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Reinforcement Learning applied in Smart Buildings: A review of present status and challenges

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Abstract

Reinforcement learning (RL) offers tremendous promise for optimizing energy efficiency, enhancing occupant comfort, and improving sustainability in smart buildings. However, a significant gap exists between the idealized performance observed in simulations and the challenges encountered during real-world implementation. This paper investigates the primary obstacles to successfully deploying RL in smart buildings. Specifically, we address the simulation-reality gap, data-related challenges, safety and robustness concerns, adaptability issues, and the role of human factors in building trust and acceptance. The paper concludes by examining existing work, highlighting open research directions, and emphasizing the potential of RL to transform the way smart buildings operate.

키워드 : 심층강화학습, 스마트빌딩, 실생활 구현, 시뮬레이션-현실 격차, 에너지효율, 안전
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1. Introduction

Smart buildings leverage interconnected systems and sensors to dynamically manage operations like heating, ventilation, air conditioning (HVAC), and lighting. Deep reinforcement learning holds great potential for automating these systems, leading to significant energy savings, increased occupant comfort, and improved alignment with sustainability goals [1]. Unlike traditional control, DRL agents can learn complex strategies, adapt to evolving conditions, and optimize performance across multiple objectives.

While simulation studies demonstrate DRL's capabilities for building control, real-world application is far less common [2]. The transition from simulation to physical implementation presents unique challenges. These challenges include managing the disconnect between simulations and complex building environments, handling limited real-world data, ensuring safety, designing robust and adaptable systems, and incorporating the crucial element of human trust and interaction.

2. Research methodology

This systematic review aims to synthesize existing research on the challenges associated with real-world implementation of reinforcement learning (RL) control in smart buildings. The following methodology guided the research:

2.1 Search Strategy

Research databases such as IEEE Xplore, ScienceDirect, ACM Digital Library, Web of Science, and Google Scholar were used for the literature search. The following search terms and their combinations were used: "reinforcement learning", "smart buildings", "real-world implementation", "implementation challenges", "HVAC control", "lighting control". The search focused on papers published within the last 5-10 years to capture the most recent advancements and challenges in the field.

2.2 Inclusion/Exclusion Criteria

Included studies met criteria: use of RL for smart building control, discussion of real-world deployment challenges, and publication as peer-reviewed research, conference proceedings, or technical reports. Excluded were studies solely on RL simulations, lacking critical discussion of implementation challenges, or existing review papers (to be analyzed separately for common themes).

2.3 Data Extraction and Analysis

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The selected papers were systematically reviewed. The focus was on extracting data about the specific smart building systems targeted by RL (HVAC, lighting, etc.), the nature of the implementation challenges identified (categorized into data-related, safety and robustness, adaptability, and human factors), proposed solutions or techniques to address those challenges, and areas identified as requiring further research.

2.4 Synthesis

The findings from the extracted data were synthesized to create a comprehensive map of real-world RL implementation challenges in smart buildings. This involved identifying common themes, highlighting limitations in existing approaches, and proposing promising research directions for bridging the simulation-reality gap and enabling practical applications of RL in building control.

3. The Simulation-Reality Gap

Simulations provide a controlled setting for RL experiments, but they often oversimplify real-world complexities. This includes simplified equipment models ignoring efficiency degradation, perfect sensor data assumptions neglecting calibration errors, and consistent occupancy patterns not reflecting real dynamics. These disparities can result in RL policies optimized for simulation but performing inadequately in reality.

4. Challenges and Potential Solutions

Addressing several challenges is crucial for the successful deployment of Reinforcement Learning (RL) in optimizing smart buildings [4]. Data-related hurdles include the scarcity of quality data for training RL models, the necessity for sensor calibration and fault detection to maintain data integrity, and the delicate balance between optimization needs and occupant privacy in multi-occupant settings. Ensuring safety and robustness is also paramount [5], requiring safe exploration methods during early training, techniques to uphold hard constraints, and robust strategies for handling unforeseen events to prevent system collapse. Adaptability is essential for long-term RL success, necessitating controllers that can adjust to changing building use, equipment upgrades, and shifting optimization priorities through techniques like transfer learning, continuous online adaptation, and dynamic reward shaping [6]. Finally, human factors must be considered, including building trust through explainable RL and providing mechanisms for human oversight and intervention [7].

5. Existing Work and Open Research Directions

Existing work on real-world RL in buildings offers some solutions but has limitations [8]. Key open research directions include developing techniques for data augmentation to bridge the simulation-to-reality gap, establishing robust safety protocols, enabling adaptive learning for continuous improvement, increasing the explainability of RL decision-making, and fostering effective human-AI collaboration in building management.

6. Conclusion

Bridging the simulation-reality gap is vital to realizing the benefits of RL in smart buildings. This paper outlined the key obstacles hindering successful deployment. Focused research on data-driven solutions, safe and robust RL, adaptability, and human-centric system design is crucial. While challenges remain, the potential payoff is immense – a new generation of smart buildings that are truly intelligent, efficient, and responsive to the dynamic needs of their occupants.

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