Intelligent optimization for building energy management considering indoor heat transfer

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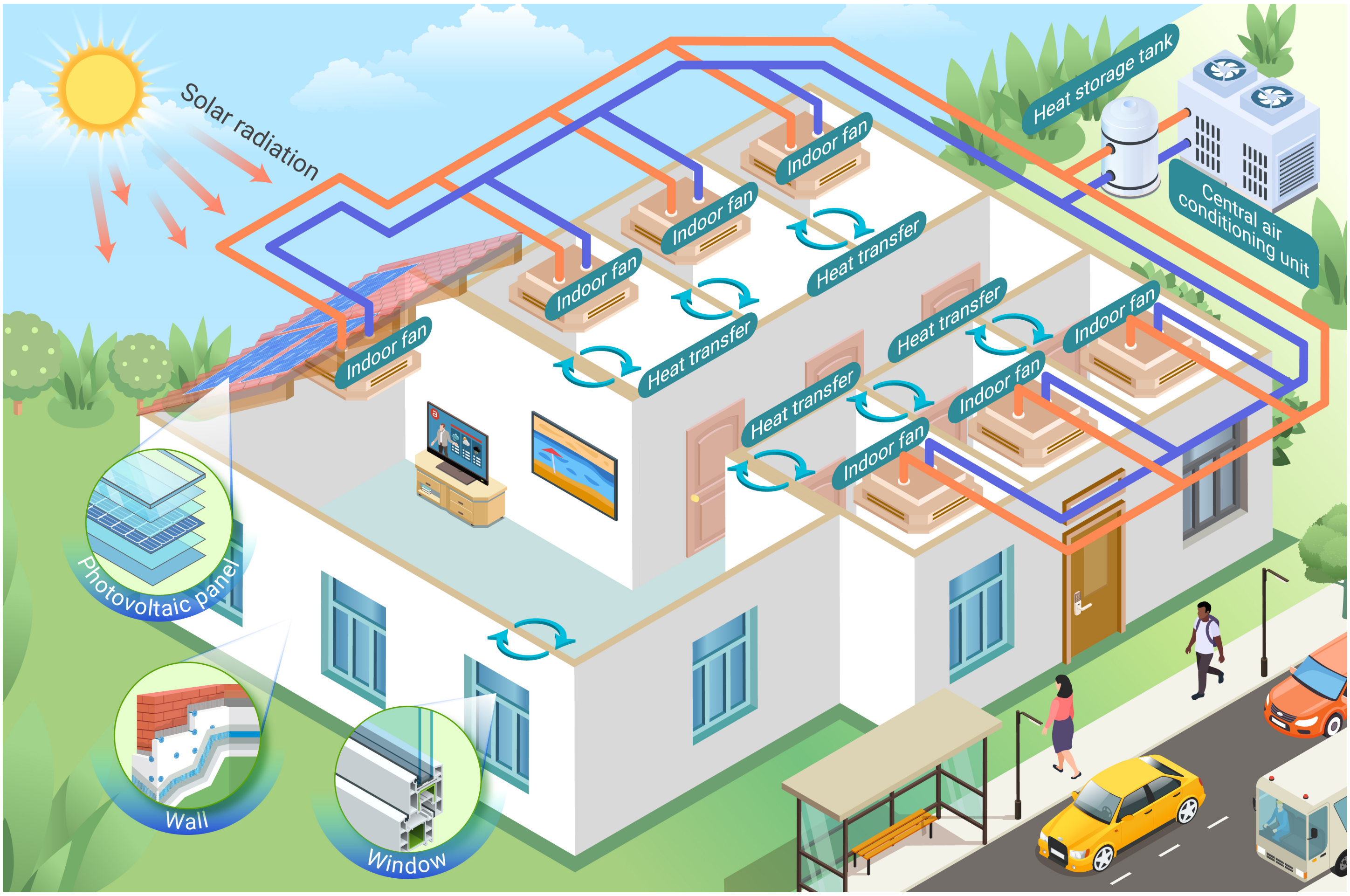
Received: November 2, 2024; Accepted: November 18, 2024; Published Online: November 24, 2024; https://doi.org/10.59717/j.xinn-energy.2024.100058

GRAPHICAL ABSTRACT



PUBLIC SUMMARY

- Whole-building comfort control ignores individual room needs, lacking precise energy use.
- DDPG algorithm optimizes comfort by modeling inter-room heat transfer.
- Achieves 9.82% cost savings while meeting varied comfort needs.

ARTICLE

Intelligent optimization for building energy management considering indoor heat transfer

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Received: November 2, 2024; Accepted: November 18, 2024; Published Online: November 24, 2024; https://doi.org/10.59717/j.xinn-energy.2024.100058

Citation: Jing Z., Chen X., Bu L., et al., (2024). Intelligent optimization for building energy management considering indoor heat transfer. The Innovation Energy 1(4): 100058.

To achieve green and low-carbon goals in the building energy sector, precise energy management strategies are essential to support user comfort and energy-saving needs during operation. However, the thermal comfort requirements of building users may conflict with societal demands for low-carbon and energy efficiency. This creates a challenge between the precision of energy use models and the speed of energy management strategies. It is necessary to combine the advantages of building physical models and deep reinforcement learning to develop faster and more accurate energy management strategies. This paper proposes a smart energy management optimization for buildings, considering indoor heat transfer. First, a third-order heat transfer model for rooms is constructed to quantify the heat transfer between them. Next, a detailed model of the central air conditioning system is developed, considering the relationships between its internal components. To achieve green and low-carbon building operations while maintaining user comfort, a multi-objective optimization algorithm based on deep policy gradient decision-making is proposed. The method is validated on actual building energy systems using real data with 15-minute resolution. We find significant differences in heat transfer between different rooms within a building, and the proposed intelligent energy management optimization method effectively balances low-carbon, energy-efficient operation with user comfort.

