Research on Microgrid Energy Management Strategy and Multi-Objective Optimization

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Abstract. With the rapid development of distributed energy resources and the increasing requirements for energy utilization efficiency, microgrids, as key carriers for integrating various distributed energy sources and achieving efficient energy management, have become a research hotspot in terms of their stable operation and optimal control. This paper focuses on microgrid energy management strategies and multi-objective optimization algorithms, and conducts an in-depth analysis of the hierarchical control architecture of microgrids, including the functions and coordination mechanisms of the power scheduling layer, local control layer, and communication control layer. By comparing the Multi-Objective Genetic Algorithm (MOGA), Multi-Objective Simulated Annealing Algorithm (MOSA), and Multi-Objective Particle Swarm Optimization (MOPSO) algorithm, the applicability of MOPSO in microgrid multi-objective optimization is verified. A power model including photovoltaic, wind, diesel generator, and battery energy storage system is constructed, and an optimal scheduling model aiming at minimizing power generation cost, equipment cost, and environmental pollution cost is designed. Energy optimization management is realized based on the improved MOPSO algorithm. The proposed strategy can effectively improve the operational efficiency, economy, and environmental protection of the microgrid, providing theoretical and technical support for the practical application of microgrids.

1. Introduction

Driven by the global energy transition and the “dual-carbon” goals, the penetration rate of distributed energy sources (such as solar energy, wind energy, etc.) continues to increase. The operation mode of the traditional centralized power grid is facing challenges such as insufficient flexibility and limited absorption capacity. As a small-scale power system integrating distributed energy sources, energy storage devices, and loads, the microgrid can realize local consumption and optimal allocation of energy, and is an effective solution to the problem of large-scale integration of distributed energy sources.

The efficient operation of a microgrid depends on scientific energy management strategies [1], whose core goals are to maximize energy utilization efficiency, minimize operating costs, and minimize environmental impact under the premise of ensuring system stability. However, a microgrid contains various forms of energy (renewable energy, traditional fossil energy, energy storage systems, etc.), and the characteristics of each energy unit are significantly different. Moreover, load demand and renewable energy output have randomness and volatility, which make energy management face complex optimization problems with multiple objectives and multiple constraints.

Current research on microgrid energy management mainly focuses on two aspects: control architecture design and optimization algorithm application. Hierarchical control, as a flexible and efficient control strategy, realizes the coordination of global optimization and local regulation by decomposing system functions into different levels. Multi-objective optimization algorithms provide technical means for solving conflicting goals such as cost, efficiency, and environmental protection.

2. Microgrid Hierarchical Control Architecture and Energy Management Mechanism

2.1 Hierarchical Control Architecture Design

The complexity of a microgrid requires that the control strategy has the ability of hierarchical coordination to realize the organic combination of global optimization and local response. The hierarchical control architecture proposed in this paper includes three key layers: the power dispatch layer, the in-place control layer, and the communication control layer [2]. Each layer realizes coordinated operation through information interaction, and its architecture is shown in Fig. 1.

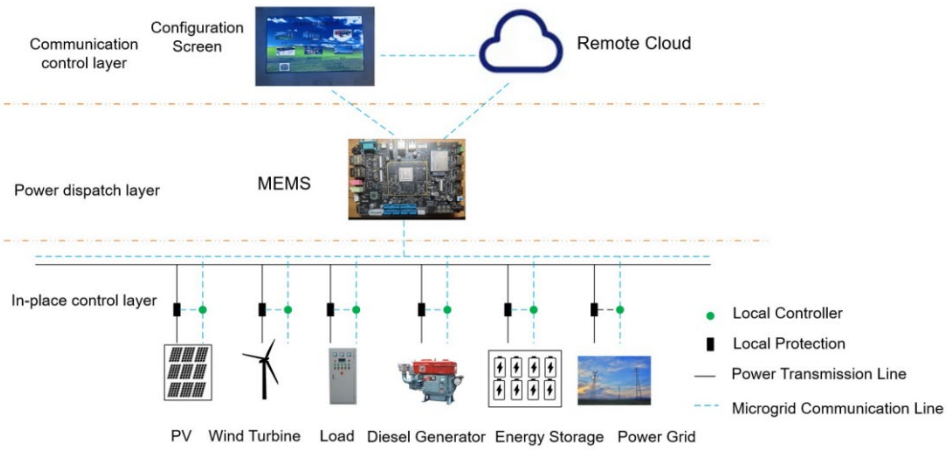


Fig. 1. Hierarchical Control Architecture of Microgrid.

