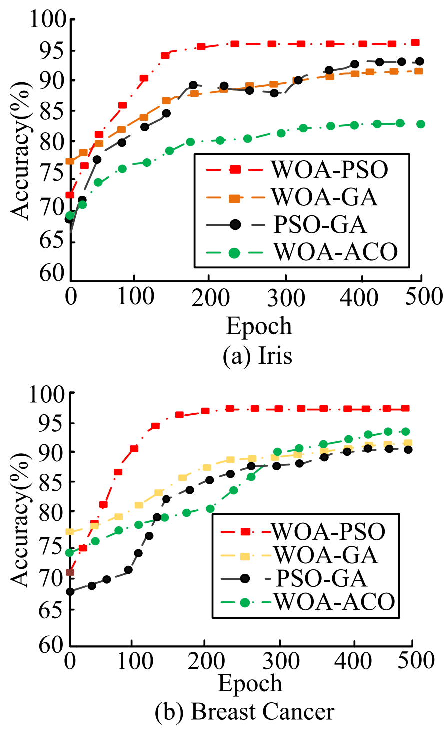
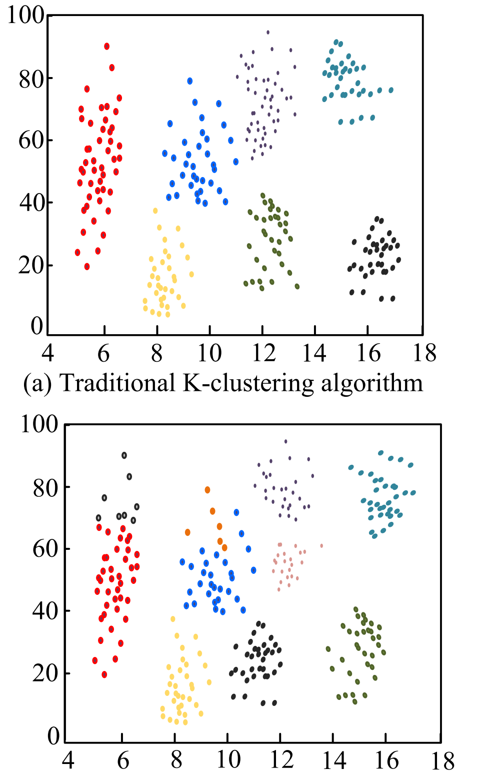


FIGURE 10. Comparison of breast cancer and open Irisdata set.

energy-supplying base stations for the throughput comparisons, introducing the improved K++ clustering algorithm proposed in the literature [29] for comparative experiments. The experimental results are displayed in Fig. 12.

In the Fig.12, the throughput of the three algorithms varies but converges at a similar rate. The throughput of the three algorithms converges after the number of energy-supplying base stations reaches 230. Among them, the proposed IK-means has the best performance with the throughput



(a) Traditional K-clustering algorithm

(b) Improving traditional K-clustering algorithm

FIGURE 11. Clustering effect of K clustering algorithm.