INTRODUCTION

With China's goals for carbon peaking and carbon neutrality, achieving a green and low-carbon transition in building energy systems is a key research focus in the construction sector.[1,2] In 2023, the total energy consumption of building operations in China accounted for approximately 21% of the nation's total energy consumption.[3-8] The energy consumption of air conditioning accounts for more than half of the total energy usage in buildings.[9,10] By improving the building envelope, buildings can achieve better temperature delay characteristics,[11] providing greater regulatory flexibility for the air conditioning system.[12] Establishing an accurate relational model between air conditioning operating power and indoor temperature changes, and using energy management optimization algorithms to achieve flexible adjustment of building air conditioning, are effective strategies for improving building energy use. As various forms of renewable energy are integrated into buildings,[13] building energy systems will have greater potential for energy savings. However, the large-scale integration of renewable energy means that buildings need to bear the risk of generation fluctuations, and users' thermal comfort requirements may be constrained by low-carbon and energy-saving goals. In research focused on energy management considering the thermal storage properties of building envelopes and the comfort of building occupants,[14] the studies primarily address the impact of heat convection, heat conduction, and thermal energy storage during the heat transfer process of building envelopes on building energy consumption.[15] A global comfort model is used to quantify the comfort requirements of building users. However, optimizing and regulating the entire building as a whole neglect the different thermal comfort needs of individual rooms. Differences in cooling area among rooms lead to varying energy demands.[16,17] Additionally, factors such as room orientation and heat radiation reception further contribute to variations in temperature changes across rooms, resulting in significant dynamic heat transfer phenomena between rooms.[18] This dynamic heat transfer process between rooms affects the cooling strategies of adjacent rooms. Therefore, treating the building as a single unit for regulation does not achieve optimal energy management for the building. Distributed regulation of multiple rooms requires the support of distributed management and control methods, and in the centralized study of building energy management, distributed devices are controlled in the building through centralized integrated control,[19] and distributed devices are able to collect real-time building operation data and regulate in real time,[20] which improves the real-time nature of the execution of building regulation strategies,[21] and enhances the rapid response capability of the building system.Against this backdrop, there is a need to establish more accurate higher-order thermal models to calculate building heat demand and dynamic transfer processes within buildings. The most commonly used comfort measures are PMV and PDD ,which have been widely used in building microgrids and can respond well to the effects of user metabolic rate, clothing insulation rate and other factors.[22-23] However, conventional energy management methods for intelligent buildings mainly use rule-based and model-based optimization control methods to optimize and control building energy use behavior.[24-26] These approaches might consider various constraints such as photovoltaic power generation, battery capacity,[27] and battery cycle aging efficiency,[28] and require the use of optimization strategies like dynamic programming[29] and distributed optimization scheduling.[30] The time efficiency of such optimization processes is poor. When using conventional optimization methods to solve building optimization problems, it is difficult to handle the complex spatiotemporal coupling relationships within building energy systems. The computation process can be very time-consuming when the solution space is extremely large, leading to an unresolved contradiction between the need for multi-objective optimization and rapid solution finding.[31,32] Deep reinforcement learning integrates the capabilities of deep learning in handling high-dimensional data and automatic feature extraction, allowing it to tackle complex high-dimensional environmental features. It offers excellent generalization and real-time decision-making abilities, making it more suitable for real-time optimization of energy consumption across multidimensional variables in buildings.[33-37] The Actor-Critic framework and the policy gradient algorithm adopted by DDPG can well take into account the multi-objective optimization and take into account the difference in comfort optimization of multiple rooms to achieve continuous policy optimization. Some studies model building systems considering unit parameters, indoor temperature, and source-load uncertainties, using interval-based multi-objective optimization methods through reinforcement learning. Other research focuses on the issue of home energy management, utilizing reinforcement learning for precise optimization and scheduling of controllable and shiftable loads.

Based on the above analysis, this paper proposes an intelligent optimization method for building management that considers indoor heat transfer using the DDPG algorithm. The main contributions are as follows:

(1) The application of a third-order thermal parameter model for buildings accurately accounts for thermal inertia and the dynamic heat transfer process between rooms.

(2) Considering the cooling process of the equipment inside the central air conditioner, the fine operation model of the central air conditioner is constructed to collect data and regulate the feedback through the distributed gateway.

(3) Based on the uncertainties in photovoltaic power generation and rigid loads, the method balances the diverse thermal comfort needs of different rooms and optimizes the building's operational cost throughout the day using the DDPG method, achieving optimal operation of the building system. Finally, the effectiveness of the method is verified through case simulations.

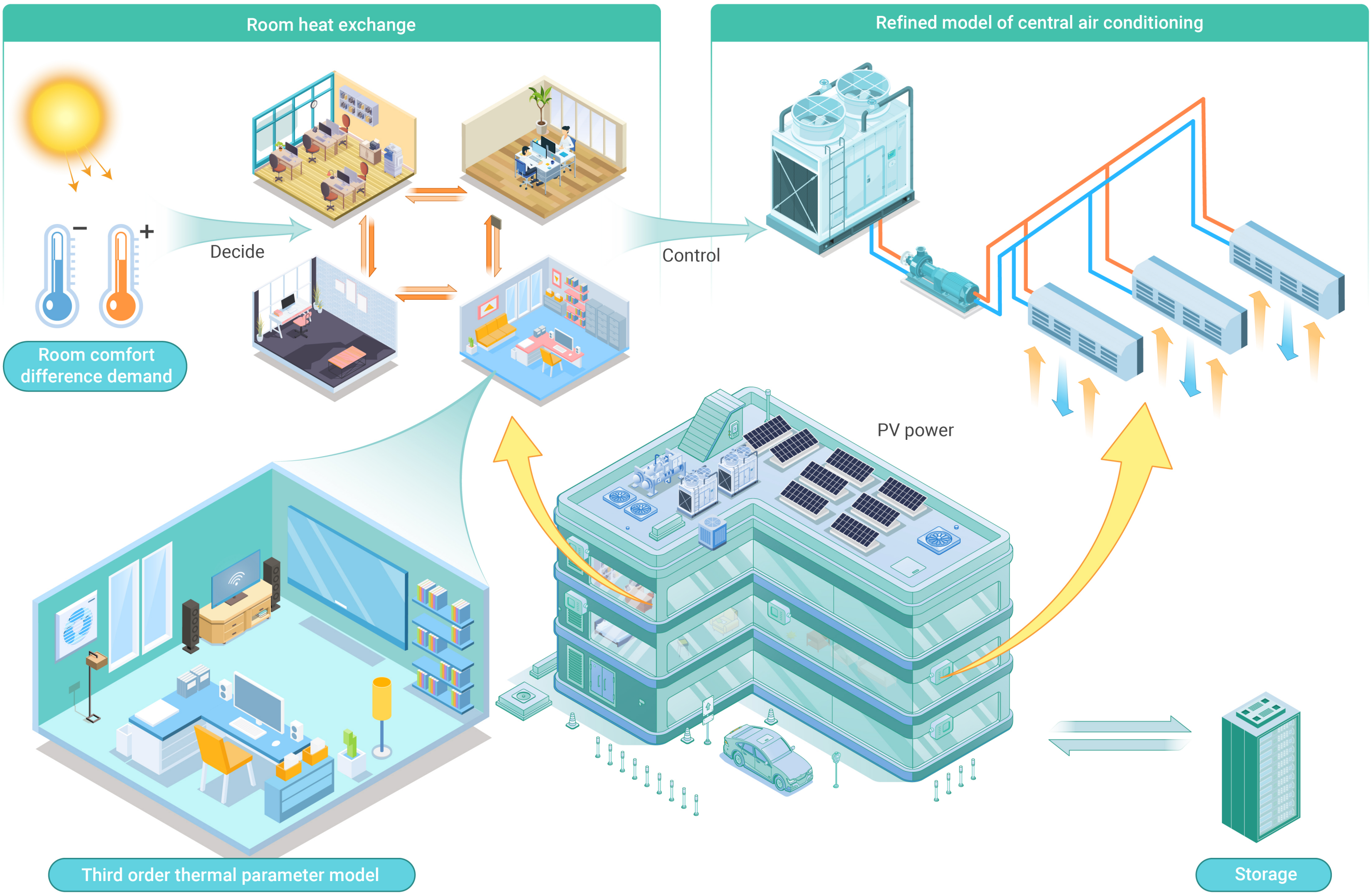

Figure 1. Schematic Diagram of Building Energy Management Structure

MATERIALS AND METHODS

Building Energy Management Model

The energy management framework for public buildings is illustrated in Figure 1. In the field of building energy management, the implementation of optimization strategies relies on identifying the difference between internal energy demand and supply, as well as precisely regulating room comfort, thermal exchange, and energy usage strategies. The energy optimization method proposed in this study aims to achieve accurate control of the building's internal thermal dynamics by dynamically analyzing a third-order thermal parameter model. The model monitors and collects building sensor data through the control of distributed gateways in each room, uses machine learning technology to centrally manage and control the terminal equipment in the building, and then sends it down to the distributed gateways to execute the control tasks in each room respectively, responds quickly to the changes in energy demand, optimizes the energy distribution, thus improving energy efficiency, reducing operating costs, and ultimately realizing sustainable management of energy use in the building.