Power dispatch layer. As the decision-making core of microgrid energy management, it is responsible for formulating global energy scheduling strategies. It generates optimal energy allocation schemes using intelligent algorithms by real-time monitoring key parameters such as distributed energy output, load demand, and energy storage status, combined with the long-term and short-term operation goals of the system. By dynamically adjusting generator output, controlling load connection, managing power transmission, as well as conducting monitoring and control, operation and maintenance personnel can remotely adjust the operating parameters of the microgrid to respond to emergencies or perform system optimization. The core functions of the power scheduling layer include:

(1) Power balance control, which ensures the balance between real-time power generation and load demand by dynamically adjusting the output of each energy unit, as shown in Eq. (1);

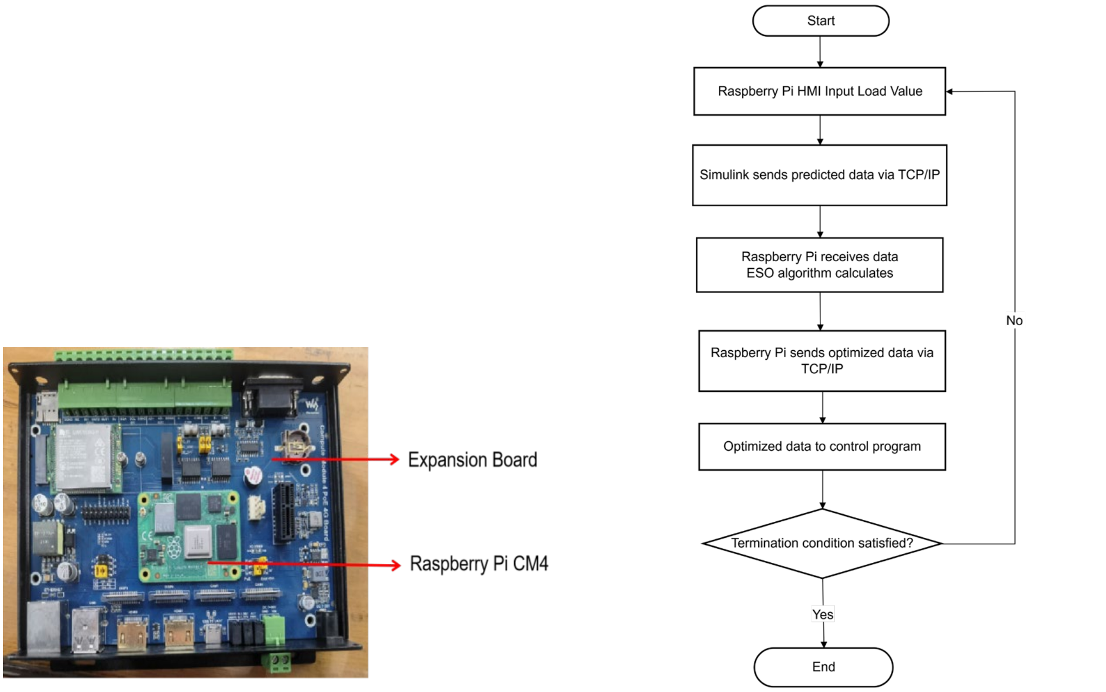
$$P_1(t) + P_2(t) + P_3(t) + \cdots = P_{Load}(t) \tag{1}$$

(2) Cost optimization, which minimizes the total operating cost of the system by comprehensively considering power generation cost, equipment maintenance cost, and environmental cost, as shown in Eq. (2);

$$W = \alpha A + \beta B + \gamma C + \cdots \tag{2}$$

(3) Emergency response, which reconfigures energy resources to maintain system stability in case of component failure or sudden load changes.

Raspberry Pi CM4 is selected as the core computing board for early data collection and optimization algorithm verification, as shown in Fig. 2(a). Simulink connects to Raspberry Pi via TCP/IP. It sends the predicted data of PV systems, wind turbines, and the external power grid to Raspberry Pi. Raspberry Pi uses the improved MOPSO algorithm to solve multi-objective optimal operation problems, and then sends the optimized power values of the battery and diesel generator back to Simulink via TCP/IP, ensuring the microgrid meets the power supply demands of the load side [3]. The data optimization processing flow is shown in Fig. 2(b).



(a) Raspberry Pi CM4 Expansion Board (b) Optimization Processing Data Flow

Fig. 2. Raspberry Pi CM4.

In-place control layer. It is under the power scheduling layer and is responsible for implementing local optimization and real-time regulation. It collects the operating status of photovoltaic panels, wind turbines, energy storage devices, etc. (such as photovoltaic panel temperature, wind turbine speed, battery SOC, etc.) in real-time through sensors and actuators, and adjusts parameters according to the instructions of the power scheduling layer or local needs. For example, when the light intensity changes, the local control layer can adjust the tilt angle of the photovoltaic panel in real-time to maximize power generation efficiency; when the load increases suddenly, it can quickly start the energy storage system to discharge to make up for the energy gap. In addition, the local control layer also undertakes the functions of fault isolation and recovery. When local equipment is abnormal, it can cut off the faulty unit in time to avoid affecting the entire system.

