Research on Energy Consumption Prediction and Intelligent Regulation of Building Electrical System Based on Artificial Intelligence

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Abstract: Aiming at the problems of high energy consumption, complex regulation and control of building electrical system, and it is difficult for traditional methods to give consideration to both global optimization and local stability, this paper proposes an intelligent regulation and control method that integrates graph neural network (GNN) and double-layer reinforcement learning (DRL). Firstly, a spatiotemporal GNN (ST-GNN) based energy consumption prediction model is constructed, which integrates BIM topology and IoT temporal data to achieve joint modeling of multi device spatial correlation and temporal dependence, significantly improving prediction accuracy. Secondly, a double-layer control architecture of "global optimization of upper DRL+local control of lower PID" is designed, which takes into account system-level energy-saving optimization and stable operation of equipment. Furthermore, the model distillation technology is used to realize the migration of the cloud model to the edge lightweight model, which meets the real-time response requirements of 100ms. The experimental results show that this method achieves 18% energy-saving effect in real office buildings, the prediction error is reduced to 2.68 kW·h (Mae), and the average response time is 87ms, which verifies its comprehensive advantages in energy consumption prediction, intelligent regulation and real-time, and provides a feasible technical path for green intelligent buildings.

1. Introduction

The global construction industry is facing the challenge of carbon emission caused by high energy consumption and the building stock that is about to double, in which the energy consumption of electrical system accounts for a large proportion, and the traditional energy management method leads to significant energy waste. AI (Artificial Intelligence) technology has demonstrated its potential in improving energy efficiency [1-2]. However, most of the existing applications are aimed at a single device or scene, and the complex network of building electrical system still faces three contradictions: data complexity and model generalization, real-time requirements and computing resources, global optimization and local constraints. More comprehensive and intelligent solutions are needed to deal with these challenges in order to realize effective prediction and regulation of energy consumption.

In this study, a spatio-temporal energy consumption prediction model based on graph neural network (GNN) is proposed, which integrates BIM topology data and IoT (Internet of Things) time series data to solve the problem of lack of spatial correlation modeling in traditional methods. Design a double-layer reinforcement learning (RL) control architecture, the upper DRL (Deep Reinforcement Learning) realizes global optimization across devices, and the lower PID control ensures the stability of single device, balancing the contradiction between exploration and utilization; The edge-cloud collaborative computing mechanism is developed, and the large cloud model is compressed into an edge lightweight model through model distillation, so as to realize 100ms real-time response.

2. System architecture design

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The "cloud-edge-end" three-tier system architecture is shown in Figure 1. Realize closed-loop control from data perception, intelligent decision-making to accurate execution. The architecture is divided into intelligent analysis and decision-making cloud platform, edge intelligent control gateway and field device execution layer from top to bottom.