The flexible load model in the building energy management system includes the rooftop photovoltaic (PV) power generation system model,[38,39] smart electricity appliance model, and energy storage model. The rooftop PV system provides green energy for the building, while smart appliances assist in achieving intelligent regulation of the building.[40] The energy storage system plays a crucial role in building energy management. On one hand, the Building Energy Storage System (BESS) can store surplus energy when solar power is abundant and release it during other periods to meet the building's load demands, thus reducing operational costs and increasing the utilization of renewable energy. On the other hand, BESS can store electricity during off-peak price periods and release it during peak price periods, thereby shifting the building's electricity load from high-price to low-price periods. This reduces operational costs and promotes the integration of renewable energy.

The operational costs of the building mainly stem from the cost of purchasing electricity externally, while thermal comfort is considered as a penalty cost for the building's thermal comfort. Users' thermal needs tend to vary from room to room, so we consider the differentiated thermal comfort needs of different rooms and quantify the differentiated needs in terms of thermal comfort penalty, and the quantification of temperature comfort is measured in terms of PMV. The thermal comfort penalty cost for each room is the product of the thermal comfort gain of that room and the Predicted Mean Vote (PMV).[32] The total comfort cost of the building is the sum of the thermal comfort costs for all rooms:[41,42]

$$minC_{total} = \sum_{t=t_0}^{T} \left(C_t^{grid} + C_t^{thermal} \right) \tag{1}$$

where,

$$C_t^{grid} = P_t^{buy,grid} \times p_t^{buy} \times \Delta t - P_t^{sell,grid} \times p_t^{sell} \times \Delta t \tag{2}$$

$$C_t^{thermal} = \sum_{k=1}^{N} G_{room}(k) \cdot PMV(k) \tag{3}$$

where C_{total} represents the total operational cost of the building; C_t^{grid} represents the cost of purchasing electricity or the revenue from selling electricity; $P_t^{buy,grid}$ is the amount of purchased electricity; p_t^{buy} is the price of purchased electricity; $P_t^{sell,grid}$ is the amount of electricity sold; p_t^{sell} is the price of electricity sold; $G_{room}(k)$ is the thermal comfort gain of the k-th room; $PMV(k)$ is the PMV value of the k-th room.

The concept of thermal comfort gain for a room refers to the significance of the room's thermal comfort. The higher the requirement for thermal comfort in a room, the greater the thermal comfort gain. This gain is positively correlated with the room's area, the purpose of the room, and the comfort requirements of the occupants. Based on the above model, this paper establishes an optimization objective that balances optimal comfort in

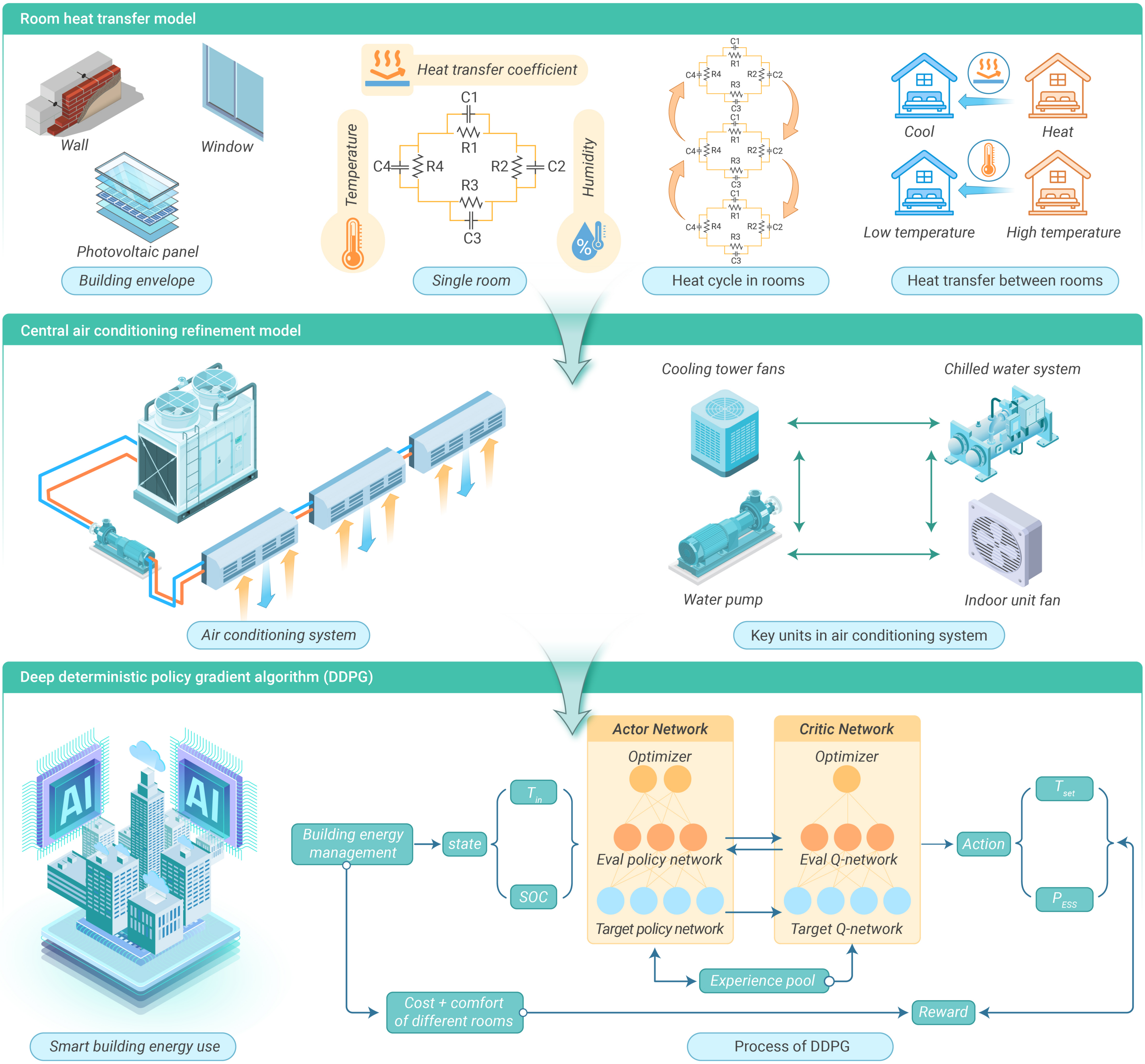

Figure 2. Intelligent Optimization Flowchart for Building Energy Management

each room with minimal operational costs of the building. The constraints include models of the central air conditioning equipment, the thermal comfort model, and the energy storage equipment model. This can be represented as problem P1:

$$P_1 : \min \sum_{t=1}^{L} \mathbb{E}\{C_{total}^{t}\} \tag{4}$$

s.t. *Equipment Operation Constraints*
Power Balance Constraints
Comfort Constraints