Communication control layer. It is the information link connecting the power scheduling layer and the local control layer, responsible for data transmission and remote monitoring. It collects parameters such as voltage, current, and frequency of each energy unit in real-time through the deployment of sensor networks and communication equipment, and transmits the data to the power scheduling layer; at the same time, it issues scheduling instructions to the local control layer to realize closed-loop control. The selection of communication protocols directly affects the real-time performance and reliability of the system. This research uses the Modbus RTU protocol to realize electricity meter data communication, uses TCP/IP and MQTT protocols to realize information interaction between devices, and builds a data visualization interface through Node-RED to improve the operability and monitoring efficiency of the system. Multi-functional electric meters are used for data collection and communication to realize communication between controllers, and between controllers and equipment.

2.2 Design of Microgrid Power Scheduling Decision

The core of microgrid energy management is to realize the coordinated optimization of "source-storage-load-grid" [4], and its key mechanisms include three aspects: real-time monitoring, dynamic adjustment, and safety guarantee.

The real-time monitoring mechanism realizes all-round perception of energy output, load demand, and equipment status through sensor networks throughout the microgrid. For example, photovoltaic output monitoring needs to consider the impact of light intensity and temperature, wind power generation monitoring needs to pay attention to wind speed and wind turbine operating status, and energy storage system monitoring needs to track SOC (State of Charge) and charge-discharge efficiency. Monitoring data provides a decision-making basis for the power dispatch layer, ensuring the pertinence and effectiveness of scheduling strategies [5].

When the microgrid system starts to operate, calculate the power of each unit of the microgrid system:

(1) When the power of photovoltaic power generation and wind power generation is greater than the load value, i.e., $P_{pv} + P_{wt} > P_{load}$, the diesel engine does not operate, and energy is stored in the battery. If the battery $SoC > 98\%$, the excess power is sold to the grid; otherwise, continue to store energy in the battery.

(2) When the power of photovoltaic power generation and wind power generation is less than the load value, i.e., $P_{pv} + P_{wt} < P_{load}$, the real-time optimization algorithm is used to analyze which total cost is lower between operating the diesel engine and the battery energy storage.

If the operating cost of the diesel engine is the lowest, the diesel engine operates. When the sum of the power of photovoltaic power generation, wind power generation, and diesel engine power generation is greater than the load value, i.e., $P_{pv} + P_{wt} + P_{de} > P_{load}$, and if the battery SoC > 98%, the excess power is sold to the grid; otherwise, continue to store energy in the battery. When the sum of the power of photovoltaic power generation, wind power generation, and diesel engine power generation is less than the load value, i.e., $P_{pv} + P_{wt} + P_{de} < P_{load}$, the battery energy storage system operates. If $P_{pv} + P_{wt} + P_{de} + P_{BESS} > P_{load}$, the excess power is sold to the grid; otherwise, purchase power from the grid.

If the operating cost of battery energy storage is the lowest, the battery discharges. When the sum of the power of photovoltaic power generation, wind power generation, and battery energy storage system is greater than the load value, i.e., $P_{pv} + P_{wt} + P_{BESS} > P_{load}$, the diesel engine does not operate, and power is sold to the grid. The excess power is sold to the grid. When the sum of the power of photovoltaic power generation, wind power generation, and battery energy storage system is less than the load value, i.e., $P_{pv} + P_{wt} + P_{BESS} < P_{load}$,, the diesel engine operates. At this time, if $P_{pv} + P_{wt} + P_{de} + P_{BESS} > P_{load}$, sell power to the grid; otherwise, purchase power from the grid.

3. Comparison and Applicability Analysis of Multi-Objective Optimization Algorithms

3.1 Algorithm Performance Comparison and Selection

The three algorithms MOGA, MOSA, and MOPSO have in common that they are meta-heuristic algorithms for solving multi-objective optimization problems, all use the concept of groups or populations for searching, and all require some parameter adjustment to optimize performance. Table 1 compares and analyzes the advantages and disadvantages of multi-objective optimization algorithms.

Table 1. Comparison and Analysis of Multi-Objective Optimization Algorithms.

Characteristics	MOGA	MOSA	MOPSO
Advantages	Has multiple solutions and can generate diverse result sets. Not easy to fall into local optimal solutions.	Effective in solving complex nonlinear optimization problems. Can find global optimal solutions in high-dimensional spaces. Can search in local neighborhoods to avoid falling into local optima.	Fast convergence speed. Stable performance for different objective functions. Relatively easy to adjust parameters.
Disadvantages	Many parameters and complex adjustment. Large amount of calculation and long execution time.	May fall into local optimal solutions. Has specific requirements for objective functions. Sensitive to initial solutions and parameters.	Low search efficiency and slow convergence speed. Requires a lot of computing resources and time.

