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Optimization Algorithms for Urban Energy Balance: The Application of Thermodynamic Methods in Low-Carbon Ecological City Design

Xuefeng Wang[1], Yugui Jia[2*], Mingyue Shao[1], Zongyue Chang[2], Pan Zhang[2]

[1] Hebei Key Laboratory of Water Quality Engineering and Comprehensive Utilization of Water Resources, Hebei University of Architecture, Zhangjiakou 075000, China
[2] Hebei Renewable Energy Heating Engineering Research Center, Hebei University of Architecture, Zhangjiakou 075000, China

Corresponding Author Email: wxf1213@hebiace.edu.cn

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ABSTRACT

As the severity of global climate change and the energy crisis intensifies, constructing sustainable urban energy systems has become a focal point of global attention. The optimization of urban energy balance is a crucial step in achieving low-carbon ecological city design. Its objectives are to reduce energy consumption and carbon emissions while ensuring the stability and economy of urban energy supply. This paper focuses on the application of thermodynamic methods in the design of low-carbon ecological cities, aiming to enhance the efficiency and sustainability of urban energy systems through optimization algorithms. Current research is concentrated on exploring efficient management of urban energy flows, yet faces challenges in computational efficiency and model adaptability concerning thermodynamic system modeling and energy allocation strategy optimization. This study first establishes an urban energy system model based on comprehensive thermodynamic principles, considering the diversity and complexity of urban energy consumption. Subsequently, it proposes an optimization algorithm based on multi-energy flow balance to improve urban energy allocation strategies. This algorithm optimizes for system dynamics and non-linearity issues, and enhances computational efficiency for processing large-scale data. The findings of this paper not only provide new theoretical perspectives and computational tools for optimizing urban energy balance but also offer scientific decision-making support for practical low-carbon ecological city planning and management, demonstrating significant theoretical innovation and practical application value.

1. INTRODUCTION

In today's era, faced with global climate change and an energy crisis, establishing sustainable energy systems has become a core issue in urban development planning [1-9]. Cities, as the main venues for energy consumption, have their energy structures and consumption patterns directly related to the level of carbon emissions [10-12]. Therefore, in the field of ecological city design, the research and implementation of optimizing urban energy balance become particularly critical. This involves not only the effective supply and consumption of energy but also the application of thermodynamic principles in urban energy management and the interaction between these principles and urban planning strategies.

The significance of related research lies in its ability to provide urban planners with a powerful tool to simulate, analyze, and optimize energy flows in a scientific and systematic manner [13, 14]. Through a deep understanding of urban energy systems, more efficient and low-carbon energy allocation schemes can be constructed, thus promoting cities to develop in a greener and more sustainable direction [15-17]. Such research not only helps reduce greenhouse gas emissions and improve the urban ecological environment but also enhances the efficiency of energy use, providing urban residents with more reliable and economical energy supply.

However, existing research methods have some flaws and deficiencies. For instance, in thermodynamic system modeling, many models have not fully considered the challenges brought by urban scale and complexity [18-21]; in terms of energy allocation strategy optimization, the dynamic characteristics and non-linear issues of multi-energy flow balance often have not been effectively addressed [22-25]. Moreover, the computational efficiency of existing methods in processing large-scale data is often not high, which limits their application in actual large urban energy systems.

The main content and research value of this paper are as follows: first, we have constructed a thermodynamic system model for low-carbon ecological city design, which comprehensively considers the diversity and complexity of urban energy systems and fully utilizes thermodynamic principles, offering a new perspective for urban energy balance. Second, we propose an optimization algorithm for urban energy allocation strategy based on multi-energy flow balance, which not only considers the dynamism and non-linearity of the energy system but also improves computational efficiency, making the algorithm applicable to large-scale urban energy planning. Through these two parts of the research, this paper not only promotes the development of low-carbon ecological city design theory but also provides feasible solutions for actual urban planning and management, having significant theoretical and practical implications.

2. THERMODYNAMIC SYSTEM MODELING FOR LOW-CARBON ECOLOGICAL CITY DESIGN

Figure 1 presents the structure diagram of the low-carbon urban energy system. This paper makes significant adjustments to traditional thermodynamic system modeling methods to suit the needs of low-carbon ecological city design. Traditional thermodynamic systems mainly include heat sources, primary networks, heat exchange stations, and heat loads, focusing on the production, transmission, exchange, and final use of thermal energy. Figure 2 shows the relationships between the basic components of the thermodynamic system. However, in the design of low-carbon ecological cities, thermodynamic system modeling needs to more comprehensively consider energy efficiency, environmental impact, and the integration of renewable energies. Firstly, this paper focuses on the primary network, i.e., the main transmission system in the thermodynamic system, and analyzes the heat exchange stations as heat loads. Considering that the secondary network can be neglected due to its shorter length and relatively lower energy consumption, this model emphasizes optimizing the efficiency of the primary network and reducing its energy loss. In the low-carbon modeling approach, this paper not only focuses on the recycling of thermal energy but also enhances the system's capacity to absorb renewable energies, such as solar or geothermal energy, thereby reducing dependence on fossil fuels. Moreover, thermodynamic system modeling in low-carbon ecological city design also emphasizes system operation optimization, including the use of advanced thermodynamic principles and algorithms to predict and manage the flow of thermal energy, ensuring maximum energy efficiency and minimal environmental impact of the heat network. This approach, while considering the complexity of urban energy systems, will also introduce more data and real-time monitoring to achieve dynamic optimization and higher operational flexibility of the thermodynamic system.

