Learning a Multi-Agent Controller for Shared Energy Storage System

Ruohong Liu and Yize Chen

Artificial Intelligence Thrust, Information Hub
The Hong Kong University of Science and Technology (Guangzhou)
rliu519@connect.hkust-gz.edu.cn, yizechen@ust.hk

Abstract—Deployment of shared energy storage systems (SESS) allows users to use the stored energy to meet their own energy demands while saving energy costs without installing private energy storage equipment. In this paper, we consider a group of building users in the community with SESS, and each user can schedule power injection from the grid as well as SESS according to their demand and real-time electricity price to minimize energy cost and meet energy demand simultaneously. SESS is encouraged to charge when the price is low, thus providing as much energy as possible for users while achieving energy savings. However, due to the complex dynamics of buildings and real-time external signals, it is a challenging task to find high-performance power dispatch decisions in real-time. By designing a multi-agent reinforcement learning framework with state-aware reward functions, SESS and users can realize power scheduling to meet the users' energy demand and SESS's charging/discharging balance without additional communication, so as to achieve energy optimization. Compared with the baseline approach without the participation of the SESS, the energy cost is saved by around 2.37% to 21.58%.

I. INTRODUCTION

Energy storage is gaining more attention since it enables higher penetration of renewables, achieving energy arbitrage and enhancing the power systems resilience [1], [2]. However, the high installation and maintenance costs of energy storage systems hinder their application [3]. In contrast, installing a shared energy storage system (SESS) for the community is a more economical and feasible solution, because users can maximize the utilization of energy storage without installing an individual energy storage system. The California Public Utilities Commission (CPUC) has broadly defined community storage as storage connected at the distribution feeder level [4], associated with a cluster of customer load. The services of these types of systems could provide capacity for excess generation from distributed energy resources (DERs) and backup power during outages. Previous works have demonstrated that shared energy storage could achieve electricity cost saving with higher utilization compared to individual energy storage [5].

Most of these existing studies on SESS assume that users' demand patterns as well as energy prices are known ahead of time or can be predicted perfectly [6], thus the system operator only needs to optimize the charging of SESS and power dispatch to each user [7]. However, due to time-varying external signals such as electricity prices and com-

plex user demand behaviors such as heating, ventilating and air conditioning (HVAC) systems, these assumptions are not realistic in practice. Therefore, we propose to consider the setting where multiple users learn to cooperatively operate a SESS to simultaneously reduce energy cost and satisfy energy demand in a distributed manner.

Simultaneously controlling the charging and discharging of the SESS and the energy demand of the users is a complex problem. Due to the limited capacity of the SESS, charging and discharging operations will affect the subsequent decisions, which makes the problem a time-coupling problem. It is hard to model such complex dynamical systems using classical dynamic programming techniques [7]. Furthermore, centralized control or reinforcement learning schemes require system operators to know their full state, which places high demands on communication and raises privacy issues when collecting the state information from individuals [8]. In our proposed distributed control approach, the energy storage system only needs to respond to price signals without predicting the energy demand of the building, while building user agents decide discharging from SESS and power injection from the grid. With multi-agent reinforcement learning (MARL) setup [9], [10], the multi-objective optimization problem can be simplified as maximizing each agent's reward.

In this paper, we consider the scenario with the collocation of energy storage and residential homes. We are interested in integrating energy storage while shifting the portion of their electricity demand load in response to time-varying electricity price, i.e., demand response. We design a collaborative learning approach based on MARL. States and actions information of all agents are provided to each agent during the training process to help each policy neural network learn the policy, while only the local state is utilized during distributed execution. We observe reward shaping are important for MARL training, where negative rewards are proposed for temperature derivation and energy cost for building agents; meanwhile, rewards are designed to encourage the energy storage can utilize electricity price fluctuations. We test our proposed method with real-world temperature and price based on a group of realistic building models, and the performance shows that around 2.37% to 21.58% of energy cost is saved compared to the baseline setup without the participation of the SESS.

