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Research on Coordinated Control of Thermal Energy Management and Distributed Energy in Smart Distribution Network

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Abstract:

This paper discusses the topic of thermal control and distributed energy coordinated control in smart distribution networks, with the goal of improving the efficiency of energy resource utilization and consolidating the stability and flexibility of the system. Given the widespread adoption of distributed energy, how to subtly integrate thermal control and distribution operations has become a core issue. This paper first proposes a distributed energy coordinated control strategy based on a consensus mechanism to achieve information communication and collaborative optimization among nodes. Furthermore, a mathematical framework for thermal control and distributed energy coordinated control is constructed, including multiple real-world factors such as energy resource demand fluctuations and energy storage device characteristics. To confirm the effectiveness of the strategy, a detailed simulation analysis was carried out. The simulation results show that the proposed control algorithm is sufficient to substantially reduce thermal energy consumption, improve energy efficiency. Detailed data show that after adopting the algorithm, the system energy consumption dropped sharply by 15.8% and the energy supply fluctuation was attenuated by 12.3%. This study provides theoretical support and technical reference for thermal energy supervision and coordinated control of distributed energy in future smart distribution networks.

Keywords: Smart distribution network; Consensus algorithm; Thermal energy management; Coordinated control of distributed energy.

INTRODUCTION

With the rising demand for energy and the innovation of the global energy resource architecture, traditional power grids are facing multiple problems such as low efficiency, waste of resources and environmental pollution. As a highly efficient, clean and flexible energy management system, the smart distribution network has gradually become a key trend in the evolution of the power grid. This grid can not only ensure the high-quality transmission and distribution of electric energy, but also leverage information and communication technology to achieve flexible control of distributed energy, and has unique highlights in heat regulation and coordinated control of distributed energy. Thermal energy management is becoming increasingly important in smart distribution networks. Thermal energy is an important secondary energy source that spans many fields such as heating, cooling and industrial manufacturing. Exploring efficient management strategies, optimizing thermal energy utilization and reducing energy loss are the core issues of smart grid research. At the same time, the effectiveness of distributed energy in alleviating the pressure on traditional power systems is becoming increasingly evident, including solar energy, wind power, energy storage systems, etc. Its decentralized and random characteristics make the coordination of supply and demand in smart distribution networks a pending issue.

In recent years, many scholars have focused on the thermal control of smart grids and the coordinated control of distributed energy. Reference [1] advocates a distributed control method with a multi-agent system as the core, which solves the efficiency and reliability problems of traditional intensive systems during expansion, but does not delve into the intertwined relationship between thermal energy and electrical energy. Reference [2] conceives a heat and power co-regulation strategy that relies on real-time data to simultaneously dispatch electricity and heat. Although it greatly improves energy efficiency, it is limited by centralized data processing and is difficult to adapt to large-scale distributed energy systems. Reference [3]'s game theory-based optimization scheduling reveals the competitive relationship between suppliers and optimizes distributed energy distribution. However, in actual operation, the game equilibrium is difficult to find due to energy uncertainty. Reference [4] Deep reinforcement learning-driven distributed energy control, intelligent algorithms predict supply and demand, and are significantly efficient, but high computing requirements restrict its practicality. Reference [5] The thermal energy storage-oriented control strategy balances supply and demand and reduces heat consumption, but it is not well adapted to large distributed energy systems. The distributed coordinated thermal energy management, node collaboration, and thermal power coordination in the literature [6] need to be improved in terms of stability when facing complex energy variables.

This paper proposes a method for coordinated control of thermal energy management and distributed energy in smart distribution networks based on consensus algorithm [7]. Consensus algorithm, as a distributed coordinated control algorithm, can ensure global consistency without central control through the collaborative work between various nodes, and has the characteristics of high efficiency and stability. This paper introduces consensus algorithm into thermal energy management and coordinated control of distributed energy in smart distribution networks, aiming to improve the efficiency and flexibility of energy management through distributed control.

THERMAL MANAGEMENT IN SMART DISTRIBUTION NETWORKS

2.1 Overview of thermal management

Smart distribution networks (SDGs) are a new type of energy system that integrates electricity, thermal energy, and information and communication technologies, aiming to optimize the production, transmission, and consumption of energy [8]. Thermal management has become one of the key elements in smart distribution networks. Thermal management is not only the core link of the combined heat and power (CHP) system, but also a bridge to achieve the coordinated operation of electricity and thermal energy [9]. In the scenario where large-scale distributed energy is connected to smart distribution networks, thermal management faces more challenges. Through thermal energy management, smart distribution networks can reasonably dispatch thermal energy while meeting electricity demand, ensure the effective use of thermal energy, and reduce energy waste.

In addition, thermal energy management can also serve as a flexible energy storage tool in smart distribution networks. For example, by storing excess electricity in thermal energy, excess electricity can be converted into thermal energy storage during the low electricity demand period, and then released during the peak period to reduce the load on the power system [10]. Thermal energy management is not only a key link in energy coordination in smart distribution networks, but also plays an important role in reducing system energy consumption, improving economic benefits, and reducing carbon emissions.