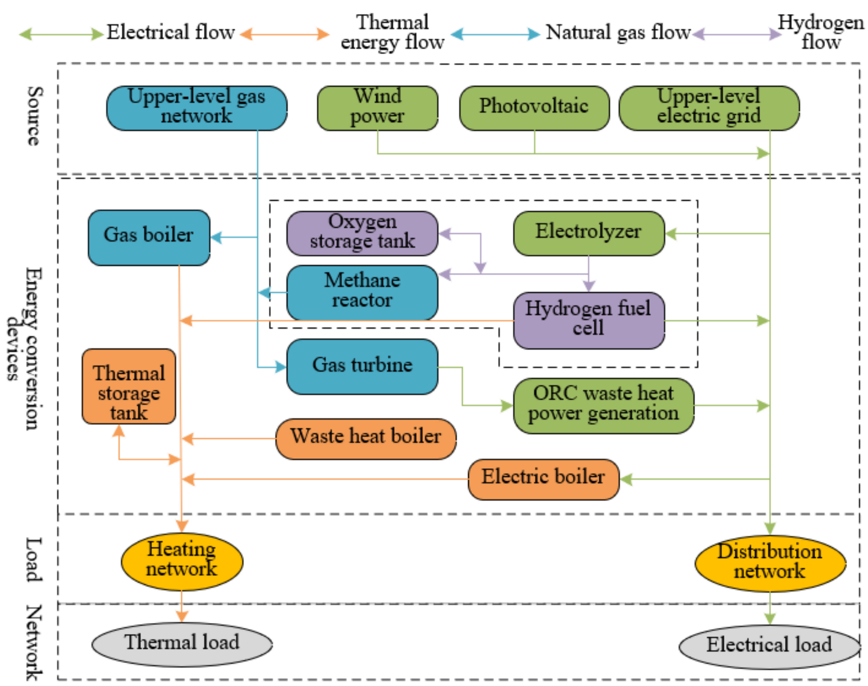


Figure 1. Structure diagram of low-carbon urban energy system

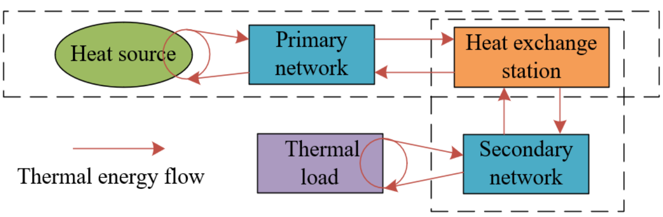


Figure 2. Basic structure of the thermodynamic system

In the design of low-carbon ecological cities, the heat source node needs to consider the integration and efficiency of renewable energies. When calculating the heat supply in a fixed period, it is necessary not only to evaluate the output of traditional heat sources but also to consider the contribution and reliability of renewable heat sources such as solar and geothermal energy. The algorithm needs to be able to dynamically adjust the heat source output based on real-time data of renewable energies to reduce reliance on non-renewable energies. Load node modeling should take into account the energy efficiency and heat retention characteristics of buildings, such as insulation performance, automated energy management systems, etc. The calculation method should comprehensively consider external climatic conditions, usage patterns of buildings, and residents' behavioral habits. Assuming the specific heat capacity of water is represented by z, the mass flow rates passing through the heat source and load are represented by $W^{GT}_{u,s}$ and $W^{M}_{u,s}$, respectively, the supply water temperature by $S^{T}_{u,s}$, and the return water temperature by $S^{e}_{u,s}$. The following equation gives the formula for calculating the heat supplied by source node u in period s:

$$g_{u,s}^{GT} = zW_{u,s}^{GT}\left(S_{u,s}^{t} - S_{u,s}^{e}\right) \tag{1}$$

The following formula calculates the heat consumed by load node u in period s:

$$g_{u,s}^{M} = zW_{u,s}^{M}\left(S_{u,s}^{t} - S_{u,s}^{e}\right) \tag{2}$$

To increase system flexibility, this paper introduces a thermal power relaxation term, allowing for some flexibility in the amount of heat supplied within a certain range. This allows the system to preheat or store thermal energy during non-peak periods, balancing the total heat supply within the period. By relaxing, the system can absorb the instability of renewable energies and optimize system operation through energy storage and demand-side management technologies. Assuming the allowable fluctuation limits of thermal load at time s are represented by $g^{M,MAX}{}_{u,s}$ and $g^{M,MIN}{}_{u,s}$, with the thermal power relaxation coefficients represented by j_{UP} and j_{DO}, respectively:

$$g_{u,s}^{M,MIN} \le g_{u,s}^{M} \le g_{u,s}^{M,MAX} \tag{3}$$

$$\begin{cases} g_{u,s}^{M,MIN} = \left(1 - j_{DO}\right) g_{u,s}^{M} \\ g_{u,s}^{M,MAX} = \left(1 + j_{DO}\right) g_{u,s}^{M} \end{cases} \tag{4}$$

Assuming the indoor temperature limits are represented by s_{xMAX} and s_{xMIN}, with the actual indoor temperature in period s represented by $S_{IN,s}$. The calculation formulas for j_{UP} and j_{DO} are:

$$\begin{cases} j_{DO} = \dfrac{\left|s_{xMIN} - S_{IN}^{f}\right|}{S_{IN}^{f}} \\ j_{UP} = \dfrac{\left|s_{xMIN} - S_{IN}^{f}\right|}{S_{IN}^{f}} \end{cases} \tag{5}$$

To avoid always being at the lower limit of indoor temperature during optimization, it is necessary to constrain the average temperature. This measure ensures that comfort in living and working is not compromised while pursuing energy efficiency. The constraint can be implemented by setting a lower limit of temperature or introducing a resident satisfaction model. Assuming the ideal indoor temperature is represented by $S^{f}{}_{IN}$, then the calculation formula is:

$$\sum_{s=1}^{S} S_{IN,s} \Big/ S = S_{IN}^{s} \tag{6}$$

Overall, thermodynamic system modeling for low-carbon ecological city design emphasizes the system's overall efficiency and environmental impact. Compared to traditional thermodynamic system modeling, it focuses more on the integration of renewable energies, enhancement of thermal energy storage, and demand-side response capabilities, as well as the impact of user behavior on the performance of the energy system. Moreover, this modeling approach should also include the ability to monitor and adjust the system in real time to adapt to dynamically changing environmental conditions and user demands.

