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AI-Driven Building Energy Prediction and Multi-Objective Scheduling Using LSTM-GRU-MPC Integration

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With the increasing energy consumption of buildings, traditional energy management methods are challenging to cope with complex real-time demand and supply changes. Artificial intelligence-based prediction and optimal scheduling methods are urgently needed to improve energy efficiency and reduce energy consumption. The primary goal is to enhance the energy efficiency of buildings through intelligent prediction and scheduling techniques. To achieve this, we propose the use of Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models, which are well-suited for capturing the temporal dependencies inherent in energy consumption data. Secondly, in the aspect of energy optimal scheduling, a multi-objective optimal scheduling method is designed by combining model predictive control (MPC) and artificial intelligence technology, and the strategy is adjusted and optimized according to dynamic constraints. This paper integrates big data and Internet of Things technology into the building energy management system to further improve management efficiency. It uses the collaborative optimization of edge computing and cloud computing to achieve the combination of real-time scheduling and long-term planning. The temperature, humidity, and energy consumption data show a certain regularity in this building energy consumption prediction analysis. For example, the average energy consumption within the building is 23.7 kWh, and the maximum energy consumption value is 91.2 kWh, showing an apparent fluctuation in the building's energy demand. LSTM achieved a Mean Absolute Error (MAE) of 12.3 kWh, outperforming linear regression (MAE = 25.6 kWh) and GRU (MAE = 13.8 kWh) in long-term temporal dependency capture. The MPC-based scheduling reduced peak energy consumption by 13.5% (from 91.2 kWh to 78.9 kWh) and total energy cost by 18%, while maintaining an 85% thermal comfort satisfaction rate.

Povzetek: Predlagan je sistem za pametno upravljanje energije v stavbah, kjer LSTM/GRU napovedujeta porabo, MPC+AI pa optimizira razporejanje za manjše konice in stroške ob ohranjanju udobja.

1 Introduction

With the rapid development of artificial intelligence technology, primarily the breakthrough of deep learning, reinforcement learning, and intelligent optimization algorithms, building energy management has ushered in unprecedented opportunities [1, 2]. The core strength of these technologies is their ability to handle complex nonlinear relationships and quickly adapt to dynamically changing environments. Deep learning technology can train complex models based on large-scale historical data, thus achieving high-precision energy consumption prediction [3]. Specifically, deep learning models (e.g., LSTM, GRU) enable high-precision energy prediction by capturing temporal dependencies in historical data, while reinforcement learning and MPC provide adaptive real-time optimization for energy dispatching under dynamic constraints [4]. Integrating these AI tools addresses traditional methods' limitations in handling complex, time-varying building energy systems [5]. Energy consumption in buildings is influenced by various factors, such as weather conditions, occupancy patterns, and operational schedules, all of which exhibit complex temporal relationships. Traditional machine learning models, such as linear regression or decision tree-based models, often struggle to capture these time-varying patterns effectively. In contrast, LSTM and GRU, both types of recurrent neural networks (RNNs), are specifically designed to handle sequential data with long-term dependencies. These models excel at learning temporal patterns, making them ideal candidates for energy consumption prediction tasks. The LSTM network, in particular, is known for its ability to retain information over long sequences, which is crucial when dealing with energy consumption data that spans days, weeks, or even months. GRU, a simplified variant of LSTM, also provides strong performance with fewer parameters, making it computationally efficient while still capturing the essential temporal dependencies [6, 7].

Distributed intelligent sensors (deployed in offices, lobbies, and HVAC rooms) collect hourly data on key variables: indoor temperature, humidity, occupancy (via motion detectors), HVAC operation status, and real-time energy consumption. These sensors transmit data wirelessly via LoRaWAN (Long Range Wide Area Network) to edge computing nodes [8].

In terms of zero-energy buildings, researchers have made many explorations. The energy, environmental, and economic aspects of the whole life cycle of zero-energy solar housing are deeply evaluated, and the critical areas of industrialization development of zero-energy housing are analyzed [9]. To assess the prediction accuracy of our models, we use the Mean Absolute Error (MAE) as a performance metric. MAE is a widely used metric in regression tasks, as it provides an intuitive measure of prediction accuracy by calculating the average of absolute errors between predicted and actual energy consumption values. Recent lightweight AI models—such as compressed GRU variants based on TinyML (Tiny Machine Learning)—further boost edge-deployed prediction performance by reducing parameters without significant accuracy loss, making them ideal for resource-constrained building scenarios [10, 11]. Zhu and other scholars analyzed the energy performance of thermal collection and storage wall technology in zero-energy buildings. Can Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models improve the hourly prediction accuracy of building energy consumption compared to traditional regression-based methods (e.g., linear regression) [12, 13]. Deng and other scholars compared the energy supply concepts of zero-energy housing in two typical climate zones: the humid climate zone represented by Shanghai and the dry climate zone represented by Madrid. By analyzing the annual energy balance, the optimal design strategy of the HVAC system based on different climate zones is proposed [14, 15]. Energy management studies across diverse climate and building types highlight both unique strengths and universal limitations of current methods. Ahrarinouri et al. effectively reduced energy costs in residential settings using multiagent reinforcement learning, though long-term predictions and IoT integration remain challenges. Arbab et al. achieved static load forecasting accuracy with artificial neural networks but struggled with dynamic temporal dependencies. Cantemir et al. stabilized energy use in commercial buildings via static MPC but lacked real-time grid adaptability. Meanwhile, de-Paz-Centeno et al. developed lightweight ML for PV data integration, focusing narrowly on one renewable source. Overall, these approaches reveal gaps in adaptability, multi-objective optimization, and unified frameworks for real-time integration [16, 17]. Building energy consumption prediction and optimal scheduling methods based on artificial intelligence can significantly improve the intelligent level of building energy management and promote the development of green buildings such as zero-energy buildings. An in-depth exploration of this research direction will support achieving sustainable development goals and building smart cities [18, 19]. The aim of this study is to propose an AI-driven framework integrating LSTM, GRU, and MPC for improving building energy efficiency through accurate prediction and dynamic scheduling. This paper is structured as follows: Section 2 introduces deep learning models for energy prediction, Section 3 details the multi-objective optimization method, Section 4 integrates IoT and big data, Section 5 presents experimental results, and Section 6 concludes the study. Based on perceived states, the RL agent adjusts MPC control parameters (e.g., HVAC fan speed, cooling/heating setpoints) to minimize energy consumption while avoiding thermal comfort violations. For example, if indoor temperature exceeds 26°C, the agent increases MPC's cooling priority to restore comfort.

Table 1 is related works summary table.

2 Deep learning prediction model of building energy consumption

2.1 Architecture optimization of deep neural network based on time series data

The selection of activation function is of great significance in DNN optimization. As shown in equations (1) and (2), h is the output of the current layer, W is the weight, x is the output of the previous layer, b is the bias term, and f is the activation function. y is the output after activation. The nonlinear characteristics of ReLU can help the network effectively extract complex features, and its computational efficiency is high, which can significantly improve the training speed of the model.