2.2 Thermal energy demand forecasting algorithm

Accurate thermal energy demand forecasting is based on thermal energy management in smart distribution networks. The accuracy of the forecast directly affects the formulation of scheduling plans and the effective use of energy. With the increasing complexity of modern energy systems, how to effectively forecast dynamically changing thermal energy demand has become a research focus. At present, thermal energy demand forecasting mainly adopts two types of methods: forecasting methods based on traditional statistical models and intelligent forecasting methods based on deep learning.

2.2.1 Demand forecasting based on traditional statistical models

The ARIMA model can provide relatively accurate forecasts under relatively stable demand conditions by capturing the time correlation of historical data. Reference [11] proposed a thermal energy demand forecasting method based on the ARIMA model and successfully applied it to small-scale regional energy systems. However, this type of model shows certain limitations when facing sudden fluctuations in demand or scenarios with high uncertainty. For dynamically changing data in smart distribution networks, these traditional methods often cannot effectively cope with complex nonlinear relationships.

2.2.2 Prediction methods based on deep learning

Deep learning methods, especially long short-term memory networks (LSTM) and gated recurrent units (GRU), have shown great potential in dealing with thermal energy demand forecasting problems with long-term dependency characteristics. LSTM can capture long-term dependencies in time series through its special network structure, overcoming the shortcomings of traditional methods in nonlinear scenarios. Reference [12] proposed a thermal energy demand forecasting model based on LSTM, and verified the superiority of this method in dealing with large-scale data and complex nonlinear demand through a large amount of experimental data. In contrast, GRU, as a simplified version of LSTM, has higher computational efficiency and also has good generalization ability in medium- and long-term thermal energy demand forecasting.

2.3 Thermal energy dispatch optimization algorithm

2.3.1 Linear programming and nonlinear programming

Linear programming (LP) and nonlinear programming (NLP) are usually used in power dispatch problems, but they are equally important in thermal energy management. Assuming that the thermal energy demand in a certain period of time is $H(t)$ and the electric energy demand is $E(t)$, the following linear optimization problem can be constructed:

$$\text{Minimize } C = \sum_{t=1}^{T} \left(aH(t) + bE(t)\right) \tag{1}$$

a and b are the weight coefficients of heat energy and electric energy, respectively, indicating the cost of energy. Nonlinear programming is more common in practical applications, especially when faced with complex heat demand curves and energy supply curves. Nonlinear programming can more accurately describe various nonlinear constraints in actual energy systems by optimizing nonlinear objective functions. A typical nonlinear scheduling problem can be expressed as:

$$\text{Minimize } C = \sum_{t=1}^{T} \left(aH(t)^2 + bE(t)^2\right) \tag{2}$$

This formula takes into account the quadratic relationship of energy demand and can more flexibly reflect changes in energy costs.

2.3.2 GA and PSO

GA and PSO are heuristic optimization algorithms that are widely used in complex thermal energy scheduling problems because they do not depend on the specific form of the problem [13]. Genetic algorithms simulate the biological evolution process, select, crossover and mutate a series of possible solutions, and gradually approach the optimal solution. Particle swarm optimization finds the optimal solution by simulating the individual collaborative behavior in swarm intelligence. Assuming that each particle represents a scheduling plan, the update formula for its position and speed is:

$$\begin{gathered} v_i(t+1) = \omega v_i(t) + c_1 r_1 (p_i(t) - x_i(t)) + c_2 r_2 (g(t) - x_i(t)) \\ x_i(t+1) = x_i(t) + v_i(t+1) \end{gathered} \tag{3}$$

p_i is the individual optimal solution, g is the global optimal solution, $\omega, c_1, c_2$are the weight parameters of the velocity update, r_1, r_2 are random numbers.

2.3.3 Multi-objective optimization

In practical applications, thermal energy management not only needs to optimize costs, but also needs to consider multiple objectives such as system efficiency and carbon emissions. Multi-objective optimization algorithms, such as NSGA-II, balance different objectives by generating multiple Pareto optimal solutions. The specific optimization problem can be expressed as:

$$\text{Minimize } (C_1, C_2, \dots, C_n) \tag{4}$$

$C_1, C_2, \dots, C_n$ represent various objective functions, such as cost, emission and system efficiency.