3. OPTIMIZATION OF LOW-CARBON URBAN ENERGY ALLOCATION STRATEGY BASED ON MULTI-ENERGY FLOW BALANCE

In the design and optimization process of low-carbon urban energy systems, economic viability is the core determinant of a project's feasibility. Compared with traditional energy systems, low-carbon urban energy systems place more emphasis on integrating various energy flows to ensure efficient operation and minimize environmental impact. For such systems, the premise of allocation optimization is to meet the known total load demand, with the optimization goal being to minimize the overall annualized costs, including initial investment and operational costs. This encompasses not only the expenses of conventional energy facilities but also the investment in renewable energy technologies and potential environmental taxes. In this way, low-carbon urban energy systems aim to achieve long-term economic and environmental benefits simultaneously. Assuming the total annual cost is represented by Q, the annualized investment construction cost of equipment by ${}_{v}Q_{INV}$, and operational expenses by Q_{OPE}, the expression is:

$$MIN\left(Q\right) = MIN\left(Q_{INV} + Q_{OPE}\right) \tag{7}$$

When constructing the energy system of a low-carbon ecological city, maintaining energy flow balance and ensuring that each facility has adequate production capacity are two basic operational constraints of the system. These constraints aim to ensure that the city's heating, cooling, and electricity loads can be reliably met, meaning that at any moment, there is a balance between energy supply and demand, and the design capacity of various energy devices can cope with the maximum demand under extreme conditions. Assuming the upper limit of the number of devices is represented by V_{MAX}, and the upper and lower limits of device capacity are represented by $Z^{MIN}{}_{u}$ and $Z^{MAX}{}_{u}$, respectively, thus we have the inequalities:

$$0 \le V_{u} \le V_{MAX} \tag{8}$$

$$Z_{u}^{MIN} \le Z_{u} \le Z_{u}^{MAX} \tag{9}$$

This paper proposes an optimization method for low-carbon urban energy allocation strategy based on multi-energy flow balance. This method combines the Particle Swarm Optimization (PSO) algorithm with the method of equal incremental. In the first phase of optimization, the PSO algorithm is used to find the optimal energy allocation scheme to minimize construction investment costs while meeting energy supply and demand balance and low-carbon constraints. The second phase employs the method of equal incremental to search for the optimal configuration where marginal costs are equal under the premise of energy flow balance. The method of equal incremental is used here to refine the solution obtained in the first phase, to minimize the system's operational costs, including fuel costs, operation and maintenance costs, carbon emission costs, etc.

In the optimization problem of this paper, each particle represents a potential energy configuration scheme, including but not limited to the size and layout of renewable energy facilities, traditional energy facilities, energy storage systems, and energy conversion units. Assuming there are V individuals in a v-dimensional space, the k-th individual is represented by V_k, with its position attribute represented by MP_k, and its velocity attribute by NR_k, the formula is:

$$V_k = \left[MP_k; NR_k\right] \tag{10}$$

The position of a particle can be mapped to the parameters of an energy configuration scheme, such as the capacity, number, and location of various energy facilities. The specific values of these parameters constitute the particle's coordinates in the solution space. The velocity of a particle represents the speed and direction of changes in the parameters of the energy configuration scheme. Each component of velocity corresponds to a dimension of the particle's position, i.e., the rate of change of an energy configuration parameter. The following expressions give the formulas for position and velocity attributes:

$$MP_k = \left[mp_{k1}, mp_{k2}, mp_{k3} \cdots\cdots mp_{kv}\right] \tag{11}$$

$$NR_k = \left[nr_{k1}, nr_{k2}, nr_{k3} \cdots\cdots nr_{kv}\right] \tag{12}$$

The update of particle positions is based on their current velocity and the individual and collective historical best positions. The update of velocity takes into account both the cognitive component of the individual and the social imitation part. The formula for updating the positions and velocities of the particle swarm is as follows:

$$d\left(MP_u\right) = d\left(mp_{u1}, mp_{u2}, mp_{u3} \cdots\cdots mp_{uv}\right) \tag{13}$$

The velocity found in the previous search represents the particle's velocity in the previous iteration, affecting the velocity update for the current iteration and providing "inertia" to avoid abrupt changes during the search process. The velocity of the current search is the particle's velocity in the current iteration, updated based on the individual and population's historical best positions as well as the previous velocity. Assuming the duration of motion is π, the formula for the previous velocity is:

$$NR_k^{u-1} = \left[nr_{k1}^{u-1}, nr_{k2}^{u-1}, nr_{k3}^{u-1} \cdots\cdots nr_{kn}^{u-1}\right] \tag{14}$$

Each particle's best solution found during the iteration process, i.e., the energy configuration scheme that minimizes construction investment costs up to that point. The formula for calculating an individual's historical best position is:

$$MP_k^{BE} = \left[mp_{k1}^{BE}, mp_{k2}^{BE}, mp_{k3}^{BE} \cdots\cdots mp_{kn}^{BE}\right] \tag{15}$$

The best solution found by all particles in the entire swarm, i.e., the best energy configuration scheme among all schemes that minimizes construction investment costs. The formula for calculating the swarm's historical best position is:

$$MP_{AL}^{BE} = \left[mp_{AL1}^{BE}, mp_{AL2}^{BE}, mp_{AL3}^{BE} \cdots\cdots mp_{ALn}^{BE}\right] \tag{16}$$

The velocity component from the current position to an individual's historical best position encourages the particle to move closer to its personal historical best position, reflecting the ability to learn from its own experience. The formula for calculating the velocity from the current position to the individual's historical best position is:

$$NR_{AL;BE}^{u} = \left(MP_k^{BE} - MP_k^{u}\right)/\pi \tag{17}$$

The velocity component from the current position to the swarm's historical best position encourages the particle to move closer to the entire group's historical best position, reflecting the ability to learn through social interaction and information sharing. The formula for calculating the velocity from the current position to the swarm's historical best position is:

$$NR_{AL;BE}^{u} = \left(MP_{AL}^{BE} - MP_k^{u}\right)/\pi \tag{18}$$

Assuming the weight coefficients are represented by Y_1, Y_2, Y_3, the current velocity can be calculated using the following formula:

$$NR_k^u = Y_1 * NR_k^{u-1} + Y_2 * NR_{k,BE}^u + Y_3 * NR_{AL,BE}^u \tag{19}$$

To prevent particles from skipping the optimal solution due to excessive velocity, the magnitude of velocity is usually limited to a range, which is specifically set based on the physical and economic limitations of the energy configuration parameters. That is, when $NR^u_k > NR_{MAX}$, then $NR^u_k = NR_{MAX}$; when $NR^u_k < NR_{MIN}$, then $NR^u_k = NR_{MIN}$. Assuming the current velocity is represented by NR^u_k, the calculation for the next position MP^{u+1}_k can be conducted using the following formula:

$$MP_k^{u+1} = MP_k^u + \pi \cdot MP_k^u \tag{20}$$

The PSO algorithm searches for the optimal energy configuration scheme through several cycles, with the final position reached by the swarm representing the optimal solution, thus achieving economic, reliable, and low-carbon energy supply.