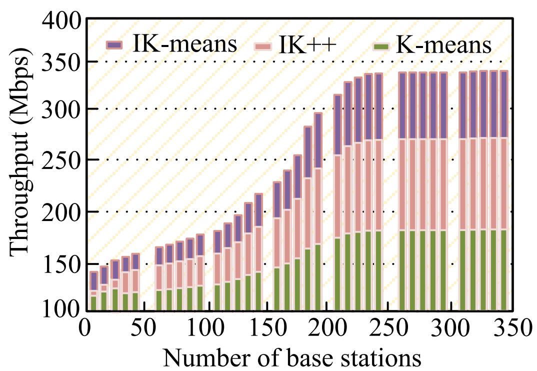
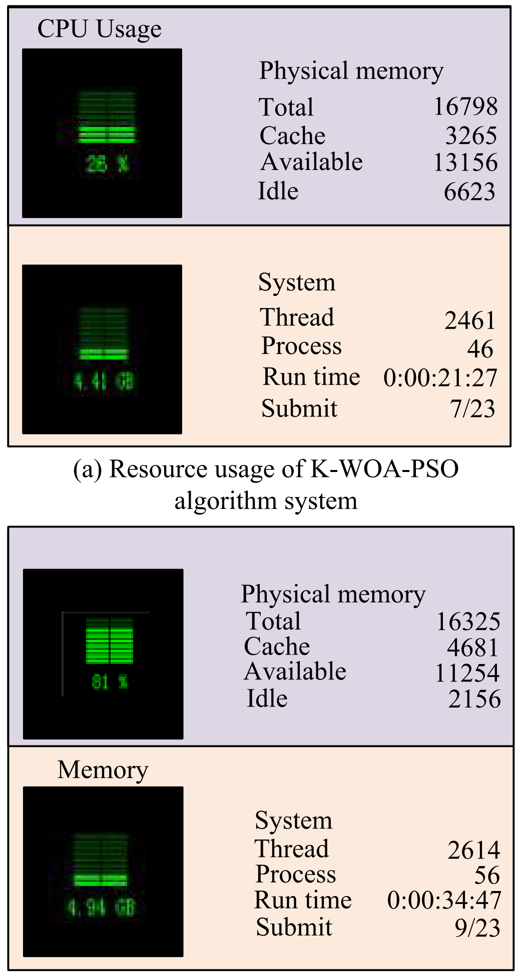


FIGURE 12. Throughput statistics of three clustering algorithms.

converging at 340 Mbps, while the IK++ algorithm converges at 265 Mbps, and the standard KCA has the worst performance with the throughput of 180 Mbps. In summary, by comparing and analyzing the throughput and convergence speed of the three algorithms, the proposed IK-means algorithm has a superiority in the field of MREHS optimization. superiority. The algorithm is not only able to achieve high throughput, but also maintains good performance after the number of energy-supplying base stations reaches a certain scale. This provides a strong technical support and theoretical basis for improving energy utilization efficiency and optimizing the energy supply system in practical applications. The study selected the optimal fitness value, convergence speed, algorithm stability, and computation time



(a) Resource usage of K-WOA-PSO algorithm system

(b) Resource usage of IACO algorithm system

FIGURE 13. System resource consumption during the operation of two algorithms.

as evaluation indicators. The rationality of selecting these indicators lies in their comprehensive consideration of the performance and practicality of the algorithm. The optimal fitness value ensures the quality of the algorithm solution, convergence speed and computation time focus on the efficiency of the algorithm, while algorithm stability ensures the reliability of the algorithm.

B. APPLICATION ANALYSIS OF THE MODEL

The study fully demonstrates the superiority of the proposed algorithm in the field of MREHS optimization, and in order to further verify that the algorithm has the same excellent performance in practical applications, the study introduces the Improved Ant Colony Optimization (IACO) model proposed in the literature [30] to compare with the proposed heterogeneous cloud access-driven hybrid K-WOA-PSO optimization algorithm to compare the two algorithms and apply them to real ESO. The study first recorded the system resource consumption of the two algorithms during operation, and the results are shown in Fig. 13.

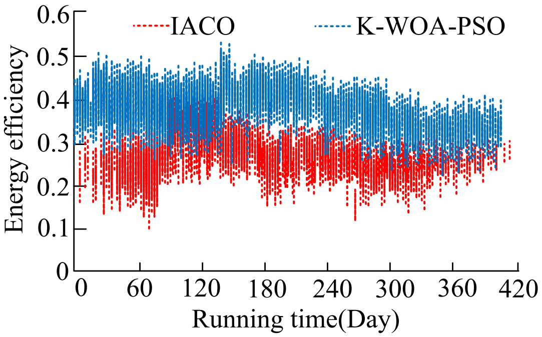


FIGURE 14. The variation of the error of the two algorithms with the passage of running time.

