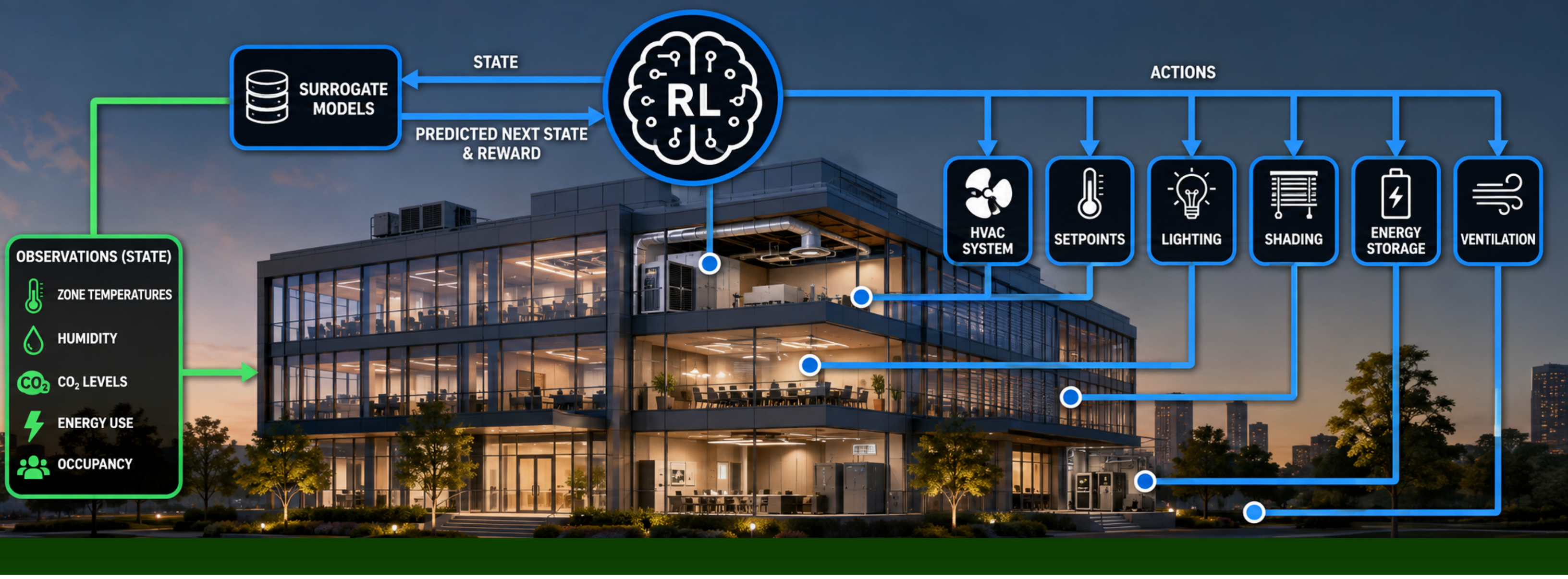

BEST Center Funded Research Summary

Making Reinforcement Learning Practical for Building Control using Surrogate Models

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Motivation

Modern buildings must do much more than simply keep occupants comfortable. Buildings must reduce energy use, lower operating costs, integrate renewable energy, respond to changing electricity prices, and support an increasingly complex electric grid. Traditional building controls rely on fixed rules that cannot easily adapt to changing weather and occupancy or integrate with devices such as solar panels, batteries, electric vehicles, and smart sensors. Reinforcement learning (RL) is a promising alternative that can continuously learn control strategies while operating building systems, rather than relying on manually programmed rules. Conventional RL learns slowly and makes poor decisions during its early training period, making it impractical for real building implementation. This project addresses this challenge by guiding the learning process with fast, data-driven surrogate models, enabling RL building control systems to learn quicker, operate safely, and achieve better energy efficiency and comfort.

Reinforcement Learning

Reinforcement learning (RL) applied to building control aims to improve building system operation by learning from experience. As an RL agent operates building systems, it gradually discovers which decisions save the most energy, reduce costs, and keep occupants comfortable. A challenge with this approach is RL requires a long learning phase, and those early experiments can waste energy and make poor control decisions. This project evaluates surrogate models, which are fast computer models that act like a virtual practice environment, allowing the RL agent to predict the results of different control actions before trying them in a real building. By using surrogate models to guide exploration (Figure 1), the RL agent learns faster, avoids costly mistakes during training, and becomes practical for real-world building energy management.

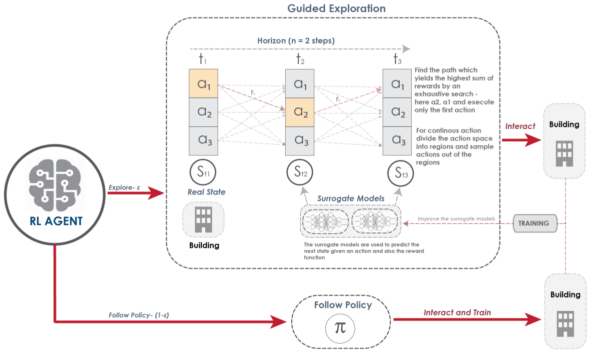

Figure 1. *Schematic of how surrogate models were used to train reinforcement learning (RL) agents*

About the BEST Center

The Building Energy Smart Technologies (BEST) Center is a partnership between the University of Colorado Boulder and City College of New York operating using the NSF's industry-university cooperative research center model. The center fosters interdisciplinary collaborations between the building industry and university research to advance energy systems through university-industry partnerships to engineer the intelligent and efficient cities of tomorrow.

