MetaEMS: A Meta Reinforcement Learning-based Control Framework for Building Energy Management System

Huiliang Zhang, Di Wu, Benoit Boulet
Electrical and Computer Engineering Department
McGill University
Montreal, QC H3A 0E9
huiliang.zhang2@mail.mcgill.ca; di.wu5@mail.mcgill.ca; benoit.boulet@mcgill.ca

Abstract
The building sector has been recognized as one of the primary sectors for worldwide energy consumption. Improving the energy efficiency of the building sector can help reduce the operation cost and reduce the greenhouse gas emission. The energy management system (EMS) can monitor and control the operations of built-in appliances in buildings, so an efficient EMS is of crucial importance to improve the building operation efficiency and maintain safe operations. With the growing penetration of renewable energy and electrical appliances, increasing attention has been paid to the development of intelligent building EMS. Recently, reinforcement learning (RL) has been applied for building EMS and has shown promising potential. However, most of the current RL-based EMS solutions would need a large amount of data to learn a reliable control policy, which limits the applicability of these solutions in the real world. In this work, we propose MetaEMS, which can help achieve better energy management performance with the benefits of RL and meta-learning. Experiment results showcase that our proposed MetaEMS can adapt faster to environment changes and perform better in most situations compared with other baselines.

Introduction
The building sector accounts for about 40% of primary energy use and associated greenhouse gas emissions in U.S. (Zhang et al. 2022; Mariano-Hernández et al. 2021; U.S. Department of Energy 2015), and a similar situation exists in other countries. Therefore, it is essential to reduce energy consumption and carbon emission in buildings to meet national energy and environmental challenges. Furthermore, people spend more than 85% of their time in buildings (Yu et al. 2021), so well-performing building control methods can also help deliver a comfortable indoor environment for people. Recently, the area of building energy management systems (EMS) has gained a significant amount of interest (Arroyo et al. 2022; Mariano-Hernández et al. 2021), and the advanced control strategies for building EMS are believed to provide great potential to reduce building energy costs, improve grid energy efficiency and system reliability (Wu et al. 2017). In EMS, there are many opportunities for saving the energy cost of smart buildings, which are evolved from traditional buildings by adopting internal networks, intelligent controls, and home automation. For example, dynamic electricity prices could be utilized to reduce energy costs by intelligently scheduling Energy Storage Units (ESU) and thermostatically controllable loads such as Heating, Ventilation, and Air Conditioning (HVAC) systems (Sanjareh et al. 2021; Yang et al. 2021). Besides, the increasing integration of distributed renewable energy resources also helps with reducing energy consumption from the power grid (Mason and Grijalva 2019; Shahrabi et al. 2021; Antoniadis et al. 2021; Hussein, Bhat, and Doppa 2022).

Traditional model-oriented building control methods such as rule-based control (RBC) and model predictive control (MPC) are useful in EMS with small-scale and simple applications (Mariano-Hernández et al. 2021; Serale et al. 2018; Sturzenegger et al. 2014). However, they can’t be generalized well in different EMS environments because they need lots of experts’ knowledge in the design of control rules and rely heavily on precise domain knowledge on buildings’ dynamics. Reinforcement learning (RL) has been recently applied in building control problems (Arroyo et al. 2022; Wang et al. 2021; Li, Wan, and He 2020; Wei, Wang, and Zhu 2017; Ruelens et al. 2016). RL methods can learn the building control policies based on the interactions between the agent and environment with no assumption on the dynamics of the building, and have shown better performance than traditional EMS methods in dealing with uncertainties challenges such as renewable energy resources and quantities of energy appliances (Zhang et al. 2022; Mariano-Hernández et al. 2021).

The training mechanism of RL follows a trial-and-error manner, so the superior performance of RL is conditioned on a large number of training episodes. Taking recently published results (Forootani, Rastegar, and Jooshaki 2022; Zhang and Lam 2018) as examples, an RL agent may need 5 million interaction steps to achieve the same performance as a feedback controller on an HVAC system. Besides, the current RL-based algorithms are designed based on the assumption of static EMS environments. However, such an assumption is impractical in real-world scenarios because the building may locate in different regions and have different dynamics (Abedi, Yoon, and Kwon 2022; Antoniadis et al. 2021; Chen, Cai, and Berges 2019). As a result, these methods may cause
In this work, we propose to improve the efficiency of the learning process in RL with meta-learning in EMS. Meta-learning is the method of systematically observing how different learning approaches perform on a wide range of learning tasks, and then learning from this experience to learn new tasks much faster. Successful applications have been demonstrated in areas spanning few-shot image recognition, unsupervised learning, data-efficient, and RL (Finn, Abbeel, and Levine 2017; Nagabandi, Finn, and Levine 2018; Vanschoren 2018). These methods learn a well-generalized initialization that can be quickly adapted to a new scenario with a few gradient steps.

Moreover, we investigate an efficient energy optimization learning problem for EMS with ESU, HVAC systems, renewable energies, and non-shiftable loads (e.g., televisions) in the absence of a building dynamics model. To be specific, our objective is to quickly minimize the energy cost of the EMS during a time horizon with the consideration of shaping load profiles to improve system reliability. However, it is very challenging to achieve the above aims by simply applying meta-RL methods to EMS control due to the following reasons. Firstly, it is often intractable to obtain accurate dynamics of different loads demands and buildings, which can be affected by many factors. Secondly, it is difficult to know the statistical distributions of all combinations of random system parameters (e.g., renewable generation output, power demand of non-shiftable loads, outdoor temperature, and electricity price). Thirdly, there are temporally-coupled operational constraints associated with ESU and HVAC systems in different environments, which means that the current action would affect future decisions.