In Fig. 13(b), the K-WOA-PSO algorithm shows obvious advantages in terms of system resource consumption. Specifically, the algorithm has a relatively low CPU demand of only 26% during the training process, which means that it is able to guarantee the performance while fully considering the reasonable utilization of computational resources and avoiding unnecessary waste. In addition, the K-WOA-PSO algorithm also performs well in terms of physical memory usage, consuming only 6135MB of memory space, which is very important for large-scale data processing tasks, as it can effectively reduce the memory pressure of the system and improve the overall operational stability. Finally, from the perspective of time efficiency, the training time of the K-WOA-PSO algorithm is relatively short at 21 minutes and 27 seconds, which means faster response time and higher work efficiency in practical applications. In contrast, the IACO algorithm illustrated in Fig. 13(a) is more massive in terms of system resource consumption. During the training process, the algorithm has a very high demand on CPU resources, reaching a staggering 81%. This means that it almost takes up most of the system's computational power during operation, which may lead to performance degradation of other parallel tasks. Meanwhile, the IACO algorithm is also relatively high in physical memory usage, consuming 8564MB of memory space. This is a relatively large burden on system resource utilization, especially when dealing with complex tasks or multi-task parallel processing, which may lead to memory resource strain or even exhaustion. In addition, in terms of training time, the IACO algorithm takes 34 minutes and 47 seconds to complete the training, which is a relatively long time that not only affects the user experience, but also may lead to inefficiency and waste of resources in practical applications. In addition the experiment also recorded the energy efficiency of the two algorithms during operation, as shown in Fig. 14.

Fig. 14 presents the dynamics of the integrated energy efficiency of the two different algorithms in the real application environment. First, it is worth noting that the ESO system based on the IACO algorithm only achieves an average value of 31.3% in terms of integrated energy efficiency over the observation period of up to 420 days. This data suggests that although the IACO algorithm may have advantages in some aspects, it does not perform well in the key metric of integrated energy efficiency. Prolonged periods of low energy efficiency may not only lead to wasted energy, but also increase the operating costs of the system, thus affecting its sustainability in real-world applications. In contrast, the hybrid K-WOA-PSO optimization algorithm driven by heterogeneous cloud access proposed in the study exhibits significantly higher integrated energy efficiency over the same observation period. Specifically, the algorithm achieves an average combined energy efficiency of 42.1%, far exceeding the performance of the IACO algorithm. This significant improvement not only proves the advanced nature of the K-WOA-PSO hybrid optimization algorithm in energy management, but also highlights the potential of heterogeneous cloud access in improving system energy efficiency. By efficiently and intelligently deploying and managing various energy resources, the algorithm successfully improves energy utilization efficiency while reducing energy waste, thus providing higher economic value and social significance in practical applications. The experiment recruited 20 power supply system experts to score the system in four aspects: cost-benefit ratio, reliability index, robustness, and user satisfaction. Based on their professional knowledge and practical experience, 20 experts have set a rating standard of 100 points for each indicator in the four dimensions. After using the designed hybrid optimization model, they have scored from various aspects based on their intuitive experience during use. And the results of the system's scores in each aspect are shown in Fig. 15.

From the data presented in Fig. 15, it can be clearly seen that the research-proposed hybrid optimization algorithm for heterogeneous cloud access-driven K-WOA-PSO obtains excellent performance in several evaluation dimensions. First, in terms of cost-benefit ratio, the algorithm scores an average of 95.1 points, which indicates that in practical applications, it can effectively balance investment and return to maximize economic benefits. Second, in terms of reliability index, the algorithm scored an average of 96.4 points, highlighting its high stability and availability in actual operation. This means that the system optimized with this algorithm is able to maintain stable performance output in various complex environments and provide users with continuous and reliable services. In addition, the average robustness score of the model is 95.6, which indicates that the algorithm has a strong resistance to uncertainties and external disturbances, and is able to maintain stable performance under complex and changing conditions. Finally, the user satisfaction score is 96.2, and this high score not only reflects the user's recognition of the algorithm, but also proves its significant effect in improving user experience. In summary, the hybrid K-WOA-PSO optimization algorithm driven by heterogeneous cloud access proposed in the study demonstrates excellent performance and utility in several key evaluation dimensions. In addition, a comprehensive experimental study was designed to determine the optimal combination of population