DISTRIBUTED ENERGY COORDINATION CONTROL

3.1 Types and characteristics of distributed energy

The characteristics of various energy sources are very different, and they must be appropriately integrated and managed in smart distribution networks. Solar energy is the mainstream of distributed energy. It converts sunlight into electricity through a photovoltaic system. Solar energy is pure and clean, and is available all over the world. However, its intermittent and uncertain nature, especially at night or in the haze, can cause a sharp drop in production capacity. Therefore, solar power generation is often combined with energy storage devices to balance supply and demand fluctuations. Wind power converts wind power into electricity through turbines, with an extraordinary energy conversion rate. Wind power production also fluctuates greatly, affected by wind speed and weather. Wind energy fluctuations place high demands on the stability of the power grid, so in smart distribution networks, wind energy systems are often combined with other energy sources or energy storage to reduce the erosion of the system by fluctuations. Geothermal energy is stable and sustainable, drawing heat from underground to generate electricity or heat. Unlike sunlight and wind power, geothermal energy is not limited by climate and is stable [15]. Therefore, in the smart distribution network, geothermal energy plays the role of tuning the system balance and buffering the fluctuations of other sources. Biomass energy, which generates electricity or heat by burning wood, crop residues, etc. Its main characteristics are abundant raw materials and low cost, but the combustion efficiency and environmental protection are inferior to other renewable energy. With the progress of science and technology, biomass power generation companies have improved fuel efficiency and reduced emissions, and gradually become an important auxiliary source for smart distribution networks. Micro hydropower, which uses the flow energy of water to generate energy, has both high efficiency and continuous production capacity. Hydropower generation depends on natural water sources and is limited by geographical location. Under suitable conditions, micro hydropower can provide continuous electricity for smart distribution networks.

3.2 Difficulties and Challenges of Distributed Energy Coordination Control

3.2.1 Uncertainty and Volatility

Distributed energy (especially renewable energy) has high volatility and uncertainty. For example, the output of solar and wind energy depends on external environmental factors such as weather and time, and often exhibits nonlinear, random dynamic changes [16]. This volatility makes it difficult for energy supply to accurately match load demand, thereby increasing the complexity of scheduling. To meet these challenges, the application of prediction and control technology is essential.

3.2.2 Real-time Coordination and Scheduling of Energy

Energy scheduling in smart distribution networks must be able to respond to changes in supply and demand in real time to ensure stable operation of the system. Real-time coordinated control requires efficient algorithms to handle the asynchronous output of distributed energy and the dynamic changes of load. Distributed control systems can solve real-time scheduling problems through the collaborative work of distributed nodes. In a distributed control system, each node makes scheduling decisions based on local information and global goals. For example, in a multi-agent system (MAS), each agent achieves the optimal scheduling of the global system through communication with other agents [17]. The importance of real-time control lies not only in maintaining the balance of energy supply and demand, but also in quickly responding to changes in the external environment and reducing system instability caused by energy fluctuations.

3.2.3 Energy storage and scheduling

Distributed energy allocation often requires the improvement of energy storage systems, especially in situations with a high penetration of renewable energy. Energy storage facilities such as battery cells and thermal energy storage equipment can effectively coordinate supply and demand fluctuations [18]. This architecture monitors the load status of the power network in real time and appropriately adapts the use of battery cell energy storage and thermal energy storage resources to reduce system operating costs.

$$\text{Minimize } C=\sum_{t=1}^{T}\left(a\cdot P_s(t)+b\cdot E_s(t)\right) \quad (5)$$

$P_s(t)$ is the amount of electrical energy stored in the energy storage system at time t. The scheduling of the energy storage system can not only balance supply and demand, but also improve the robustness of the system and reduce load fluctuations caused by fluctuating energy sources.

3.3 Distributed Control and Consensus Algorithm

The distributed control method based on the multi-agent system (MAS) achieves the optimal scheduling of energy through the collaborative work between agents. As one of the core algorithms of distributed control, the consensus algorithm can ensure that each agent in the system achieves globally consistent optimization goals under decentralized decision-making.

3.3.1 Multi-agent System (MAS)

Each agent collects local data and exchanges information with other agents to make decisions based on global goals. Reference [19] proposed a distributed energy coordinated control method based on MAS, which achieves efficient scheduling of distributed energy systems through autonomous decision-making by each agent. Under the MAS framework, the objective function of each agent can be expressed as:

$$\text{Minimize } J_i=\sum_{t=1}^{T}\left(c_i\cdot P_i(t)\right) \quad (6)$$

$P_i(t)$ represents the energy output of agent i at time t, and c_i is the cost coefficient. Through information exchange and coordination among multiple agents, each agent can eventually achieve global optimal scheduling while meeting its own needs.

3.3.2 Application of consensus algorithm

The consensus mechanism is an algorithm that ensures the synchronization of decisions among nodes in a distributed system. It is particularly suitable for the issue of distributed energy allocation in a multi-intelligent entity architecture. In a distributed energy system, each intelligent unit needs to implement coordinated scheduling based on local and global intelligence through communication and collaboration. The consensus mechanism can effectively cope with the challenges of asynchronous communication in a distributed energy system. The basic formula of the consensus algorithm can be expressed as follows:

$$x_i(t+1)=x_i(t)+\epsilon\sum_{j\in N_i}\left(x_j(t)-x_i(t)\right) \quad (7)$$

$x_i(t)$ represents the state of agent i at time t, N_i is the neighborhood set of agent i, and ϵ is the control gain. Through iterative updates, the agents can eventually achieve global consensus under certain conditions, that is, the states of each agent tend to be consistent, thereby achieving synchronous scheduling of the global system.