To evaluate the applicability of the three algorithms in microgrid optimization, this paper uses the MATLAB platform, takes typical multi-objective test functions as the optimization objects, and compares them from three dimensions: solution quality, convergence speed, and computational efficiency. The test function is Eq. (3):

$$W = \begin{cases} x_1^2 + x_2^2 \\ (x_1 - 2)^2 + (x_2 - 2)^2 \end{cases} \qquad (3)$$

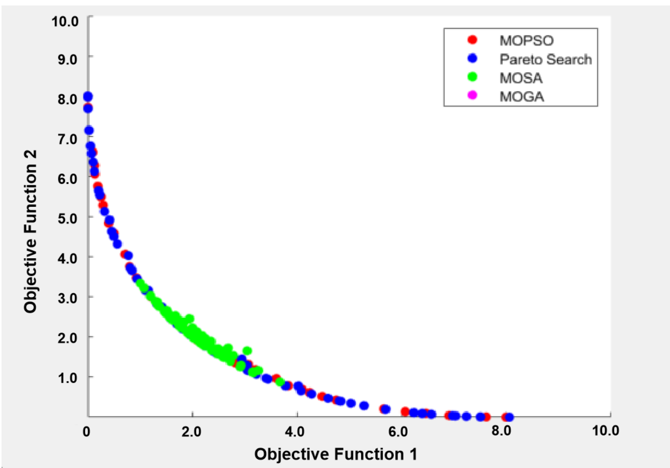


Fig. 3. Comparison of Pareto Fronts in Multi-Objective Optimization Algorithms.

The comparison result of the Pareto front is shown in Fig. 3. Overall, MOPSO performs better and is particularly suitable for multi-objective optimization scenarios in microgrids. Therefore, this paper selects MOPSO as the basic algorithm and further improves its performance by optimizing the inertia weight strategy.

3.2 Optimization Solution Based on Improved MOPSO

The design of the microgrid energy management system is based on multi-objective optimization operation. As an improved MOPSO algorithm is adopted, the iterative update calculation formula used is as follows:

$$\begin{cases} x_i^{d+1} = x_i^d + v_i^d \\ v_i^d = wv_i^{d-1} + c_1 r_1 (p_{best\_i}^d - x_i^d) + c_2 r_2 (g_{best\_i}^d - x_i^d) \\ w = w_{\max} - [(w_{\max} - w_{\min}) \cdot i] / i_{\max} \end{cases} \tag{4}$$

X_i^d and v_i^d are the current position and current velocity of the particle, respectively;

x_i^{d+1} is the next position of the particle;

V_i^d is the previous velocity of the particle;

w is the inertia weight;

$p^d{}_{best\_i}$ and $g^d{}_{best\_i}$ are the individual local extremum and the global optimal extremum, respectively;

c_1 and c_2 are the individual learning factor and the social learning factor, respectively;

r_1 and r_2 is a random number uniformly distributed in [0,1];

$w_{\max}$ and $w_{\min}$ are the maximum and minimum values of the initial weight, respectively;

i and $i_{\max}$ are the iteration count and the total number of iterations, respectively.

The specific steps of the improved MOPSO algorithm are as follows:

Step 1: Based on the microgrid system operation model, input the forecasted data for photovoltaic power generation, wind power generation, and grid interaction, and initialize the various parameters of the population.
Step 2: Calculate the multi-objective function values of the particle population.
Step 3: Update the particle's velocity v_i^d ,position x_i^d and adaptive inertia weight w iteratively according to formula (4).
Step 4: Update the individual local extremum and the global optimal extremum based on fitness.
Step 5: Determine whether the termination condition—either the maximum number of iterations or the global optimum—is met. If the requirement is satisfied, output the optimal solution; otherwise, repeat Steps 2 to 5.

3.3 Optimal Energy Dispatch Model Structure

With continuous research on energy management strategies, building upon previous modeling and analysis of various components of microgrids and studies on optimal scheduling models for microgrid energy optimization, an optimal scheduling model for a photovoltaic-wind-diesel-battery microgrid system has been established. This model enables real-time rolling optimization based on varying data at different times, ensuring the stable, efficient, and orderly operation of the microgrid energy management system. The framework is illustrated in Fig. 4 below.