The equal incremental method is a traditional optimization technique used for economic dispatch in power systems, aiming to find the generator operation combination with the lowest generation cost. In low-carbon urban energy systems, this method can be used to optimize the operation of various energy devices to minimize operational costs while meeting energy demands. In low-carbon urban energy systems, the multi-energy flow balance configuration involves the integration and optimization of various energy sources (such as wind power, solar energy, biomass energy, and traditional fossil fuel energies). Compared to traditional urban energy configurations, the design of low-carbon ecological cities needs to pay more attention to the proportion of renewable energies, the comprehensive utilization efficiency of energy, control of carbon emissions, and the reliability of energy supply.

In the energy balance optimization algorithm for low-carbon ecological cities, considering the dynamic adjustment and optimization of the heating system is crucial for achieving multi-energy flow balance. Unlike the static design of traditional urban energy configurations, the energy system of low-carbon ecological cities needs to have high flexibility and adaptability to respond to real-time changes in load and the variability of renewable energies. In this context, the load allocation for each period is not an independent event starting from zero but is based on a continuous process based on the load allocation of the previous moment. This means that when adjusting the load, the goal is to balance the load difference between the current moment and the previous one, rather than reallocating the entire system's load. Specifically, assuming the electricity and heat load demands at time u are represented by $W^u{}_{rr}$ and $W^u{}_{gr}$, with the initial state W^0=0, then:

$$\begin{cases} \Delta W_{rr} = W_{rr}^{u} - W_{rr}^{u-1} \\ \Delta W_{gr} = W_{gr}^{u} - W_{gr}^{u-1} \end{cases} \tag{21}$$

For the management of thermal loads, if there is an increased demand, the first step is to assess whether the heating equipment with the lowest operational cost has the capacity to increase the load. If the load of these devices cannot meet the increased demand, it is necessary to consider the next lowest-cost equipment. This process requires real-time monitoring and evaluation of the operational costs and available capacity of the equipment. Similarly, if the thermal load demand decreases, priority should be given to reducing the load of the highest operational cost equipment to maintain the economic efficiency of the energy system. If the reduction capacity of the highest-cost equipment is insufficient to meet the demand decrease, adjustments need to be made to the next highest-cost equipment. Figure 3 shows the energy balance calculation process when thermal load demand increases.

