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Multi-objective particle swarm optimization method for operation optimization of Combined Cooling, Heating, and Power (CCHP) integrated energy systems

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Abstract

This paper proposes an optimization method based on Multi-Objective Particle Swarm Optimization (MOPSO) for addressing the operational optimization challenges of Combined Cooling, Heating, and Power (CCHP) integrated energy systems. CCHP systems enhance energy efficiency and reduce environmental pollution, thus possessing significant economic and environmental benefits. Despite existing research progress, current methodologies still inadequately address the simultaneous optimization of economic and environmental aspects. The key contributions of this research include constructing an operational optimization model for the CCHP system, improving the MOPSO algorithm, specifically in terms of inertia weight, learning factors, and individual optimal values, and applying these improvements to solve the model. The theoretical foundations of the CCHP system, multi-objective optimization problems, principles of Particle Swarm Optimization (PSO), and the characteristics and advantages of MOPSO are discussed comprehensively. The optimization model targets minimizing economic costs and optimizing environmental performance, clearly defining decision variables and constraints, and rigorously evaluating MOPSO algorithm applicability. A detailed procedure for constructing and solving the optimization model is provided. A case study is conducted by establishing background information, setting system parameters, configuring MOPSO algorithm parameters, and performing the optimization. Results are thoroughly analyzed, comparing the method's effectiveness against other optimization methods to validate its superiority. The study concludes that this approach effectively optimizes CCHP operations, providing a reference for coordinated planning in integrated energy systems, and discusses future research directions.

Keywords: Combined Cooling Heating and Power (CCHP) system; Multi-objective Particle Swarm Optimization (MOPSO); Operation optimization; Economic costs; Environmental performance

1. Introduction

1.1. Background and Significance

With rapid global economic development and accelerated industrialization, energy demand continuously rises. Traditional energy systems, typically planned and operated independently, suffer from low efficiency and exacerbate environmental pollution. Consequently, the Combined Cooling Heating and Power (CCHP) integrated energy system emerges as an advanced method of energy utilization. Utilizing natural gas combustion in internal combustion engines or gas turbines, the CCHP system generates electricity and employs waste heat for heating and cooling, significantly improving energy efficiency and reducing environmental impacts, thus offering substantial economic and environmental advantages.

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1.2. Current research status at home and abroad

Literature Review In recent years, extensive research has been conducted both domestically and internationally on the operational optimization of CCHP systems. International research began relatively earlier and has reached a more advanced stage, focusing primarily on system modeling, algorithmic improvements, and practical engineering applications. For example, studies have proposed optimal capacity allocation methods based on linear models for electricity, natural gas, and thermal systems to enhance energy efficiency. Additionally, research addressing carbon emissions and the integration of renewable energy sources has introduced new hybrid power-flow calculation methods to ensure economic and stable operation of combined heat and power microgrids. Domestic research has closely followed international developments, achieving significant progress. Chinese researchers have extensively explored system operational characteristics under varying conditions and investigated optimization scheduling strategies to enhance energy efficiency. However, despite these advancements, existing research still falls short in simultaneously addressing economic efficiency and environmental sustainability. There remains substantial room for improvement, particularly regarding enhancements in optimization algorithm performance, adaptability, and the effective handling of complex constraints.

2. Theoretical Foundations for Operational Optimization of CCHP Integrated Energy Systems

2.1. Overview of CCHP Systems

A CCHP system is an advanced integrated energy utilization system that employs equipment such as natural gas internal combustion engines and gas turbines to generate electricity from natural gas combustion while utilizing the residual heat produced during this process for heating and cooling, thereby achieving cascading energy utilization. CCHP systems primarily consist of gas turbines, gas boilers, electric chillers, and absorption chillers, which operate collaboratively to satisfy user demands for electricity, heat, and cooling. The operating principle involves gas turbines or internal combustion engines burning natural gas to generate electricity while simultaneously producing high-temperature exhaust gases. These gases are directed into gas boilers to produce steam or hot water for heating purposes. In summer, the excess heat can be converted into cooling through absorption chillers or electric chillers. Notably, CCHP systems significantly enhance energy efficiency, achieving utilization rates above 70%, effectively reduce environmental pollution by lowering emissions of carbon dioxide and other pollutants, and decrease user energy costs, thereby improving overall economic efficiency.