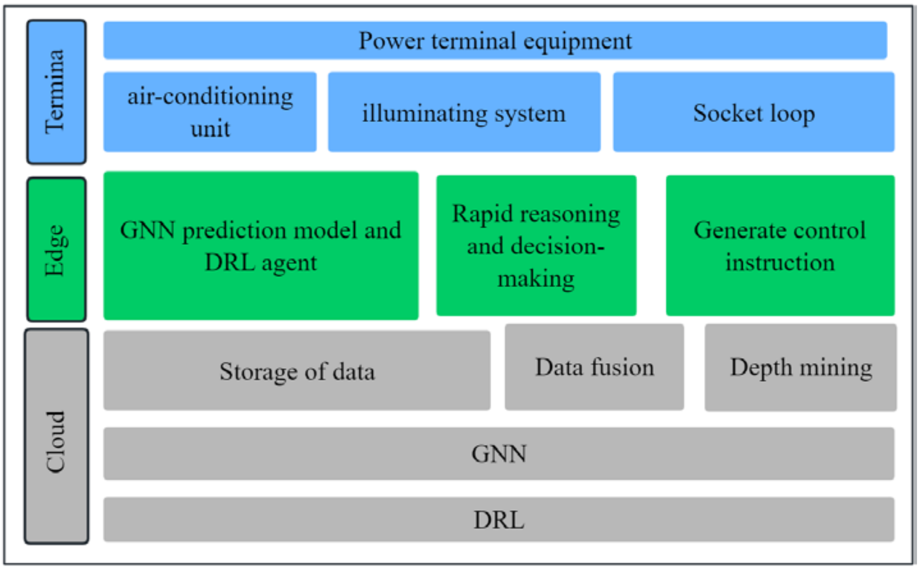

Figure 1 "Cloud-edge-end" three-tier system architecture

Intelligent analysis and decision cloud platform. As the "brain" of the system, it is responsible for the storage, fusion and deep mining of massive historical and real-time data [3]. At this level, we will train a huge spatio-temporal prediction model and a complex global optimization strategy model. Its core advantage lies in its powerful computing resources, which can be used for heavy model training and periodic global strategy re-planning without millisecond response. Integrate static topology data from BIM model and dynamic timing data from IoT platform [4]. The trained lightweight prediction model and optimization strategy model are sunk to the edge layer by "model distillation" and other technologies.

Edge intelligent control gateway (edge). As the "nerve center" of the local system, the lightweight GNN prediction model and DRL agent are deployed. It is responsible for receiving the model sent by the cloud, and making millisecond-level (target 100ms) rapid reasoning and decision based on local real-time data, and generating control instructions [5-6]. It solves the delay problem of complete cloud control and ensures the real-time regulation. Directly collect the real-time data stream of the local IoT sensor. Synchronize data and models with the cloud upwards, and send specific control settings to the device execution layer downwards.

Field device execution layer (terminal). Including all kinds of electricity terminal equipment in the building, such as air conditioning units, lighting systems, socket circuits, etc. They receive the control instructions from the edge gateway, and execute the actions accurately and stably through the local controller at the lower level, so as to avoid the equipment oscillation that may be caused by directly adopting AI instructions [7]. Receiving a set value instruction of the edge layer. The actual running status and energy consumption data of the equipment are fed back to the edge and cloud through sensors to form a closed loop. The architecture effectively balances the contradiction between computing resources and real-time requirements through the design of cloud collaboration and clear division of labor.

3. Key technology

3.1 Spatial-temporal energy consumption forecasting model based on GNN

To overcome the limitation of traditional prediction methods in modeling building spatial topology relationships, this study innovatively constructs the building electrical system as a graph structure. Consider each electrical device or spatial unit as a node in the graph, with node features including real-time energy consumption, environmental data, etc. Based on the physical connections and spatial adjacency relationships in the BIM model, edges are defined to embed the spatial topology information of the building into the model [8]. Adopting spatiotemporal GNN (ST-GNN). This model uses a Graph Convolutional Network (GCN) module to capture spatial correlations between nodes at the same time; Use Gated Recurrent Unit (GRU) module to capture the time series dependencies of each node itself [9-10]. Through this design, the model can simultaneously learn spatiotemporal features, significantly improving energy consumption prediction accuracy in multi device and complex environments, and solving the challenges of data complexity and model generalization.

3.2 Double-layer DRL intelligent control architecture

A double-layer DRL intelligent control architecture is proposed to realize the coordination of global optimization and local control stability of energy system. As shown in Figure 2, the architecture adopts hierarchical design, and the upper layer is the DRL global optimizer deployed in the edge gateway, which is responsible for making intelligent decisions from the overall perspective of the system [11]. Based on the DRL algorithm, the optimizer constructs a state space by integrating the future energy consumption predicted by GNN, real-time environmental parameters, electricity price signals and equipment status. By optimizing the reward function (taking into account energy saving, comfort and economy), it outputs globally optimal setting suggestions for all energy-using equipment, such as air conditioning temperature target value.