II. PROBLEM SETUP

In our paper, we consider energy storage system which is set up to be controlled or dispatched by a utility or third party to maximize its service values for a given community. Similar to [11], we assume each building (customer) in a microgrid can schedule the shiftable loads based on user preferences and manage the interaction with the grid and the SESS. As HVAC system usually accounts for about half of building energy consumption [12], and HVAC loads are flexible to provide incentives for users to use energy storage as the external power source during peak time, we choose to model HVAC as energy users in this paper. Fig. 1 demonstrates a building cluster equipped with SESS. The SESS charges from grid and dispatches its stored energy to buildings. Buildings schedule their power injection from both SESS and grid to minimize energy cost while keeping the indoor temperature within the preferred range of users.

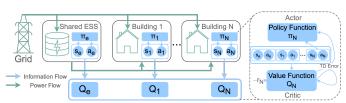


Fig. 1. Schematic of proposed data-driven control strategies based on a multi-agent RL framework. A community-shared battery learns to cooperate with multiple buildings. Here the subscript e denotes SESS, $1, \ldots, N$ denotes buildings

A. HVAC Model

Thermal resistor-capacitor networks (RC models) are a kind of typical models used to model the thermal dynamics of buildings [13]. The indoor temperature of a building is influenced by heating transfer from HVAC systems and outdoor temperature. Assume that there is a set of $\mathcal{N} :=$ $\{1, 2, 3, \dots, N\}$ buildings and each of them has an HVAC system which operates in slotted time, $\mathcal{K} := \{1, 2, 3, \dots, K\}.$ Mathematically, RC model is represented as ¹

$$C_{i}\frac{dT_{i}^{in}}{dk} = \frac{T^{out} - T_{i}^{in}}{R_{i}} + w_{i}^{d}P_{i}^{d} + w_{i}^{g}P_{i}^{g}; \tag{1}$$

$$P_{i,min}^d < P_i^d < P_{i,max}^d; \tag{2}$$

$$P_{i\,min}^g < P_i^g < P_{i\,max}^g; \tag{3}$$

 $P_{i,min}^{d} < P_{i}^{d} < P_{i,max}^{d}; \qquad (2)$ $P_{i,min}^{g} < P_{i}^{g} < P_{i,max}^{g}; \qquad (3)$ where C_{i} is the thermal capacity of the i^{th} building; R_{i} is the thermal resistance between the i^{th} building and outdoor; T_i^{in} and T^{out} represent the temperature of i^{th} building and outdoor temperature respectively; P_i^d and P_i^g denote the heating input from SESS and grid along with weighting factors w_i^d and w_i^g ; $P_{i,min}^g$, $P_{i,max}^g$, $P_{i,min}^d$ and $P_{i,max}^d$ are lower and upper power rate limitation. In our paper we consider both heating and cooling of the HVAC system, thus positive (negative) P_i^d and P_i^g means heating (cooling) input. In order to formulate the thermal dynamics to an Markov decision process (MDP) form, we give its discrete form:

$$T_{i,k+1}^{in} = \delta_1 T_{i,k}^{in} + \delta_2 P_{i,k}^d + \delta_3 P_{i,k}^g + \delta_4 T_k^{out},$$
 (4)

¹We note that the proposed RL method can be generalized to a variety of dynamics other than RC models.

where δ_i^1 , δ_i^2 , δ_i^3 , and δ_i^4 are model parameters after discretization.