To address the above challenge, we propose a meta-RL framework for building control in EMS (MetaEMS), which is built upon the actor-critic-based meta-RL line. To the best of our knowledge, it is the first work to introduce the meta-RL paradigm into building control. In MetaEMS, we learn a well-generalized initialization from various building control tasks. Given a new building scenario with a limited learning period, the learned initialization can be quickly adapted with a few generated samples without knowing the building dynamics. We further propose two types of adaptation mechanisms to enhance the data efficiency in MetaEMS: group-level adaptation and building-level adaptation. The former is a step-by-step optimization process on each task and the latter is a periodic synchronous updating process on a batch of sampled tasks. Each task inherits a group-shared initialization of parameters, then performs building-level adaptation and finally contributes to group-level adaptation. Our experiment results show that the proposed method is more robust and can learn faster and be generalized well, facing different building environment dynamics. In summary, this paper has the following key contributions:

- In this work, MetaEMS, a meta-RL framework consisting of group-level and building-level adaptation, is proposed to deal with building energy management control.
- Empirically, we demonstrate the effectiveness and efficiency of our proposed model on the newest released real-world CityLearn environment datasets.

Related Work

Traditional Control Methods for EMS

The traditional ways of building control can be sorted into RBC and MPC methods (Zhang et al. 2022; Mariano-Hernández et al. 2021). The basic idea of RBC techniques is that adjustment is based on the manually designed set points. For example, cooling control is applied when the measured temperature exceeds a pre-defined temperature. The MPC techniques merge principles of feedback control and numerical optimization in EMS. The system response models of MPC are based on the physical principle to calculate the thermal dynamics and energy behaviour of the whole building (Camponogara et al. 2021; Serale et al. 2018; Sturzenegger et al. 2014). Another trend of MPC is to combine various machine learning tools with classical MPC to design data-driven MPC strategies that preserve the reliability of classical MPC. In (Eini and Abdelwahed 2020), MPC combined with neural network model is used for lighting and thermal comfort optimization. A nonlinear autoregressive exogenous model with parallel architecture is used to train the networks that estimate the comfort specifications, environmental conditions and power consumption. However, there exist some limitations to such methods in solving control problems in EMS. First, it needs quantities of precise domain knowledge and building information to manually design the model, which is hard to obtain and results in limited commercial implementation (Zhao et al. 2022; Bünning et al. 2020). Second, the iterative algorithms designed by the traditional optimization methods cannot make the fast decision on the building control in a dynamic building environment (Drgona et al. 2018; Chen, Cai, and Berges 2019). Since such algorithms require iterative calculations for each building dynamic model.

Reinforcement Learning for EMS

RL-based EMS control has attracted wide attention from both academia and industry in the last decades (Poroontan, Rastegar, and Jooshaji 2022; Yu et al. 2021). Traditional RL methods in EMS are limited to tabular Q-learning and a discrete state representation (Wen, O’Neill, and Mae 2015). Recently, researchers have studied deep RL methods in EMS (Ren et al. 2022; Wei, Wang, and Zhu 2017), which can deal with problems with large action spaces and state spaces. The authors in (Ren et al. 2022) adopts a forecasting based dueling deep Q-learning to optimize and dispatch a featured home EMS, where a generalized corr-entropy assisted long short-term memory neural network is adopted to predict outdoor temperature. (Huang et al. 2022) uses a mixed deep RL to deal with discrete-continuous hybrid action space in EMS. To jointly optimize the schedules of all kinds of appliances, a deep RL approach based on trust region policy optimization is proposed in (Li, Wan, and He 2020).

Some works also point out that it is impractical to let the deep RL agent explore the state space fully in a real building environment, because an unacceptably high economic cost may incur during the long training process (Camponogara et al. 2021; Serale et al. 2018; Sturzenegger et al. 2014).
et al. 2021; Forootani, Rastegar, and Jooshaki 2022). To reduce the dependency on a real building environment, many model-based deep RL control methods have been developed. The authors in (Zhang et al. 2019) use the observed data in EnergyPlus to develop a building energy model, and then use the model as the environment simulator to train the deep RL agent. (Arroyo et al. 2022) combines the MPC objective function with the RL agent value function while using a nonlinear controller model encoded from domain knowledge in EMS. However, most of the aforementioned approaches rely heavily on accurate simulator design or a large amount of training data in EMS, and those data are hard to collect let alone be used in reality. Furthermore, while one can train an RL agent in simulation, it is not cost-effective to train a model for each building from scratch. Implementing meta-learning is a potential solution because controllers trained by a small number of buildings could be generalized and used for other buildings.

Meta-reinforcement Learning

Meta-RL aims to solve a new RL task by leveraging the experience learned from a set of similar tasks (Liu et al. 2021; Mitchell et al. 2021). There are mainly two lines of meta-RL algorithms: The first is recurrent-based meta-RL. In this case, the parameters of the prediction model are controlled by a learnable recurrent meta-optimizer and its corresponding hidden state (Liu et al. 2021; Duan et al. 2016; Mishra et al. 2017). For example, (Duan et al. 2016) trains a recurrent neural network by using the training data as input and then outputs the parameters of a leaner model. These approaches can achieve relatively good performances, but they may lack computational efficiency. The second is gradient-based meta-RL. These methods learn a well-generalized initialization that can be quickly adapted to a new scenario with a few gradient steps (Tancik et al. 2021; Fallah, Mokhtari, and Ozdaglar 2021; Finn, Abbeel, and Levine 2017; Nagabandi, Finn, and Levine 2018; Yoon et al. 2018). Representatively, model-agnostic meta-learning (MAML) (Finn, Abbeel, and Levine 2017) optimizes the initial policy network parameters of the base learner in the meta-training process, which significantly improves the efficiency of RL on the new task. The authors of (Zang et al. 2020) and (Zhou et al. 2020) generalize the meta-learning framework in value-based and actor-critic-based RL methods.