2.2. Overview of multi-objective optimization problems

Fundamental Concepts of Multi-objective Optimization Problems Multi-objective optimization refers to problems where multiple conflicting objectives must be optimized simultaneously. These objectives often conflict with each other, making simultaneous optimality challenging. Mathematically, a multi-objective optimization problem is expressed as follows: given a decision variable vector $x \in R^n$, find the optimal solutions that simultaneously optimize multiple objective functions $f_i(x)$, where $i = 1, 2, \ldots, m$. A distinctive characteristic of multi-objective optimization is the presence of multiple conflicting objectives, implying the non-existence of a single solution optimizing all objectives simultaneously. Instead, there exists a set of solutions known as Pareto optimal solutions. A solution x is defined as Pareto optimal if there is no other solution x' that improves at least one objective without worsening others, mathematically denoted as: $f_i(x') \le f_i(x)$ for all objectives, with at least one strict inequality $f_i(x') \le f_i(x)$. Common methods for addressing multi-objective optimization include transforming multi-objective problems into single-objective formulations or directly applying multi-objective optimization algorithms.

2.3. Principles of Particle Swarm Optimization

Particle Swarm Optimization (PSO), proposed by Kennedy and Eberhart in 1995, is a population-based intelligent optimization algorithm. The basic principle of PSO mimics the foraging behavior of bird flocks. Each particle in the algorithm represents a potential solution and moves through the solution space by continuously updating its velocity and position to find an optimal solution. The velocity and position update formulas for particles are defined as follows:

$$v_{di}(t+1) = \omega v_{di}(t) + c_1 r_1 (pbest_i - x_{di}(t)) + c_2 r_2 (gbest - x_{di}(t)) \quad \ldots\ldots\ldots\ldots (1)$$

$$x_{di}(t+1) = x_{di}(t) + v_{di}(t+1) \quad \ldots\ldots\ldots\ldots (2)$$

Here, $v_{di}(t)$ is the velocity of particle i in dimension d at iteration t, $x_{di}(t)$ is the position of particle i in dimension d at iteration t, $pbest_i\ x_{di}(t)$ denotes the historical best position of particle i, $gbest$ represents the global best position across the entire swarm, ω is the inertia weight, c_1 and c_2 are learning factors, r_1 and r_2 are random numbers. The PSO algorithm is characterized by simplicity, high computational efficiency, and strong memory capabilities, although it faces challenges such as premature convergence and local optima.

2.4. Features and Advantages of Multi-Objective Particle Swarm Optimization (MOPSO)

Multi-Objective Particle Swarm Optimization (MOPSO) is an extension of the PSO algorithm specifically tailored for multi-objective optimization problems. The key characteristics of MOPSO include: (1) utilizing an external archive to store and maintain a diverse set of Pareto optimal solutions, preserving solution diversity; (2) employing techniques such as crowding distance to manage the distribution and maintain diversity within the external archive; (3) specially handling individual best ($pbest$) and global best ($gbest$) positions by selecting non-dominated solutions from the external archive as $gbest$. The primary advantages of MOPSO are its capability to effectively solve multi-objective optimization problems, its excellent performance in maintaining solution diversity and convergence, and its retention of the simple implementation and high computational efficiency of PSO, while addressing and overcoming the limitations encountered by conventional PSO in multi-objective optimization scenarios.

