Sample efficient reinforcement learning for building control: Leveraging physics-informed latent representations

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ABSTRACT

Given that the residential sector accounts for over 40% of final energy consumption, unlocking its flexibility will be a key step in energy transition. However, accessing this flexibility requires a control framework that (1) easily scales across different, diverse households, and (2) is easy to design, deploy and maintain. While data-driven reinforcement learning based control has emerged as a potential solution for such problems, its widespread commercialization is still limited. A major challenge being the large amount of data required for training such RL-based controllers. To address this problem, our preliminary work investigates the application of physics-informed neural networks for improving the (training) sample efficiency of RL-based controllers. Specifically, we employ physics-informed neural networks to learn low-dimensional, physically relevant representations that can be used with any standard RL algorithm to learn high quality control policies. Using a two-state building simulator, we show that our proposed physics-informed framework can learn high quality control policies (5-10% improvement over business-as-usual controller) using fewer training samples.

CCS CONCEPTS

• **Theory of computation** → **Reinforcement learning**; • **Hardware** → **Smart grid**; • **Computing methodologies** → *Neural networks.*

KEYWORDS

Reinforcement Learning, physics-informed neural networks, building control, Deep Q-network

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1 INTRODUCTION

The residential sector is gaining importance as a potential source for demand-side flexibility to support the modern power grids [2]. In this preliminary work, we focus specifically on accessing the potential energy flexibility related to the heating/cooling systems of residential buildings. Such energy flexibility is typically characterized by the ability to shift the heating/cooling energy for a period without jeopardizing the comfort of the user. Effectively unlocking this flexibility necessitates a control framework that can leverage the intrinsic thermal mass of the building, taking control decisions in a sequential manner and under uncertain operating conditions.

Developing such building controllers has been a major research area with works such as [3, 6] presenting exhaustive reviews of different types of control algorithms used. While several different control algorithms have been studied, the two prominent research directions include (i) model-based Model Predictive Control (MPC) and (ii) data-driven Reinforcement learning (RL) based control. Conceptually, MPC relies on a mathematical model of the system to anticipate its future behavior and an optimizer that uses this model to obtain optimal control actions [1]. While previous studies have shown the benefits of using an MPC-based controller for building control, the need for an accurate building model that is simple enough to be solved analytically has been a major bottleneck in widespread adoption of MPC.

Consequently, an increasing amount of research now focuses on data-driven control techniques and especially reinforcement learning algorithms that circumvent the need for modelling altogether. Such RL-based controllers learn a good control policy by continually interacting with the building, collecting experiences (data) from these interactions, and incrementally improving their control policy. While prior works have shown promising results, a major bottleneck in the large-scale adoption of RL-based control is the requirement of large amount of training data [5].

Through this preliminary study, we aim to address this specific challenge related to RL-based controllers and investigate the potential of physics-informed neural networks for improving sample-efficiency of RL-based controllers. Our key idea involves utilizing physics-informed neural networks to encode state information into a low dimensional, physically relevant representation. With this, the high dimensional state space can be significantly reduced without much information loss, leading to an RL-based control framework that can still learn high quality control policies while requiring less training samples. We test this control framework using a two-state building simulator (based on [7]), a standard DQN algorithm[1] and demonstrate the gains in sample efficiency using our physics-informed approach.

2 METHODOLOGY

We consider a residential building control problem with the objective of minimizing the cost the energy consumed whilst maintaining user thermal comfort. We focus on a single zone building with a controller regulating the power of a single heating source [7]. To learn a high quality control strategy, the RL controller must learn the thermal behavior of this building given exogenous factors such as weather conditions, daily price profiles. Like most real-world systems, this building control problem is described by a state that includes some observable components (e.g., indoor room temperature, outside air temperature) and some components that cannot be observed or measured (e.g., building thermal mass).

This building problem is formalized as a partially observable Markov decision process and a standard DQN algorithm is implemented to learn good control policies. We now present our proposed physics-informed framework that can be augmented with any standard RL algorithm to improve their sample efficiency.

2.1 Proposed Physics-informed Framework

We propose a two-step algorithm that leverages prior physics knowledge to obtain high quality control policies as illustrated in Fig. 1. The key idea behind this physics-informed architecture is to use an encoder module to obtain a physically relevant, low-dimensional representation of the hidden state (**z**). This encoder module is part of our physics-informed neural network architecture [4] which is designed to support next-state prediction, while approximately adhering to a set of differential equations of the physical model of the system (D_Ω). In Step 1, we train this Encoder module together with an auxiliary Prediction module, where the Physics module represents the physics model of the system. Then, in Step 2, we train the Policy module (using any standard RL algorithm), based on the physically relevant representations of the system state along with other observed state components.

3 RESULTS

We investigate the training data requirements of our physics-informed control framework, compared to the conventional (non physics-informed) RL agents. For each agent type, 5 different instances were trained on different set of batches to obtain a representative performance for each agent type. Figure 2 compares our proposed agents to that of vanilla agents, both following the DQN algorithm. The figure illustrates the mean performance for different training data sizes with the error bars indicating the standard deviations. As observed, the physics-informed controllers clearly outperform the vanilla controllers over all training data sizes. Additionally, the physics-informed controllers converge to high performing control policies using less training data as compared to the vanilla RL controllers. This clearly demonstrates the gains in sample efficiency obtained using our proposed physics-informed approach.

[1]While we experiment using the DQN algorithm, our method is agnostic to the choice of RL algorithms.

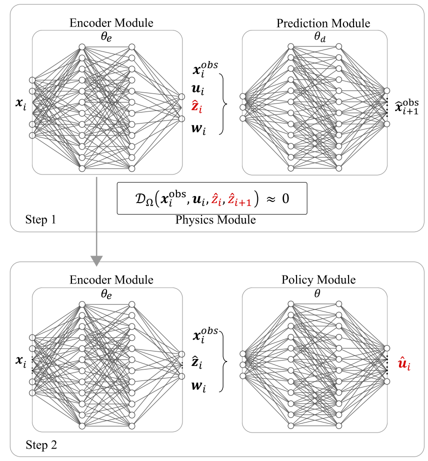

Figure 1: Proposed physics-informed RL control framework.

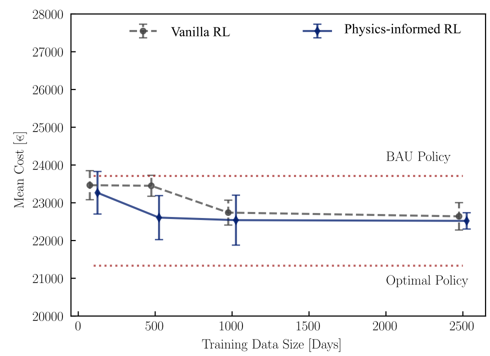

Figure 2: Simulation results comparing the performance of DQN agents with and without physics-based representations for increasing training data sizes.

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