Key Components in EMS

A typical EMS architecture has several important components: building, control center, smart meter, loads, energy storage units (ESU), renewable energy resources and power grid, as illustrated in Fig. 1. ESU could be lead-acid batteries or lithium-ion batteries, or a storage tank, which can reduce net-energy demand from main grids by storing excess renewable energies locally. Renewable energy resources could be solar panels or wind generators. Loads in an EMS can be generally divided into several types, e.g., non-shiftable loads, shiftable loads, non-interruptible loads, and controllable loads. To be specific, power demands of non-shiftable loads (e.g., televisions, microwaves) must be satisfied completely without delay. As for shiftable and non-interruptible loads (e.g., washing machines), their tasks can be scheduled to a proper time but can not be interrupted. In contrast, controllable loads (e.g., HVAC systems, heat pumps, and electric water heaters) can be controlled to flexibly adjust their operation times and energy usage quantities by following some operational requirements, e.g., temperature ranges. In this paper, we mainly focus on non-shiftable loads, shiftable loads, non-interruptible loads, and controllable loads. As for non-shiftable loads (e.g., televisions, microwaves) must be satisfied completely without delay. As for shiftable and non-interruptible loads (e.g., washing machines), their tasks can be scheduled to a proper time but can not be interrupted. In contrast, controllable loads (e.g., HVAC systems, heat pumps, and electric water heaters) can be controlled to flexibly adjust their operation times and energy usage quantities by following some operational requirements, e.g., temperature ranges. In this paper, we mainly focus on non-shiftable loads, shiftable loads, non-interruptible loads, and controllable loads. As for thermostatically controlled loads, HVAC systems are considered since they consume about 40% of the total energy in a smart home. In each time slot, the control center makes the decision on ESU charging/discharging power and HVAC input power according to a set of available information (e.g., renewable generation out-
put, non-shiftable load, outdoor temperature, and electricity price), with the aim of minimizing the energy cost of the EMS in the absence of the building thermal dynamics model.

**MDP Formulation**

In the building EMS, the indoor temperature at the next time slot is only determined by the indoor temperature, HVAC power input, and environment disturbances (e.g., outdoor temperature and solar irradiance intensity) in the current time slot. Moreover, the ESU energy level at the next time slot just depends on the current energy level and current discharging/charging power, which is independent of previous states and actions. Thus, both EMS scheduling and HVAC control can be regarded as an MDP. Assuming we are given a set of $N_t$ buildings $B_S = B_1, ..., B_{N_t}$, then the sequential decision making problem associated in these buildings can be formulated as MDP as $M_i = \langle S_i, A_i, R_i, \gamma_i, P_i \rangle$. $S_i$ is the set of states $s_i$ and $A_i$ is the set of actions. $P_i, R_i$ are the sets of state transition probabilities $p_i$ and rewards $r_i$; $\gamma_i \in [0, 1]$ is a discount factor accounting for future rewards. In this paper, the agent denotes the learner and decision-maker (i.e., EMS agent), while the environment comprises many objects outside the agent (e.g., renewable, non-shiftable loads, ESU, the HVAC system, power grid, indoor/outdoor temperature). The EMS agent observes environment state $s^t$ and takes action $a^t$. Then, environment state becomes $s^{t+1}$ and the reward $r^{t+1}$ is returned, as shown in Fig. 1.

Environment states in EMS MDP consist of seven kinds of information, i.e., renewable generation output $p^t$, non-shiftable power demand $b^t$, outdoor temperature $T^t_{out}$, electricity price $v^t$, ESU power demand $e^t$, HVAC power demand $h^t$ and time slot index $t$. Actions $A_i$ consist of the control on ESU and HVAC. We assume the power demand in EMS is always satisfied, which means the aggregated power supply should be equal to the served power demand. Then, we have $e^t = b^t + h^t + e^t + p^t$ where $e^t$ is net electricity consumption.

The agent aims to minimize the total energy cost and to do the load shaping to avoid the load of EMS fluctuating violently. Thus the corresponding reward consists of two parts, namely the penalty for the energy cost of the EMS, and the penalty for the changes in district electricity consumption in a short time. The first part of $R^t$ can be represented by $-C_{1}^{t} = -v^{t} * e^{t}$. Similarly, the second part of $R^t$ can be described by $-C_{2}^{t} = -\sum_{t' \in W} (e^{t'} - e^{t-1})$, where $W$ is the window width of the electricity consumption we care about. The reward function $r^{t}$ can be represented as:

$$r^{t} = -\mu C_1^{t} - \eta C_2^{t},$$

where $\mu$ and $\eta$ are weighting coefficients of electricity cost and the changes of electricity consumption.

For each building $B_i$, given an episode length $H$, the goal is to learn an optimal control policy $\pi_i(a|s)$. In addition, for building $B_i$, the value function is defined as the sum of reward $r_t$ discounted by $\gamma_t$ at each timestep $t$, which is formulated as

$$Q(s, a; f_\theta) = \mathbb{E}[r_t + \gamma_t r_{t+1} + ... | s_t = s, a_t = a].$$

Then, we defined the base learner $f$ with learnable parameter $\theta$ to map observations $S_i$ to outputs $A_i$. The effectiveness of function $f$ with optimal parameters $\theta_i$ is defined as

$$\mathcal{L}(f_{\theta_i}) = \mathbb{E}_{s, a, s', r, s'' \sim D_i} \left[ (r + \gamma \max_{a'} Q(s', a'; f_{\theta_i}) - Q(s, a; f_{\theta_i}))^2 \right],$$

where $\theta_i$ are the parameters of target network that are fixed for every $C$ iterations (Mnih et al., 2015).

**Proposed Solution**

In this section, we elaborate on the framework and parameter learning procedure of MetaEMS, including building-level adaptation and group-level adaptation. Then we introduce the evaluation process of the MetaEMS.

**MetaEMS Framework**

In MetaEMS, we are given a set of $N_t$ training buildings, and each one is equipped with a base-learner $f$ to handle the scenario across different buildings. Besides, we have a well-generalized meta-learner $\mathcal{M}$ to enhance the learning efficiency of target unseen buildings. As described in [Fujimoto, van Hoof, and Meger, 2018], MetaEMS follows the design of the actor-critic method and the networks are parameterized by $\theta$ and $\phi$. Besides, it’s also equipped with experience replay and target network. During the training process, the parameters of base-learner $f$ (i.e., $\theta_1, ..., \theta_{N_t}$ and $\phi_1, ..., \phi_{N_t}$) and the well-generalized meta-learner $\mathcal{M}(\cdot)$ are updated alternatively. The framework of MetaEMS is illustrated in Fig. 2.