Dynamic heat transfer model

In actual buildings, factors such as the structure of room enclosures, room area, window size, and orientation all affect the amount of solar radiation received. The usage attributes of a room also indirectly cause differences in internal heat sources; for example, data centers typically receive more heat gain than office areas. These factors determine that the cooling required for unit temperature change in a room varies, which results in differing air conditioning cooling power. Different cooling rates in two adjacent rooms will lead to temperature differences, causing heat transfer between adjacent rooms. This dynamic process affects the cooling control of each room in the central air conditioning system. Rooms with higher temperatures, due to receiving cooling from adjacent rooms, effectively reduce their cooling demand and consequently reduce the operational power of the air conditioning. Therefore, considering the thermal transfer process of indoor temperatures can have potential impacts on the central air conditioning and overall energy management strategies of the building. The third-order thermal model of each room is shown in Equation. 5:

$$\frac{d}{dt}\begin{pmatrix} T_{ew} \\ T_{in} \\ T_{iw} \end{pmatrix} = A\begin{pmatrix} T_{ew} \\ T_{in} \\ T_{iw} \end{pmatrix} + B\begin{pmatrix} T_{out} \\ I_{ew} \\ I_e + I_{in} \\ I_t^{dev} \\ T_{adj} \end{pmatrix} \tag{5}$$

where T_{ew} is the external wall temperature. T_{in} is the indoor temperature. T_{iw} is the internal wall temperature. T_{out} is the outdoor temperature. T_{adj} is the temperature of the adjacent room. I_{ew} is the solar radiation absorbed by the external wall. I_e is the solar radiation entering the room through the window. I_{in} is the internal heat load generated within the building. I^{dev} is the cooling capacity of the HVAC system. The thermal coefficient matrices $\boldsymbol{A}$ and $\boldsymbol{B}$ in Eq.5 are:

$$A = \begin{bmatrix} \frac{1}{C_{ew}}\left[\frac{R_{ec}}{R'_{ew}(R'_{ew}+R_{ec})} - \frac{2}{R'_{ew}}\right] & \frac{1}{C_{ew}R'_{ew}} & 0 \\ \frac{1}{C_{in}R'_{ew}} & \frac{-1}{C_{in}}\left(\frac{1}{R'_{ew}} + \frac{1}{R'_{iw}} + \frac{1}{R_{gs}}\right) & \frac{1}{C_{in}R'_{iw}} \\ 0 & \frac{1}{C_{iw}R'_{iw}} & \frac{-2}{C_{iw}R'_{iw}} \end{bmatrix} \tag{6}$$

$$B = \begin{bmatrix} \frac{1}{C_{ew}}\frac{1}{R_{ec}+R'_{ew}} & \frac{R_{ec}}{C_{ew}(R'_{ew}+R_{ec})} & 0 & 0 & 0 \\ \frac{1}{C_{in}R_{gs}} & 0 & \frac{1}{C_{in}} & \frac{-1}{C_{in}} & 0 \\ 0 & 0 & 0 & 0 & \frac{1}{C_{iw}R'_{iw}} \end{bmatrix} \tag{7}$$

where R_{ec} is the equivalent thermal resistance for convection. R'_{ew} is half of the equivalent thermal resistance of the external wall. R'_{iw} is half of the equivalent thermal resistance of the internal wall. R_{gs} is the equivalent thermal resistance of the window. C_{ew} is the equivalent thermal capacitance of the external wall. C_{iw} is the equivalent thermal capacitance of the internal wall. C_{in} is the equivalent thermal capacitance of the indoor air.

Heat transfer between rooms is affected by the room temperature of neighboring rooms as well as the temperature of the interior walls between them and the thermal resistance coefficient of the interior walls, and the transfer of cold from a room with a low temperature to a room with a high temperature is a dynamic process in real time. The dynamic heat transfer between rooms is:

$$Q_{change} = \frac{T_1 - T_{iw}}{R_{ec1} + R_{iw}} + \frac{T_{iw} - T_2}{R_{ec2} + R_{iw}} \tag{8}$$

where T_1 is the indoor temperature of the room. T_2 is the indoor temperature of the adjacent room. R_{ec1} is the equivalent convective thermal resistance of the room. R_{ec2} is the equivalent convective thermal resistance of the adjacent room.[43]

Central air conditioning refinement model

In conventional building energy management, the air conditioning model does not consider the interconnections between the internal units of the air conditioning system. In such systems, the chiller unit typically consumes 60%-70% of the energy,[44] the pump system uses 25%-30%, and the fan system accounts for 15%-20% of the total energy consumption.[45] The interactions among the internal air conditioning units can influence the overall performance of the system, highlighting the need for a more detailed model of air conditioning to enable precise control of central air conditioning.[43]

(1) Energy consumption model of the chiller. The chiller is a fundamental part of the central air-conditioning system, and its energy usage accounts for a significant portion of the system's total energy consumption. Therefore, optimizing the chiller is crucial for enhancing the energy efficiency of the air-conditioning system. Given that the chiller often operates in either part-load or full-load conditions, it is essential to create an energy consumption model that accurately represents the correlation between variations in cold load and the chiller's power consumption.

$$P_{chiller} = W_{chiller} \cdot LDR_{chiller} \tag{9}$$

where $P_{chiller}$ is the actual operating power of the chiller. $W_{chiller}$ indicates the operating power of the chiller under rated working condition. $LDR_{chiller}$ indicates the partial load rate of the chiller. Among them, the chiller operating power under rated working condition is:

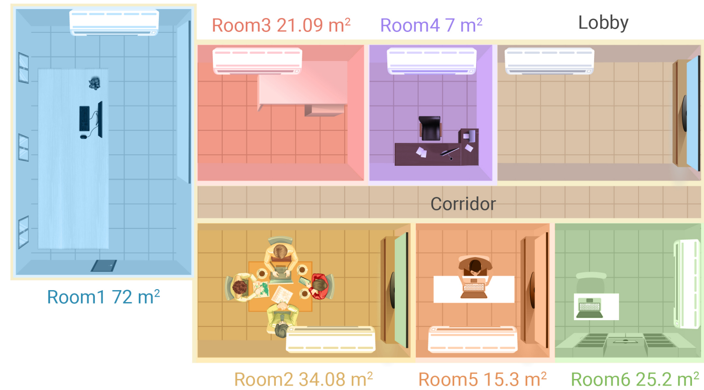

Figure 3. Schematic diagram of rooms' location in the building

$$W_{chiller} = \frac{Q_{rate}}{COP_{rate}} \cdot T_{chiller} \tag{10}$$

$$T_{chiller} = c_0 + c_1 \cdot T_{chws} + c_2 \cdot T_{chws}{}^2 + c_3 \cdot T_{cws} + c_4 \cdot T_{cws}{}^2 + c_5 \cdot T_{cws} \cdot T_{chws} \tag{11}$$

where Q_{rate} denotes the rated cooling capacity of the chiller. T_{chws} and T_{cws} denote the chilled water supply temperature and cooling water supply temperature, respectively. COP_{rate} is the energy efficiency coefficient of central air conditioners. c_0, c_1, c_2, c_3, c_4, and c_5 are the temperature regression coefficients, which can be derived based on the building historical data. The partial load rate $LDR_{chiller}$ of the chiller is:

$$PLR_{chiller} = m_0 + m_1 \cdot \left(\frac{Q_{chiller}}{Q_{rate}}\right) + m_2 \cdot \left(\frac{Q_{chiller}}{Q_{rate}}\right)^2 \tag{12}$$

where $Q_{chiller}$ represents the actual cooling capacity of the water-cooled unit. m_0, m_1, m_2 represent the partial load correction coefficients.