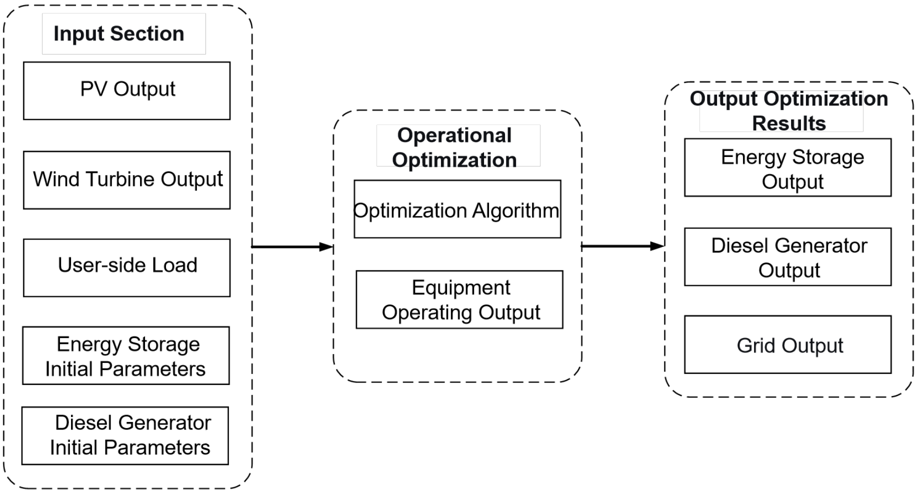


Fig. 4. System Operational Optimal Scheduling Model Architecture.

The microgrid optimal scheduling model primarily consists of the following three components:
(1) Input Section: This involves the initial parameters of various components in the microgrid before initiating operational optimization. Key parameters include photovoltaic power output, wind turbine power output, user-side load data, initial parameters of battery energy storage equipment, and initial parameters of diesel generators, among others.
(2) Operational Optimization Section: This pertains to the various aspects of energy management during operational optimization. It primarily includes multi-objective optimization functions, operational constraints, an improved MOPSO algorithm, optimization variables, and equipment operating output strategies.
(3) Output Optimization Results: This involves the results generated after operational optimization is completed. Key outputs include battery energy storage output, diesel generator power output, and grid power output, among others.

4. Construction and Solution of Microgrid Optimal Scheduling Model

4.1 System Power Model

The power characteristics of each energy unit in the microgrid are the basis of optimal scheduling. This research constructs mathematical models of photovoltaic, wind, diesel generator, and battery energy storage systems:

Photovoltaic cells generally work in *MPPT* mode, and the output power model can be expressed as Eq. (5):

$$P_{\mathrm{pv}} = \eta_{\mathrm{pv}} A_{\mathrm{pv}} G(1-\tau)[1+\beta(T-T_{\mathrm{stc}})] \tag{5}$$

P_{pv} is the output power of the photovoltaic cell;
η_{pv} is the conversion efficiency of photovoltaic cells;
A_{pv} is the area of the photovoltaic panels;
G is the ratio of light intensity to light intensity under standard test conditions;
τ is the light transmittance of photovoltaic cells;
β is the temperature coefficient of photovoltaic cells;
T is the current operating temperature of the photovoltaic cell;
T_{stc} is the temperature under standard test conditions.

The output power model of wind power generation can be expressed as Eq. (6):

$$P_{\mathrm{WT}}=\begin{cases}0 & 0\le v\le v_{\mathrm{ci}}\\ P_{\mathrm{r}}\dfrac{v^{3}-v_{\mathrm{ci}}^{3}}{v_{\mathrm{r}}^{3}-v_{\mathrm{ci}}^{3}} & v_{\mathrm{ci}}\le v\le v_{\mathrm{r}}\\ P_{\mathrm{r}} & v_{\mathrm{r}}\le v\le v_{\mathrm{co}}\\ 0 & v_{\mathrm{co}}\le v\le v\end{cases} \tag{6}$$

P_{WT} is the output power of the fan；
P_{r} is the rated output power of the fan；
V_{ci}、V_{r}、V_{co} are the cut-in wind speed, the rated wind speed, and the cut-out wind speed.

The output power model of diesel engine power generation can be expressed as Eq. (7):

$$P_{\mathrm{DE}}=P_{\mathrm{rated}}\cdot[1-k_{1}\cdot(\frac{P_{\mathrm{rated}}}{\mathrm{P}_{\mathrm{rated\_fuel}}})]\cdot[1-k_{2}\cdot(\frac{L}{L_{\mathrm{rated}}})] \tag{7}$$

P_{DE} is the output power of the diesel generator；
P_{rated} is the rated power of a diesel generator；
$P_{\mathrm{rated\_fuel}}$ is the fuel consumption of the diesel engine at the rated load；
L is the load demand of the diesel engine；
L_{rated} is the load demand of the diesel engine；
k_1 is the fuel consumption coefficient of the diesel engine, which is used to describe the relationship between the output power of the generator and the fuel consumption；
k_2 is the load loss coefficient of the diesel engine, which is used to describe the relationship between the output power of the generator and the load.