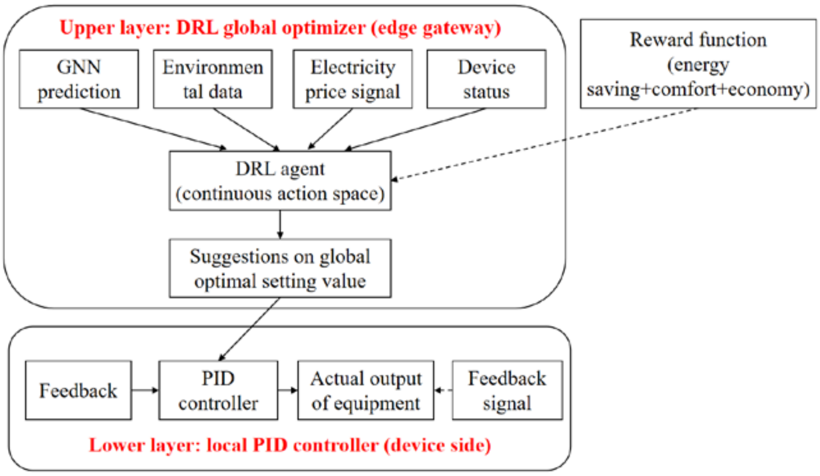

Figure 2 Double-layer DRL intelligent control architecture

The lower layer is composed of local PID controllers distributed at each device end, which undertakes specific execution tasks. The PID controller receives the set value provided by the upper DRL as the control target, and uses the classical feedback control mechanism to accurately adjust the running state of the equipment to ensure that the actual output approaches the target value smoothly and accurately. This division of labor mechanism effectively separates the functions of "decision-making" and "execution": DRL focuses on long-term strategy exploration and global optimization, while PID ensures the stability and security of dynamic response at the equipment level, thus successfully balancing the exploration-utilization contradiction in RL while avoiding the shock or equipment loss caused by direct control, and improving the intelligence and robustness of the overall system.

3.3 Edge-cloud collaborative mechanism based on model distillation

In order to empower the ability of cloud large model to edge devices with limited resources, model distillation technology is adopted in this study. Train a huge and accurate "teacher model" in the cloud. Then, the teacher model is used to guide and train a small "student model" (neural network with simpler structure), so that the learning goal of the student model is not only to fit the real data, but also to imitate the output and behavior of the teacher model. Finally, the lightweight "student model" is deployed to the edge gateway. Although it has a small number of parameters, it inherits the core knowledge of the teacher model and can achieve the performance close to the large model with very low computational overhead and delay, thus meeting the real-time requirements.

4. Experiment and result analysis

In order to verify the practical effect of the proposed GNN-based forecasting model and the double-layer DRL control architecture, a one-month field experiment was carried out in an office building equipped with a perfect IoT sensing system. The experimental platform adopts an edge-cloud collaborative architecture, in which the edge gateway uses NVIDIA Jetson Xavier NX for local data processing and real-time decision-making, and the cloud relies on AWS EC2 p3.2xlarge instance to complete high-complexity GNN training and model updating. Through long-term operation in real environment, the system has collected comprehensive energy consumption, environment and equipment status data, which provides a reliable basis for performance evaluation.

Three comparative schemes were set up in the experiment: traditional rule-based control based on a fixed timetable, constant setpoint strategy relying solely on PID feedback control (PID Only), and the GNN+DRL collaborative optimization scheme proposed in this paper.

Select one week of test data and compare the predictive performance of our GNN model with two traditional models (LSTM and CNN-LSTM). The results are shown in Table 1. As shown in Table 1, the ST-GNN model proposed in this paper significantly outperforms the comparison models in terms of mean absolute error (MAE) and root mean square error (RMSE). This proves that modeling the spatial topology relationship between devices through graph structure can effectively capture complex energy consumption interactions, greatly improve prediction accuracy, and provide an effective solution to solve data complexity.

Table 1 Error comparison of one-hour scale energy consumption prediction under different models

Model	MAE (kW·h)	RMSE (kW·h)
LSTM	4.52	6.31
CNN-LSTM	3.89	5.47
Our (ST-GNN)	2.68	3.95

The total energy consumption and comfort of the whole experimental period are compared as shown in Figure 3. It can be seen that the energy consumption of PID Only scheme is 95%, and that of GNN+DRL scheme is 82%, which shows remarkable energy-saving effect. The deviation rate of Rule-Based scheme is 25% (because the timing switch can't meet the dynamic demand), PID Only scheme is 5% (its goal is to keep constant), and GNN+DRL scheme is 7%, which shows that it can save a lot of energy and maintain the comfort in an acceptable range. The results show that the double-layer DRL architecture proposed in this study successfully achieves the balance between global optimization and local constraints. The upper DRL agent realizes 18% energy saving by exploring the global optimal strategy. The lower PID controller ensures the smooth execution of instructions and avoids the violent fluctuation of comfort.