(2) Variable frequency water pump energy consumption model. Inverter water pumps adjust the speed of the motor by changing the current frequency, which in turn regulates the water flow rate of the pump.

$$P_{pump} = P_{pump,rate}(n_0 + n_1 \cdot PLR_{pump} + n_2 \cdot P_{pump}{}^2 + n_3 \cdot P_{pump}{}^3) \tag{13}$$

$$PLR_{pump} = \frac{m_{chw}}{m_{rate}} \tag{14}$$

where P_{pump} represents the actual power of the pump. $P_{pump,rate}$ represents the rated power of the pump. m_{rate} represents the rated flow rate of the pump. m_{chw} represents the actual flow rate of the pump. n_0, n_1, n_2, n_3 are the polynomial fitting coefficients.

(3) Energy consumption model of cooling tower fans. The fan is the main energy consumption of the cooling tower, and the energy consumption of the infinitely variable fan is related to the airflow of the fan.

$$P_{tfan} = P_{tfan,rate}(k_0 + k_1 \cdot LDR_{tfan} + k_2 \cdot PLR_{tfan}{}^2 + k_3 \cdot PLR_{tfan}{}^3) \tag{15}$$

$$LDR_{tfan} = \frac{m_{atfan}}{m_{atfan,rate}} \tag{16}$$

where P_{tfan} denotes the power of the cooling tower fan. $P_{tfan,rate}$ denotes the rated power of the cooling tower fan. k_0, k_1, k_2, k_3 are the polynomial fitting coefficients. LDR_{tfan} denotes the loading rate of the fan. m_{atfan} denotes the actual airflow of the fan. $m_{atfan,rate}$ denotes the rated airflow of the fan.

(4) Indoor unit fan energy consumption model. The energy consumption of indoor units of central air-conditioning systems is mainly generated by fans, mainly end-end equipment such as fan coils and fresh air systems.

$$P_{cfan} = P_{cfan,rate}(l_0 + l_1 \cdot PLR_{cfan} + l_2 \cdot PLR_{cfan}{}^2 + l_3 \cdot PLR_{cfan}{}^3) \tag{17}$$

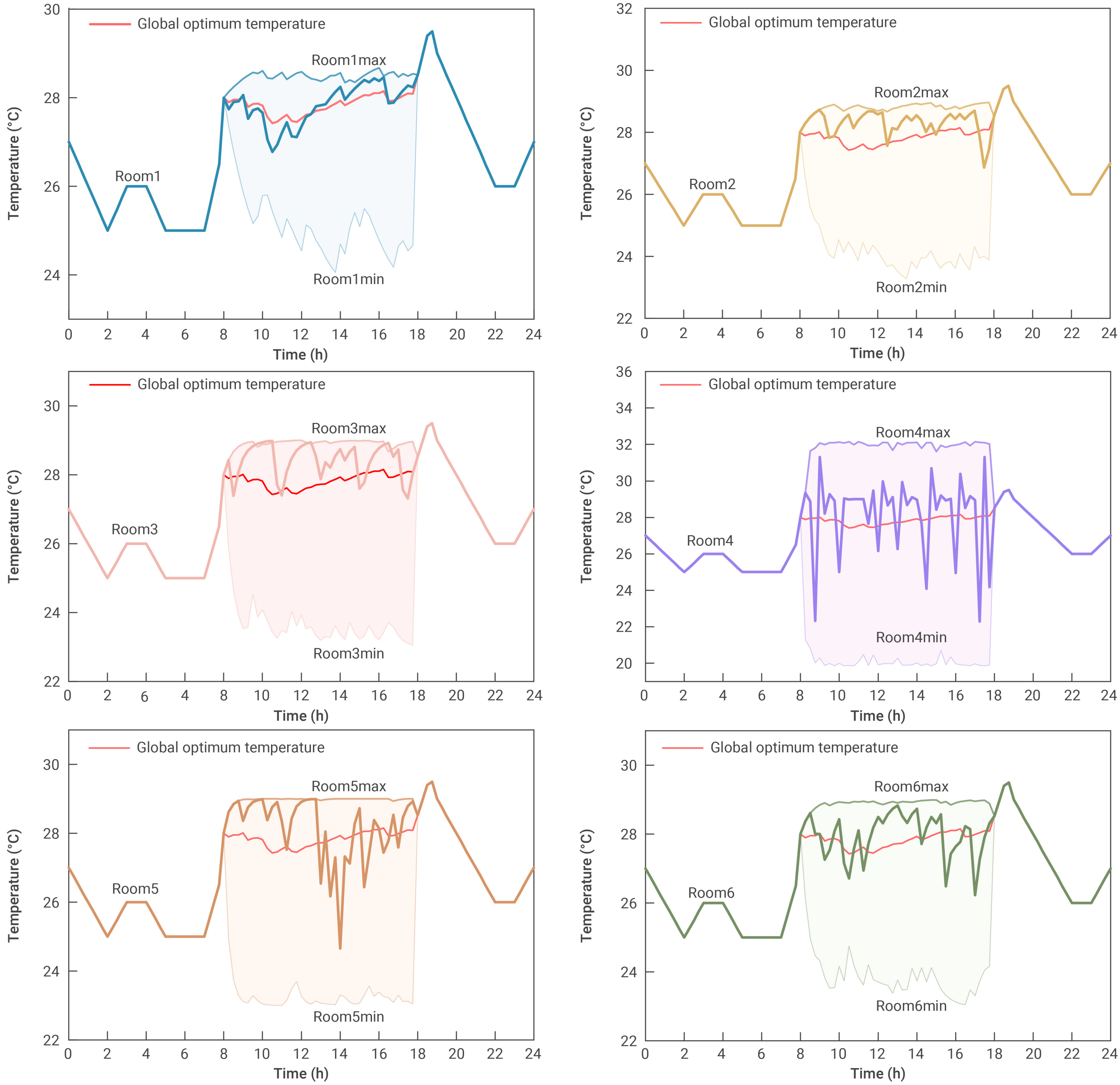

Figure 4. Comparative analysis of indoor temperature changes in rooms considering heat transfer and without heat transfer

$$PLR_{tfan} = \frac{m_{acfan}}{m_{acfan,rate}} \tag{18}$$

where $P_{cfan,rate}$ denotes the rated power of the fan. P_{cfan} denotes the actual power of the fan. l_0, l_1, l_2, l_3 are the fitting coefficients of the polynomial model. PLR_{cfan} denotes the loading rate of the fan. $m_{acfan,rate}$ denotes the rated airflow of the fan. m_{acfan} denotes the actual airflow of the fan.

Intelligent optimization of building energy management based on deep reinforcement learning

The optimization flowchart is shown in Figure 2. To minimize computational complexity, previous research typically treats the building as a single entity and focuses on optimizing just one comfort level. However, in actual building operations, various rooms have distinct comfort requirements, and applying a single comfort value fails to accurately represent the building's real operational needs. Consequently, this paper develops a multi-objective intelligent optimization model using DDPG, which accounts for the varying comfort needs of different rooms and the operational costs of the building. It also evaluates the overall importance of the two objectives and considers the effects of heat transfer between rooms on energy management within the building.