The output power model of the battery energy storage system can be expressed as Eq. (8) by the charge-discharge state model：

$$SOC(t+1)=\begin{cases}SOC(t)+\eta_{\mathrm{ES}}\cdot[P_{\mathrm{all}}(t+1)-\dfrac{P_{\mathrm{load}}(t+1)}{\eta_{\mathrm{inv}}}]\cdot\Delta t\\ SOC(t)+\eta_{\mathrm{ES}}'\cdot[\dfrac{P_{\mathrm{load}}(t+1)}{\eta_{\mathrm{inv}}}-P_{\mathrm{all}}(t+1)]\cdot\Delta t\end{cases} \tag{8}$$

$SOC(t+1)$、$SOC(t)$ are the capacity of the battery at $t+1$ and t respectively；
η_{inv} is the efficiency of the inverter；
η_{ES}、η'_{ES} are the charging and discharging efficiency of the battery；
$P_{\mathrm{all}}(t+1)$ is the sum of the output power of the distributed power generation at $t+1$；
$P_{\mathrm{load}}(t+1)$ is the total load of the system at time $t+1$.

4.2 Multi-Objective Optimization Function and Constraint Conditions

The objective function of future microgrid optimal scheduling models may comprise a multi-objective optimization problem encompassing the following three core dimensions:
（1）Economy: Minimization of total operating costs (including all cost items discussed).
（2）Environment: Maximization of renewable energy penetration rate / Minimization of carbon emissions.

（3）Reliability: Minimization of power outage risk / Minimization of load shedding.
The objective function for the optimal scheduling of the microgrid discussed in this paper is the minimization of the total operating cost, which includes three parts, namely power generation cost, equipment cost and environmental pollution cost[6]. Therefore, the objective functions are listed below:

$$W = \alpha Y_1 + \beta Y_2 + \gamma Y_3 \tag{9}$$

$$\begin{cases} Y_1 = \alpha \sum_{t=1}^{T} [C_{\mathrm{PV}}(t) + C_{\mathrm{DE1}}(t) + C_{\mathrm{BA1}}(t) + C_{\mathrm{grid}}(t)] \\ Y_2 = \beta \sum_{t=1}^{T} [C_{\mathrm{DE2}}(t) + C_{\mathrm{BA2}}(t)] \\ Y_3 = \gamma \sum_{t=1}^{T} [C_{\mathrm{DE\_EN}}(t) + C_{\mathrm{grid\_EN}}(t)] \end{cases} \tag{10}$$

W is the total cost of the microgrid；

Y_1, Y_2, Y_3 are the cost of power generation, the cost of equipment, and the cost of environmental pollution；

α, β, γ are the proportions of power generation costs, equipment costs, and environmental pollution costs in the total cost of microgrid, satisfy $\alpha+\beta+\gamma=1$；

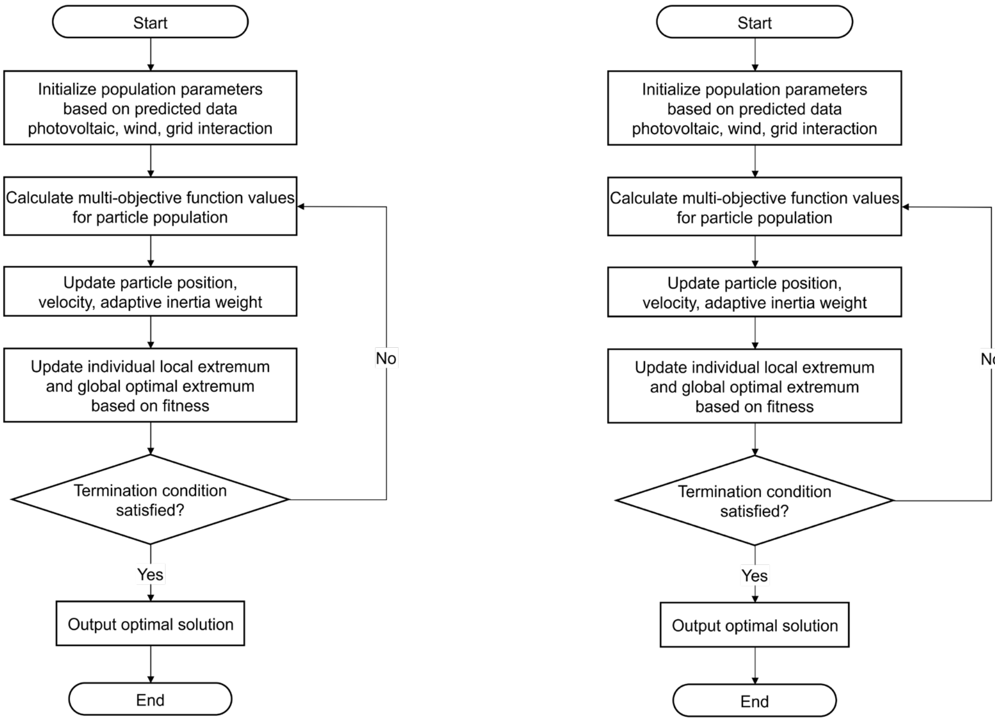
$C_{\mathrm{PV}}(t)$, $C_{\mathrm{DE1}}(t)$, $C_{\mathrm{BA1}}(t)$, $C_{\mathrm{gird}}(t)$ are the total cost of photovoltaic power generation at time t, the power generation cost of diesel engine, the power generation cost of battery energy storage system, and the total cost of interaction between the microgrid and the external main power grid；