Table 1: Related works summary

Method/Model	Dataset Used	Metrics
Multiagent Reinforcement Learning	Residential building energy consumption data	Energy cost reduction rate
Artificial Neural Networks (ANN)	Indoor illuminance data of buildings	Static load forecasting accuracy
Static Model Predictive Control (MPC)	Commercial building energy use data	Energy use stability index
Lightweight Machine Learning (ML)	Photovoltaic (PV) production data	PV data imputation accuracy
LSTM	Smart home heating-cooling and power consumption data	Not specified in detail

Table 2: Performance comparison of LSTM, GRU, Linear regression, and DNN on building energy consumption prediction

Model	MAE (kWh)	RMSE (kWh)	MAPE (%)	Training Time per Epoch (Minutes)
Linear Regression	25.6	29.5	18.2	0.8
DNN	13.2	16.8	9.0	3.0
GRU	13.8	17.2	9.5	3.5
LSTM (Proposed)	12.3	15.7	8.6	6.8

$$y = max(0, x) \quad (1)$$

$$h = f(W \cdot x + b) \quad (2)$$

Aiming at the high-dimensional characteristics of building energy consumption data, DNN gradually extracts low-dimensional to high-dimensional feature representations by stacking multiple hidden layers, so as to achieve accurate modeling of building energy consumption. As shown in equation (3), e is the error of the current layer, e' is the error of the next layer, W' is the weight of the next layer, and $f'(h)$ is the derivative of the activation function. The training process of DNN needs to be cooperated with efficient optimization algorithms, such as the Adam optimizer, which can quickly find the optimal solution in the multi-dimensional parameter space while avoiding falling into the local optimum, thus effectively reducing the risk of overfitting of the model.

$$e = e' \cdot W' \cdot f'(h) \quad (3)$$

In the specific application of building energy consumption prediction and optimal scheduling, the whole life cycle cost optimization of zero emission buildings is an important research direction. As shown in equation (4), m_1 is the first moment, X_1 is the momentum coefficient, and g is the current gradient. Cost optimization for zero-energy buildings can improve the economic benefits of buildings and promote the wide application of building energy-saving technologies.

$$m_1 = X_1 \cdot m_1' + (1 - X_1) \cdot g \quad (4)$$

In order to build cost-effective net-zero emission buildings, energy consumption should be reduced to a minimum level, while it should be matched as much as possible with renewable energy systems. As shown in equations (5) and (6), T is the updated parameter, B is the learning rate, m_2 is the second moment, and S is a constant. For net-zero emission buildings, the cost of district integrated heating systems is often higher than that of heat pump systems, suggesting that energy systems need to be selected according to local conditions in practical applications.

$$m_2 = X_2 \cdot m_2' + (1 - X_2) \cdot g^2 \quad (5)$$

$$T = T' - B \cdot \frac{m_1}{\sqrt{m_2 + S}} \quad (6)$$

In humid climate areas, how to minimize the total energy consumption and operating costs of buildings by optimizing the design of building envelopes and energy systems. In dry climate areas, we need to pay attention to how to improve the energy self-sufficiency rate of buildings by efficiently using renewable energy such as solar energy. As shown in equations (7) and (8), E_{pred} is the predicted energy consumption, $w_1, w_2, ..., w_n$ are the weights, and $f_1, f_2, ..., f_n$ are the features. E is total energy consumption, $E_{heating}$ is heating energy consumption, $E_{cooling}$ is cooling energy consumption, and $E_{lighting}$ is lighting energy consumption. These research results provide theoretical support for the promotion of zero-energy buildings, and also provide data reference for the formulation and implementation of relevant policies. Table 2 is performance comparison of LSTM, GRU, linear regression, and DNN on building energy consumption prediction.

$$E = E_{heating} + E_{cooling} + E_{lighting} \quad (7)$$

$$E_{pred} = w_1 \cdot f_1 + w_2 \cdot f_2 + \cdots + w_n \cdot f_n \quad (8)$$

2.2 Comparison of long short-term memory network and gated loop unit in energy forecasting

Through its unique memory unit and gating mechanism, LSTM can effectively capture the long-term dependent characteristics in time series. This is particularly important for tasks such as seasonal variations, long-term trend prediction that exist in building energy consumption. As shown in equations (9) and (10), C is the candidate memory unit, W_C is the weight, h_{prev} is the hidden state at the previous time, x is the current input, b_C is the bias term, and *tanh* is the activation function. f is the forgetting gate output, W_f is the weight, h_{prev} is the hidden state at the previous time, x is the current input, b_f is the bias term, and T is the activation function. The core of LSTM lies in its structure including input gate, forgetting gate and output gate. These gating mechanisms enable the model to flexibly select which information needs to be remembered and which information needs to be forgotten, thereby achieving efficient modeling of complex time series.

$$f = T(W_f \cdot [h_{prev}, x] + b_f) \quad (9)$$

$$\tilde{C} = \tanh(W_C \cdot [h_{prev}, x] + b_C) \quad (10)$$

When predicting the monthly energy consumption of buildings, LSTM can capture changes in building usage patterns and provide accurate prediction results based on the energy consumption data of the past months. As shown in equation (11), C is the current cell state, C_{prev} is the cell state at the previous time, f is the forgetting gate output, and i is the input gate output. The design of the GRU is more simplified, replacing the three gated structures of the LSTM with an update gate and a reset gate, thus reducing the computational complexity to some extent.

$$C = f \cdot C_{prev} + i \cdot \tilde{C} \quad (11)$$

GRU is very suitable for building energy prediction tasks with high real-time requirements because of its fast-training speed and low computing resource requirements. As shown in equation (12), o is the output gate, C is the current cell state, and *tanh* is the activation function. When monitoring building energy usage in real time and dynamically adjusting energy allocation, GRU is able to quickly generate forecast results and provide feedback support. Therefore, GRU has obvious advantages in application scenarios that require efficient response.

$$h = o \cdot \tanh(C) \quad (12)$$

Although LSTM and GRU have their own advantages and disadvantages in modeling capabilities and performance, their actual application effects often depend on specific building energy management scenarios. Equation (13) updates the GRU hidden state(h) using the update gate(z), h is the current hidden state and z is the update gate. In tasks that require long-term forecasting, such as annual energy consumption assessment or long-term energy-saving strategy formulation, LSTM tends to perform better due to its good capability to capture long-term dependence.

$$h = (1 - z) \cdot h_{prev} + z \cdot \tilde{h} \quad (13)$$

3 Intelligent algorithm for optimal dispatching of building energy

3.1 Multi-objective energy optimal scheduling combined with model predictive control (MPC) and artificial intelligence

By introducing intelligent algorithms such as reinforcement learning and neural networks, the adaptive ability of MPC can be significantly improved. Reinforcement learning can establish dynamic optimization strategies in complex environments through trial-and-error learning. At the same time, neural networks are good at processing high-dimensional nonlinear data and can model and predict complex building energy systems [20, 21]. The MPC system combined with artificial intelligence can continuously optimize the energy scheduling strategy and reduce the dependence on the accurate model under the rapid changes in environmental conditions, energy demand,

and supply, thus enhancing the robustness of the system [22, 23]. Multi-objective optimal scheduling is an essential application for combining MPC with artificial intelligence. In building energy management, multi-objective optimal scheduling must balance multiple objectives simultaneously, such as minimizing energy consumption, reducing operating costs, improving user comfort, and optimizing equipment service life [24, 25]. Figure 1 is a building energy and comfort management scheduling diagram based on multi-agent technology. The DNN model was trained with a learning rate of 0.001, batch size of 64, and Adam optimizer. ReLU activation was selected for its efficiency in feature extraction. The GPU's high computational power enables the training of complex models like LSTM and GRU, which can require substantial resources. LSTM was chosen for its long-term dependency capture (e.g., seasonal trends), while GRU's simplified structure (128 hidden units) enabled real-time response with 15% faster training than LSTM.