Each room utilizes an independent central air conditioning control strategy, with multiple states in each room. The combination of these states presents a dimensionality challenge for solutions using the deep Q neural network (DQN) algorithm. Therefore, this paper employs the deep deterministic policy gradient algorithm (DDPG) to address this issue, as it can handle continuous action spaces and accurately represent the changes in indoor temperature for each room. Additionally, the Actor-Critic structure of DDPG allows for the generation of deterministic actions, which accelerates the training process.

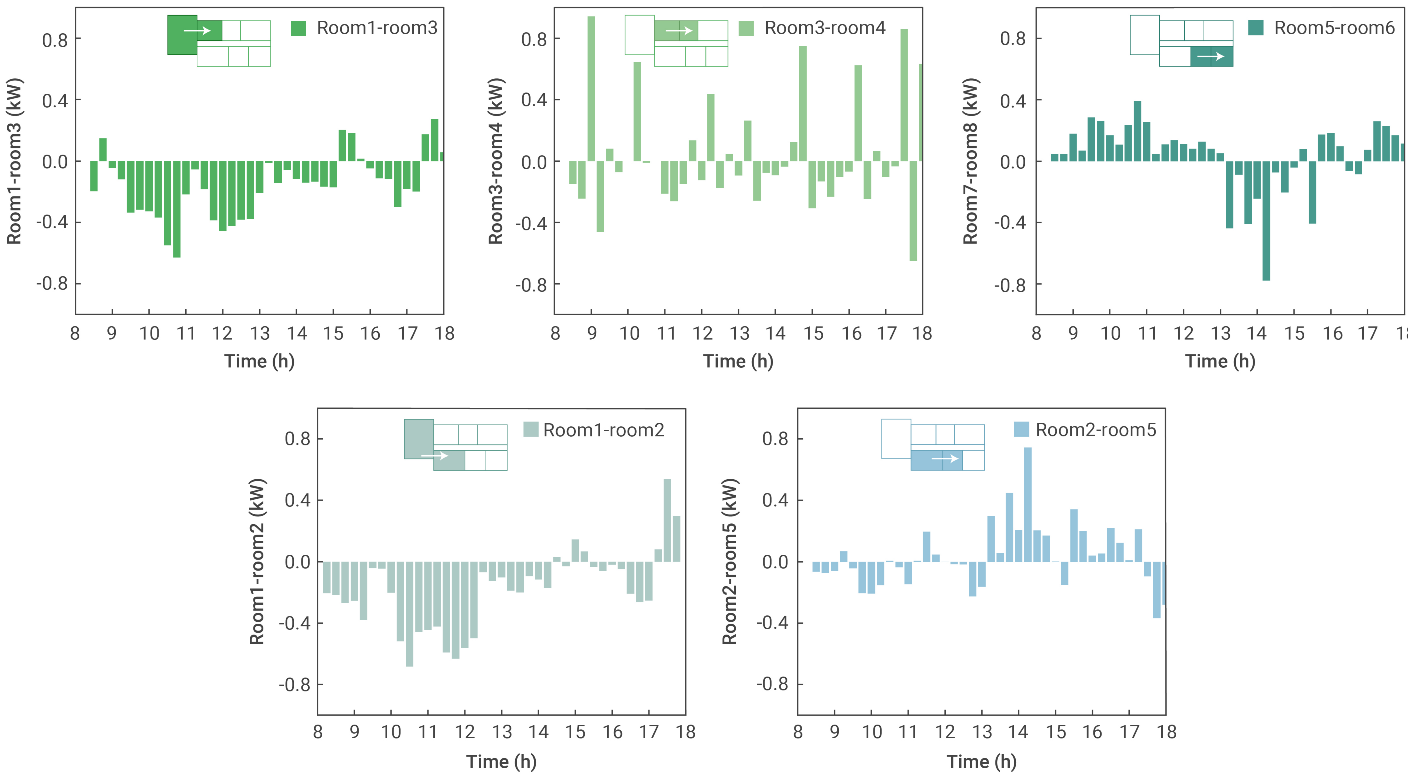

Figure 5. Heat transfer between rooms

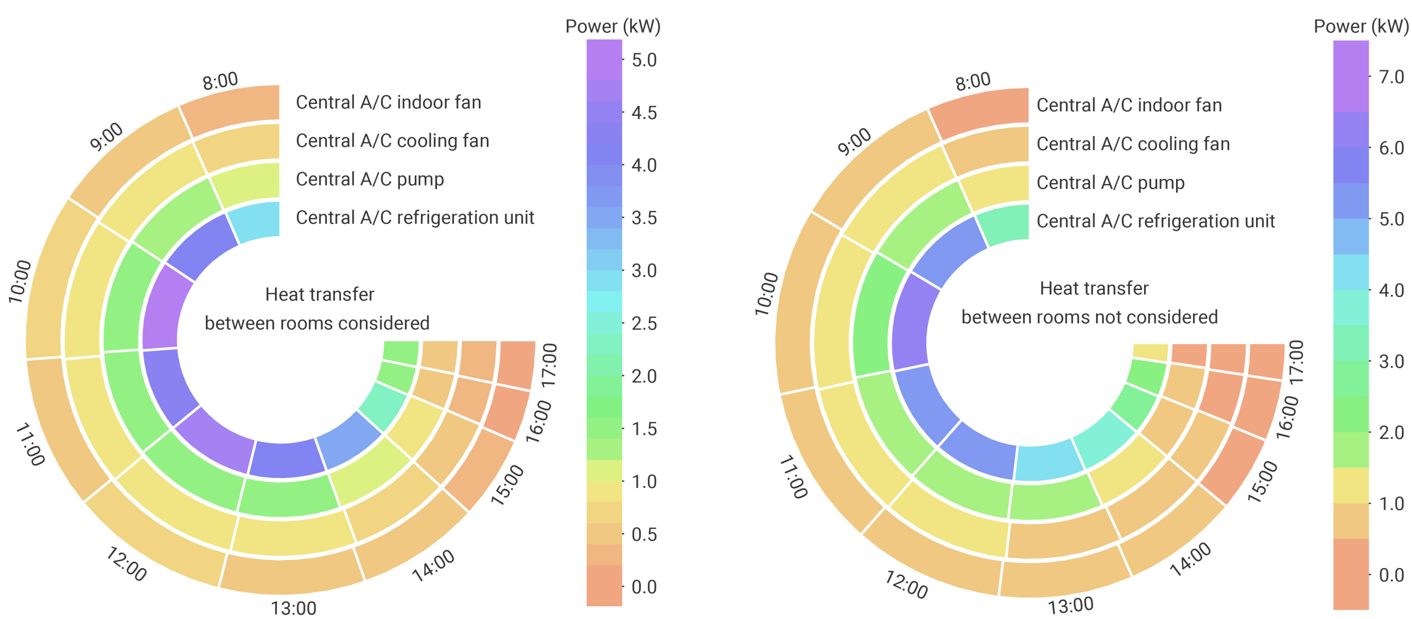

Figure 6. Central A/C system's internal unit power in rooms considering heat transfer and without heat transfer

Consequently, the *P1* problem is reformulated as a Markov decision-making process to achieve optimal building operation.

The condition of the building is characterized by the indoor temperatures of each room and the status of the energy storage system, which is collectively referred to as STATE. The building's action set includes the temperature settings for the air conditioning in each room and the charging and discharging power of the energy storage. Since the central air conditioner's temperature setting is a discrete variable in practice, it is represented in a discretized form, and this set of actions is referred to as action. The reward set represents the goals of optimizing building energy use and is labeled as reward.