$C_{\mathrm{DE2}}(t)$, $C_{\mathrm{BA2}}(t)$ are the equipment cost of diesel engine power generation and the equipment cost of battery energy storage system at time t；

$C_{\mathrm{DE\_EN}}(t)$, $C_{\mathrm{grid\_EN}}(t)$ are the environmental pollution cost of diesel generators at time t and the environmental pollution treatment cost of the external main power grid.

The multi-objective optimization process of the microgrid is divided into two parts, namely the improved MOPSO algorithm process and the overall operation process, as shown in Fig. 5(a) and Fig. 5(b).

The specific steps are as follows to solve the multi-objective optimal scheduling model of microgrid combined with the improved Multi-objective Particle Swarm Optimization (MOPSO) algorithm [7].
Step 1: Establish a mathematical model of the operation of the microgrid system according to photovoltaic power generation, wind power generation, battery energy storage, diesel engine power generation, etc.
Step 2: Determine that the multi-objective function is the minimum total cost, including three parts, namely power generation cost, equipment cost and environmental pollution cost.
Step 3: According to the improved MOPSO algorithm, the multi-objective optimization operation problem is solved.
Step 4: Solve the optimized battery energy storage output and the power generation power of the diesel engine.
Step 5: According to the output of each power generation unit of the microgrid, the effectiveness of the design is verified by building a micromodel in Simulink.



(a) MOPSO Algorithm Flowchart (b) Operation Flowchart

Fig. 5. The multi-objective optimization process of the microgrid.

4.3 Data collection and optimization algorithm verification

Simulink successfully connects to Raspberry Pi through TCP/IP and inputs the load data on the user side of the microgrid [8].

In the Simulink model, the predicted data of photovoltaic power generation, wind power generation, and main grid interaction are imported in advance through the Signal Builder module, then converted into data format through the signal_to_byte module, and finally sent to the Raspberry Pi end through the TCP/IP Send module, as shown in Fig. 6.

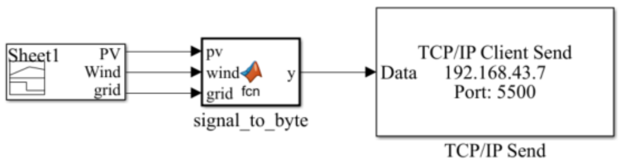


Fig. 6. TCP/IP Data Transmission.

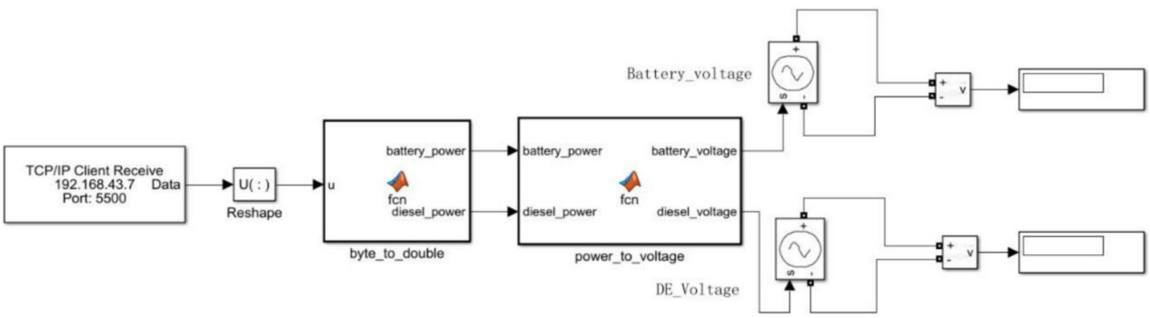
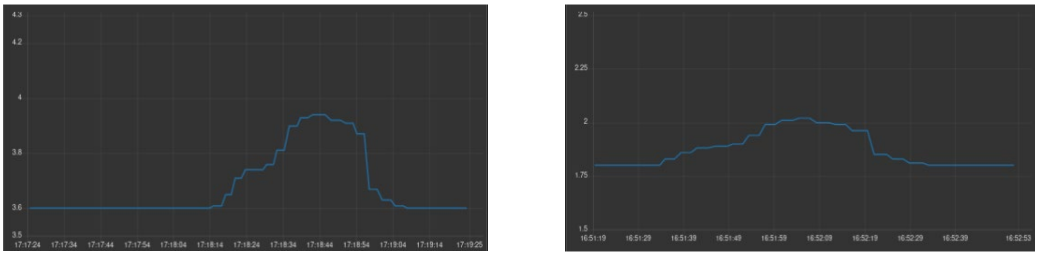


Fig. 7. TCP/IP data receiving and control.