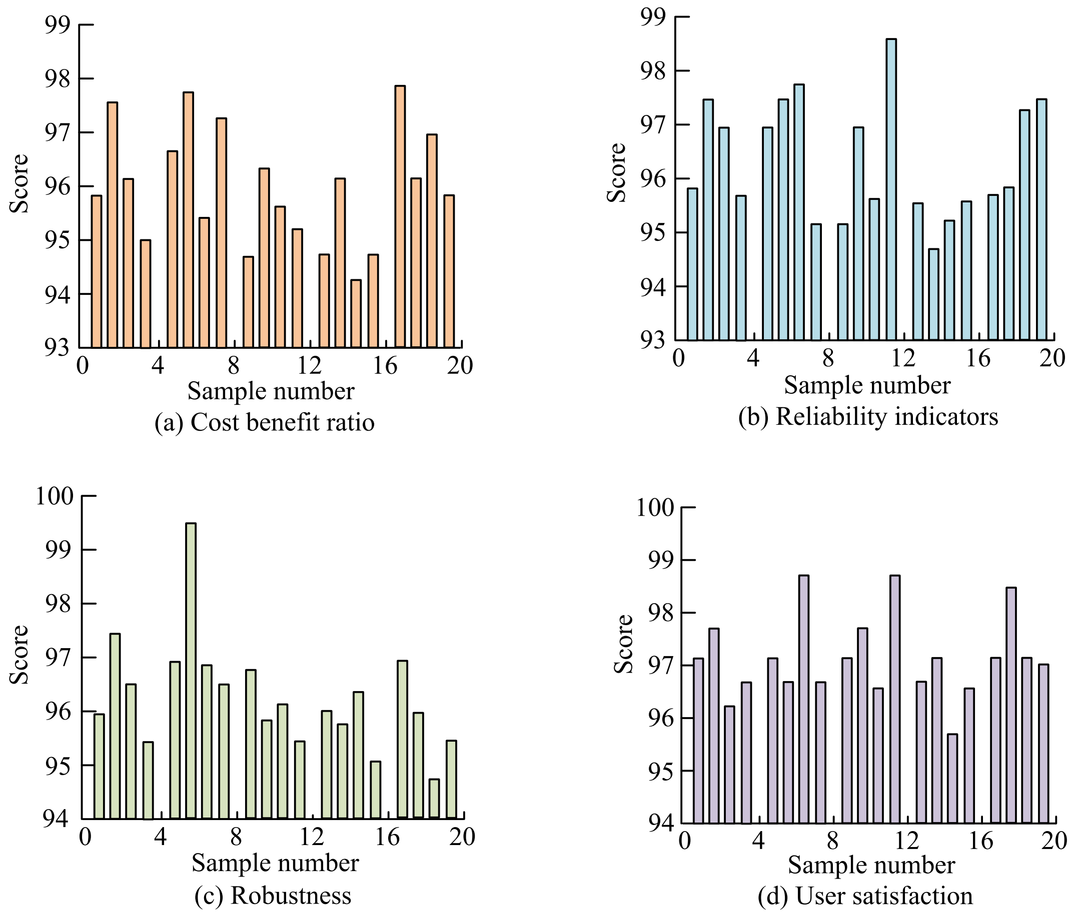


FIGURE 15. Score of the multimodal renewable energy hybrid energy supply optimization model based on heterogeneous cloud wireless access in all aspects.

size (n), inertia weight (w), and individual/global learning factors (c, c) in Particle Swarm Optimization (PSO) algorithm. The experiment aims to evaluate the impact of these parameters on PSO performance by systematically adjusting them and using the best fitness value, convergence speed, algorithm stability, and computation time as evaluation criteria. The experimental results are shown in Table 2.