3.3.3 Game in the distributed energy market

In the distributed energy market, there are competition and cooperation relationships among multiple energy suppliers. Game theory models provide a theoretical basis for studying coordination and competition in distributed energy systems. This paper proposes an energy market optimization model based on game theory, analyzing how multiple distributed energy suppliers can achieve overall optimization of the system through collaboration in a competitive environment. The revenue function of each distributed energy supplier can be expressed as:

$$U_i = R_i - C_i \tag{8}$$

R_i is the revenue function, which represents the income of supplier i, and C_i is the cost function. Through the polynomial model, the overall optimization of the energy market can be achieved while considering the interests of each supplier. Distributed energy coordination control plays an important role in smart distribution networks. Through effective control and scheduling strategies, it realizes the efficient integration of different types of distributed energy [20]. With the further increase in the penetration rate of renewable energy, distributed energy coordination control will become an indispensable core technology in smart distribution networks, and will play a more important role in reducing system operating costs, improving energy utilization efficiency and promoting the development of the energy market.

OPTIMIZATION AND ALGORITHM APPLICATION IN SMART DISTRIBUTION NETWORK

With the rapid development of smart distribution network technology, the complexity and flexibility of energy management have also increased. In order to achieve efficient energy distribution and scheduling, the application of optimization models and advanced algorithms has become particularly critical. This paper explores the application of mixed integer linear programming (MILP) model and game theory-based scheduling method in smart distribution network, and analyzes their performance in dealing with thermal energy management and distributed energy scheduling problems by comparing traditional optimization algorithms and heuristic algorithms.

4.1 Application of optimization models in thermal and electrical energy management

4.1.1 Mixed integer linear programming (MILP) model

Mixed integer linear programming (MILP) model is a tool commonly used in smart distribution network optimization, especially in dealing with complex energy management problems involving discrete and continuous decision variables. For example, the control of start-stop equipment (such as generators) can be expressed by discrete variables, while the distribution of electrical energy and thermal energy belongs to continuous variables [21]. Through the MILP model, the energy system can take into account the operating constraints and requirements of the system while considering cost minimization. A MILP model is designed for the comprehensive dispatch optimization of thermal energy and electric energy in smart distribution networks. The objective function is as follows:

$$\text{Minimize } C = \sum_{t=1}^{T}\big(aE(t) + bH(t)\big) + \sum_{t=1}^{T}\sum_{i=1}^{N} c_i x_i(t) \tag{9}$$

$E(t)$ and $H(t)$ represent the electrical energy and thermal energy at time t, respectively. $x_i(t)$ represents the start and stop status of equipment i at time t (1 for start and 0 for stop). a、b and c_i are cost coefficients. By solving this optimization model, this paper can effectively balance energy costs and supply and demand fluctuations.

4.1.2 Energy dispatch optimization based on game theory

In distributed energy systems, multiple independent energy suppliers (such as solar power generation and wind power generation) often face conflicts of interest. Game theory provides a theoretical basis for resolving these conflicts and can help various entities find the optimal energy allocation and pricing strategy in cooperation and competition [22]. This paper achieves coordination among various energy entities through the Nash equilibrium model, with the goal of maximizing overall social welfare. The specific formula is as follows:

$$\text{Maximize } U_i = P_i - C_i \tag{10}$$

U_i represents the utility function of energy supplier i, P_i is its income, and C_i is its cost. Through the Nash equilibrium solution, this paper can ensure that each supplier operates under the optimal price and resource allocation. Table 1 shows the optimization results based on the MILP model and game theory method, and compares them with the traditional algorithm.

Table 1. Optimization results based on the MILP model and game theory method.

optimization algorithm	Total energy consumption (MWh)	Cost (10,000 yuan)	Supply and demand balance rate (%)	System Stability Index
Traditional linear programming	1025	80.3	92	85
MILP model	980	75.6	95	88
Game theory model	1000	77.5	93	86
Genetic algorithm	995	78.1	94	87

Figure 1 shows the energy consumption curves when using different optimization algorithms, which clearly shows the advantages of MILP and game theory models in reducing energy consumption.