Consequently, the building energy optimization problem is reformulated as *P2*.

$$P_2\left\{\begin{array}{c} state=\{T_{in}(room(k)),SOC\} \\ action=\{T_{set},P_{\_BESS}\} \\ reward=-minC_{total} \end{array}\right\} \tag{19}$$

Correction of Optimization Problem Considering Building PV Generation with Rigid Load Uncertainty

In the operation phase of the building, there is significant unpredictability in both PV power generation and fixed loads. To address this when determining the reward, a stochastic optimization approach is employed, which involves creating multiple scenario sets. Each set is randomly generated based on forecasted data within a specific range of variations. The overall reward for actions across all scenarios is then computed, ensuring that the training outcomes are more aligned with real-world conditions.

The balance between the electricity expenses of the building and its overall comfort is crucial for managing both energy costs and comfort levels. If the emphasis is placed heavily on reducing electricity costs, the intelligent system may prioritize minimizing energy expenses excessively, leading to discomfort in the rooms. Conversely, if the system places too much emphasis on comfort, the system may overlook energy efficiency, resulting in higher electricity costs. Thus, during the control process, the weights can be modified based on the desired levels of energy savings and overall comfort in the building.

Based on stochastic optimization method, the modified Markov decision process for the building optimization problem is represented as follows:

$$P_2\left\{\begin{array}{c} state=\{State_{temp}(room(k)),T_{in}\} \\ action=\{T_{set},SOC\} \\ reward=-\{\omega_1\cdot\dfrac{1}{N_s}\left(\sum_{s\in S}^{N_s}F_{buy,s}-\sum_{s\in S}^{N_s}F_{sell,s}\right)+\omega_2\sum_{k=1}^{N}\omega_{room}(k)\cdot Beneifit_{room}\}\end{array}\right\} \qquad (20)$$

where ω_1 is the weight of the energy cost of the building. ω_2 is the total weight of the total comfort of each room in the building.

RESULTS

Algorithm parameterization

This paper presents a case study of a building located in Nanjing, which has a total area of 528.08 m^2, a height of 7.2 m, and consists of two above-ground floors. The building is equipped with PV and wind power generation systems, as well as energy storage facilities. Additionally, the building's envelope has been enhanced with energy-efficient characteristics, such as walls and windows with high light transmission rates and excellent thermal insulation properties. The primary function of the building is for meetings and office use. The dimensions of the rooms are as follows: Room 1 is 72 m^2, Room 2 is 34.08 m^2, Room 3 is 21.9 m^2, Room 4 is 7 m^2, Room 5 is 15.3 m^2, and Room 6 is 25.2 m^2, with their layout illustrated in Figure 3. The energy management for the building is scheduled from 8:00 to 9:00, with an optimization duration of 15 minutes.

Case Analysis

The daily energy expense for the building, excluding room heat transfer, amounts to 91.68.When room heat transfer is considered,the daily energy cost drops to 91.68.When room heat transfer is considered,the daily energy cost drops to 83.48, resulting in a savings of 9.82% on building energy expenses. The DDPG algorithm was used for training and the training time was 43 minutes for considering room heat transfer and 34 minutes for not considering room heat transfer

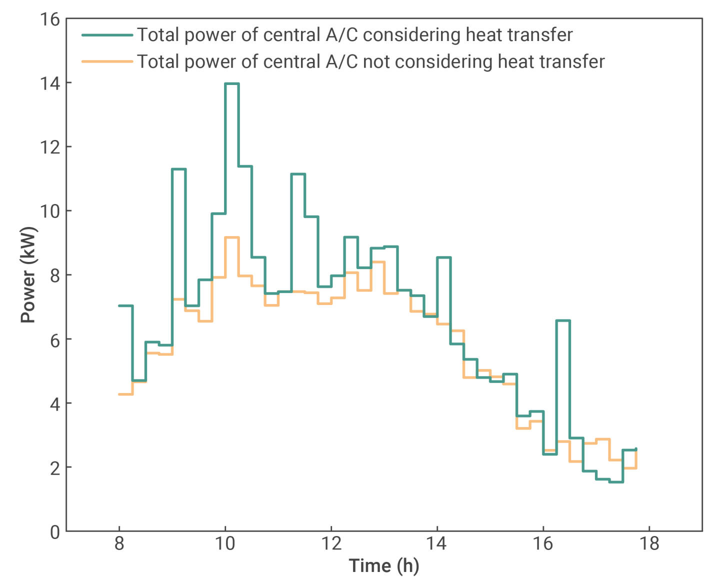

Figure 7. Central A/C system's internal unit power in rooms considering heat transfer and without heat transfer

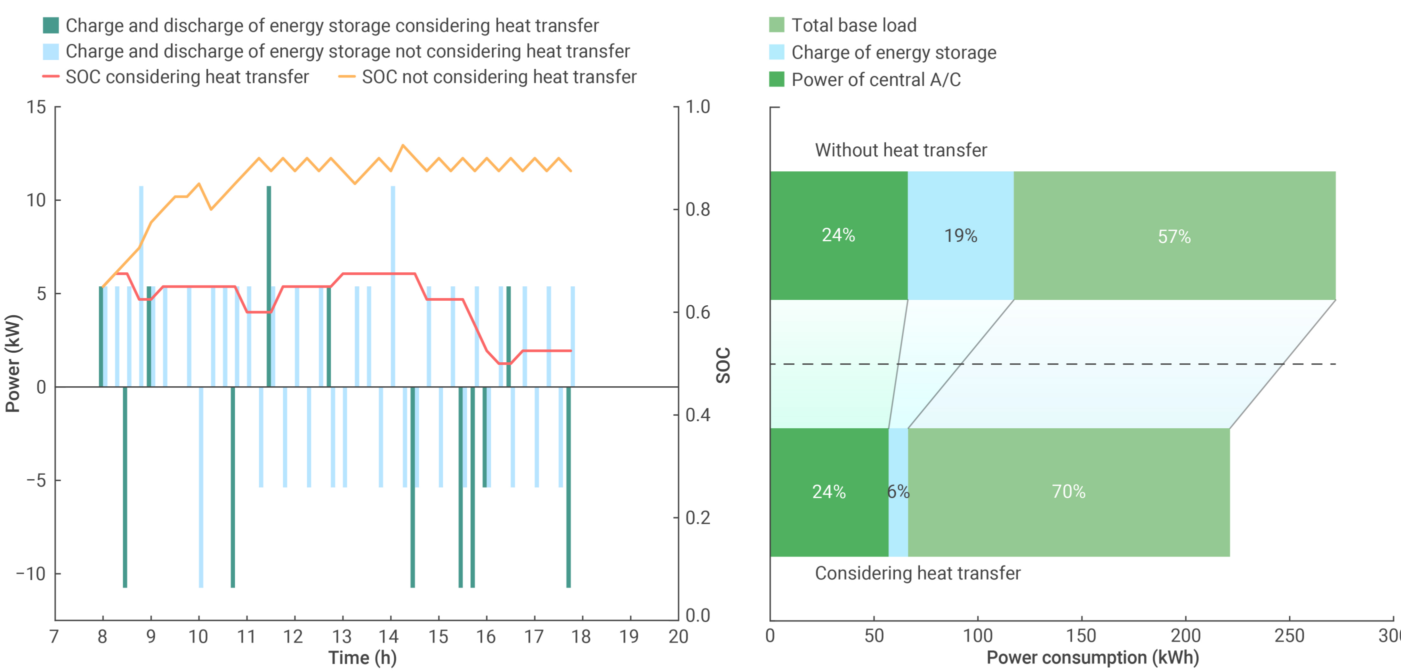

Figure 8. Energy storage state and energy consumption ratio analysis considering room heat transfer and not considering room heat transfer

From Figure 4, it can be known that the varying thermal comfort gains in each room lead to different cooling strategies and distinct indoor temperature variations. Room 1, being the largest, is followed by Room 2, which is also relatively spacious. Both of these rooms experience smoother temperature fluctuations, indicating that larger rooms have a slower cooling effect from the A/C. In contrast, Rooms 4 and 5, which are smaller, show more pronounced temperature fluctuations, suggesting that smaller rooms benefit from a more significant cooling effect. Additionally, Room 6 exhibits a higher thermal comfort gain compared to Room 3, resulting in greater temperature fluctuations in these two similarly sized rooms, indicating that thermal comfort gain has a positive feedback effect on the control of the room's temperature.