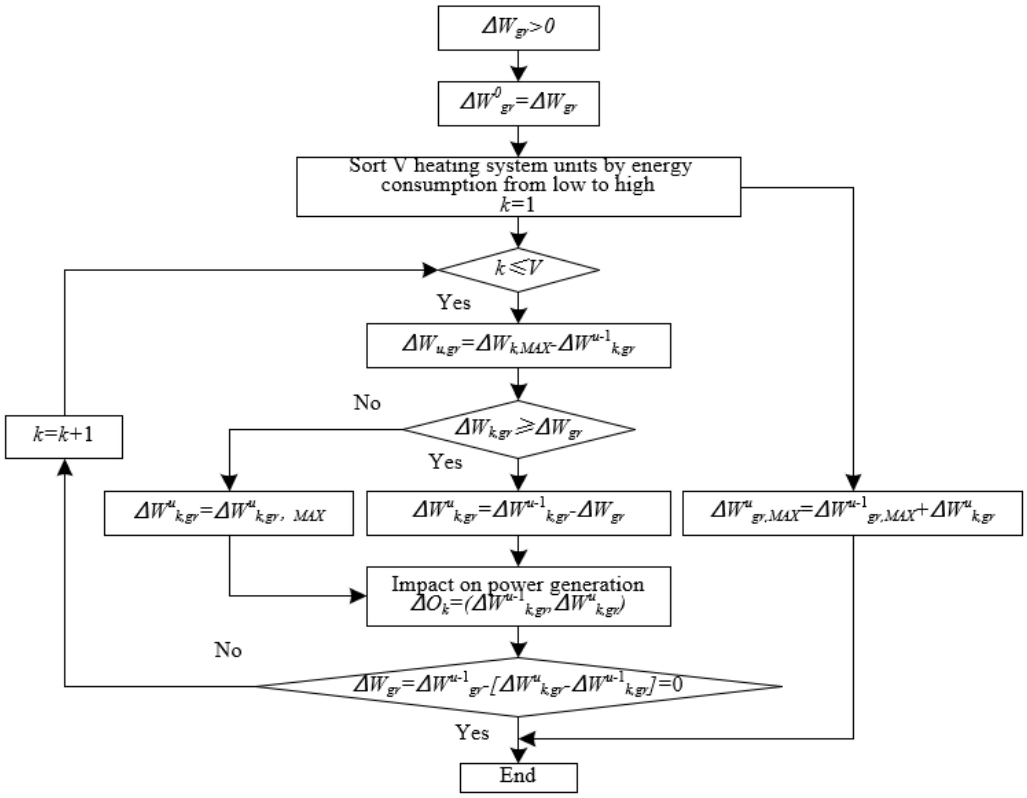


Figure 3. Energy balance calculation process for increased thermal load demand

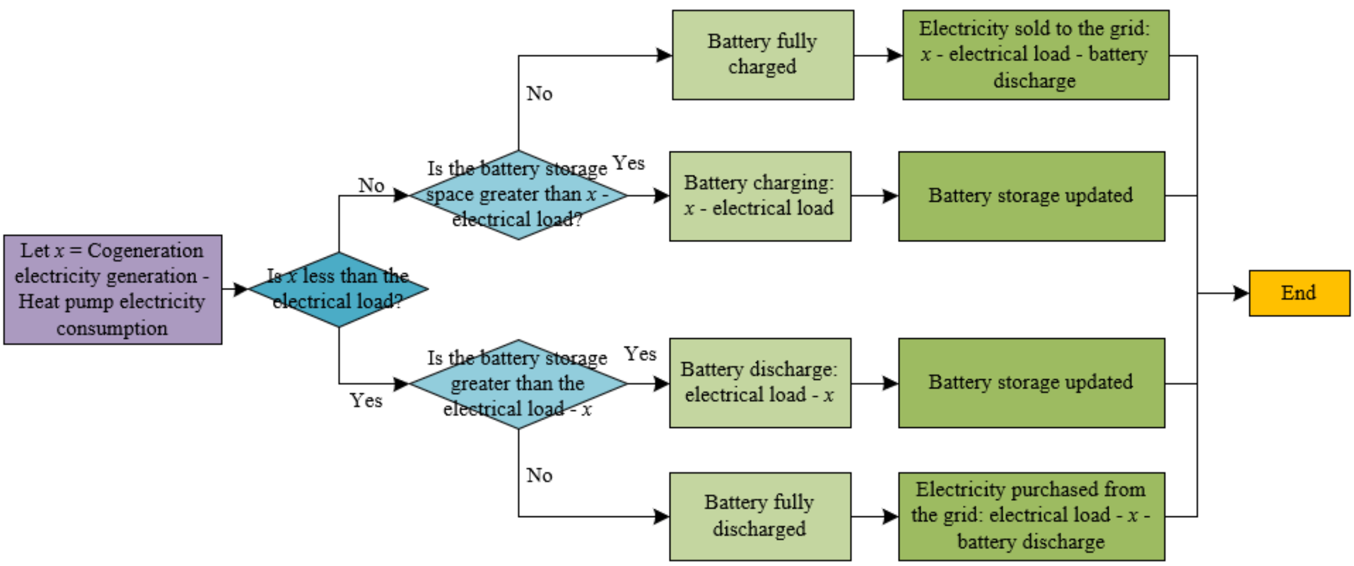


Figure 4. Principle of thermal load distribution affecting electric load distribution

Unlike traditional urban energy configurations, in the energy system of low-carbon ecological cities, energy stations are usually located close to users to minimize energy transmission distances and losses, especially for thermal and cooling energy. Electric energy, due to its relatively high transmission efficiency, can be balanced through electricity grid purchases and sales. However, because of the lower transmission efficiency of thermal energy, it usually needs to be distributed and adjusted at nearby energy stations. During the process of balancing electric loads, the heating loads of combined heat and power units and heat pumps have been determined, meaning their power supply capabilities and electricity consumption are also fixed. Therefore, the main variables to be determined are the charging and discharging states of battery storage systems and the electricity purchase and sale conditions of the grid. The core of this process is to optimize the use of electricity, ensuring supply and demand balance while enhancing system energy efficiency and reducing environmental impact. If the current power supply load cannot meet the electricity demand and there is enough stored electricity, priority should be given to using battery discharge to balance the electric load. When the battery level is insufficient, consider purchasing electricity from the grid. Conversely, if the power supply load exceeds the electricity demand, priority should be given to storing the excess electricity in batteries, and if the batteries are fully charged, consider selling the excess electricity back to the grid. Figure 4 shows the principle of how thermal load distribution affects electric load distribution.

In the multi-energy flow balance configuration for low-carbon ecological city design, the equal incremental method is particularly important, being an effective computational method for dealing with nonlinear problems. In the low-carbon urban energy system, especially when involving combined heat and power systems, the system's efficiency changes are highly nonlinear, meaning that the generation efficiency and waste heat utilization efficiency are not constant but vary with the change in equipment workload. Assuming the efficiency of the *k*-th unit at time *u* is represented by $\lambda^u{}_k$, and the output of the *k*-th unit at time *u* is represented by $W^u{}_k$, the calculation formula is:

$$\lambda_k^u = d\left(W_k^u\right) \tag{22}$$

The equal incremental method allows us to precisely predict the efficiency of equipment at the current moment based on the working state of the equipment in the previous moment. This method considers the efficiency changes of different units under different load segments, making the management of the energy system more refined and the optimization results closer to actual working conditions. To maintain the nonlinearity of the equipment model, assuming the output of the *k*-th unit at time *u*-1 is represented by $W^{u-1}{}_k$, with the initial state $\lambda^0{}_k$=0, this paper uses the method of equal division, and there are:

$$\begin{cases} \lambda_k^u = d(W_k^{u-1}) \\ \lambda_k^0 = 0 \end{cases} \tag{23}$$

In the application of low-carbon ecological city design, using the equal incremental method to update and adjust equipment efficiency not only allows for a more precise matching of supply and demand but also achieves optimization of energy use, thereby reducing energy waste and lowering carbon emissions. Additionally, this method is specifically designed to handle nonlinear problems, capable of adapting to the characteristics of efficiency changes with load in complex systems like combined heat and power. Therefore, this method helps achieve more efficient and greener energy management strategies in the balance configuration of multi-energy flows, which is the core goal pursued by low-carbon ecological city design.

4. EXPERIMENTAL RESULTS AND ANALYSIS

The research area of this study is a newly constructed campus (as shown in Figure 5), covering an area of 960 mu. Within the campus boundary, there is a drainage ditch running from north to south, which undertakes the task of draining and flood discharge for part of the eastern bridge area during the rainy season. Normally, the riverbed is exposed, and its water conservation function needs to be enhanced. The climate is characterized by a temperate continental monsoon climate, with an average annual precipitation of 409mm, indicating a severe lack of water resources in this arid and semi-arid region. The research area is divided into two geomorphological units: the plateau above the dam and the area below the dam. The plateau above the dam has an elevation between 1300 and 1600 meters, boasting rich scenic resources, with the potential for development in the tens of millions of kilowatts.

The project implements a "wind energy - electrical energy - thermal energy" conversion and local consumption engineering, with the system design plan as shown in Figure 6. The main construction content of the project includes: two 20MW and one 24MW electrode boilers, dismantling the original coal-fired boiler facilities, constructing new electric boiler rooms and test rooms, building a supporting 110kv substation, and constructing about 4km of 110kv lines, with a total investment of 0.68 million yuan, all of which are corporate investments. Upon completion of the project, the campus can fully achieve heating through wind power, saving 7,818.59 tons of standard coal annually.