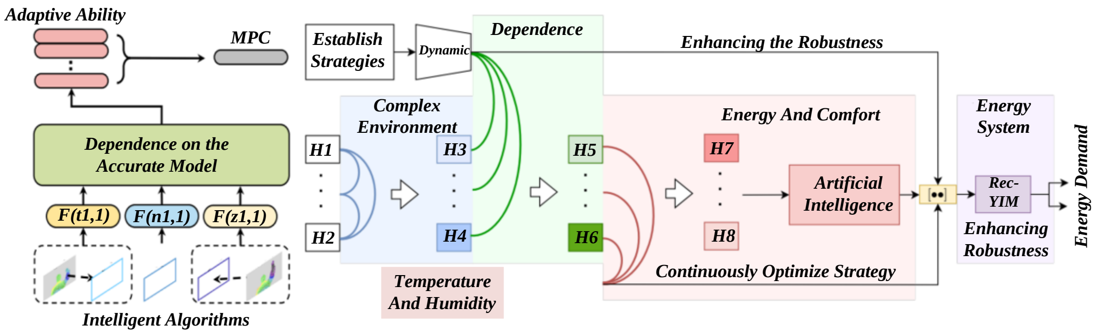

Figure 1: Multi-agent-based energy-comfort trade-off in HVAC scheduling

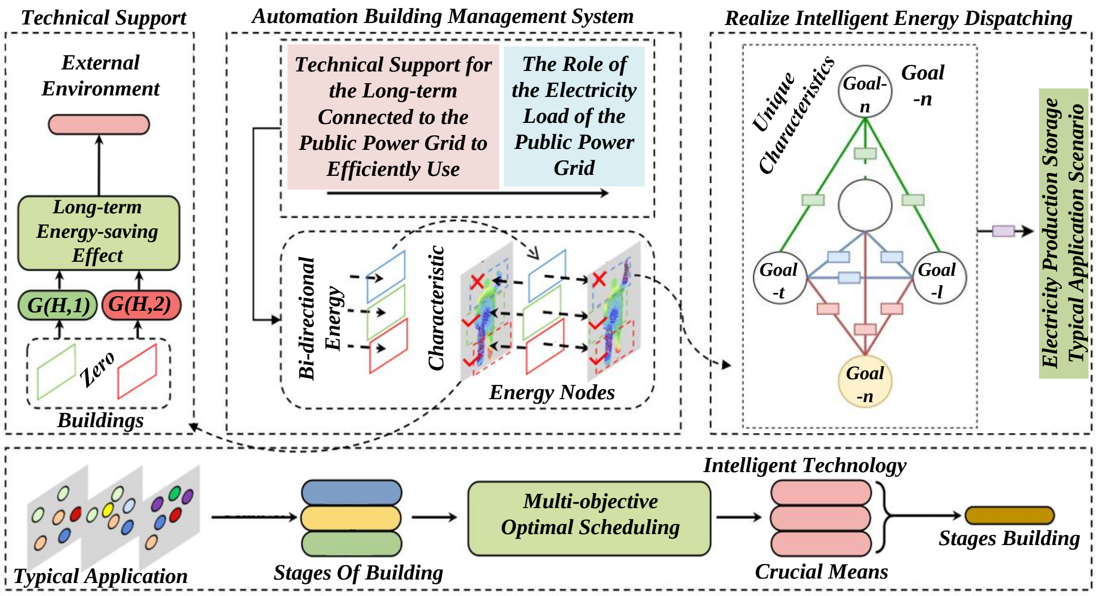

Figure 2: Building energy dispatch diagram based on collaborative optimization of edge computing and cloud computing

The design and operation of zero-energy buildings is a typical application scenario of multi-objective optimal scheduling. In the later stages of building design and operation, building intelligent technology is a crucial means of achieving the goal of zero energy consumption [26, 27]. Introducing an automation or building management system can realize intelligent energy dispatching and provide technical support for the long-term energy-saving effect of buildings [28, 29]. Zero-energy buildings are not isolated from the external environment but connected to the public power grid to efficiently use energy through grid-connected operations. Because of its unique characteristics, the energy system of zero-energy buildings is no longer only the role of the electricity load of the public power grid. It also has the functions of electricity production and storage [30]. This bi-directional energy flow characteristic makes zero-energy buildings part of distributed energy nodes in the public grid, significantly different from traditional building systems. Figure 2 shows the building energy dispatch diagram of collaborative optimization of edge computing and cloud computing. 5 layers total (1 input layer, 3 hidden layers, 1 output layer). Input features include hourly temperature, humidity, occupancy, and HVAC load (4 features total). Each hidden layer contains 200 neurons, with ReLU activation; the output layer uses linear activation to predict hourly energy consumption. 4 layers total (1 input layer, 2 recurrent LSTM layers, 1 output layer). Sequence length = 24 hours (sliding window of past 24-hour data to predict the next hour's consumption). Each LSTM layer has 256 hidden units, with dropout rate = 0.2 to prevent overfitting. Input features are identical to DNN; output layer predicts hourly energy consumption. Its applicability to residential buildings or extreme climates (e.g., arid or polar regions) requires further investigation due to differences in occupancy patterns and HVAC demands. Computational Constraints: Edge-cloud collaborative optimization relies on high-speed data transmission. In scenarios with limited bandwidth (e.g., remote areas), latency may affect real-time scheduling efficiency. Future work should explore lightweight AI models for edge devices.