3. MOPSO-based Operational Optimization Model for CCHP Systems

3.1. Objective Functions for CCHP System Operation Optimization

The definition of objective functions is crucial for the operational optimization of CCHP systems, as it directly determines the optimization direction and priorities. This research primarily focuses on two core objective functions: minimizing economic costs and optimizing environmental performance, aiming to achieve efficient, economic, and environmentally friendly operations for CCHP systems.

3.1.1. Minimization of Economic Costs

Economic costs in CCHP systems encompass several aspects, including investment costs of equipment, electricity purchase costs, and natural gas purchase costs. Investment costs of units are closely associated with equipment-rated power and operational costs. Electricity purchase costs depend on electricity prices and consumption across various time intervals, whereas natural gas purchase costs are influenced by gas prices and consumption rates. A comprehensive and accurate economic cost objective function is developed through precise calculation and consideration of these cost factors, guiding economic optimization in CCHP system operations.

3.1.2. Optimization of Environmental Performance

The environmental performance objective function mainly addresses the environmental costs resulting from carbon dioxide emissions during system operation. In CCHP systems, burning natural gas for power generation and heating constitutes the primary source of CO_2 emissions. By analyzing and quantifying CO_2 emissions from each equipment component and integrating unit costs, a reasonable environmental cost objective function is constructed. This ensures the full consideration of environmental impacts in the optimization process, promoting the transition of CCHP systems towards low-carbon and environmentally sustainable operations.

3.1.3. Integration of Multi-objective Optimization

Due to the inherent trade-offs and conflicts between economic and environmental objectives, direct simultaneous optimization of these two aspects can introduce complexity. Therefore, an effective method is required to integrate and balance these objectives. A weighted sum approach combines economic and environmental costs into a unified optimization objective. This approach simplifies the optimization problem and allows decision-makers to express their preferences and weighting on economic and environmental considerations, thereby providing a feasible pathway for solving multi-objective optimization problems.

3.2. Decision Variables and Constraints

Clearly defining decision variables and constraints is a critical step in constructing the optimization model for CCHP systems, as it ensures the model's rationality and feasibility. Decision variables represent operational parameters that can be adjusted and controlled within the system, whereas constraints reflect physical laws, equipment performance limitations, and practical operational restrictions.

3.2.1. Decision Variables

Decision variables primarily include the operational status and power output levels of equipment such as gas turbines, gas boilers, and electric chillers. For example, the on/off status of these units and their corresponding power output levels directly influence system efficiency, economic performance, and environmental impact. By optimizing these decision variables, operational strategies that achieve optimal values of the objective functions can be identified.

3.2.2. Constraints

Constraints form the basis for ensuring the normal, safe, and economical operation of the CCHP system, including energy balance constraints, equipment operational constraints, and environmental constraints. Energy balance constraints ensure equilibrium between energy supply and demand across electrical, thermal, and cooling loads, preventing issues of excess or shortage. Equipment operational constraints include restrictions on equipment power output ranges and startup or shutdown times, ensuring equipment operates safely and efficiently. Environmental constraints mainly limit emissions, such as carbon dioxide, to comply with environmental standards. Collectively, these constraints define the feasible solution space, restricting the values of decision variables to ensure that optimization outcomes meet practical operational requirements while achieving desired optimization objectives.

3.3. Applicability Analysis of MOPSO Algorithm in CCHP Systems

As an efficient multi-objective optimization algorithm, MOPSO demonstrates notable applicability and advantages in addressing operational optimization issues within CCHP systems. Its unique mechanisms and characteristics enable it to effectively manage the complexity and multi-objective challenges involved in CCHP system optimization.

3.3.1. Global Search Capability

MOPSO inherits the global search advantage from the particle swarm optimization algorithm, enabling extensive exploration of potential solutions within the solution space. In the operational optimization of CCHP systems, which involves various equipment combinations and operational parameters, MOPSO can quickly locate globally optimal solution regions through particle collaboration and information sharing. This capability helps prevent premature convergence to local optima, thus achieving comprehensive improvements in system performance.