Table 1 presents the calculation results for the nodes in the thermal system network of the research area. Based on the data from Table 1, it can be observed that the relative errors in supply temperature are generally very small, all below 0.5%, demonstrating the model's high precision in temperature control. The supply temperatures from node 1 to node 5 remain within a stable range, consistent with the minor changes expected under ideal conditions, indicating the model's effective simulation of thermodynamic behaviors in the real system. Especially noteworthy is node 6, where the supply temperature is accurate to an integer, and the relative error is 0. This could be due to its special role in the system or an optimization result in the calculation process. Regarding thermal power, nodes 2 to 5 all have a small amount of heat output, with their relative errors still maintained at a low level, showing that the model's prediction for heat output is similarly accurate. The thermal power for node 6 is negative, which in thermal systems usually indicates the recovery of heat energy or its transport to other parts of the system. Its relative error is still kept within a reasonable range, further verifying the model's precise capability in simulating energy flow and system efficiency.

Table 2 provides the calculation results for the thermal network pipelines of the research area, including the pipeline numbers, the head and tail node numbers for the pipelines, the flow rates through the pipelines, and the relative errors in flow rate calculations. The data shows that the relative errors in flow rate calculations for all pipelines are kept below 0.5%, indicating the model's high accuracy in simulating the dynamics of water flow. Pipeline 1 has the largest flow rate at 1.2154 kg/s, with a relative error of 0.48%, while pipeline 5 has the smallest flow rate at 0.2635 kg/s, with the smallest relative error of 0.24% among all the pipelines. This distribution of flow rates reflects the flow driven by temperature differences between pipelines or differences in flow demand designed into the system. The precise calculation of flow rates and low levels of error across the pipelines demonstrate that the model can accurately predict the flow of the heat carrier between different pipelines, which is crucial for ensuring effective heat distribution and overall energy efficiency of the system.

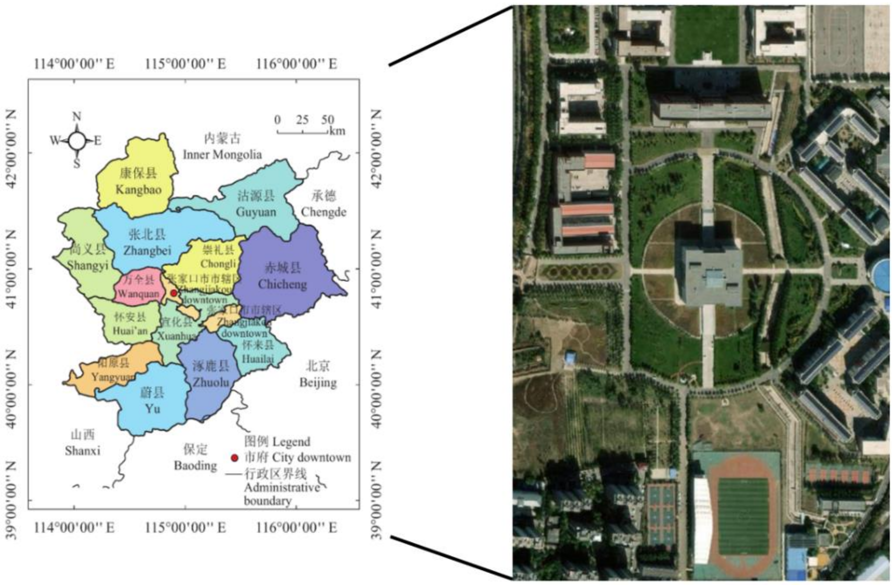


Figure 5. Location of the research area

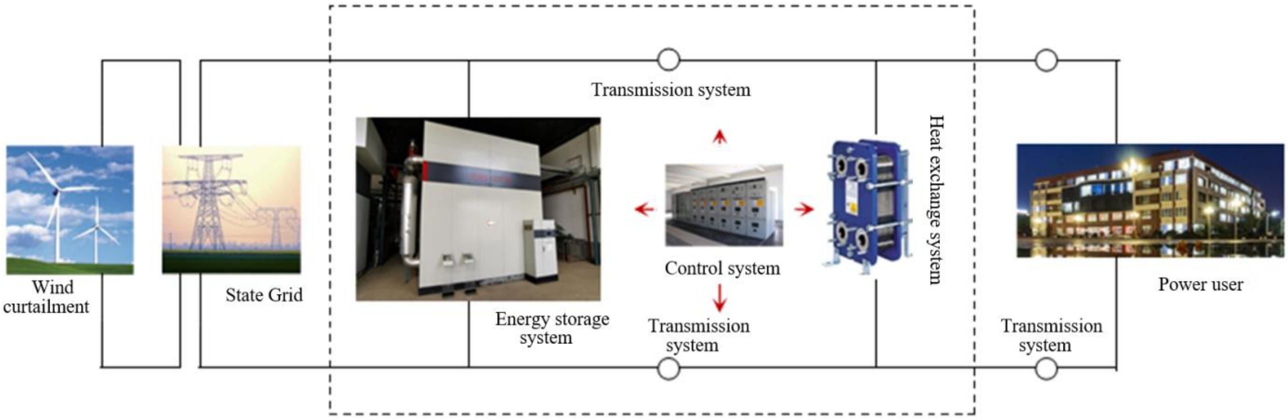


Figure 6. Local consumption wind power heating system

Table 1. Calculation results for the nodes in the thermal system network

Node Number	Supply Temperature (℃)	Relative Error (%)	Thermal Power (*MW*)	Relative Error (%)
1	128.2658	0.08	0	/
2	126.3569	0.16	0.114	/
3	127.5245	0.11	0.139	/
4	127.7841	0.22	0.125	/
5	123.1215	0.33	0.108	/
6	126	0	-0.52	0.12

Table 2. Calculation results for thermal network pipelines

Pipeline Number	Head Node	Tail Node	Pipeline Flow ($m/(kg.s^{-1})$)	Relative Error (%)
1	6	1	1.2154	0.48
2	1	2	0.2563	0.47
3	1	3	0.3458	0.4
4	1	4	0.5789	0.52
5	4	5	0.2635	0.24

Figure 7 displays the electricity generation efficiency of cogeneration units in a low-carbon city energy system of the research area over a 24-hour period, with two sets of data representing efficiency predictions from linear and nonlinear models. In the linear model, the generation efficiency remains constant at 0.3, representing the use of traditional methods or the assumption that efficiency does not change throughout the day. However, the nonlinear model shows variations in efficiency over time, particularly during the high-demand period from 8:00 to 20:00, where efficiency significantly drops to a minimum of 0.12. This variation reflects the impact of various factors on the efficiency of cogeneration units in actual operation, such as load fluctuations, fuel supply changes, or equipment performance. The efficiency changes in the nonlinear model more realistically represent the performance of cogeneration systems in actual operation, demonstrating the ability to respond to changes in energy demand at different times.