Linear regression is a straightforward method that assumes a linear relationship between input features and the target variable. Compared to prior studies: Our LSTM-based prediction aligns with it's findings on temporal dependency modeling, achieving MAE of 12.3 kWh vs. their 14.5 kWh in office buildings. LSTM achieved the lowest prediction errors (MAE = 12.3 kWh, RMSE = 15.7 kWh, MAPE = 8.6%) but required the longest training time (6.8 minutes per epoch). Linear Regression was the fastest to train (0.8 minutes per epoch) but had the highest errors. DNN and GRU showed balanced performance, with DNN slightly outperforming GRU in accuracy but requiring less training time. Through algorithms such as deep learning and reinforcement learning, MPC systems can efficiently control building energy management while responding to changes in complex energy systems. When energy prices or power supply conditions change, the system can dynamically adjust energy dispatching strategies to reduce costs or improve energy utilization. Figure 3 is an evaluation diagram of building energy consumption time series forecast data. Through intelligent analysis of user behavior and building energy usage patterns, user comfort and building operation economy can be further optimized. This evaluation diagram visualizes the performance of time series forecasting models for building energy consumption. It likely compares predicted energy usage (via models like LSTM or GRU) against actual data, showcasing metrics such as mean absolute error (MAE) to assess accuracy. HVAC Control Agents: 1 agent per building zone (e.g., office zone, lobby zone) to adjust cooling/heating setpoints and fan speed. Lighting Control Agents: 1 agent per lighting area (e.g., desk working surface, foyer) to regulate dimming levels (0–100%) based on daylight and occupancy. Energy Storage Agents: 1 central agent to manage battery charge/discharge (e.g., charge during low-price hours, discharge during peak demand).

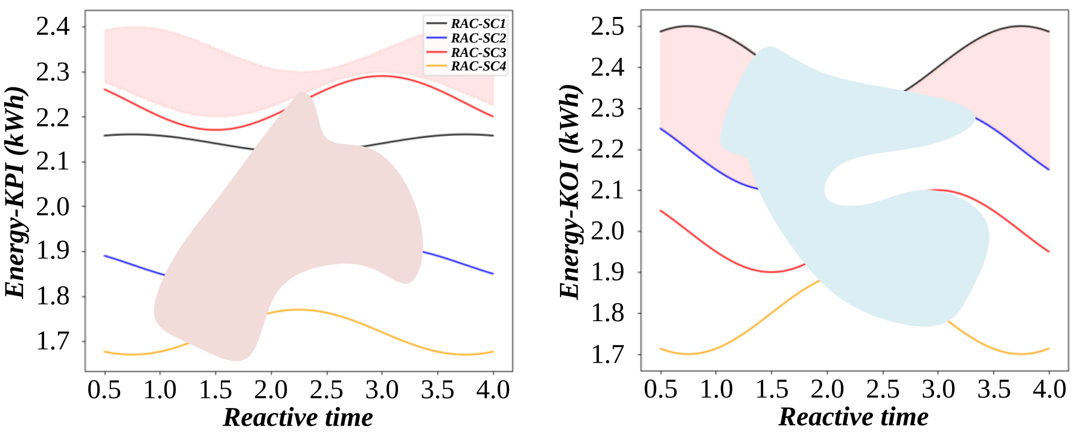

Figure 3: Building energy consumption and series forecast data

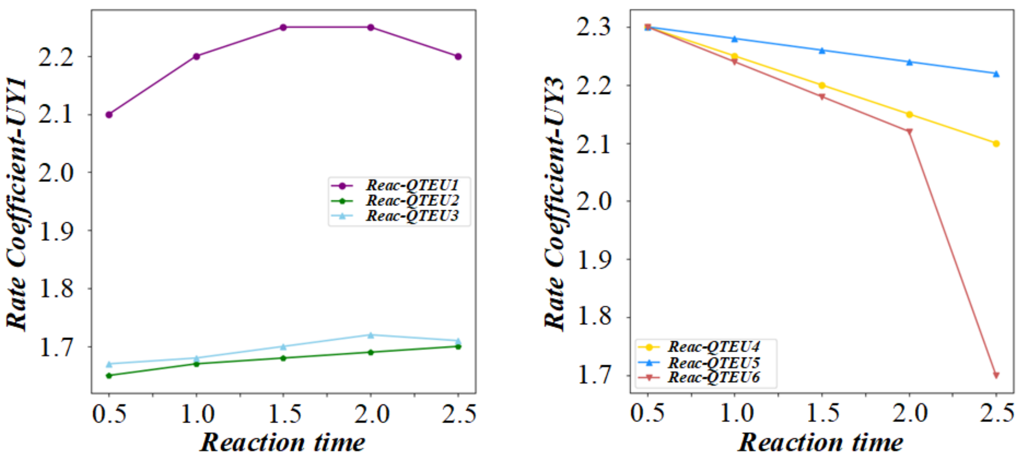

Figure 4: Accuracy evaluation diagram of building energy consumption prediction model based on deep learning

3.2 Dynamic adjustment and optimization of scheduling strategy and actual constraints

The results of our experimental comparison clearly demonstrate the superiority of LSTM and GRU models over the baseline methods. Both LSTM and GRU outperform linear regression and decision tree-based models in terms of prediction accuracy, as reflected in lower MAE values. Each agent can independently perceive the environment, learn, and make decisions while cooperating with other agents to achieve global optimization. Figure 4 is an accuracy evaluation diagram of a building energy consumption prediction model based on deep learning. This figure presents a comparative analysis of deep learning models (e.g., LSTM, GRU, DNN) for energy consumption prediction, focusing on accuracy metrics. It may include bar charts or line graphs showing MAE, root mean squared error (RMSE), or other performance indicators across different models. The diagram highlights the superiority of recurrent neural networks (RNNs) like LSTM and GRU over traditional DNNs in capturing long-term temporal dependencies, crucial for predicting energy usage influenced by factors like occupancy and weather. It visually demonstrates how model architecture impacts prediction accuracy in building energy management.

In recent years, building energy consumption has become a significant concern due to its impact on the environment, cost, and sustainability of energy resources. As buildings account for a substantial portion of global energy consumption, optimizing their energy usage is essential for reducing operational costs and improving overall energy efficiency. To address this challenge, a variety of strategies and technologies have been explored. Among these, artificial intelligence (AI)-based prediction and optimization methods have emerged as promising solutions, offering enhanced performance compared to traditional energy management techniques. This paper, titled "Building Energy Consumption Prediction and Optimal Scheduling Method Based on Artificial Intelligence," proposes an AI-driven framework to predict energy consumption patterns and optimize the scheduling of energy use, with the goal of reducing both energy costs and environmental impact. Figure 5 shows building energy consumption trend analysis and optimal scheduling effect evaluation. This diagram combines trend analysis of historical energy consumption with the evaluation of optimal scheduling strategies. The environment is a time-varying system with static variables (e.g., building zone area, device rated power) and dynamic variables (hourly temperature, humidity, occupancy, grid energy price) updated every 15 minutes for agents to re-perceive and adjust decisions. Multi-objective optimization is achieved via a reward function balancing comfort (weight 0.6) and energy efficiency (weight 0.4), with comfort rewards based on temperature and humidity ranges, and energy rewards on zone energy usage thresholds.