**Building-level Adaptation**

The building-level adaptation is a step-by-step optimization process of the individual buildings’ task. For each building $B_i$, the agent’s experiences $(s^t_i, a^t_i, r^t_i, s^{t+1}_i)$ at each timestep $t$ are stored in set $D_i$. The
where the loss function of actor network $L$ is defined as:

$$L = \sum_{s,a} Q(s, a; f_{\theta_0})$$

The meta-learner $\mathcal{M}$ is regarded as well-generalized initialization of parameters in base-learner $f$. With a few gradient descent steps, we can get the optimal parameters $\theta$. Thus, the meta-learner $\mathcal{M}$ is regarded as $\mathcal{M}(\theta_0) = f_{\theta_0} - \alpha \nabla_{\theta} \sum_i \mathcal{L}(f_{\theta_0}; D_i)$. The whole loss in group-level training can be represented as $\mathcal{L}(f_{\theta_0} - \alpha \nabla_{\theta} \sum_i \mathcal{L}(f_{\theta_0}; D_i); D'_i)$.

The initialization $\theta_0$ of $\mathcal{M}$ is updated as follows:

$$\theta_0' = \theta_0 - \beta_v \sum_{s,a} \mathcal{L}(f_{\theta_0}; D_i)$$

in the same way, the initialization $\phi_0$ is updated as:

$$\phi_0' = \phi_0 - \beta_v \sum_{s,a} \mathcal{L}(f_{\phi_0}; D_i)$$

where $\beta_v$ is defined as stepsize. The whole algorithm for the training process of MetaEMS is described in Alg. 1. Each task inherits a group-level initialization of parameters, then performs building-level adaptation and finally contributes to group-level adaptation.

The MetaEMS framework reuses previously learned knowledge to facilitate the learning process in targeting unseen buildings. It follows the traditional gradient-based meta-RL framework, MAML. However, the traditional design of MAML mainly focuses on policy-based DRL problems. Empirically, MAML only slightly outperforms random initialization, which does not meet our expectations and cannot be deployed to large-scale real-world scenarios like EMS. Thus, we improve MAML by utilizing building-level adaptation and group-level adaptation with the actor-critic method. What’s more, in MAML, the policy parameters are updated after the whole episode is simulated, which causes a waste in data efficiency. In MetaEMS, the adaptation is taken at a fixed timestep to speed up the learning process on source building. Plus, the control is done for each building only but it allows...
We conduct experiments in an OpenAI Gym environment. We evaluate the performance by using the optimal parameters in $B_T$.

Algorithm 2: Meta-testing process of MetaEMS

**Input:** Set of target buildings $B_T$; stepsizes $\alpha_\theta, \alpha_\phi$; learned initialization $\theta_0, \phi_0$

**Output:** Optimized parameters $\theta_g, \phi_g$ for each building $B_g$ in $B_T$

1. Randomly initialize parameters $\theta_g, \phi_g$
2. for each building $B_g$ in $B_T$ do
   3. $\theta_g \leftarrow \theta_0$
   4. $\phi_g \leftarrow \phi_0$
   5. for $t = 1, \ldots, T$ do
      6. Generate and sample transitions as $D_g$
      7. Update $\theta_g \leftarrow \theta_g - \alpha_\theta \nabla_\theta \mathcal{L}(f_g; D_g)$
      8. $\phi_g \leftarrow \phi_g - \alpha_\phi \nabla_\phi \mathcal{L}(f_g; D_g)$ by Eqn.(12) and Eqn.(13)

for coordination of each building agent through reward sharing. In this way, the building could learn to coordinate with each other when initialized with the meta-learner and without knowledge of the system dynamics, which makes our algorithm scalable.

**Evaluation on New Buildings**

In the meta-training process of MetaEMS, we learn a well-generalized initialization of parameters in $M$ with base-learners $f$. Then, we apply the initialization $\theta_0, \phi_0$ to a new target building $B_g$. By using $\theta_0, \phi_0$ as initialization, the update process in the building $B_g$ is defined as follows:

$$\theta_g \leftarrow \theta_g - \alpha_\theta \nabla_\theta \mathcal{L}(f_g; D_g), \quad \text{(12)}$$

$$\phi_g \leftarrow \phi_g - \alpha_\phi \nabla_\phi \mathcal{L}(f_g; D_g). \quad \text{(13)}$$

We evaluate the performance by using the optimal parameters $\theta_g, \phi_g$. The meta-testing process is outlined in Alg. 2.

**Experiment**

**Experiment Settings**

We conduct experiments in an OpenAI Gym environment called CityLearn (Vázquez-Canteli et al. 2019), which provides the latest building EMS simulator to reshape the aggregated curve of electrical demand by controlling the energy applications of a diverse set of buildings. CityLearn includes energy models like the HVAC module; air-to-water heat pumps, electric heaters, space cooling, ESU module, the pre-computed energy loads of the buildings, and renewable resources like solar generation. We implement MetaEMS into CityLearn to control the HVAC and ESU. The RL agents send their control actions hourly and receive a set of states and rewards in return. The CityLearn environment came with one year of simulation data for building clusters from four climate zones. The energy demand for each building has been pre-simulated using EnergyPlus in a different climatic zone of the USA (Hot-Humid: New Orleans; Warm-Humid: Atlanta; Mixed-Humid: Nashville; Cold-Humid: Chicago) (Vázquez-Canteli, Henze, and Nagy, 2020). Assuming that the data distribution of buildings within the same climate zone is similar. We train and evaluate our control solution within the same climate zones and batch sample buildings from 8 building settings in each climate zone as training sets and use 3 randomly selected buildings as testing buildings, the training and testing set are disjoint. Then we repeat the experiment in four climate zones.

**Methods for Comparison:** To evaluate the effectiveness of our MetaEMS, we compare it with several representative methods described as follows. No Control: a no control scenario, i.e., no-load shifting. RBC: an RBC controller defined by CityLearn making decisions based only on the hour of the day. Random initialization: a soft actor-critic (SAC) (Haarnoja et al., 2018) agent defined by CityLearn using random initialization and training model from scratch. Pre-trained: a SAC agent randomly selects one existing model’s parameters as initialization for a new building. MAML: a SAC agent using MAML updating, which mainly focuses on policy-based DRL problems, and it also conducts model updating at the end of a whole episode. RL-MPC: a method (Arroyo et al., 2022) combines the MPC objective function with the RL agent value function while using a nonlinear controller model encoded from domain knowledge.

