論 文 の 内 容 の 要 旨

論文題目　Development of Operational Optimization Methodology for Renewable Building Energy Systems Applying Reinforcement Learning and Model Predictive Control (強化学習とモデル予測制御を応用した再生可能建築物エネルギーシステムの運用最適化手法の開発)

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With the development of the world economy and the increasing level of urbanization, people spend more and more time in constructions and buildings (People spend more than 80 % of their time inside buildings. This situation has led to a rapid increase in building energy consumption in recent years. By 2021, the proportion of building energy consumption in the total energy consumption of the whole society has reached as high as 40 %, including both residential and commercial buildings. With the further advancement of urbanization, the proportion of building energy consumption in total energy consumption is also expected to continue to rise.

The huge energy consumption on the building side also brings a lot of CO2 emissions. Due to the utilization of a large amount of primary energy in the building energy system, the greenhouse gas emissions caused by the entire building account for about 30% of the global total. In fact, countries have reached a certain sense of consensus on CO2 emission reduction after the Paris Agreement. Japan plans to achieve its own carbon emission reduction targets by 2050, and in the field of buildings, a plan to reduce carbon emissions from non-residential buildings by 51% and residential buildings by 66% by 2030 and achieve carbon neutrality by 2050. Due to such a huge demand for carbon reduction, the coupling of renewable energy and building energy systems is naturally on the agenda. The combination of renewable energy and building energy systems can better reduce primary energy consumption and carbon emissions on the building side. However, considering the uncertainty of introducing renewable energy, we need more advanced and intelligent control algorithms to effectively configure various equipment and renewable energy in the system. Besides, it should be noted that the deployment of renewable energy in building energy systems still has certain limitations. For example, the utilization of wind energy requires sufficient space to house wind turbines. In addition, due to the investment cost of wind turbines, the installation feasibility of the utilization also determines the utilization potential of wind energy.

Considering the abundance of resources and the convenience of building deployment, the coupling of solar energy and building energy systems has become an effective solution to reduce building carbon emissions. Among all renewable energy sources, solar energy is at the heart of power generation technology because it is inexhaustible, environmentally sustainable, readily available in large areas and at low cost globally. In fact, the utilization potential of solar energy is at least 1500 EJ and the annual average global horizontal irradiation at over 2200 kWh/m2 in maximum, which is enough to meet the current global primary energy demand. If 0.1% of the solar energy reaches the earth's surface, the efficiency of conversion to electricity is 10%, and the output power is 7 times the global average instantaneous electricity consumption. Therefore, in Japan, and even in the world, solar energy, as a high-quality renewable energy, undoubtedly has a huge potential for utilization.

Among all solar energy application technologies, solar power generation accounts for 99% of the global installed solar capacity. The cost of photovoltaic technology and photovoltaic modules continues to decrease due to continuous improvements in technology and policy support from governments around the world. In fact, when the global installed capacity of solar power is doubled, its installation cost falls by about 23%. Above all, the method of coupling solar power generation and building energy system can effectively reduce the carbon emissions on the building side, which has great application potential and convenient deployment method.

Although the application of solar power generation in building energy systems has made great progress, there is still a lack of more refined control methods to ensure its efficiency. For operation, considering the uncertainties (solar radiation, human behaviors, etc.) in building energy system, there are numerous wastes in this stage. For instance, the solar energy waste in Japan in about 23%. In addition, due to the introduction of renewable energy, the uncertainty and complexity of the building energy system is greatly increased. The traditional method is completely unable to cope with the multi-objective operation optimization that integrates multiple devices. After the introduction of renewable energy, a reasonable optimization strategy undoubtedly needs to take into account the amount of renewable energy used, and traditional methods are even less experienced in this regard. Thus, this thesis aims to develop a framework to improve operational optimization of renewable building energy system. Model Predictive Control (MPC) and Deep Reinforcement Learning (DRL) are considered as two possible algorithms to solve this kind of problem. However, the research on these two algorithms in building energy systems is still in its infancy, especially the application of DRL algorithms is still small. Few papers use real data to compare the pros and cons of the two algorithms. Therefore, this thesis will develop two different frameworks of MPC and DRL and verify the effect of the two algorithms. The research objective of this paper is a real office building in Tsukuba, Japan. The entire energy system includes solar photovoltaic (PV) power generation equipment, two combined heating and power (CHP) generators, and battery, which belongs to a typical renewable building energy system.