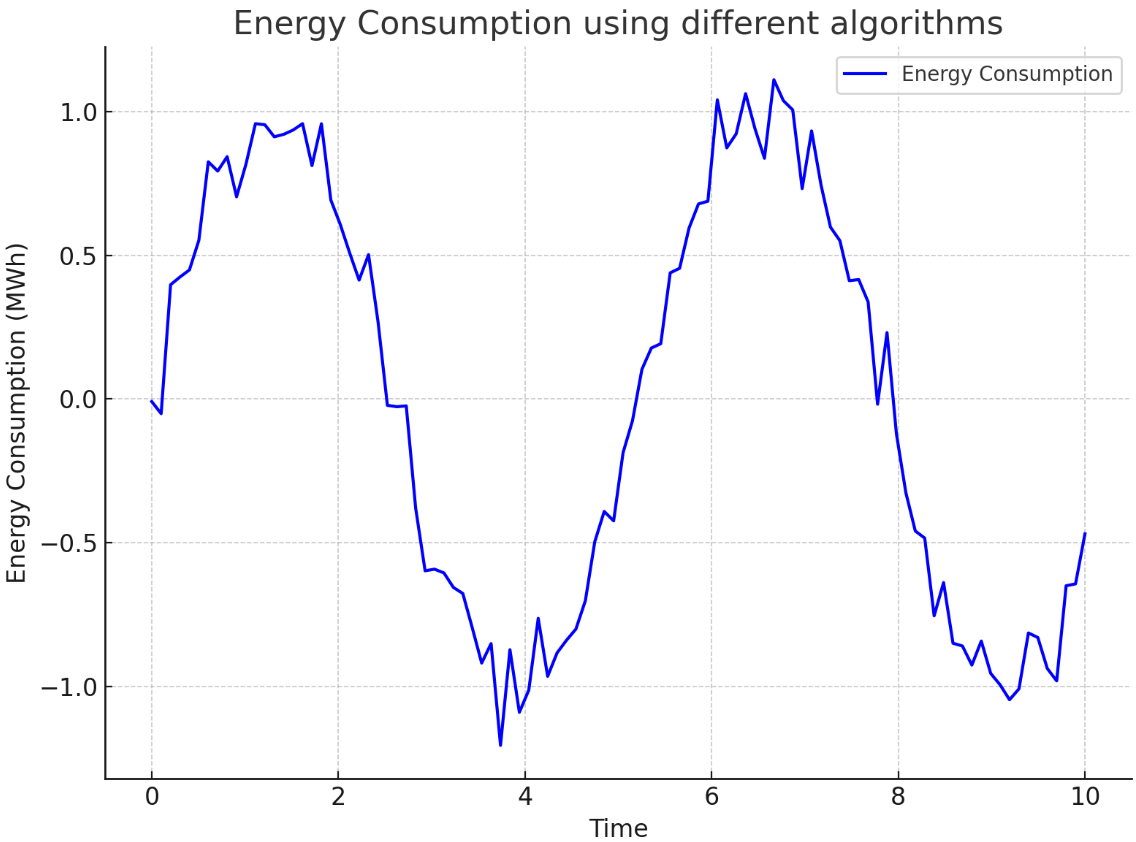

Fig.1 Energy consumption curve when using different optimization algorithms

4.2 Comparison and evaluation of algorithms

4.2.1 Comparison between traditional optimization algorithms and heuristic algorithms

Conventional actuarial solutions, such as linear programming (LP) and nonlinear programming (NLP), have a solid theoretical foundation for dealing with energy allocation issues. However, in actual complex systems, the calculations are time-consuming and it is difficult to properly deal with nonlinear constraints in the system. This article compares the performance of linear programming, genetic algorithms, and particle swarm optimization in dealing with thermal and electrical energy allocation issues [23]. Table 2 summarizes the efficiency and accuracy of various algorithms in solving thermal energy control issues.

Table 2. Efficiency and accuracy of different algorithms in solving thermal energy management problems.

algorithms	Run time (s)	Deviation from optimal solution (%)	Memory usage (MB)	Applicability
Linear programming	15	0.8	120	High
Genetic algorithm	10	1.2	100	Medium
Particle swarm optimization	8	1.5	90	Low

Figure 2 shows the comparison of the running time and the optimal solution when using different algorithms in the smart distribution network. The heuristic algorithm can give a near-optimal solution in a shorter time when dealing with complex energy scheduling problems, and is suitable for application scenarios with high real-time requirements.