3.3.2. Multi-objective Optimization Handling

For the multi-objective characteristics in CCHP system operation optimization, MOPSO employs mechanisms such as external archives and crowding distances to effectively handle conflicting objectives. The external archive stores non-dominated solutions, maintaining diversity and distribution of solutions. Crowding distance measures solution density in the objective space, favoring the retention of more dispersed solutions and enhancing the quality of the Pareto optimal set. This ability allows MOPSO to comprehensively consider economic and environmental objectives, providing decision-makers with a well-distributed Pareto optimal solution set that supports informed decision-making.

3.3.3. Complex Constraint Handling

The operational optimization of CCHP systems involves numerous complex constraints, such as equipment power output limitations and energy balance constraints. The MOPSO algorithm effectively manages these constraints through appropriate constraint-handling mechanisms. For example, during particle position updates, solutions exceeding equipment power output ranges are corrected to meet realistic operational conditions. Additionally, during fitness evaluations, the degree to which solutions satisfy constraints is thoroughly considered, and solutions that violate constraints are suitably penalized. This approach directs particles toward feasible regions of the solution space. This efficient handling of complex constraints ensures the practicality and feasibility of the optimization results, highlighting the strong applicability of the MOPSO algorithm in the operational optimization of CCHP systems.

3.4. Establishment and Solution Procedure of the Optimization Model

To achieve the operational optimization objectives for CCHP systems, it is necessary to establish a comprehensive and systematic optimization model along with a scientifically designed solution process. This involves clearly defining the model's inputs and outputs, detailing the specific steps of the optimization algorithm, and outlining how the MOPSO algorithm is utilized to solve the model.

3.4.1. Model Inputs and Outputs

When constructing the optimization model, clearly identifying the inputs and outputs is essential. Inputs primarily include equipment parameters, operational cost data, energy pricing information, and user demands for electricity, heat, and cooling. These input data provide the foundational basis and references for optimization. The outputs represent optimized operational schemes, including decision variables such as the operational status and power output of each piece of equipment, as well as the corresponding objective function values such as economic and environmental costs. By accurately defining inputs and outputs, the optimization process for CCHP systems is clearly described, providing clear guidance for subsequent model solutions.

3.4.2. Initialization of MOPSO Algorithm Parameters

Before employing the MOPSO algorithm to solve the optimization model, it is necessary to initialize various algorithm parameters. These include particle swarm size, maximum iterations, inertia weight, and learning factors. The particle swarm size determines the diversity of the search and computational complexity; larger swarms can improve solution quality but also increase computational time. The maximum number of iterations limits algorithm execution time and should be adjusted based on problem complexity. The inertia weight and learning factors influence particle search behavior, balancing global search capabilities and local exploitation abilities. Additionally, particle positions and velocities must be initialized, typically generated randomly within feasible solution regions, and velocities are set within a defined range.

3.4.3. Iterative Solving Process

The iterative solving process of the MOPSO algorithm is central to solving the optimization model. In each iteration, the fitness value of each particle is first calculated based on the economic and environmental costs defined in the objective functions, alongside checking their adherence to constraints. Subsequently, the individual best position (pbest) and global best position (gbest) of each particle are updated. Individual best positions are updated based on each particle's historical optimal solutions, while global best positions are selected from non-dominated solutions in the external archive, using mechanisms such as crowding distance for selection and update. Particle velocities and positions are then adjusted according to velocity and position update formulas, directing particles towards improved solutions within the solution space. Throughout the iterations, the external archive is continually updated and maintained to preserve a set of high-quality non-dominated solutions. The algorithm stops once the predetermined maximum number of iterations or other termination criteria are reached, outputting the final Pareto optimal solution set.