Chapter 1, Introduction: This chapter provides necessary background information and motivation of this research. Relevant literature on model predictive control and reinforcement learning are being reviewed. Finally, the research gaps, research scope, and objectives of this study are being determined in this chapter.

Chapter 2, MPC framework: short-term prediction: This chapter introduces the short-term forecasting models that will be used in the MPC framework. Using graph neural network and recurrent neural network, the short-term prediction model proposed in this paper can simultaneously consider the temporal variation and spatial relationship of data. Besides, the graph structure of graph neural network can be the output of interpretable deep learning model. We found that the attention mechanism can well capture temporal dependencies in the temporal dimension. The interpretability of the graph structure shows that solar radiation has the greatest correlation with variables such as month, hour, temperature, rainfall, and radiation time.

Chapter 3, MPC framework: long-term prediction: This chapter presents a method for long-term time series forecasting using deep generative models. By using recurrent neural networks, we can avoid the error accumulation problem that arises from iteratively using single-step prediction models. In addition, we discuss the impact of weather forecast accuracy on solar radiation predictions. The proposed long-term prediction model is also used in the MPC framework. We found that not all temperature forecast data could be fed into the model. When the time span between the release forecast time and the forecast target is greater than 3 days, the input temperature forecast data has a negative impact on the forecast accuracy.

Chapter 4, Model predictive control with hybrid prediction model: Using the two forecasting models proposed in Chapters 2 and 3, this chapter proposes an MPC framework based on a long-term and short-term mixed forecasting model. The proposed MPC framework is trained, validated, and tested on a measured dataset of real buildings in Japan. According to the experimental results, the influence of the prediction accuracy of different prediction models on the MPC framework is analyzed.

Chapter 5, Deep reinforcement learning for renewable BES: This chapter uses advanced deep reinforcement learning algorithms to optimize the operation of renewable building energy systems. A completely continuous action space is designed with certain assumptions and case studies are carried out. state/action/reward design for reinforcement learning, approaches to solve reward design challenges, analyze the results of both convergence performance and control performance. Through the results of the case study we selected the best performing deep reinforcement learning algorithm for future use.

Chapter 6, Multi-agent reinforcement learning for hybrid action space: To smoothly compare the MPC algorithm and the reinforcement learning algorithm, this chapter proposes the use of a multi-agent framework to allow the reinforcement learning algorithm to solve the operation optimization problem of the mixed action space. Using the experimental results in Chapter 5, we construct a multi-agent framework with a mixture of continuous and discrete agents. The proposed multi-agent algorithm is tested under the same experimental conditions as MPC.

Chapter 7, Comparing between MADRL and MPC: Using the measured data of real existing buildings, this chapter tests and compares the operational optimization results of MPC and MADRL under the same objective. To ensure the robustness of the comparison, we randomly selected different optimization scenarios to compare the algorithms.

Chapter 8, Conclusion, and future work: Summarize the major findings of this study; summarize the limitations of this study; list the future work. The author suggests two areas for further research. Firstly, the robustness control of Model Predictive Control (MPC) needs improvement, as relying solely on point prediction can result in errors. Future research should focus on obtaining a better operation strategy by considering deviations. The author believes that the quality of data determines the upper limit of prediction accuracy, and future research should focus on practical engineering applications such as online updating and model interpretability. Secondly, the author suggests exploring multi-agent reinforcement learning in areas such as energy trading, pricing, and carbon trading. The MADRL framework used in the study is cooperative, and the author hopes to use it to provide necessary information such as faster pricing strategies for dynamic energy prices, demand-side response, and carbon trading. This research requires interdisciplinary knowledge in finance, computing, and building energy systems, and researchers need to put in more effort.