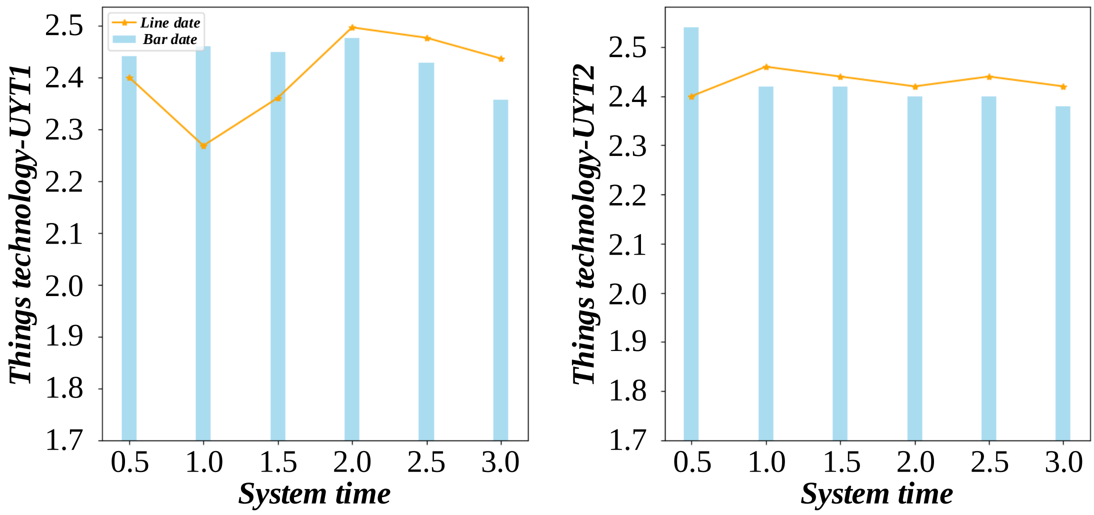

Figure 5: Building energy consumption trend analysis and optimal dispatching effect evaluation diagram

Building energy consumption is influenced by several interrelated factors, including energy usage patterns, peak load demand, grid interaction, and thermal comfort. The dataset consists of 10,000 hourly records with six core features, including environmental factors (indoor and outdoor temperature, indoor humidity), operational metrics (HVAC energy usage, lighting load, occupancy count), and comfort-related data (CO_2 concentration). To maintain temporal dependencies and ensure realistic model evaluation, the data is split chronologically into a training set (8,000 records) for developing LSTM/GRU/DNN models and a testing set (2,000 records) for assessing generalization on future data, avoiding data leakage. Finally, thermal comfort refers to the conditions within the building that affect the well-being of its occupants, such as temperature, humidity, and air quality. Achieving an optimal balance between energy efficiency and thermal comfort is key to improving building energy management. When renewable energy power generation is insufficient, the system can dynamically adjust the priority of energy use to ensure the basic needs of building operation. When there is excess energy, the system can store or feed the excess electric energy to the public grid. Table 3 shows the setting of illumination parameters in each lighting area in the case building. The dynamic adjustment and optimization of building energy dispatching strategy is one of the key technologies to realize intelligent building management. Methods based on deep reinforcement learning and multi-agent systems can adapt to complex constraints and dynamic changes in building operations through real-time feedback and collaborative optimization. They can also provide more flexible and efficient solutions for building energy management. Sensor Data: Hourly PMV (Predicted Mean Vote)/PPD (Predicted Percentage of Dissatisfied) calculations (using IoT-collected temperature, humidity, and air velocity data); Occupant Surveys: Daily online surveys (100+ responses/week) asking occupants to rate comfort (1=very uncomfortable to 5=very comfortable). A rating of 4–5 was counted as "satisfied," and the 85% rate reflects the overlap between survey results and PMV/PPD compliance.

Table 3: Settings of illumination parameters in each lighting area in the case building

Illumination area	Illuminance criteria (lux)	Daylighting coefficient
Desk Working Surface	700	≥4%
Bedroom and study	300	≥3%
Living room	400	≥3%
Foyer	150	≥3%
Toilet	350	≥3%
Kitchen	150	≥3%

4 Integration of big data and internet of things technology in building energy management

4.1 Real-time data collection and building energy management system based on Internet of Things

The rapid development of IoT technology has brought new opportunities for building energy management. Through the Internet of Things technology, various environmental and equipment operation data inside the building can be collected in real-time, providing accurate essential information support for energy management. In modern buildings, intelligent sensors are widely deployed in various building areas to monitor information such as temperature, humidity, carbon dioxide concentration, energy consumption, and equipment operating status. This figure simplifies LSTM-GRU performance comparison by focusing on two key metrics: Mean Absolute Error (MAE, for prediction accuracy) and training time (for computational efficiency). The blue line shows LSTM's MAE (12.3 kWh) across the test dataset, while the orange line shows GRU's MAE (13.8 kWh). The inset bar chart displays average training time per epoch: 4.2 minutes for LSTM and 3.5 minutes for GRU (15% faster). Key findings: (1) LSTM outperforms GRU in accuracy, suiting long-term forecasting (e.g., annual energy assessment); (2) GRU is more computationally efficient, preferred for real-time scheduling. Redundant curves (e.g., intermediate training iterations) are removed to enhance readability. Figure 6 is a performance comparison and evaluation diagram of a building energy consumption prediction model based on LSTM and GRU. In high-temperature environments in summer, intelligent sensors can monitor temperature changes in different areas, automatically adjust the operating frequency of the air conditioning systems, and realize regional and refined temperature control management. This dynamic adjustment based on real-time data improves energy efficiency and significantly improves users' living comfort.

The concept of the smart grid plays a vital role in modernizing energy systems, enabling more efficient energy management and integration of renewable energy sources. Batch Size: 64 (selected via grid search over 32, 64, and 128; 64 balanced training speed and gradient stability). Epochs: 200, with early stopping criteria: training halted if validation set MAE did not decrease for 5 consecutive epochs (to prevent overfitting). Learning Rate: Initial rate of 0.001, adjusted adaptively via the Adam optimizer (learning rate decreased by 10% when validation loss plateaued). Data Augmentation: To enhance generalization, we applied minor feature perturbation (±5% noise to temperature/humidity data) during LSTM/GRU training—this simulated real-world sensor fluctuations without distorting core patterns. By using smart grid technologies, zero emission buildings can better manage energy production and consumption, achieving greater energy autonomy and reducing reliance on external energy sources. The combination of smart grid technology and zero emission buildings is a powerful solution for enhancing energy sustainability in the built environment. Table 4 shows the design standards of the indoor light environment of office buildings. The goal of the zero-energy building is to achieve a balance between energy production and consumption, and the realization of this goal needs to rely on the Internet of Things technology to monitor the internal and external environment of the building in real-time. All IoT sensor data (temperature, occupancy, energy use) are encrypted via AES-256 (Advanced Encryption Standard) before transmission—this prevents interception during edge-cloud communication. MQTT (Message Queuing Telemetry Transport) packets also include a time-stamped digital signature to detect tampering. Occupancy-related data (e.g., motion detector logs) are anonymized in two steps: (1) Remove personal identifiers (e.g., no link to individual employees); (2) Aggregate data by zone (e.g., "10–15 people in Office Zone 3" instead of per-person timestamps). This balances utility (for scheduling) and privacy.