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Surrogate Model Training Case Study

The Advanced Controls Test Bed (ACTB) was used to evaluate the ability of surrogate-models to train an RL building controller. The ACTB is an open-source platform that combines Spawn of EnergyPlus (SoEP) with Modelica-based HVAC component models to create a high-fidelity simulation of commercial building operation. The case study modeled a 511 m² U.S. Department of Energy Reference Small Office Building located in Chicago, consisting of four perimeter zones and one core zone served by packaged rooftop HVAC units. The building included rooftop solar photovoltaic (PV) systems, six batteries, and demand response events that required the controller to reduce building power during peak grid demand (Figure 2). The RL controller interacted with the building through the OpenAI Gym interface, allowing it to receive sensor information and directly control the building's temperature setpoints and battery operation in a realistic online learning environment.

A Soft Actor-Critic (SAC) reinforcement learning algorithm was implemented due to its ability to efficiently learn control actions while balancing exploration and exploitation. Six different learning strategies were compared, including a baseline direct RL approach, several surrogate model-guided RL methods that used machine learning models to predict building behavior, an imitation learning approach, and a combined imitation learning plus surrogate-guided exploration method. The surrogate models consisted of random forest models that predicted future building temperature and power consumption, along with a deep neural network that estimated the reward associated with different control decisions. Each controller was trained for 60 simulated days and then evaluated on unseen test scenarios by comparing energy consumption, thermal comfort, demand response performance, and overall operating costs to determine which learning strategy produced the fastest, most stable, and most effective building control policy.

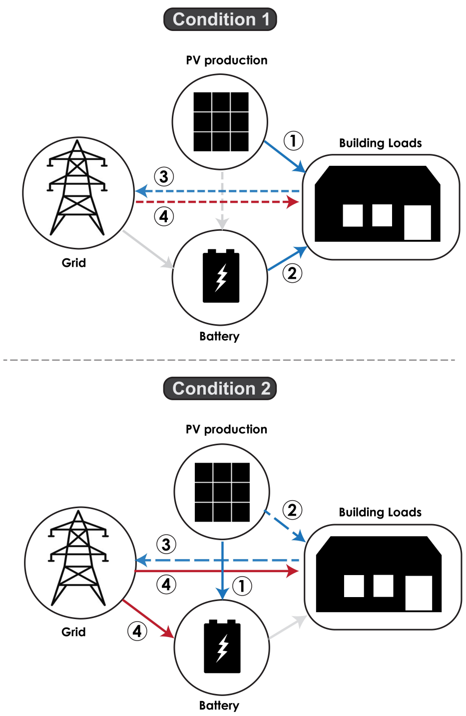
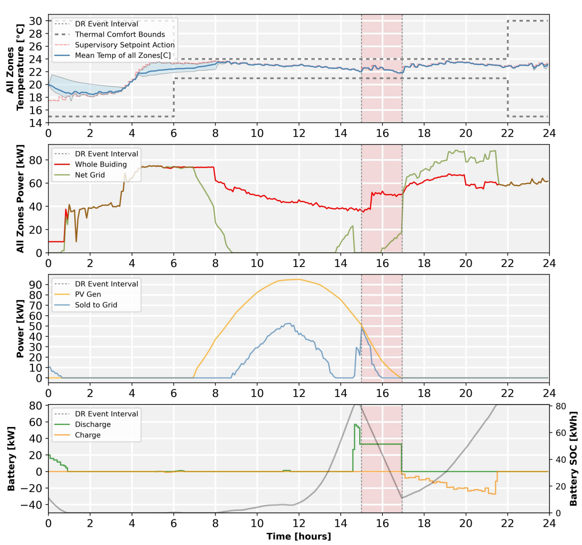


Figure 2. *Diagram of the control modes of the battery with grid, solar PV, and building loads*



Surrogate Model-Trained RL Performance

The case study found that RL controllers assisted by surrogate models learned faster and behaved more reliably than a conventional RL approach. The combined imitation learning and surrogate-guided exploration approach showed the most stable training performance by using existing rule-based controls as a starting point while allowing the RL agent to safely explore better operating strategies (Figure 3). Surrogate models helped the controller avoid repeating poor decisions by predicting the consequences of different actions before they were applied, reducing costly mistakes during the learning process. After training, the best-performing controllers learned to coordinate HVAC operation, battery charging and discharging, solar generation, and demand response events to balance energy costs and comfort. Results demonstrate that guided reinforcement learning could make RL-based building controls practical for real commercial buildings by reducing the lengthy, unstable training period that traditionally limited real-world deployment.

Figure 3. *Performance of the combined imitation learning and surrogate-guided exploration approach after training*

Research Products

1. Sourav Dey, Gregor P. Henze (2024). Reinforcement Learning Building Control: An Online Approach with Guided Exploration Using Surrogate Models. J. Eng. Sustain. Bldgs. Cities, 5(1): 011005. https://doi.org/10.1115/1.4064842.
2. Sourav Dey, Thibault Marzullo, Xiangyu Zhang, Gregor Henze (2023). Reinforcement learning building control approach harnessing imitation learning. Energy and AI, 14: 100255. https://doi.org/10.1016/j.egyai.2023.100255. (PDF)

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