3.4.4. Result Analysis and Decision Making

Upon obtaining the Pareto optimal solution set, an in-depth analysis and interpretation of the results are required. By plotting the Pareto front of the objective functions, the trade-offs between economic and environmental costs are visually demonstrated, aiding decision-makers in understanding the characteristics and advantages of different solutions. Furthermore, solutions within the Pareto optimal set should be assessed and ranked based on actual operational conditions and user demands, selecting the most suitable operational strategy. This may involve detailed evaluations of different solutions in terms of equipment efficiency, energy utilization efficiency, and environmental impacts. Ultimately, the selected operational strategy is applied to actual CCHP system operations to achieve optimized operation, enhance energy efficiency, reduce operational costs, and minimize environmental pollution.

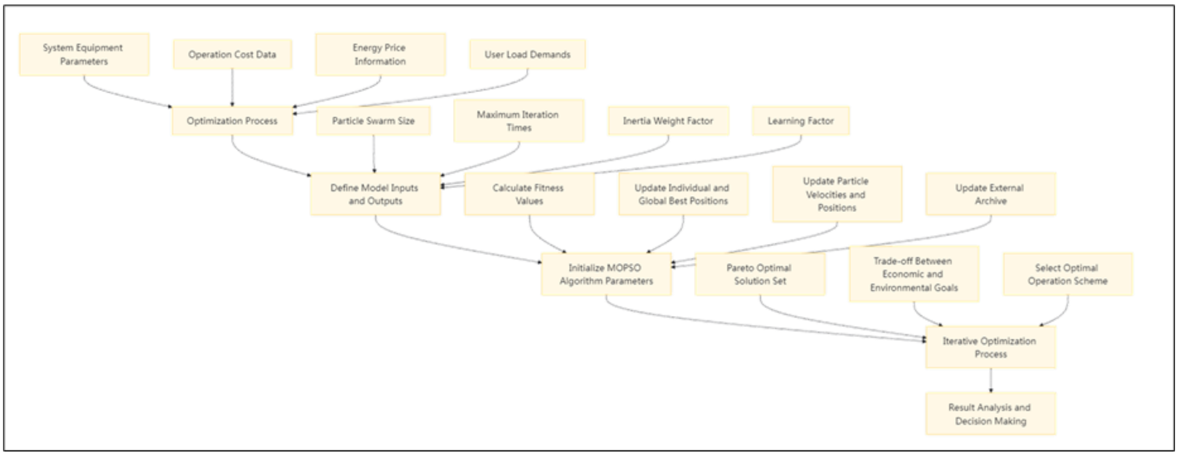

Figure 1 Optimization process

4. Case Study and Results Discussion

4.1. Case Background and System Parameter Settings

This case study examines a typical commercial building's CCHP system, which includes major equipment such as gas turbines, gas boilers, and electric chillers, designed to meet the building's electricity, heating, and cooling demands. Regarding parameter settings, the rated electric power of the gas turbine is 500 kW, the maximum thermal power of the gas boiler is 400 kW, and the maximum cooling power of the electric chiller is 300 kW. Operational cost parameters for equipment are established based on market research data, for instance, the operating cost coefficient for the gas turbine is 0.2 yuan/kW, for the gas boiler 0.15 yuan/kW, and for the electric chiller 0.1 yuan/kW. Energy prices include time-of-use electricity pricing fluctuating between 0.5 to 0.9 yuan/kW, and natural gas priced at 3 yuan/m^3. User demands for electricity, heating, and cooling are set according to historical data and building usage characteristics, with peak electricity loads during working hours, heating demands concentrated during winter heating periods, and cooling demands peaking during summer air conditioning periods.

4.2. MOPSO Algorithm Parameter Configuration and Solution Process

In configuring parameters for the MOPSO algorithm, the particle swarm size was set to 100, and the maximum number of iterations was set to 200. The inertia weight factor was initialized at 0.9 and linearly decreased to 0.4, while the learning factors c1 and c2 were both set at 2. The external archive size was limited to 100, and a crowding distance mechanism was employed to maintain archive diversity. At the start of the solution process, particle positions and velocities were randomly initialized, with positions generated within feasible ranges of equipment power outputs, and velocities initialized within the range of [-1,1].