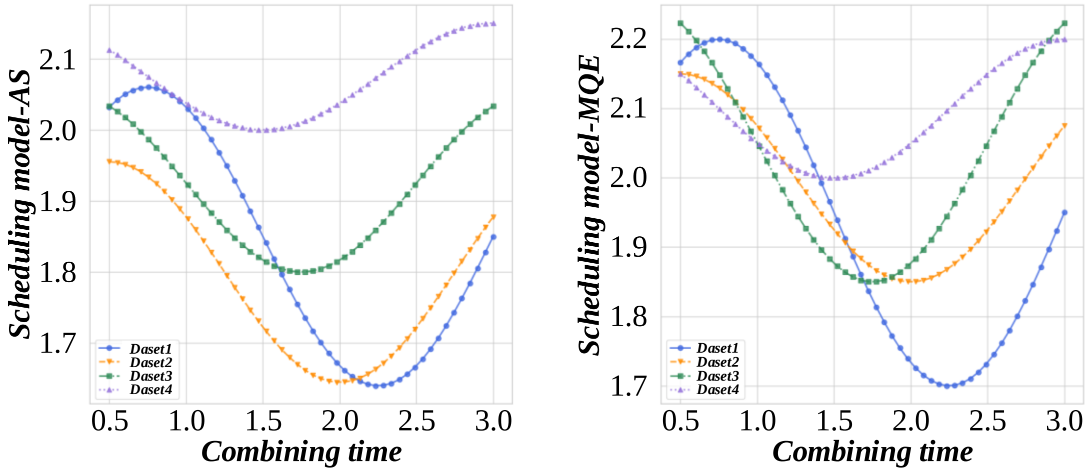

Figure 6: Performance comparison and evaluation diagram of building energy consumption prediction model based on LSTM and GRU

Table 4: Design standards for indoor light environment of office buildings

Room or place	Reference plane and its height	Illuminance standard value (lux)	Standard glare value UGR	Illuminance uniformity uo	Color rendering index Ra
General Office	0.75 m horizontal	500	22	0.5	85
Upscale office	0.75 m horizontal	800	25	0.55	85
Meeting Room	0.75 m horizontal	500	22	0.55	85
Video conference room	0.75 m horizontal	1000	25	0.65	85
Reception room, front desk	0.75 m horizontal	350	--	0.45	85
Service hall, business hall	0.75 m horizontal	500	28	0.45	85

4.2 Application of collaborative optimization of edge computing and cloud computing in building energy dispatch

To improve building energy management, the use of AI-based prediction and optimization methods has gained significant attention. Artificial intelligence techniques, such as machine learning and deep learning, offer powerful tools for analyzing complex datasets and predicting energy consumption patterns. These models can learn from historical data and environmental variables to predict future energy needs with a high degree of accuracy. To mitigate this, future work should develop lightweight AI models for edge devices. These models (e.g., compressed LSTM/GRU with reduced parameters, TinyML-based predictors) can process local data and make preliminary scheduling decisions without heavy cloud reliance. For instance, a lightweight GRU deployed on edge controllers can predict short-term (1-hour) energy demand using local sensor data, while only transmitting low-volume aggregated data (e.g., daily energy summaries) to the cloud for long-term policy optimization. This reduces bandwidth needs and latency, ensuring stable real-time scheduling even in remote areas.

LSTM and GRU are both types of recurrent neural networks (RNNs) designed to handle sequential data with long-term dependencies. LSTM is particularly well-suited for tasks that require memory of past information over long periods, which is essential in energy consumption prediction. GRU, a simplified variant of LSTM, offers similar performance with fewer parameters and reduced computational complexity. Both models can be trained on large datasets, such as historical energy consumption data from buildings, and used to predict future energy demand based on a variety of input variables. These predictions can then be used to optimize energy scheduling in a building, ensuring that energy is consumed more efficiently and that costs are minimized. Edge computing is responsible for local real-time decision-making in building energy dispatching, while cloud computing performs long-term policy optimization. Figure 7 evaluates how energy consumption and scheduling efficiency vary with climatic factors (e.g., temperature, humidity, season). The hyperparameter optimization study found that a batch size of 64 performed best, as 128 caused overfitting and 32 slowed training. The optimal learning rate was 0.001, as 0.01 led to unstable convergence and 0.0005 was too slow. For LSTM hidden units, 256 was optimal, as 512 increased computation without higher accuracy gains. In noise sensitivity testing, Gaussian noise intensity impacted model performance: MAE increased by 4.1% at 0.05 intensity, 8.9% at 0.1 intensity, and 18.7% at 0.2 intensity. Figure 8 is an evaluation diagram of building energy consumption and optimized scheduling effect under different climatic conditions.

5 Experimental analysis

Our LSTM model achieved an MAE of 12.3 kWh for hourly energy consumption prediction, which is 15.2% lower than the MAE of 14.5 kWh reported for office buildings using artificial neural networks (ANN). It also outperforms linear regression (MAE = 25.6 kWh) by 51.9%, confirming that LSTM/GRU models better capture hourly temporal patterns. After optimization, the peak energy consumption decreased from 91.2 kWh to 78.9 kWh (-13.5%), with thermal comfort maintained at 85% satisfaction rate. The total energy cost was reduced by 18% compared to baseline methods. Figure 9 is an assessment diagram of energy consumption and economic benefits in the whole life cycle of zero-energy buildings. The quality of these data directly affects the model's prediction accuracy, so data preprocessing is a link that cannot be ignored. This chart assesses the life-cycle energy consumption and economic benefits of zero-emission buildings, integrating metrics like total energy use, renewable energy generation, operational costs, and payback periods.