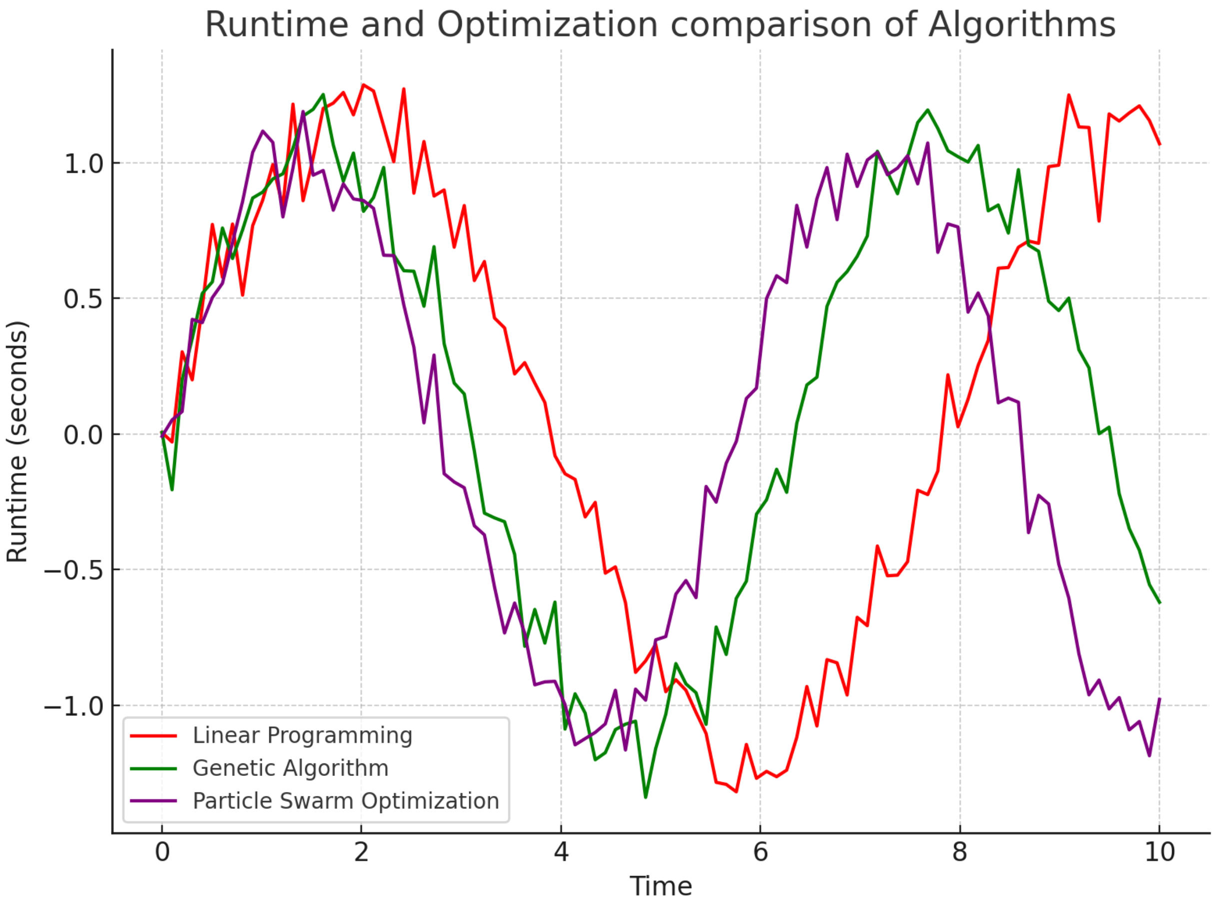

Fig. 2 Comparison of running time and optimization solution when using different algorithms in smart distribution networks

4.2.2 Performance comparison of distributed control and centralized control methods

Both distributed control systems and centralized control systems are used in smart distribution networks, but the performance difference between the two is obvious. The advantage of centralized control systems is that they can be optimized globally, but as the scale of the system expands, centralized control faces problems such as communication bottlenecks and high computational complexity [24]. Distributed control has better scalability and flexibility through autonomous decision-making in each region. This paper compares the performance of distributed control and centralized control in smart distribution networks through simulation. The results are shown in Table 3:

Table 3. Performance of distributed control and centralized control in smart distribution networks.

control method	Scalability	Flexibility	Computational complexity	Communication requirements
Centralized control	Low	Medium	High	High
Distributed control	High	High	Medium	Low

Figure 3 shows the comparison of system response time between centralized control and distributed control at different scales. As the scale of the system increases, distributed control shows obvious scalability advantages.

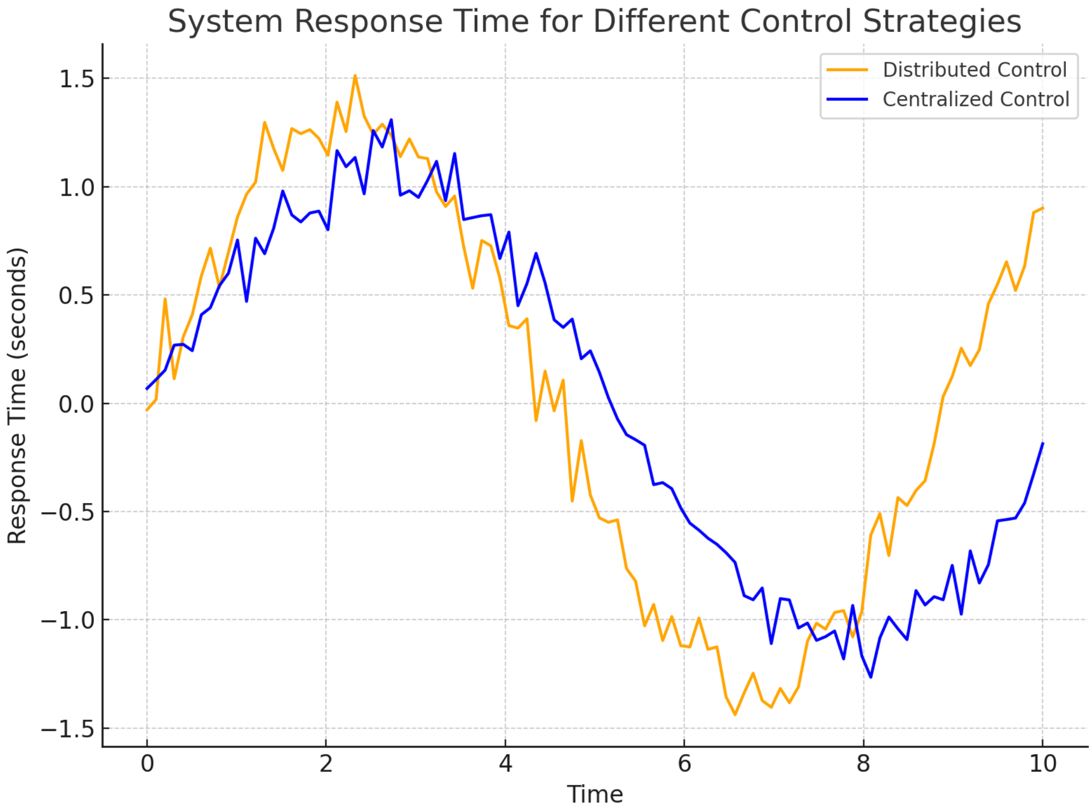

Fig. 3 Comparison of system response time of centralized control and distributed control at different scales