The Raspberry Pi end returns the optimized power of the battery and diesel engine to the Simulink end through TCP/IP, converts its data format, and then converts the power into the corresponding voltage through the power_to_voltage module to two controlled voltage sources that simulate actual conditions, as shown in Fig. 7.

Through the predicted data of photovoltaic power generation, wind power generation, and main grid interaction, under the condition of meeting the multi-objective optimization of minimizing power generation cost, equipment cost, and environmental pollution cost, it can simulate the output power of the battery energy storage system and diesel generator after rolling optimization in different time periods and different situations, so as to meet the power supply needs of the microgrid according to the load side [9].



（a）PSO algorithm （b）Improved MOPSO algorithm

Fig. 8. Comparison of Operating Costs.

The entire data processing and optimization process took approximately 60 seconds. Fig. 8 shows the operating costs derived from the standard PSO algorithm and the improved MOPSO algorithm, respectively. It can be observed that, due to its faster convergence, the improved algorithm reduces the system operating cost by approximately 50%, enabling low-cost system operation.

5. Conclusions and Prospects

This paper conducts research on microgrid energy management strategies and multi-objective optimization [10], and the main conclusions are as follows:

1. The hierarchical control of the microgrid is analyzed, and MOGA, MOSA, and MOPSO are also analyzed and compared. MATLAB simulation verifies that MOPSO is more suitable, providing a decision-making basis for the multi-objective energy management optimization strategy.
2. The power models of each unit of the microgrid system, the optimization objective function, and the constraint conditions are studied. Combined with the actual operation situation, through the communication between Simulink and Raspberry Pi CM4, the data of photovoltaic power generation, wind turbine power generation, main grid interaction, and user-side load value in a day are sent through TCP/IP.
3. Optimization was performed using the improved MOPSO algorithm, obtaining the optimized battery energy storage output and diesel generator power, which verified the feasibility of the microgrid energy management system design. Furthermore, tests demonstrated that the improved algorithm achieves faster convergence and reduces system operating costs by approximately 50% compared to the standard PSO algorithm.

References

[1] J. S. Jamal, N. M. L. Tan, J. Pasupuleti, “A review of energy management and power management systems for microgrid and nanogrid applications”, ***Sustainability***, Vol. 13, No. 18, 10331, 2021.

[2] E. Hu, M. Zhu, F. Zhao, et al., “Distribution Network Automation Technology based on Low-voltage Intelligent Switch”, in ***Proceedings of 2022 IEEE 6th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)*** (venue not specified), pp.1145-1149, 2022.

[3] M. Nasir, H. A. Khan, A. Hussain, et al., "Solar PV-based scalable DC microgrid for rural electrification in developing regions", ***IEEE Transactions on Sustainable Energy***, Vol. 9, No. 1, pp. 390–399, 2017.

[4] L. Tan, C. Wei, S. Chen, "Application research of computer big data technology in monitoring intelligent terminal of urban power distribution system", in ***Proceedings of 2022 IEEE 2nd International Conference on Data Science and Computer Application (ICDSCA)*** (venue not specified), pp. 556–560,2022.

[5] J. Liu, Z. Zhao, J. Ji, "Research and application of wireless sensor network technology in power transmission and distribution system", ***Intelligent and Converged Networks***, Vol. 1, No. 2, pp. 199–220, 2020.

[6] M. Amyotte, M. Ordonez, "Power loss prediction for distributed energy resources: rapid loss estimation equation", ***IEEE Transactions on Industrial Electronics***, Vol. 68, No. 3, pp. 2289–2299, 2020.

[7] Y. Li, Z. Yang, G. Li, "Optimal scheduling of an isolated microgrid with battery storage considering load and renewable generation uncertainties", ***IEEE Transactions on Industrial Electronics***, Vol. 66, No. 2, pp. 1565–1575, 2018.

[8] H. J. Kim, M. K. Kim, "Multi-objective based optimal energy management of grid-connected microgrid considering advanced demand response", ***Energies***, Vol. 12, No. 21, 4142, 2019.

[9] K. Anoh, S. Maharjan, A. Ikpehai, et al., "Energy peer-to-peer trading in virtual microgrids in smart grids: A game-theoretic approach", ***IEEE Transactions on Smart Grid***, Vol. 11, No. 2, pp. 1264-1275, 2019.

[10] F. Ahsan, N. H. Dana, S. K. Sarker, et al., "Data-driven next-generation smart grid towards sustainable energy evolution: techniques and technology review", ***Protection and Control of Modern Power Systems***, Vol. 8, No. 3, pp. 1-42, 2023.