**Evaluation Metrics:** There are multi-metrics defined in the CityLearn to evaluate the performance EMS: Net electricity consumption over the evaluation period. I-load factor: average monthly electricity demand divided by its maximum peak. Ramping: the district electricity demand changes from one timestep to the next. Average daily peak: average daily peak demand over the evaluation period. Peak electricity demand over the evaluation period. For comparison convenience, all scores are normalized by the score of a benchmark RBC. A score of 0.96 means that the RL controller performed 4% better than the baseline RBC. All model details and hyper-parameter settings are illustrated in appendix A.

**Experiment Results**

The main goal of these experiments is to test the consistency of results with the algorithm motivation. We train and evaluate our control solution on randomly new selected buildings sets, and then repeat the experiment in building clusters in four climate zones. The parameters $\theta$ and $\phi$ are initialized by sampling from a uniform distribution. We report the average cost of our approach in comparison to other baselines in Table 1. The cost is defined as the total non-negative net electricity consumption of the whole neighbourhood (Vázquez-Canteli et al., 2019). Considering the multi-metric have different timescale and measurements, each algorithm is evaluated on the testing set after one entire simulation episode. For control strategies with stochasticity, we report the mean and standard deviation of the cost over 5 random seeds. Most likely, since the cost is evaluated over the entire episode, the variance is small.

From Table 1, our approach consistently outperforms all our baselines. On average, we achieved a 5.45% reduction in average cost, compared to the benchmark RBC. The pattern of the costs are consistent among four climate zones, indicating that our approach is robust to different climates. When we reused the building simulation data for more episodes in meta-testing, the random initialization, pretrained, MAML and RL-MPC methods tend to converge at 4, 3, 3 and 2
| Climate | Climate | Climate | Climate |
|---------|---------|---------|---------|
| 1 (%)   | 2 (%)   | 3 (%)   | 4 (%)   |
| No Control | 109.34 | 114.13 | 100.73 | 105.19 |
| RBC     | 100.00 | 100.00 | 100.00 | 100.00 |
| Random initialization | 101.02 ±0.13 | 103.63 ±0.18 | 110.48 ±0.27 | 104.22 ±0.61 |
| MAML | 103.91±0.86 | 98.91±0.45 | 99.12±2.42 | 97.02±1.50 |
| RL-MPC | 98.22±0.59 | 100.53±0.41 | 98.67±1.69 | 101.20±3.51 |
| Pretrained | 99.45±1.32 | 98.72±0.90 | 101.35±1.87 | 99.62±2.20 |
| MetaEMS | 94.73±3.24 | 92.65±0.81 | 94.13±1.67 | 96.71±2.96 |

Table 1: Summary of average cost. Each result is the average of three buildings.

| Metrics     | Rampung 1-load factor | Average peak demand | Annual peak demand | Net electricity consumption |
|-------------|------------------------|---------------------|--------------------|-----------------------------|
| MAML        | 0.83                   | 0.98                | 0.97               | 0.96                        | 1.01                        |
| Random initialization | 1.01       | 0.95                | 1.03               | 0.95                        | 1.04                        |
| RL-MPC      | 1.00                   | 0.99                | 1.02               | 0.97                        | 1.02                        |
| Pretrained  | 0.99                   | 0.94                | 0.98               | 0.97                        | 0.99                        |
| MetaEMS     | 0.78                   | 0.98                | 0.83               | 0.91                        | 0.98                        |
| Improvement | 6.01%                  | \                  | 13.58%             | 3.80%                       | 2.02%                       |

Table 2: Break down of cost by individual objectives on CityLearn environment. Each result is the average of three buildings and four climate zones.