The temperature curve for each room is represented in the overall temperature curve of the building, which is treated as a single unit for optimization purposes. Since there is no heat transfer between rooms, the temperature in each room should ideally be uniform. The indoor temperature variations are minimal because the building's total area is extensive, making it functionally similar to a large room. The cooling impact of the A/C is limited, and even if thermal comfort levels are increased, the overall comfort of the building remains inadequate. This approach fails to address the varied comfort requirements of different users in separate rooms.

Room 1 to Room 3 illustrates the heat transfer dynamics between these spaces. From the analysis of Figure 5, it is evident that during the building's intelligent optimization, Room 3 primarily provides cooling to Room 1, while Room 2 also contributes cooling to Room 1. This occurs because Room 1 is larger and experiences a slower cooling effect, whereas Rooms 2 and 3 are smaller and cool down more quickly. Consequently, during the optimization phase, Rooms 2 and 3 assist in cooling Room 1, which reduces the cooling demand for Room 1 and subsequently lowers the power consumption of the central A/C system serving Room 1. The heat transfer process between Rooms 3 and 4 is more intricate, as these two rooms engage in a mutual cooling process. This is due to Room 4's small size, which allows for a rapid cooling effect. When the temperature in Room 4 is lowered, it quickly becomes cooler than Room 3, leading to a transfer of cold air from Room 4 to Room 3. Once the temperature in Room 3 rises above that of Room 4, the cooling process reverses, Room 3 begins to cool Room 4. This procedure repeats continuously. Similarly, the heat exchange between Rooms 2 and 5 also alternates, but the impact is less pronounced due to their similar sizes. In the case of Rooms 5 and 6, Room 6 initially experiences a greater gain in thermal comfort, causing its temperature to drop more quickly. As a result, Room 5 transfers heat to Room 6. However, at noon, with its larger area and increased number of windows, absorbs more solar radiation, leading to a temperature increase and a subsequent heat transfer from Room 6 back to Room 5. As solar radiation decreases in the afternoon, Room 6 cools down again, prompting another heat transfer from Room 5 to Room 6.

Figure 6 and Figure 7 illustrates the power dynamics among the components of the central A/C system. The chiller accounts for the majority of the power usage, followed by the pumps, while the cooling tower fan and indoor fan consume less power. Additionally, it is evident that regardless of whether the overall power of the central A/C system rises or falls, a consistent proportional relationship among the units is preserved.

Figure 8 analyzes the comparison of the energy storage system and energy consumption share between considering heat transfer and not considering heat transfer. When the indoor temperature heat transfer is not considered, the energy storage is charged and discharged more frequently, and the total energy consumption share is 19%, which is 13% higher than the energy consumption share when heat transfer is not considered, reflecting the fact that the building has a greater energy demand when heat transfer is not considered, which requires frequent charging and discharging of the energy storage to regulate the energy use. When the indoor temperature heat transfer is considered, it can be found that the cumulative energy consumption of the total daily electricity use of the central air conditioner is significantly lower than that when heat transfer is not considered, which further illustrates that the building management optimization strategy that considers the indoor heat transfer can achieve energy-efficient operation of the building.

DISCUSSION

Our study analyzes the role played by dynamic heat transfer between building rooms in intelligent energy management in buildings. It is proved that the cooling transfer between rooms reduces the amount of cooling originally needed in the room and saves central A/C's power consumption. Room heat transfer is affected by the temperature of the internal wall and the equivalent thermal resistance of the internal wall, according to the temperature difference between the two rooms to produce heat transfer, as an example of summer refrigeration, the room with a low temperature will be transferred to the room with a high temperature of the cold, each time the optimization of the calculation of the transfer of the cold, so as to cut down on the temperature of the room air conditioning corresponding to the amount of refrigeration required, and thus optimize the cooling power of air conditioning of the room with a high temperature. At the same time, the room's thermal comfort gain has a regulating effect on the room temperature's control. When thermal comfort gain is large, the room refrigeration regulation is more frequent and accurate in order to maintain the indoor temperature in the human body around the optimal comfort range. When thermal comfort gain is small, the room refrigeration regulation frequency is reduced, and the indoor temperature fluctuation becomes larger. Therefore, the intelligent optimization method of building management proposed in this paper considering building heat transfer has great application space in building energy management, which can help building energy management to further save building's operational cost and promote the realization of green low-carbon energy use in the building.

CONCLUSION

We implement the intelligent optimization method of building management considering building heat transfer and verify it based on real data in the intelligent management of building energy, and the main work consists of two parts:

(1) The third-order thermal parameter model of the building is used in our study, and we consider the thermal inertia of the building, the dynamic heat transfer process between rooms. Also, we analyze the multidimensional influencing factors affecting the room temperatures by combining with the real building's data, and validate the effectiveness of the heat transfer of the room in saving the A/C's power.

(2) Using the DDPG algorithm for efficient and fast solution, the results show that the intelligent optimization method of building management considering building heat transfer saves costs by 9.82%, which is proved to have a significant role in saving building's operational costs. At the same time, this intelligent optimization algorithm is able to optimize the weight between the overall comfort of the building and the building costs, and it can also satisfy the demand for the difference in the comfort of each room of the building, which has a great potential for application.

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FUNDING AND ACKNOWLEDGMENTS

This work was supported by National Natural Science Foundation of China (No. U22B20112) and The Carbon Emission Peak and Carbon Neutrality Innovative Science Foundation of Jiangsu Province"The key research and demonstration projects of future low-carbon emission buildings" (No. BE2022606). The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

AUTHOR CONTRIBUTIONS

Conceptualization, Z.Jing, and K.Yu; investigation, J.Shen and L.Bu; methodology, Z.Jing, and K.Yu; writing—original draft preparation, L.Bu and J.Chen; writing—review and editing, Z.Jing, K.Yu, L.Bu and W.Xu; supervision, Z.Jing , K.Yu X.Chen and J.Shen. All authors have read and agreed to the published version of the manuscript.

DECLARATION OF INTERESTS

Jun Shen serves as an Editorial Board Member for The Innovation Energy. The authors declare no other competing interests that could appear to have influenced the submitted work reported in this paper. This role did not influence the objectivity, peer review process, or editorial decisions regarding this manuscript.

ETHICAL STATEMENT AND PATIENT CONSENT

Not Applicable.

DATA AND CODE AVAILABILITY

Data are available from the corresponding author upon reasonable request.