During each iteration, particle fitness—economic and environmental costs—was evaluated to determine compliance with constraints, such as equipment power output limitations and energy balance constraints. Individual best positions (pbest) were updated based on each particle's historical optimal solutions, and global best positions (gbest) were selected from non-dominated solutions stored in the external archive, using crowding distance to ensure solution diversity. Subsequently, particle velocities and positions were updated according to the standard velocity and position update equations, ensuring effective exploration within the solution space.

The external archive was updated after each iteration, removing duplicate solutions and those with smaller crowding distances to maintain a uniformly distributed set of solutions. Once the maximum number of iterations was reached, the algorithm terminated, and the Pareto optimal solution set stored in the external archive was outputted.

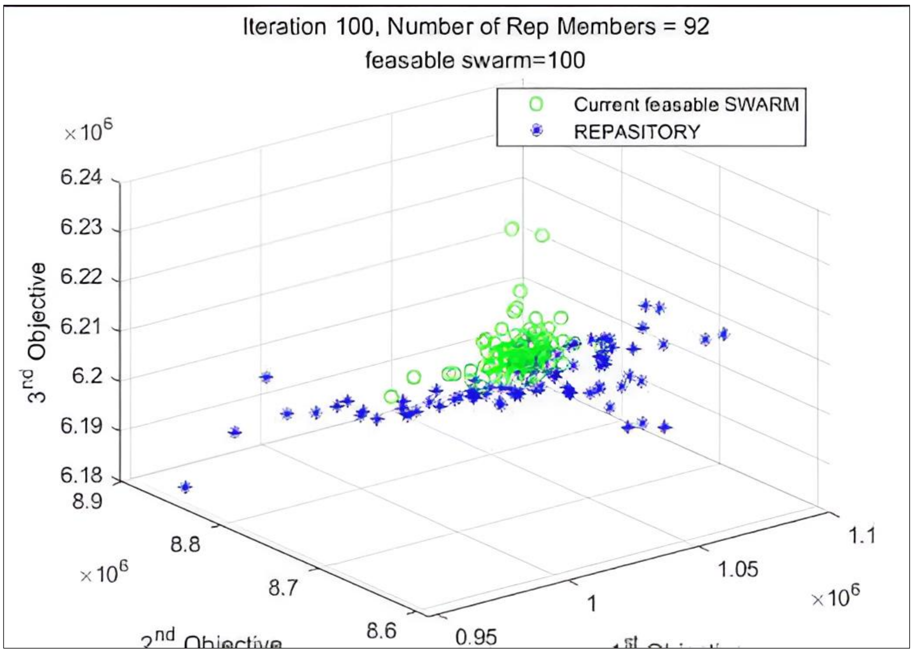

Figure 2 Iterative optimization process

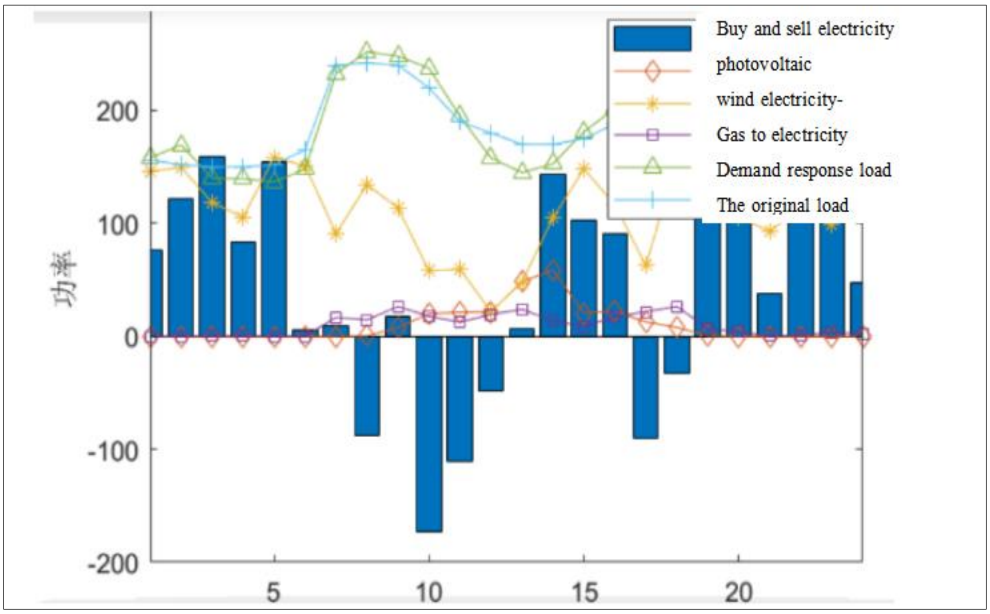

Figure 3 Grid operation plan

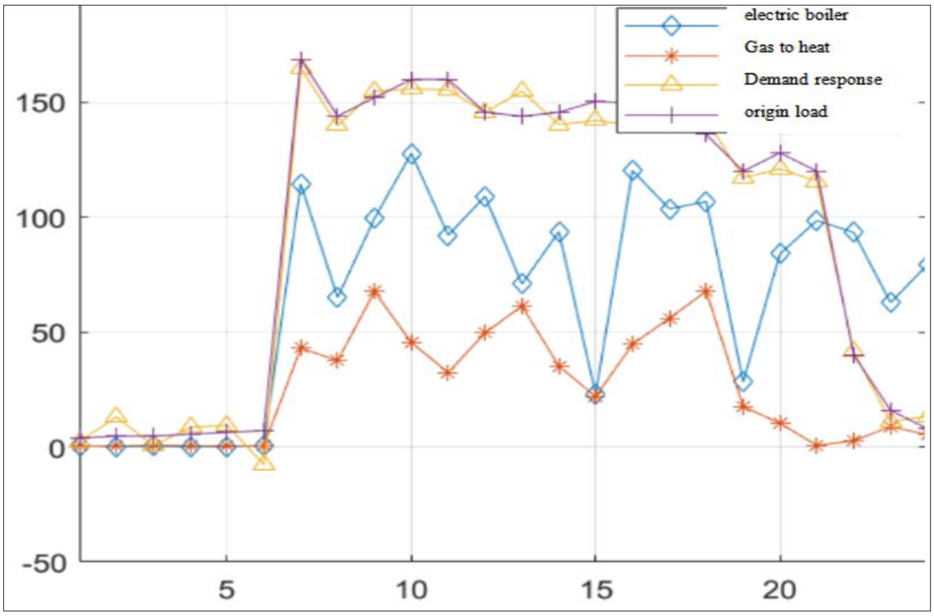

Figure 4 Heating network operation plan

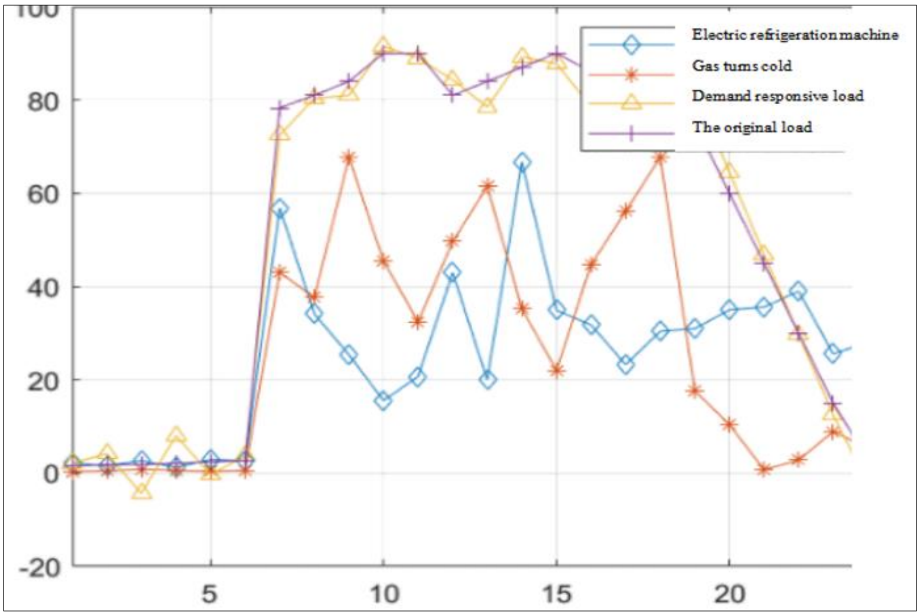

Figure 5 Cold network operation plan

4.3. Optimization Results Analysis

The operational optimization of CCHP systems based on the Multi-Objective Particle Swarm Optimization (MOPSO) algorithm achieved significant economic and environmental benefits. Economic costs substantially decreased by rationally scheduling equipment operations, reducing energy waste, equipment wear, and maintenance