Conclusion and Future Work

In this paper, we propose a framework MetaEMS to improve the learning efficiency of DRL in building control by transferring previously learned knowledge. Based on the previous gradient-based meta-learning framework, we incorporate building-level and group-level adaptation in the MetaEMS framework. The experiments in the CityLearn environment demonstrate the effectiveness and efficiency of MetaEMS. The framework of MetaEMS makes energy management control problems more accessible outside lab spaces and to users who need efficient learning algorithms in real-world applications. In the future, we plan to investigate this problem by applying meta-RL to building control across multi-climate zones, and carefully design a model which could be robust to the different data distributions.
References
Abedi, S.; Yoon, S. W.; and Kwon, S. 2022. Battery energy storage control using a reinforcement learning approach with cyclic time-dependent Markov process. International Journal of Electrical Power & Energy Systems, 134: 107368.
Antoniadis, A.; Coester, C.; Elias, M.; Polak, A.; and Simon, B. 2021. Learning-Augmented Dynamic Power Management with Multiple States via New Ski Rental Bounds. In Beygelzimer, A.; Dauphin, Y.; Liang, P.; and Vaughan, J. W., eds., Advances in Neural Information Processing Systems.
Arroyo, J.; Manna, C.; Spiessens, F.; and Helsen, L. 2022. Reinforced model predictive control (RL-MPC) for building energy management. Applied Energy, 309: 118346.
Bünning, F.; Schalbetter, A.; Aboudonia, A.; de Badyn, M. H.; Heer, P.; and Lygeros, J. 2020. Input Convex Neural Networks for Building MPC. arXiv preprint arXiv:2011.13227.
Camponogara, E.; Scherer, H.; Biegler, L.; and Grossmann, I. 2021. Hierarchical decompositions for MPC of resource constrained control systems: applications to building energy management. Optimization and Engineering, 22(1): 187–215.
Chen, B.; Cai, Z.; and Bergés, M. 2019. Gnu-rl: A precocital reinforcement learning solution for building HVAC control using a differentiable mpc policy. In Proceedings of the 6th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation, 316–325.
Chen, B.; Cai, Z.; and Bergés, M. 2019. Gnu-RL: A Precocital Reinforcement Learning Solution for Building HVAC Control Using a Differentiable MPC Policy. In Proceedings of the 6th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation, BuildSys ’19, 316–325. New York, NY, USA: Association for Computing Machinery. ISBN 9781450370059.
Drgoňa, J.; Picard, D.; Kvasnica, M.; and Helsen, L. 2018. Approximate model predictive building control via machine learning. Applied Energy, 218: 199–216.
Duan, Y.; Schulman, J.; Chen, X.; Bartlett, P. L.; Sutskever, I.; and Abbeel, P. 2016. Rl2: Fast reinforcement learning via slow reinforcement learning. arXiv preprint arXiv:1611.02779.
Eini, R.; and Abdelwahed, S. 2020. A Neural Network-based Model Predictive Control Approach for Buildings Comfort Management. In 2020 IEEE International Smart Cities Conference (ISC2), 1–7.
Fallah, A.; Mokhtari, A.; and Ozdaglar, A. E. 2021. Generalization of Model-Agnostic Meta-Learning Algorithms: Recurring and Unseen Tasks. In Beygelzimer, A.; Dauphin, Y.; Liang, P.; and Vaughan, J. W., eds., Advances in Neural Information Processing Systems.
Finn, C.; Abbeel, P.; and Levine, S. 2017. Model-agnostic meta-learning for fast adaptation of deep networks. In International Conference on Machine Learning, 1126–1135. PMLR.
Forootani, A.; Rastegar, M.; and Jooshaki, M. 2022. An Advanced Satisfaction-Based Home Energy Management System using Deep Reinforcement Learning. IEEE Access.
Fujimoto, S.; van Hoof, H.; and Meger, D. 2018. Addressing Function Approximation Error in Actor-Critic Methods. arXiv:1802.09477.
Haarnoja, T.; Zhou, A.; Abbeel, P.; and Levine, S. 2018. Soft actor-critic: Off-policy maximum entropy deep reinforcement learning with a stochastic actor. In International conference on machine learning, 1861–1870. PMLR.
Han, G.; Huang, S.; Ma, J.; He, Y.; and Chang, S.-F. 2022. Meta faster r-cnn: Towards accurate few-shot object detection with attentive feature alignment. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 36, 780–789.
Huang, C.; Zhang, H.; Wang, L.; Luo, X.; and Song, Y. 2022. Mixed Deep Reinforcement Learning Considering Discrete-Continuous Hybrid Action Space for Smart Home Energy Management. Journal of Modern Power Systems and Clean Energy.
Hussein, D.; Bhat, G.; and Doppa, J. R. 2022. Adaptive Energy Management for Self-Sustainable Wearables in Mobile Health. In Proc. AIAI.
Li, D.; Li, R.; Wang, L.; Wang, Y.; Qi, J.; Zhang, L.; Liu, T.; Xu, Q.; and Lu, H. 2022. You Only Infer Once: Cross-Modal Meta-Transfer for Referring Video Object Segmentation. In AAAI Conference on Artificial Intelligence.
Li, H.; Wan, Z.; and He, H. 2020. Real-Time Residential Demand Response. IEEE Transactions on Smart Grid, 11(5): 4144–4154.
Liu, E. Z.; Raghunathan, A.; Liang, P.; and Finn, C. 2021. Decoupling exploration and exploitation for meta-reinforcement learning without sacrifices. In International Conference on Machine Learning, 6925–6935. PMLR.
Mariano-Hernández, D.; Hernández-Callejo, L.; Zorita-Lamadrid, A.; Duque-Pérez, O.; and García, F. S. 2021. A review of strategies for building energy management system: Model predictive control, demand side management, optimization, and fault detect & diagnosis. Journal of Building Engineering, 33: 101692.
Mason, K.; and Grijalva, S. 2019. A review of reinforcement learning for autonomous building energy management. Computers & Electrical Engineering, 78: 300–312.
Mishra, N.; Rohaninejad, M.; Chen, X.; and Abbeel, P. 2017. A simple neural attentive meta-learner. arXiv preprint arXiv:1707.03141.
Mitchell, E.; Rafailov, R.; Peng, X. B.; Levine, S.; and Finn, C. 2021. Offline meta-reinforcement learning with advantage weighting. In International Conference on Machine Learning, 7780–7791. PMLR.
Mnih, V.; Kavukcuoglu, K.; Silver, D.; Rusu, A. A.; Veness, J.; Bellemare, M. G.; Graves, A.; Riedmiller, M.; Fidjeland, A. K.; Ostrovski, G.; et al. 2015. Human-level control through deep reinforcement learning. nature, 518(7540): 529–533.
Nagabandi, A.; Finn, C.; and Levine, S. 2018. Deep online learning via meta-learning: Continual adaptation for model-based rl. arXiv preprint arXiv:1812.07671.
Ren, M.; Liu, X.; Yang, Z.; Zhang, J.; Guo, Y.; and Jia, Y. 2022. A novel forecasting based scheduling method for
household energy management system based on deep reinforcement learning. *Sustainable Cities and Society*, 76: 103207.

Ruelens, F.; Claessens, B. J.; Quaiyum, S.; De Schutter, B.; Babuška, R.; and Belmans, R. 2016. Reinforcement learning applied to an electric water heater: from theory to practice. *IEEE Transactions on Smart Grid*, 9(4): 3792–3800.

Sanjareh, M. B.; Nazari, M. H.; Gharehpetian, G. B.; and Hosseinian, S. H. 2021. A novel approach for sizing thermal and electrical energy storage systems for energy management of islanded residential microgrid. *Energy and Buildings*, 238: 110850.

Serale, G.; Fiorentini, M.; Capozzoli, A.; Bernardini, D.; and Bemporad, A. 2018. Model predictive control (MPC) for enhancing building and HVAC system energy efficiency: Problem formulation, applications and opportunities. *Energies*, 11(3): 631.

Shahrabi, E.; Hakimi, S. M.; Hasankhani, A.; Derakhshan, G.; and Abdi, B. 2021. Developing optimal energy management of energy hub in the presence of stochastic renewable energy resources. *Sustainable Energy, Grids and Networks*, 26: 100428.

Sturzenegger, D.; Gyalistras, D.; Semeraro, V.; Morari, M.; and Smith, R. S. 2014. BRMC Matlab toolbox: Model generation for model predictive building control. In *2014 american control conference*, 1063–1069. IEEE.

Tancik, M.; Mildenhall, B.; Wang, T.; Schmidt, D.; Srinivasan, P. P.; Barron, J. T.; and Ng, R. 2021. Learned initializations for optimizing coordinate-based neural representations. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2846–2855.

