Optimal Demand Responsive Control for Buildings with Multi-Energy Systems

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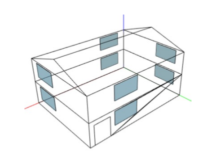
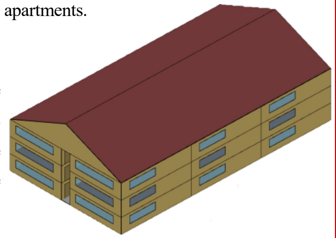
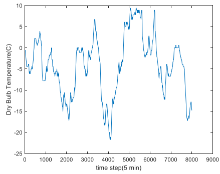
Building Model

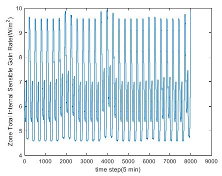


The building system contains 10 single family houses and a multi-family house which has can be divided into18 apartments.

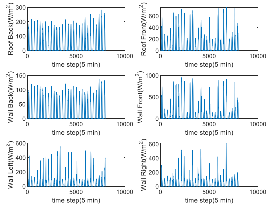


The stretch of the single family house (the framework) and the multiple family house (with roofs and walls) are represented in OpenStudio®.

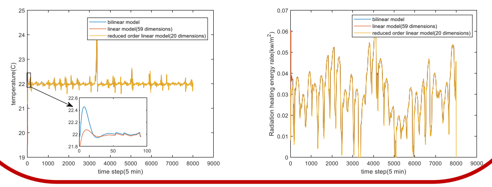




The environment data is critical for the simulation. The weather data (outdoor temperature, internal sensible gain rate, solar rate) observed in central New York state is used as environmental variables.

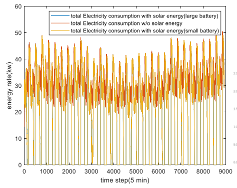


Based on the structure of the building system, we constructed a bilinear system model based on the physical characters of the housed and linearized model which contains 61 state variables. To simplify the following optimization problem, we reduced the order of the linear model to 20 dimensions. Based on the environmental data, we simulated the temperature controlling process based on multiple PID controllers and compared the outputs of the three models. The derivation of models is relatively small and is only observable at the beginning of the simulation.

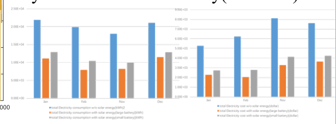


Case study

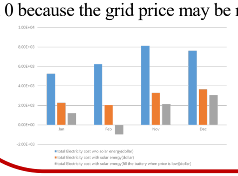
Based on the model we presented, we first investigated the influence of solar energy. We simulated the building system with PID controller and compare the energy usage with and without solar panels. The line chart below shows the power of the system of 8971 steps(a month). The power may reduce to 0 during daytimes because of the solar energy. We also present the energy consumption and cost in four winter months in the histograms which show that the solar energy can reduce the energy usage and cost to half of the original result.

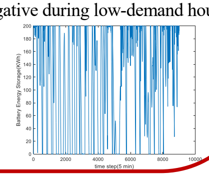


Besides, the system with a large battery(200 kWh) perform better than the system with a small battery(100 kWh)

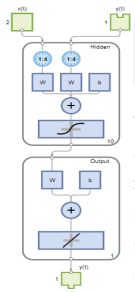


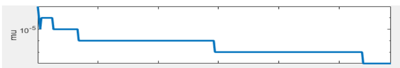
Based on the real-time electric price, we developed a demand-responsive method to control the energy usage. By charging the battery when price is low, we can significantly reduce the cost and the price may even be less than 0 because the grid price may be negative during low-demand hours.





NARX Network

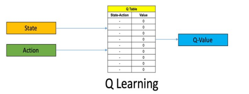




To capture the time-dependant nature of building dynamics, a recurrent neural network (RNN) with nonlinear autoregressive exogenous (NARX) architecture, suitable for time-series prediction, is employed in this study.The NARX RNN is based on a multi-layer perceptron (MLP) ANN with time-delayed inputs and feedback of outputs .

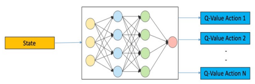
Reinforcement Learning

We applied reinforcement learning algorithms as the main control system to replace traditional control mechanisms like PID to reach high robustness and accuracy. One significant advantage of reinforcement learning is that we can easily transfer-learn a new high-performance model each time we have a new building model.



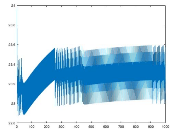
Q Learning

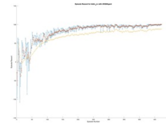
The primary RL model we used is Q-learning, an algorithm that is suitable for discrete environments. Q-learning is simple yet powerful algorithm to create a cheat sheet for our agent, and helps the agent figure out exactly which action to perform.



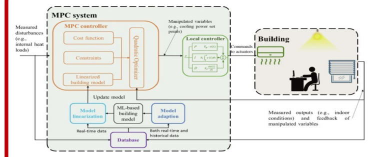
Deep Q Learning

We extended the strength of Q-learning and replaced the Q-table backbone with a deep neural network, with which we can train the model to control our building system to fulfill complex requirements. For example, our RL model can not only control physical variables but also constrain the expense while maintaining the cost budget.





Model predictive control



The system consists of a MPC controller, a local controller, a model adaption module, a model linearization module and a database module

Historical building data (for example, indoor conditions, system variables, weather conditions, energy, consumption, local time) will be introduced as input parameters into this MPC model. The building data is then used to develop a machine/deep learning-based building model, which is then used in this controller. Controllers based on deep learning will adopt demand response predictive control. Finally, accurate demand response control is given in the simulation model..

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