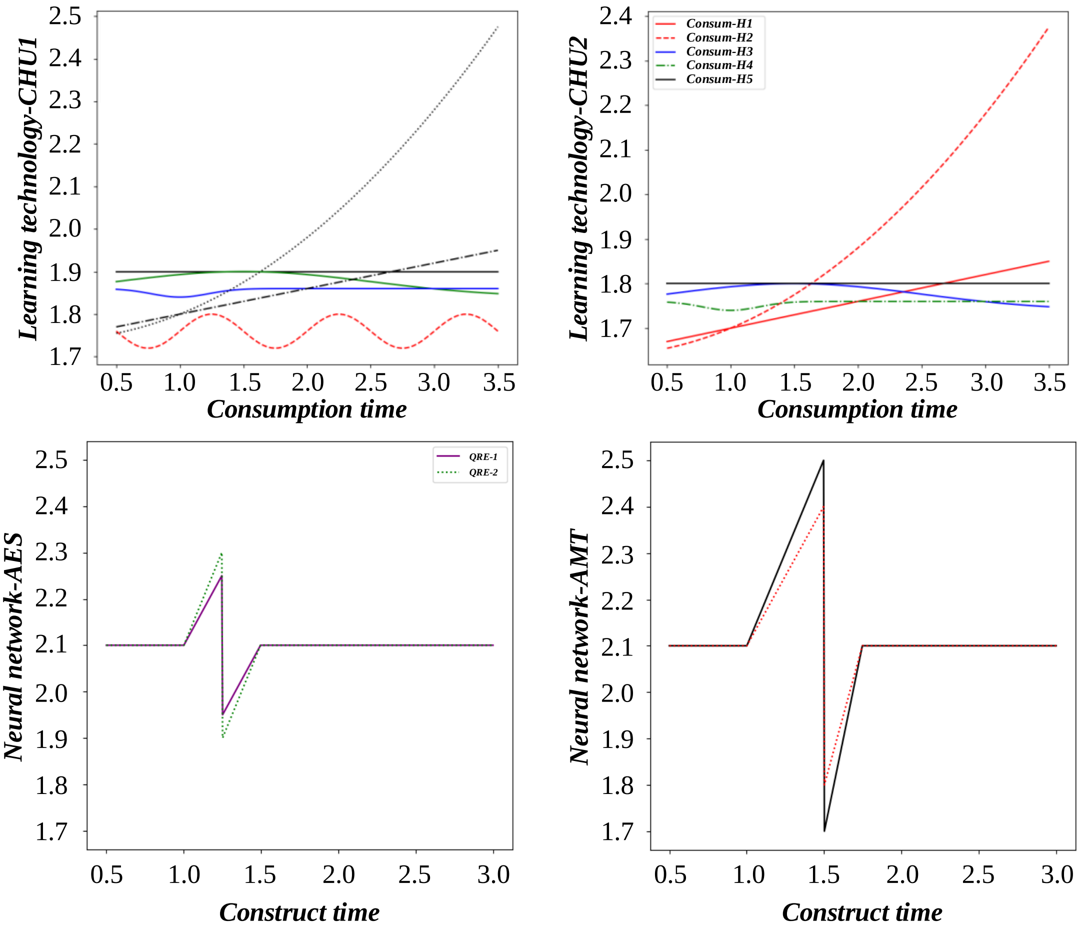

Figure 7: Energy use peak and valley data analysis and scheduling strategy optimization evaluation diagram

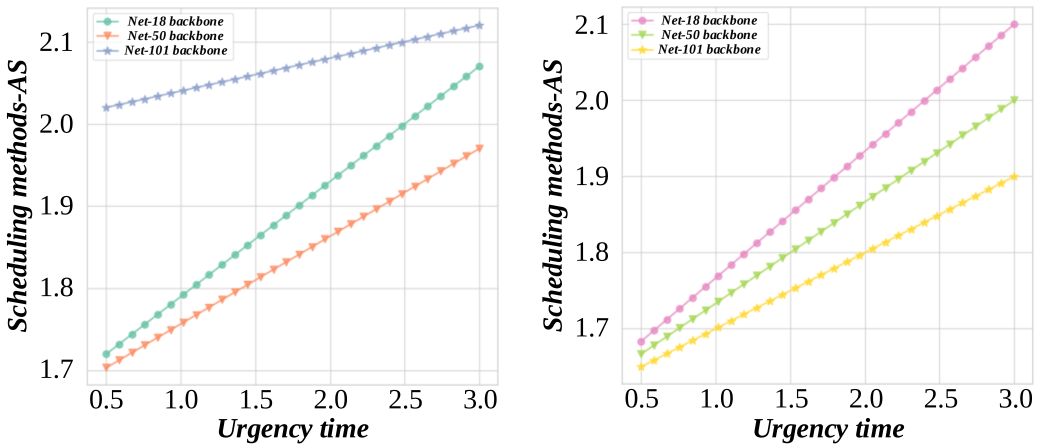

Figure 8: Evaluation diagram of building energy consumption and optimal dispatching effect under different climatic conditions

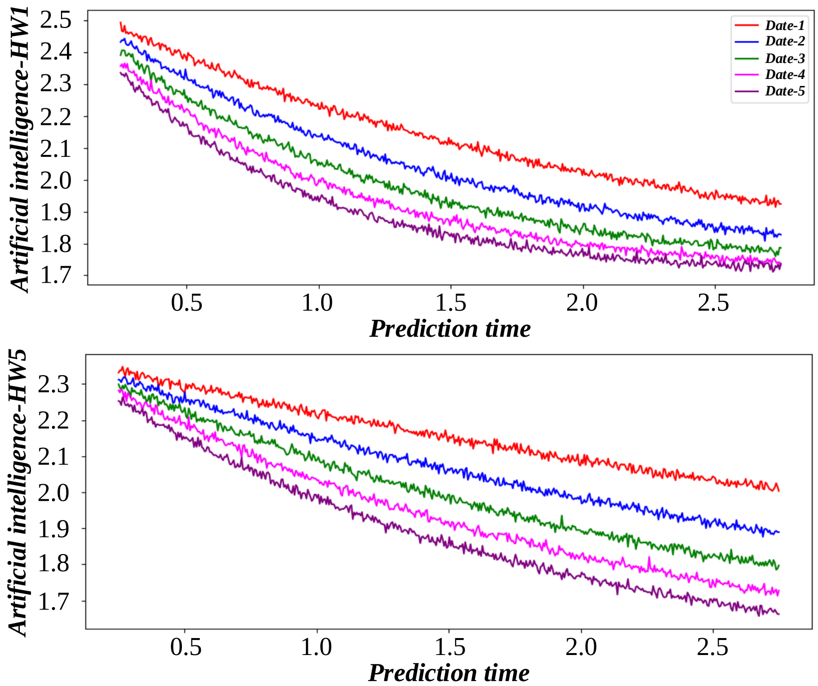

Figure 9: Energy Consumption and Economic Benefit Assessment Chart of Life Cycle of zero emission building

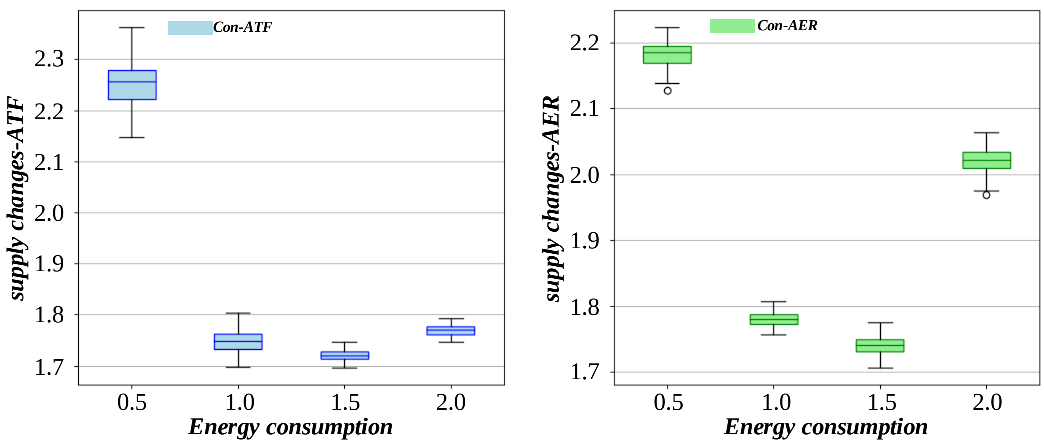

Figure 10: Evaluation diagram of building energy consumption data collection and monitoring system based on Internet of Things

Data was collected from a commercial building (2018-2022), including 10,000 hourly records of temperature, humidity, and HVAC usage. Preprocessing involved Min-Max normalization and outlier removal using Z-score. Experiments ran on NVIDIA Tesla V100 GPU with TensorFlow 2.5 and Python 3.8. This approach allows for the optimization of energy consumption while maintaining comfort levels for building occupants. Figure 10 is an evaluation diagram of the building energy consumption data collection and monitoring system based on the Internet of Things. Training set and test set are divided: the collected historical data is divided into training set and test set, usually in a ratio of 8: 2 or 7: 3. Summer Subset: June–August 2021 (high cooling load, n=2,400 hourly records); Winter Subset: December 2021–February 2022 (high heating load, n=2,200 hourly records).