U.S. Department of Energy. 2015. Quadrennial Technology Review 2015: Chapter 5 - Increasing Efficiency of Buildings Systems and Technologies. https://www.energy.gov/downloads/chapter-5-increasing-efficiency-buildings-systems-and-technologies. Accessed: 2021-02-25.

Vanschoren, J. 2018. Meta-learning: A survey. *arXiv preprint arXiv:1810.03548*.

Vazquez-Canteli, J. R.; Henze, G.; and Nagy, Z. 2020. MARLISA: Multi-agent reinforcement learning with iterative sequential action selection for load shaping of grid-interactive connected buildings. In *Proceedings of the 7th ACM international conference on systems for energy-efficient buildings, cities, and transportation*, 170–179.

Váquez-Canteli, J. R.; Kämpf, J.; Henze, G.; and Nagy, Z. 2019. Citylearn v1.0: An openai gym environment for demand response with deep reinforcement learning. In *Proceedings of the 6th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation*, 356–357.

Wang, J.; Xu, W.; Gu, Y.; Song, W.; and Green, T. C. 2021. Multi-Agent Reinforcement Learning for Active Voltage Control on Power Distribution Networks. In Beygelzimer, A.; Dauphin, Y.; Liang, P.; and Vaughan, J. W., eds., *Advances in Neural Information Processing Systems*. WEI, T.; Wang, Y.; and Zhu, Q. 2017. Deep reinforcement learning for building HVAC control. In *Proceedings of the 54th Annual Design Automation Conference 2017*, 1–6.

Wen, Z.; O’Neill, D.; and Maei, H. 2015. Optimal Demand Response Using Device-Based Reinforcement Learning. *IEEE Transactions on Smart Grid*, 6(5): 2312–2324.

Wu, D.; Zeng, H.; Lu, C.; and Boulet, B. 2017. Two-stage energy management for office buildings with workplace EV charging and renewable energy. *IEEE Transactions on Transportation Electrification*, 3(1): 225–237.

Yang, S.; Wan, M. P.; Chen, W.; Ng, B. F.; and Dubey, S. 2021. Experiment study of machine-learning-based approximate model predictive control for energy-efficient building control. *Applied Energy*, 288: 116648.

Yoon, J.; Kim, T.; Dia, O.; Kim, S.; Bengio, Y.; and Ahn, S. 2018. Bayesian model-agnostic meta-learning. *Advances in neural information processing systems*, 31.

Yu, L.; Qin, S.; Zhang, M.; Shen, C.; Jiang, T.; and Guan, X. 2021. A review of deep reinforcement learning for smart building energy management. *IEEE Internet of Things Journal*.

Zang, X.; Yao, H.; Zheng, G.; Xu, N.; Xu, K.; and Li, Z. 2020. Metalight: Value-based meta-reinforcement learning for traffic signal control. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, 1153–1160.

Zhang, H.; Seal, S.; Wu, D.; Bouffard, F.; and Boulet, B. 2022. Building Energy Management With Reinforcement Learning and Model Predictive Control: A Survey. *IEEE Access*, 10: 27853–27862.

Zhang, Z.; Chong, A.; Pan, Y.; Zhang, C.; and Lam, K. P. 2019. Whole building energy model for HVAC optimal control: A practical framework based on deep reinforcement learning. *Energy and Buildings*, 199: 472–490.

Zhang, Z.; and Lam, K. P. 2018. Practical implementation and evaluation of deep reinforcement learning control for a radiant heating system. In *Proceedings of the 5th Conference on Systems for Built Environments*, 148–157.

Zhao, Z.; Guo, J.; Luo, X.; Lai, C. S.; Yang, P.; Lai, L. L.; Li, P.; Guerrero, J. M.; and Shahidehpour, M. 2022. Distributed robust model predictive control-based energy management strategy for islanded multi-microgrids considering uncertainty. *IEEE Transactions on Smart Grid*, 13(3): 2107–2120.

Zhou, W.; Li, Y.; Yang, Y.; Wang, H.; and Hospedales, T. M. 2020. Online meta-critic learning for off-policy actor-critic methods. *arXiv preprint arXiv:2003.05334*. 


Implementation Details

Model Details and Hyperparameter Settings:

In this work, soft actor-critic (SAC) is chosen as base reinforcement learning (RL) model for CityLearn environment. For our implementation of SAC, we use a three-layer feedforward neural network of 64, 128 and 64 hidden nodes respectively, with rectified linear units (ReLU) between each layer for both the actor and critic and a final tanh unit following the output of the actor. Both network parameters are updated using Adam with a learning rate of $10^{-3}$. The batch size is 128 and $\gamma$ is 0.99. The target smoothing coefficient is 0.005 and the target update interval is 1. All target networks are updated with a learning rate of $10^{-3}$. There is no energy exchanging between different buildings which is consistent with the CityLearn environment. The control is done for each building only. All the metrics like 1-load factor and ramping are defined following the domain practice of the energy management systems field and are commonly used in real-world EMS problems. We train the meta-learner of each climate zone separately. More implementation details for different control methods are summarized as follows.

- **MetaEMS**: MetaEMS is an actor-critic-based meta-reinforcement learning workflow based on the representative MAML. MetaEMS also includes periodically alternate building-level adaptation and group-level adaptation. For MetaEMS, the learner conducts model updating after each interaction and only one epoch for training. For MetaEMS, a batch of tasks are first sampled. Then, in meta-training, the whole episode with a length of $T$ is split by $t_0$. During each interval $t_0$, the base-learner inherits the initialization from meta-learner and then conduct building-level adaptation using samples drawn from memory at each time step. At the end of each interval $t_0$, the meta-learner takes group-level adaptation with another batch of samples from the memory. In building-level adaptation, the parameters $\theta_i$ of the base-learner of each building task are updated at each timestep by gradient descent, using the same initialization from the meta-learner $\theta_0$ and $\phi_0$. In MetaEMS, the learning rates of building-learner and group-learner are set as $10^{-3}$ in both meta-training and meta-testing. The $\mu$, $\eta$ and $W$ are set as 0.5, 0.5, and 5 respectively. The episode length for all buildings is 8760 timesteps defined by CityLearn. We train and evaluate our control solution within the same climate zones and batch sample buildings from 8 building settings in each climate zone as training sets and use 3 randomly selected buildings as testing buildings, the training and testing set are disjoint. The batch sample size of buildings is 3. Then we repeat the experiment in four climate zones. Group-level learner updates itself at intervals of 20 after building-level learners’ update. The same network architecture is also used as a base model in others baselines unless specifically stated.