costs. Electricity purchasing costs dropped during off-peak hours, and natural gas costs decreased due to more efficient equipment operation. Environmentally, carbon dioxide emissions significantly reduced, promoting environmentally friendly operations. Equipment operating efficiency improved, with power outputs aligning closely with user demands, thus minimizing frequent startups and shutdowns, extending equipment lifespan.

The Pareto frontier generated from optimization results illustrated trade-offs between economic and environmental objectives clearly. Decision-makers can select suitable operational schemes from the Pareto optimal set based on practical requirements and policy considerations. These optimization outcomes serve as robust references for collaborative planning in integrated energy systems, confirming the efficacy and superiority of MOPSO in solving operational optimization challenges in CCHP systems, steering energy systems towards greater efficiency, economy, and environmental friendliness.

4.4. Comparative Analysis with Other Optimization Methods

The MOPSO algorithm was compared with other multi-objective optimization algorithms, such as Genetic Algorithm (GA) and NSGA-II, in solving the operational optimization problem of CCHP systems. In terms of solution quality, MOPSO produced more uniformly distributed Pareto optimal solutions with smaller variations in objective function values among solutions, highlighting its superior capability in finding diverse, high-quality solutions. Regarding convergence speed, MOPSO converged faster, approaching the optimal region with fewer iterations, whereas GA and NSGA-II exhibited slower convergence in early iterations, requiring more iterations to achieve comparable results. Concerning computational efficiency, MOPSO showed shorter computation times, particularly noticeable with larger-scale problems due to its simpler particle position and velocity updates. Conversely, GA and NSGA-II had higher computational complexity due to operations such as selection, crossover, and mutation. However, under certain complex constraints, MOPSO occasionally showed decreased solution quality, while GA and NSGA-II tended to exhibit greater robustness.

5. Research Conclusions and Future Prospects

This study proposed an optimization method based on the MOPSO algorithm for operational optimization in CCHP systems, constructing an optimization model aimed at minimizing economic and environmental costs. Case analyses validated the effectiveness and advantages of this approach. The optimization results demonstrated that this method substantially reduces system operating and environmental costs, enhances energy utilization efficiency, and improves equipment operational efficiency, providing scientifically reasonable optimization schemes for practical CCHP system operations. Future research may expand the optimization model further by incorporating more practical operational factors, such as dynamic equipment characteristics and renewable energy integration, to adapt to more complex energy system environments. Additionally, in-depth research into improving MOPSO strategies to enhance performance under complex constraints can further elevate the quality and reliability of optimization outcomes.

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