By analyzing the experimental results of particle swarm optimization (PSO) algorithm parameter settings, some key conclusions can be drawn. Firstly, the population size (n) has a significant impact on algorithm performance. In smaller populations (such as 10), although the algorithm can converge quickly, it has high stability, with the best fitness values of −14.8 and −15.1, and relatively short computation times of 36.2 seconds and 29.8 seconds, respectively. This indicates that when solving optimization problems, a smaller population can reduce the consumption of computing resources while ensuring solution quality. Secondly, the inertia weight (w) has a significant impact on the convergence speed and stability of the algorithm. The experimental data shows that as the inertia weight increases, the optimal fitness value slightly decreases, from −14.8 to −15.5, while the convergence speed slows down, from fast to slow. This may be because higher inertia weights increase the tendency of particles to maintain their original direction, which helps to explore the solution space. However, they play an important role in regulating the exploration and development capabilities of algorithms. In the experiment, the different combinations of c_1 and c_2 resulted in different convergence rates and stability. For example, the combination of $c_1 = 1.1$ and $c_2 = 1.2$ provides the fastest convergence speed and moderate stability at a population size of 10, while the combination of $c_1 = 1.3$ and $c_2 = 1.4$ results in the slowest convergence speed and higher stability at a population size of 10. By analyzing the data in the table above, it can be seen that the sample size (i.e. population size n) has a significant impact on the experimental results. Under the same inertia weight and learning factor settings, smaller population sizes often converge faster, but may sacrifice some optimal fitness. As the population size increases, although better solutions can be found, the calculation time will also increase accordingly. Finally, with the PSO and WOA algorithms as the baseline, the cross-validation study proposed the model performance of MREHS, and the three models respectively optimized the

TABLE 2. Results of the algorithm parameter tuning.

Population Size(n)	Inertia Weight (w)	Individua Learning Factor (cl)	Globa Learning Factor (c2)	Best Fitness Value	Convergence Speed	Algorithm Stability	Computation Time(seconds)
10	4	1.0	1.1	-14.8	Fast	High	36.2
10	0.6	1.1	1.2	-15.1	Faster	Medium	29.8
10	0.8	1.2	1.3	-15.3	Moderate	Low	26.5
10	1.0	1.3	1.4	-15.5	Slow	High	33.1
20	0.4	1.0	1.1	-14.6	Fast	High	45.6
40	1.0	1.3	1.4	-15.7	Slow	ow	42.9

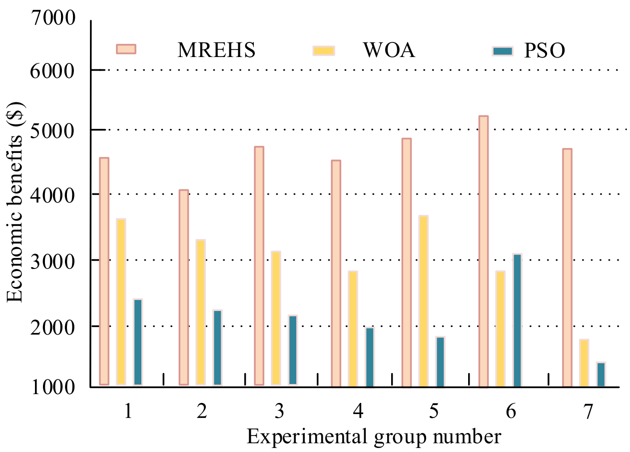


FIGURE 16. Comparison of economic benefits of various algorithms.

power supply system of seven power stations in the UK for one month. The systems based on three algorithms were run for one month each, with economic benefits as the evaluation criterion. The experimental results are shown in Figure 16.

Based on the data shown in Figure 16, we can clearly see that the MREHS model proposed by the research team has brought significant economic benefits to each power station, averaging over $4000. This number not only represents the efficiency of the model, but also highlights the potential for optimizing power supply strategies. In contrast, although the power supply system based on Whale Optimization Algorithm (WOA) performs well, its economic benefits remain stable at around $3000, slightly inferior to the MREHS model. The power supply system based on Particle Swarm Optimization (PSO) has the lowest economic benefits in this comparison. This data comparison not only provides us with directions for optimizing power supply systems, but also further validates the advantages and value of the MREHS model in practical applications, demonstrating its outstanding ability in improving power supply economic benefits.