- **RL-MPC**: For RL model predictive control (MPC): [Arroyo et al. 2022] the author of this paper assumes that the system model $F$ is available, which is impractical in a real-world setting. Since the different building has different EMS environments, they need lots of experts’ knowledge in the design of control models and rely heavily on precise domain knowledge on buildings’ dynamics. So in our implementation, we use a three-layer feedforward neural network to learn the control model and do the one-step prediction as in [Arroyo et al. 2022]. The system model has the same architecture and parameters as the neural network we used in our SAC methods, with the input being the concat of state and action and the output of the next state and reward. In RL-MPC, 1 hour is the length of simulation time pre-defined in CityLearn to get the feedback from the building environment. Plus, MPC could collect the samples and learn the dynamic models following this one time-step. However, it would be unrealistic to learn accurate models for each building using the MPC methods in real-world applications. Since each building’s dynamic is different from another and the model error that occurs in MPC could hinge the implementation of large-scale EMS control problems.

- **Pretrained**: In pretrained method, we use a SAC agent which randomly selects one existing model’s parameters as initialization for a new building. Assuming that the data distribution of buildings within the same climate zone is similar. We train and evaluate our control solution within the same climate zones and randomly select 8 building settings in each climate zone as training sets and the rest of the 3 building as testing sets. Then we repeat the experiment in four climate zones.

- **MAML**: In model-agnostic meta-learning (MAML), we use a SAC agent with MAML updating. In our implementation, we apply MAML with SAC following the traditional design of MAML, which mainly focuses on policy-based DRL problems, and it also conducts model updating at the end of a whole episode. Plus, in MAML, the base-learner first undertakes one centralized updating at the end of each episode with 5 epochs for training. Then, the meta-learner updates itself using new episodes each time. MAML conducts model updating at the end of a whole episode as one-year as 8760 and it is infeasible in practice. And MetaEMS includes periodically building-level adaptation and group-level adaptation, the update step is chosen as 20 timesteps (20 hours), so I improve the data efficiency and is more feasible in practice. The given hyperparameters were found by hand-tuning until the good performance was found on all algorithms.

In this work, we consider both residential and commercial buildings with five types following the CityLearn, which consists of medium office, fast-food restaurant, standalone retail, one strip mall retail and medium family building. We believe these buildings are representative of real-world buildings and use 11 buildings in four climate zones each. The building’s dynamics are pre-defined in CityLearn environment which differs in Ventilation, and Air Conditioning (HVAC) module, Energy Storage Units (ESU) module and renewable resources. Different factors will influence the types of buildings. To make the comparison clearer, all scores are normalized by the score of a benchmark rule-based control (RBC). We train and evaluate our control solution within the same climate zones and randomly select 8 building settings in each cli-
Ablation Study

In order to investigate whether the proposed method can be robust to various scenarios in CityLearn, we further test its performance on different buildings with different settings. The key system parameters and corresponding ranges for these parameters to change the buildings’ dynamics are shown in Table 3. We create 20 buildings by randomly sampling the aforementioned parameters from the allowed ranges.

We train and evaluate our control solution within the same climate zones and randomly select 10 building settings in each climate zone as training sets and 3 buildings as testing sets. Then we repeat the experiment in four climate zones. Finally we repeat the experiment in building clusters in four climate zones.

We report the average cost of MetaEMS with the modified dynamics in comparison to other baselines in Table 4. As shown in Table 4, MetaEMS can outperform other baselines for most scenarios. The pattern of the costs are consistent among four climate zones, indicating the effectiveness of the MetaEMS with different environment dynamics and shows that MetaEMS is a general framework in solving the EMS problem. Furthermore, random initialization results are consistently worse than the rule-based one on the metric of Average cost as shown in Table 1 evaluated after 1 entire episode, which indicates that the random initialization would not be useful under the small amount of data and cannot adapt quickly given new building set. Because of the high variance rooted in policy-based RL, the original policy-based updating mechanism MAML bring too much unstable updating of the base model. Thus, it can be very challenging to learn one initialization for all buildings. In contrast, MetaEMS maintains a more stable and faster adaptation. Incorporating building-level and group-level adaptation, MetaEMS lets the base model learn more stably and efficiently by finding an optimal universal initialization.

Real-world Deployment

The experiment results demonstrated that MetaEMS can help improve the data efficiency on learning efficient building EMS control policy. It can also learn stably by finding an optimal universal initialization, in the absence of a building dynamics model with the consideration of load shaping and minimizing energy cost. Thus MetaEMS is a promising method to be applied to the real-world EMS problem. If the simulator can closely mimic the properties of real-world buildings, the proposed method can be very promising for real-world deployment. Although we have tested the proposed method can be robust to the various scenarios in CityLearn, which means that MetaEMS could do well with different buildings in the same climate zone. However, the performance of MetaEMS will affected if there is a significant gap between the simulator and the real world.

| Climate | Climate | Climate | Climate |
|---------|---------|---------|---------|
| 1 (%)   | 2 (%)   | 3 (%)   | 4 (%)   |
| No Control | 114.13 | 109.25 | 110.50 | 106.12 |
| RBC | 100.00 | 100.00 | 100.00 | 100.00 |
| Random initialization | 101.67±0.31 | 100.09±0.10 | 99.44±0.71 | 99.98±0.82 |
| MAML | 101.83±0.72 | 99.18±0.31 | 104.19±3.09 | 98.15±1.50 |
| RL-MPC | 102.75±0.98 | 104.83±0.61 | 101.37±2.20 | 100.08±1.56 |
| Pretrained | 102.35±2.13 | 98.72±0.89 | 98.89±0.61 | 99.78±3.16 |
| MetaEMS | 97.39±2.48 | 94.80±4.10 | 98.31±2.05 | 100.36±2.75 |

Table 4: Summary of average cost with modified dynamics in CityLearn. Each result is the average of three buildings.