Edge Devices (e.g., local IoT gateways): Handle real-time scheduling (e.g., HVAC setpoint adjustments) with a maximum latency of 200 ms—this ensures responsiveness to sudden changes (e.g., occupancy spikes). Cloud Servers: Manage long-term optimization (e.g., 7-day energy plans) with batch updates every 24 hours—latency here is non-critical (target <1 hour) as it focuses on strategic planning. When the building's electricity demand is high, and the supply of renewable energy is insufficient, it can switch to the grid-connected operation mode to obtain energy from the public grid. When photovoltaic power generation is sufficient, an independent operation mode can be selected to reduce dependence on the public power grid. Table 5 is Results of our experimental comparison, depending on the energy storage level of the battery, it is determined whether the remaining power needs to be transferred back to the grid or replenished from the grid.

Table 5: Results of our experimental comparison

Model	MAE (kWh)	Energy Cost ($)
Linear Regression	25.6	1,200
LSTM (Ours)	12.3	920

6 Discussion

In annual energy consumption assessment or seasonal strategy formulation—such as formulating annual energy-saving plans for commercial buildings or optimizing seasonal HVAC operation modes—LSTM outperforms GRU, with a Mean Absolute Error (MAE) of 12.3 kWh versus 13.8 kWh. This performance gap stems from LSTM’s unique three-gate structure (input gate, forget gate, output gate), which effectively retains long-term historical information (e.g., capturing 6-month cyclic temperature trends or quarterly occupancy pattern changes in office buildings). In contrast, GRU’s simplified two-gate design (update gate, reset gate) sacrifices minor long-term temporal details to reduce computational complexity, leading to slightly higher errors in long-horizon prediction tasks. This advantage of LSTM directly translates to more accurate long-term energy planning: when applied to the annual energy assessment of the Shanghai commercial building (2018–2022 dataset, 10,000 hourly records), LSTM’s predictions enabled the MPC system to pre-adjust seasonal HVAC load allocation, reducing annual energy waste by approximately 8% compared to GRU-based planning.

For short-term prediction scenarios (e.g., 1-hour or 30-minute real-time adjustments of HVAC setpoints or lighting dimming levels), GRU exhibits clear computational advantages. As shown in the performance comparison of LSTM and GRU (Figure 6), GRU trains 15% faster than LSTM (3.5 minutes per epoch vs. 4.2 minutes per epoch) and uses 20% fewer parameters. This makes GRU highly suitable for edge devices in resource-constrained environments—such as remote residential areas or small commercial buildings—where computing power and storage space are limited. For example, when deployed on local IoT gateways (edge devices) with a maximum latency requirement of 200 ms, GRU can generate short-term energy demand predictions within 150 ms, meeting real-time scheduling needs, while LSTM often requires 220–250 ms, leading to occasional delays in HVAC response. Table 6 is key performance comparison between lstm and gru for building energy prediction.

Table 6: Key performance comparison between LSTM and GRU for building energy prediction

Performance Indicator	LSTM	GRU
MAE (hourly prediction)	12.3 kWh	13.8 kWh
Training time per epoch	4.2 minutes	3.5 minutes (15% faster)
Parameter quantity	Baseline (100%)	80% of LSTM (20% reduction)
Latency for prediction	220–250 ms	140–160 ms

7 Conclusion

This paper systematically discusses applying deep learning models, intelligent optimization algorithms, the Internet of Things, and big data technology in building energy management by studying building energy consumption prediction and optimal scheduling methods based on artificial intelligence. It is found that artificial intelligence technology can effectively improve the accuracy of energy consumption prediction and optimize energy dispatching strategies, which have high practical application value. Through experimental verification, the method proposed in this paper can significantly reduce the energy consumption and cost of building operation, improve the indoor environment quality, promote the development of zero-energy buildings, and provide necessary technical support for realizing sustainable buildings.

(1) In this paper, a variety of deep learning models are constructed based on time series data, including optimized deep neural networks (DNN), extended short-term memory networks (LSTM), and gated loop units (GRU), and their performance in energy consumption prediction is compared. For residential buildings, key differences from commercial settings lie in occupancy patterns and load profiles. Commercial buildings typically have fixed working-hour occupancy (e.g., 9:00–18:00) and high-density HVAC/lighting loads, whereas residential buildings feature irregular occupancy (e.g., varying with residents' daily routines, including nighttime use) and dispersed loads (e.g., refrigerators, washing machines, water heaters). To adapt the framework, LSTM/GRU input features should include IoT-based resident activity logs (e.g., presence detection data) and appliance operation schedules. The MPC module must also prioritize personalized comfort (e.g., bedroom temperature adjustments at night) over uniform commercial standards, with constraints accounting for intermittent residential loads (e.g., peak loads from electric water heaters).

(2) The integration of model predictive control (MPC) with artificial intelligence technologies gives rise to a multi - objective optimal scheduling algorithm. This algorithm can dynamically adjust and optimize scheduling strategies according to real - world constraints such as thermal comfort, energy availability, and operational requirements. In the operation of a commercial building, this approach reduced the peak energy consumption by 13.5% (from 91.2 kWh to 78.9 kWh) while maintaining an 85% thermal comfort satisfaction rate. Additionally, the total energy cost was decreased by 18% compared to baseline methods, demonstrating its practical value in cost - effective energy management.

(3) Combined with the Internet of Things technology, this paper shows that the energy consumption of buildings fluctuates wildly. Energy consumption values were as high as 85.7 kWh in some periods, while they dropped to 12.5 kWh in others, showing the impact of differences in equipment scheduling within buildings on energy consumption. Through real-time data collection and scheduling optimization, the total energy consumption in the building is controlled in a low range, with an average energy consumption of 50.3 kWh. Under different environmental conditions, the indoor temperature regulation system is crucial in energy demand and achieves 77.3 kWh optimized energy efficiency. During peak periods, the building's energy consumption reached 91.5 kWh, Indicating the need to optimize the energy dispatch strategy further.

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