V. CONCLUSION

To solve the problem that traditional ESO methods are easily trapped in local optimal solutions and cannot find the global optimal solution, the study establishes the MREHS optimization model of the heterogeneous cloud access-driven K-WOA-PSO hybrid optimization algorithm. In the second generalized penalty function, the convergence of the K-WOA-PSO hybrid optimization algorithm and its three variants (lack of WOA module, lack of K-clustering module, and lack of PSO module) are different. Among them, the K-WOA-PSO algorithm achieved convergence at about the 160th iteration, showing a relatively fast convergence rate. In contrast, the other three variants of the algorithm converged relatively slowly, reaching convergence at the 80th, 90th, and 390th iterations, respectively. The K-WOA-PSO algorithm outperformed the other three algorithm versions, which all hovered around -8, in terms of fitness, reaching a minimum of -15.1. The accuracy of all algorithm models varied when using the Breast Cancer dataset. However, the change in accuracy of the WOA-PSO model was relatively stable, showing only a slight decrease of 0.5%. In contrast, the WOA-ACO model had the largest change in accuracy, with a significant 14.8% increase in accuracy at convergence, eventually converging to 90.9% accuracy. These results indicated that the WOA-PSO model has excellent performance in problem solving and that the selection of an appropriate algorithmic model for the Breast Cancer dataset is also very important for accuracy stability and convergence. In summary, the model effectively addresses the issue of the traditional ESO method being prone to local optimal solutions. It achieves this by utilizing the hybrid K-WOA-PSO optimization algorithm, which enables exploration and identification of the global optimal solution, thereby enhancing the effectiveness of ESO. However, while the model has several advantages, there are still areas that require attention and improvement. For instance, the model's complexity may be relatively high, and in the future, methods such as parameter pruning and network compression can be used to reduce the complexity of the model and further optimize it.

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FENG TIAN was born in Shenyang, Liaoning, China, in April 1978. She received the bachelor's and master's degrees in digital media from the Luxun Academy of Fine Arts, in 2003 and 2008, respectively.

From 2003 to 2022, she was a full-time Teacher in the digital media major with the School of Information Technology, Shenyang Institute of Engineering. Since 2022, she has been the Deputy Director of the School Innovation and Entrepreneurship Education Center and the Director of the School Innovation and Entrepreneurship Education Teaching and Research Center, Shenyang Institute of Engineering. She is currently an Associate Professor. Her study directions are digital media applications in modeling, smart grids, and clean energy. She has published 26 articles, including four journals with a Chinese core period or above, six textbooks, more than ten scientific research, teaching, and research projects at the provincial level or above.

HONGJIANG WANG was born in Suizhong, Liaoning, China, in October 1977. He received the bachelor's degree in computer science and technology from Shenyang Institute of Engineering, in 2002, and the master's degree from Northeastern University, in 2010. He is currently pursuing the Ph.D. degree.

From 2002 to 2019, he was the Head of the Digital Media Department, Shenyang Institute of Engineering. From 2019 to 2022, he was the Vice Dean of Research with the School of Information, Shenyang Institute of Engineering. Since 2022, he has been the Dean of the School of Information, Shenyang Institute of Engineering. His study directions is electric power computer vision technology. He is also a Professor and a Master Supervisor. He has published over 30 articles more than 20 scientific research projects.

HE JIANG was born in Shenyang, Liaoning, China, in June 1991. He received the bachelor's and master's degrees from Northeastern University, in 2013 and 2016, respectively, and the Ph.D. degree, in 2019. His study directions include reinforcement learning, nonlinear optimal control, source load prediction, optimal scheduling and their applications in new power systems, and integrated energy systems under the background of "two-carbon." Since 2019, he has been the Director of the Office of the Innovation and Entrepreneurship Center of the New Energy College, Shenyang Institute of Engineering. He is currently an Associate Professor. He has published 45 papers, six textbooks, and more than eight scientific research projects. He also has eight invention patents.

BAIDA ZHAO was born in Shenyang, Liaoning, China, in May 1990. He received the bachelor's degree in mechanical design and manufacturing and it's automation from Shenyang Jianzhu University, in 2012, and the master's degree in control engineering from Northeastern University, in 2020.

From 2013 to 2021, he was a full-time Mechanical Teacher with the College of Mechanical, Shenyang Institute of Engineering. Since 2021, he has been with the Center of Innovation and Entrepreneurship Education. His study areas are mechanical engineering, control engineering, and intelligent manufacturing. He has published three articles, including one Chinese core journals and above. He also co-edited two textbooks.