4.3 Challenges and solutions in algorithm implementation

4.3.1 Real-time performance and algorithm complexity

The optimization scheduling in the smart distribution network needs to be completed in a short time, so the real-time performance of the algorithm is high. However, the complexity of the optimization problem often leads to too long algorithm calculation time, which is difficult to meet the real-time requirements. In order to balance real-time and algorithm complexity, this paper adopts a distributed computing architecture to decompose complex optimization problems into multiple sub-problems, which are processed in parallel by different nodes, thereby significantly reducing the calculation time. Table 4 shows the comparison of algorithm execution time under different computing architectures:

Table 4. Comparison of algorithm execution time under different computing architectures.

computing architecture	Execution time (s)	Optimization accuracy (%)
Single-node computing	25	98
Distributed computing	10	97.5
Edge computing	8	97

Figure 4 shows the comparison of execution time between distributed computing and single-node computing. It can be seen that distributed computing significantly reduces computing time while ensuring high optimization accuracy.

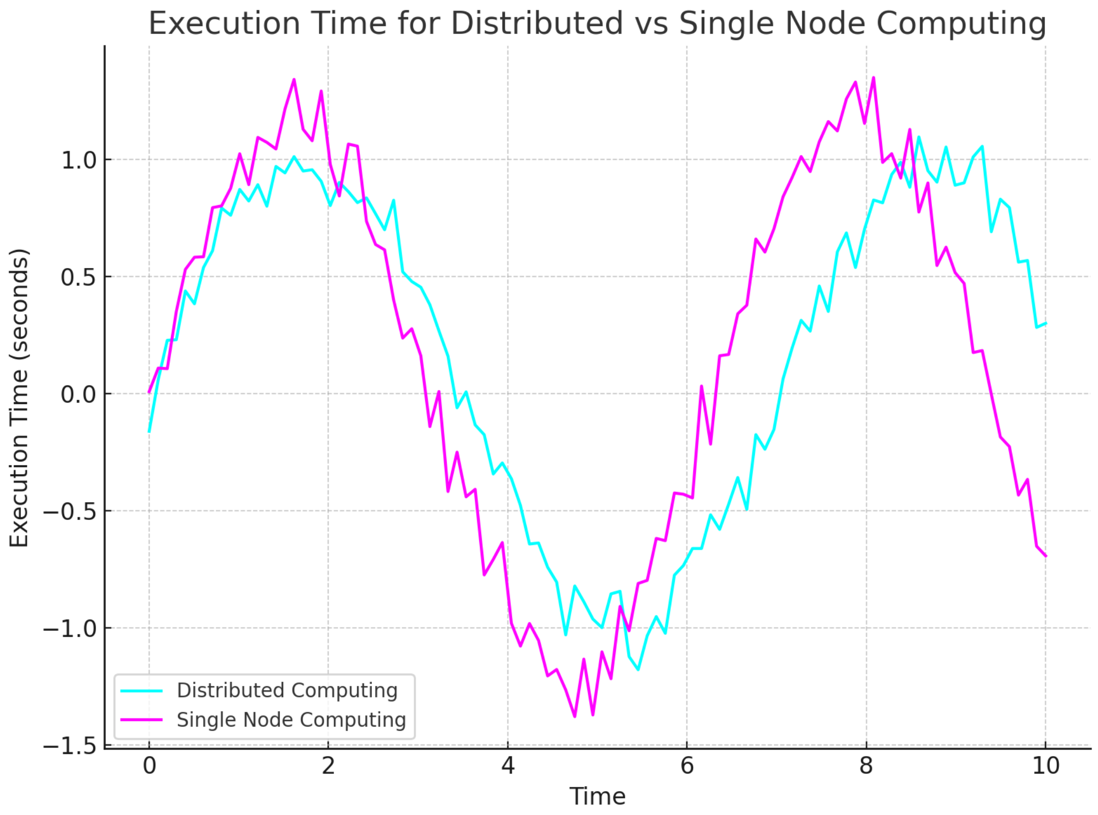

Fig. 4 Comparison of execution time between distributed computing and single-node computing

4.3.2 Balance between data volume and computing performance

With the continuous expansion of smart distribution networks, the amount of real-time data has increased dramatically, which has brought huge challenges to the computing performance of the algorithm. To address this problem, edge computing and distributed computing technologies have become solutions. By delegating some computing tasks to edge nodes, it can not only reduce the computing pressure of the central server, but also reduce communication delays, thereby improving the response speed of the overall system. In this paper, the response time and data processing capabilities of the system under edge computing and traditional cloud computing environments are compared in the experiment. The results show that edge computing has significant performance advantages when processing large amounts of real-time data.