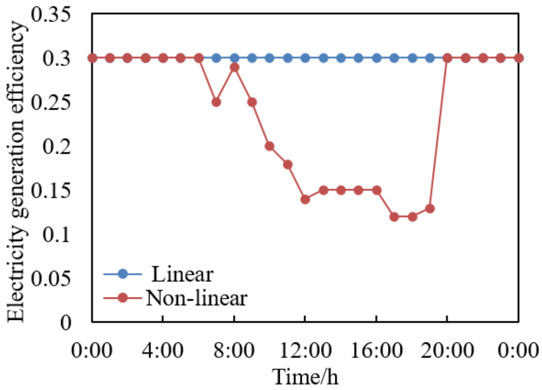


Figure 7. Electricity generation efficiency of cogeneration units in low-carbon urban energy system

Figure 8 shows two sets of data representing the waste heat utilization efficiency of cogeneration units of the research area at different times of the day, from both linear and nonlinear model predictions. The linear model predicts a constant waste heat utilization efficiency of 0.92 throughout the day, a simplification that ignores the complex variations that occur in actual operation. In contrast, the nonlinear model reveals slight fluctuations in waste heat utilization efficiency, especially during the evening and morning periods (16:00-8:00), with efficiency slightly decreasing to a minimum of 0.87. These fluctuations correspond to daily changes in energy demand, such as the reduction in thermal load during the night leading to a decrease in waste heat utilization efficiency. The dynamic predictions of the nonlinear model offer a more refined perspective that reflects efficiency changes due to load variations in actual operation.

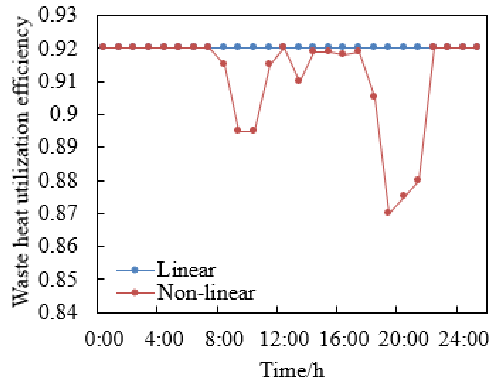


Figure 8. Waste heat utilization efficiency of cogeneration units in low-carbon urban energy system

In summary, the multi-energy flow balance urban energy configuration strategy optimization algorithm proposed in this paper demonstrates the effectiveness of capturing the dynamic nonlinear characteristics of waste heat utilization efficiency in cogeneration systems. The nonlinear model, compared to the linear model, can more accurately simulate minor changes in efficiency throughout the day, which are crucial for optimizing energy use and enhancing system energy efficiency. Particularly during low-load periods at night, the nonlinear model correctly reflects the phenomenon of reduced efficiency, aiding in the precise adjustment of energy configuration strategies to reduce energy wastage.

Table 3. Flexibility indicators of energy configuration in a low-carbon urban energy system under four thermal energy supply methods

Thermal Energy Supply Method	Upward Flexibility		Downward Flexibility		Total Flexibility
	Electric Output Units	Thermal Output Units	Electric Output Units	Thermal Output Units	
1	73265.4	55689	158795	55689	343438.4
2	74512	62315.2	156398	62548.2	355773.4
3	77895.2	62785	189654	61741	392075.2
4	78954.2	68956	185325	63215.2	396450.4

Table 3 compares the flexibility of energy configuration in a low-carbon urban energy system under four different thermal energy supply methods, through three indices: upward flexibility, downward flexibility, and total flexibility. These indices reflect the system's capability to respond to changes in energy demand. Methods 1 and 2 show lower upward and downward flexibility, especially the flexibility of thermal output units compared to electrical output units. With the introduction of new energy systems in Methods 3 and 4, a significant improvement in both upward and downward flexibility is observed, particularly the increase in upward flexibility for electrical output units, indicating that the integration of new energy systems enhances the system's responsiveness to demand fluctuations. Methods 2 and 4 exhibit higher total flexibility compared to Methods 1 and 3, due to the consideration of thermal dynamic balance and the introduction of thermal power relaxation items, suggesting that the application of thermal dynamic balance and relaxation items can further improve the system's adaptability and resilience. The data analysis concludes that the multi-energy flow balance urban energy configuration strategy optimization algorithm proposed in this paper effectively enhances the flexibility of the low-carbon urban energy system. Especially with the introduction of new energy systems and consideration of thermal dynamic balance and thermal power relaxation items, the system's flexibility is significantly improved, indicating that the algorithm can adapt to diversified energy supply methods and complex changes in energy demand.

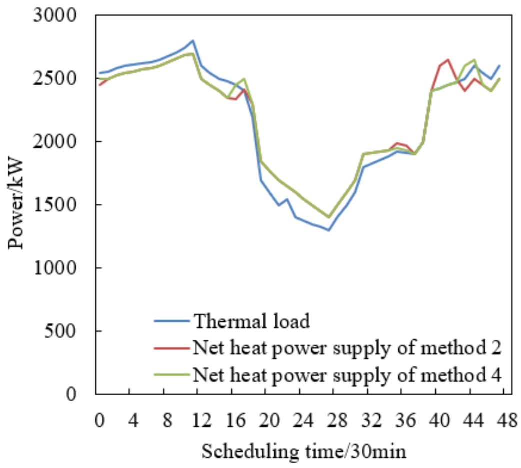
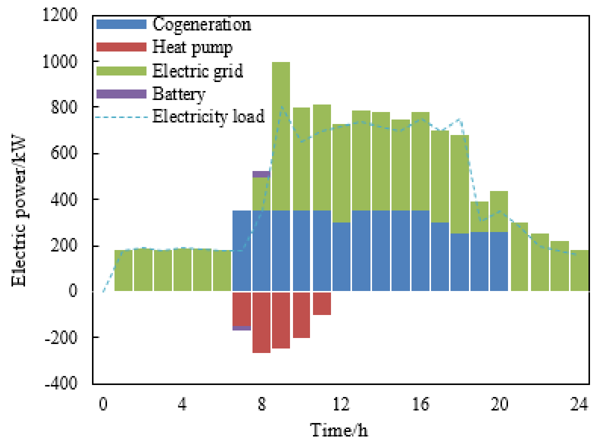