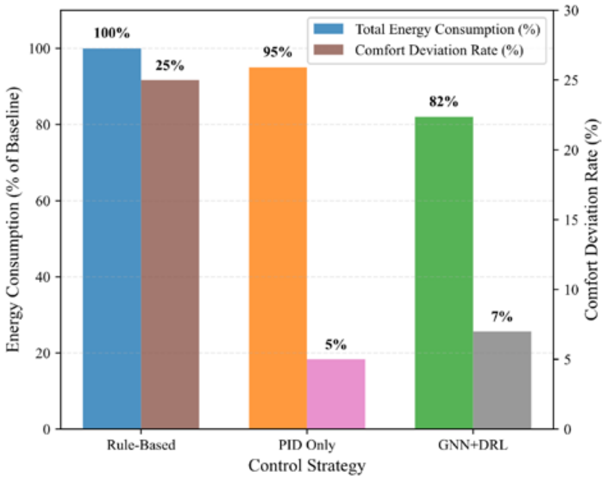

Figure 3 Comparison of comprehensive performance under different control strategies

The distilled lightweight model is deployed in the edge gateway, and the response time distribution (10,000 requests in total) for processing sensor data and generating control instructions is counted, as shown in Figure 4. The results show that the response time of 99.7% requests is less than 100ms, and the average response time is 87ms, which fully meets the demand of real-time regulation of building electrical system. This verifies the effectiveness of cloud-edge collaboration mechanism based on model distillation, successfully migrates the capabilities of complex cloud models to edge devices with limited resources, and solves the contradiction between real-time requirements and computing resources.

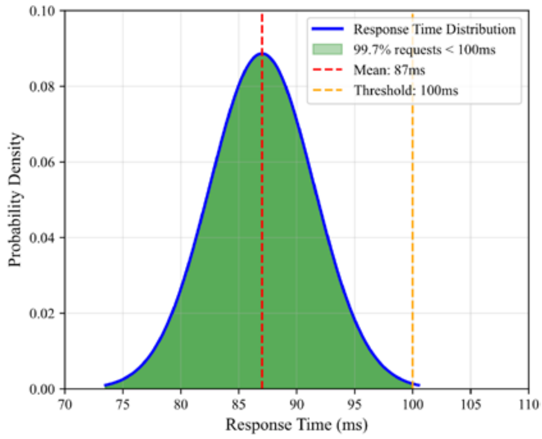

Figure 4 Decision response time distribution of edge gateway

The experimental results show that the comprehensive solution proposed in this study is significantly superior to the traditional methods in terms of energy consumption prediction accuracy, energy saving effect and system real-time performance. It successfully combines the global optimization ability of AI with the stability of traditional control, providing an effective technical path for building a green, intelligent and comfortable building environment.

5. Conclusion

The comprehensive solution of energy consumption prediction and intelligent regulation of building electrical system based on AI effectively solves the contradiction between data complexity, real-time requirements, global optimization and local constraints in traditional methods by constructing the space-time energy consumption prediction model of GGN and designing a double-layer DRL intelligent regulation architecture, combined with the edge-cloud collaborative mechanism. The experimental results show that the prediction model based on ST-GNN is significantly better than the traditional models LSTM and CNN-LSTM in MAE and RMSE, which proves that it can effectively capture the complex energy consumption interaction in the building electrical system and improve the prediction accuracy. The double-layer DRL architecture realizes the balance between global optimization and local control stability of the energy system through the cooperation of the upper DRL global optimizer and the lower PID controller, which significantly reduces the total energy consumption and maintains high comfort. In addition, the edge-cloud collaboration mechanism based on model distillation successfully migrates the capabilities of the cloud model to the edge devices with limited resources, ensuring that the demand for real-time regulation is met. The comprehensive solution proposed in this study is significantly superior to the traditional methods in terms of energy consumption prediction accuracy, energy saving effect and system real-time, which provides an effective technical path for building a green, intelligent and comfortable building environment.

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