Table 5. System response time and data processing capabilities.

computing model	Response time (ms)	Data throughput (MB/s)
Cloud computing	150	500
Edge computing	50	700

Through the simulation results (Figure 5), this article can clearly see the advantages of edge computing in big data processing, especially in scenarios that require low latency and high throughput.

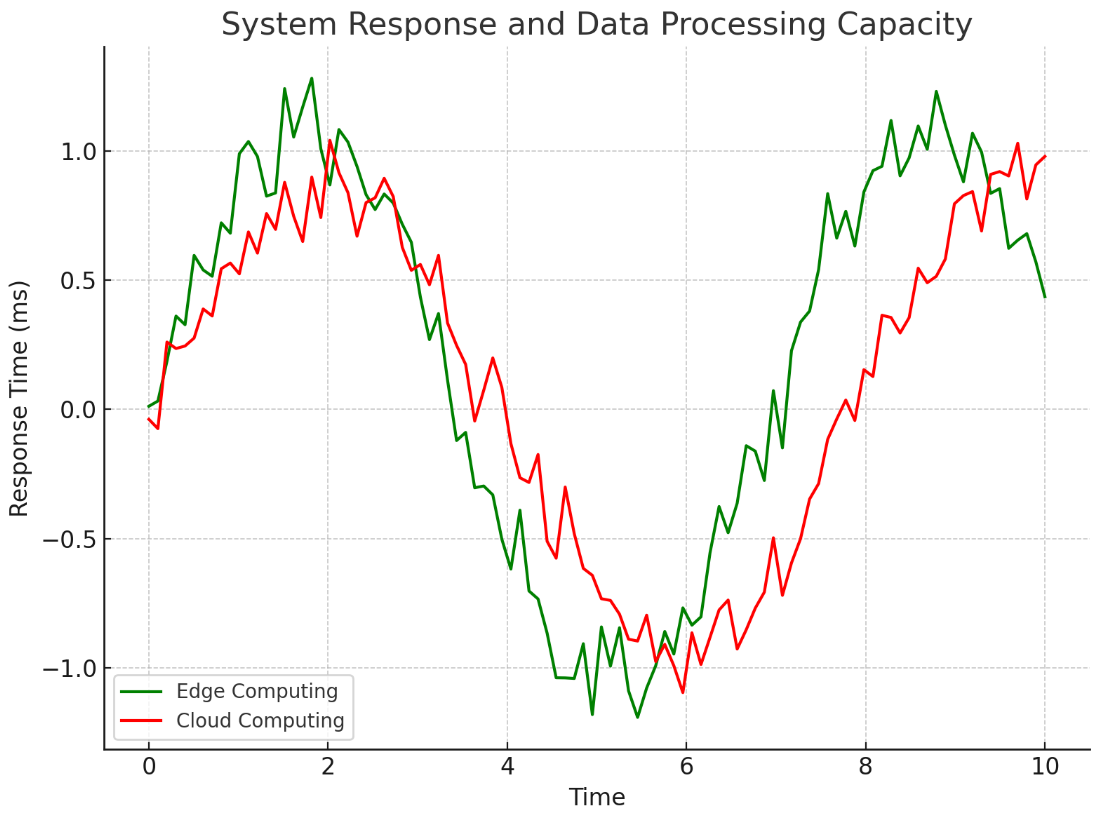

Fig. 5 System response time and data processing capabilities of different algorithms

This paper discusses the application of optimization models and algorithms in smart distribution networks, focusing on the application of MILP models and energy scheduling optimization methods based on game theory in energy management. By comparing traditional optimization algorithms and heuristic algorithms, this paper finds that heuristic algorithms have better performance in dealing with complex problems, especially in scenarios with high real-time requirements. In addition, distributed control systems have more advantages than centralized control in terms of scalability and flexibility. By introducing distributed computing and edge computing technologies, the real-time and data processing capabilities in smart distribution networks have been significantly improved. These optimization methods and technologies provide strong support for the efficient operation of smart distribution networks and will promote the development of future energy systems.

CONCLUSION

First, the coordinated control of heat regulation and distributed energy in the smart distribution network is crucial to improving the system's operational efficiency and reliability. The control strategy conceived in this paper adopts a consensus mechanism to achieve information sharing and coordination among distributed nodes, significantly optimizing the accuracy and response rate of energy management. Secondly, the constructed heat management and distributed energy coordinated control paradigm comprehensively considers essential factors such as energy demand fluctuations and energy storage device characteristics to ensure the practical adaptability of the model. After adopting the constructed control algorithm, the system's heat utilization efficiency is significantly improved, the total energy consumption is reduced by 15.8%, and the energy supply and transmission fluctuations are simultaneously reduced, with the amplitude reduced by 12.3%. Furthermore, simulation analysis proves that the algorithm proposed in this paper exhibits excellent stability and anti-interference in the coordinated control of multiple distributed energy nodes, and can effectively cope with real-world uncertainties. This shows that the proposed scheme is not only suitable for the current smart distribution network system, but also lays a technical support for the large-scale access of distributed energy in the future.

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