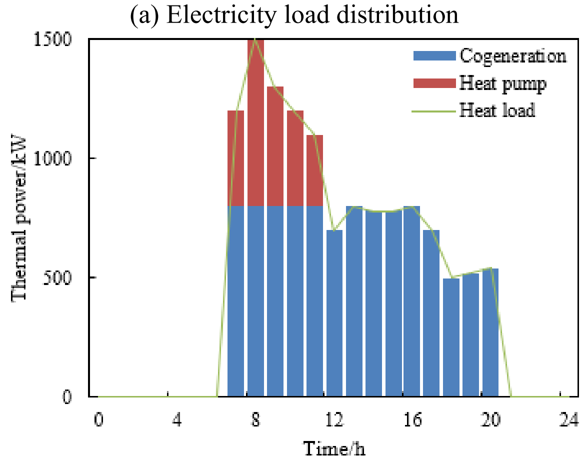
Figure 9. Comparison of net heat power supply and thermal load in low-carbon urban energy system

Figure 9 illustrates the comparison between the net heat power supply and the thermal load of the research area using Methods 2 and 4, showing good consistency with the changes in thermal load, indicating the optimization algorithm's effectiveness in tracking and meeting thermal load demands. At various times, the net heat power supply in Method 4 is slightly higher than in Method 2, especially during periods of decreasing demand (e.g., 20:00 to 24:00), where Method 4's net heat power supply is closer to the thermal load. This is attributed to the addition of new energy systems and the use of thermal power relaxation items, allowing the heating system to adjust the heat supply more precisely, reducing over or under heating. Moreover, during peak hours (e.g., 4:00), Methods 2 and 4 can provide net heat power supply close to or slightly above the thermal load, ensuring the reliability of heat supply. This analysis concludes that the multi-energy flow balance urban energy configuration strategy optimization algorithm proposed in this paper is efficient and reliable in practice. The algorithm, especially Method 4, which considers new energy systems and thermal power relaxation items, allows the heat supply system to flexibly respond to changes in thermal load, ensuring efficient matching of energy supply and the economic operation of the system.

The electricity load distribution graph of the research area given in Figure 10 shows that cogeneration contributes no electricity from 0:00 to 7:00 and 25:00 to 24:00 but provides stable electricity from 8:00 to 24:00, especially during peak hours (12:00 to 20:00) to meet increased electricity load demands. Additionally, heat pumps consume electricity during the morning peak period (8:00 to 11:00), corresponding to their heat supply needs at the same time, and are inactive during off-peak periods. The grid adjusts its electricity contribution dynamically throughout the day, especially providing basic electricity needs when cogeneration is not operating (0:00 to 7:00 and 25:00 to 24:00) and rapidly increasing supply during peak periods (12:00 to 20:00), particularly from 12:00 to 16:00. Batteries perform minor electricity adjustments at 8:00 and 9:00, showcasing their role as an energy buffer. Overall, a dynamic balance between electricity load and supply is achieved through the reasonable distribution of different energy sources, especially during demand peaks, ensuring electricity load demands are met.



(a) Electricity load distribution



(b) Heat load distribution

Figure 10. Results of urban energy configuration based on multi-energy flow balance in a low-carbon city

In the heat load distribution graph of the research area shown in Figure 10, cogeneration, as the main source of thermal energy, provides stable output from 8:00 to 24:00, especially during peak hours (8:00 to 16:00) to meet the highest heat load demands. Heat pumps supply heat only from 8:00 to 12:00, corresponding to their electricity consumption times, indicating the use of electricity to drive heat pumps to meet thermal load demands. This configuration allows for the reasonable use of heat pumps when electricity load is low, and heat load is high, optimizing energy use efficiency. Overall, the satisfaction of heat load also shows the flexible adjustment capability of the heating system, with strong heat supply capacity during peak periods and reduced output on-demand during off-peak periods, avoiding unnecessary energy wastage.

The comprehensive data analysis concludes that the multi-energy flow balance urban energy configuration strategy optimization algorithm effectively achieves a dynamic balance between electricity and thermal loads. The algorithm considers the dynamism and non-linearity of the energy system, coordinating the output of various energy forms (e.g., cogeneration, heat pumps, grid, and batteries) not only to meet electricity and thermal load demands but also to enhance energy use efficiency and reduce energy wastage. The collaborative operation of different energy forms during peak periods is particularly evident, ensuring the reliability of energy supply and the economic operation of the system.

5. CONCLUSION

This paper focuses on designing an efficient thermodynamic system model for low-carbon ecological cities and proposes a new urban energy configuration strategy optimization algorithm. The core objective of the research is to achieve optimal configuration of the energy system to meet the city's electricity and heat energy demands while enhancing the system's low-carbon operational efficiency. An integrated energy system model was developed, based on thermodynamic principles and considering the diversity and complexity of urban energy systems. The model aims to provide a new method for urban energy balance analysis. An optimization algorithm based on multi-energy flow balance was introduced, addressing the system's dynamism and non-linearity while also improving computational efficiency, making it suitable for large-scale urban energy planning.

The model's precision and reliability in simulating urban thermodynamic systems were validated through the analysis of network nodes and thermal network pipelines. The electricity generation and waste heat utilization efficiency of cogeneration units in the low-carbon urban energy system were evaluated to determine their contribution to the system's overall efficiency. The flexibility of the low-carbon urban energy system under four different thermal energy supply methods was assessed, and the match between actual net heat power supply and heat load was evaluated. A comprehensive analysis and optimization of the city's energy system's electricity and heat load configurations were performed based on multi-energy flow balance.

The thermodynamic system model and optimization algorithm proposed in this paper provide an efficient and feasible solution for the design of low-carbon ecological city energy systems. With the development of new technologies, such as artificial intelligence and the Internet of Things, future research could further integrate these technologies to enhance the model's predictive accuracy and the optimization algorithm's computational speed. Considering the importance of renewable energy resources in achieving low-carbon city goals, future research could explore more deeply how to better integrate renewable energy resources into urban energy systems.

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