B. SESS Model

SESS schedules its charging and discharging from a realtime electricity market to minimize the charging cost while providing requested power to building customers. We assume that the SESS is a price taker which intends to charge at low prices and its operation will not affect the market prices [14]. SESS is modeled as follows:

$$SOC_{k+1} = SOC_k + \delta_c c_k - \sum_{i}^{N} d_{i,k}; \tag{5}$$

$$d_{i,k} = \frac{1}{\delta_d} |P_{i,k}^d|;$$

$$0 \le SOC_k \le S\bar{O}C;$$
(6)

$$0 \le SOC_k \le S\bar{O}C; \tag{7}$$

$$0 \le d_{i,k} \le \bar{d}_i; \tag{8}$$

$$0 \le c_k \le \bar{c}; \tag{9}$$

where $P_{i,k}^d$ denotes the power dispatch to the i^{th} building at time k given SESS's discharging power $d_{i,k}$; $S\bar{O}C$ denotes the capacity of SESS; \bar{c} and \bar{d}_i denotes the maximum charging/discharging power; c_k represents the charging power rate from grid at time k; δ_c and δ_d are charging and discharging efficiency term.

C. Optimization problem

The objectives of the optimization problem include minimizing the difference between building indoor temperature and users' preferred temperature as well as energy cost:

$$\min_{\mathbf{c_k}, \mathbf{P_{i,k}^d}, \mathbf{P_{i,k}^g}} \sum_{k \in \mathcal{K}} \sum_{i \in \mathcal{N}} \left(p_k \left(c_k + P_{i,k}^g \right) + \lambda \left| T_{i,k}^{in} - T_i^{target} \right| \right)$$

s.t.
$$(2) - (9)$$
;

where p_k denotes the real-time price; T_i^{target} represents the preferred temperature of the i^{th} building user; and λ is the weighting factor of optimization objectives.

However, due to the complicated dynamics involving temporally coupled SESS and multiple buildings, it is hard to solve the problem with conventional methods like dynamic programming. Moreover, as typical approaches like model predictive control (MPC) require accurate building and SESS models, while it is hard to model the systems exactly and implement distributed control in practice. Moreover, since the future price signal is always unknown, we need to design decision-makers which are informative of future price patterns. We provide an online MARL framework to solve the optimization problem mentioned above.

III. MULTI-AGENT LEARNING FRAMEWORK A. MDP Process

To solve the optimization problem with a MARL based approach, we firstly reformulate it as a multi-agent extension of MDP. Each agent can only use its own state s_i during implementation, while we allow the use of full state s when training the RL policy.

State: We use $s = s_1, \dots, s_{N+1}$ to denote a set of states for N+1 agents. For each building agent,

$$\mathbf{s}_{i,k} = \left(T_{i,k}^{in}, T_k^{out}, p_k, SOC_k\right)$$
. For SESS, $\mathbf{s}_{SESS,k} = (T_k^{out}, p_k, \bar{p}_k, SOC_k)$.

Action: $\mathbf{a} = \mathbf{a}_1, \dots, \mathbf{a}_{N+1}$ denotes a set of actions for N+1 agents. For each building agent, its actions include power input from the grid and discharged from SESS $\mathbf{a}_{i,k} =$ $\left(P_{i,k}^g, P_{i,k}^d\right)$. For SESS, its action is the charging power $\mathbf{a}_{SESS,k} = (c_t)$. We use this design such that it is easier to train the SESS agent with simplified action space.

Reward Function: For each building agent, it aims to minimize the temperature difference between indoor temperature and user's preferred temperature and energy cost, thus we give negative reward based on the temperature difference and energy cost, respectively:

$$r_{i,k}^{temp} = \left| T_{i,k}^{in} - T_{i}^{target} \right|; \quad r_{i,k}^{energy} = p_k P_{i,k}^g; \qquad (11)$$

$$r_{i,k} = \alpha_{temp} r_{i,k}^{temp} + \alpha_{energy} r_{i,k}^{energy}, \qquad (12)$$
where α_{temp} and α_{energy} are weighting factors of tem-

$$r_{i,k} = \alpha_{temp} r_{i,k}^{temp} + \alpha_{energy} r_{i,k}^{energy}, \tag{12}$$

perature difference and energy cost. For SESS agent, we encourage it to charge when the price is lower:

$$r_{SESS,k} = (\bar{p}_k - p_k) c_k, k \in (1, K - 1)$$
(13)

where \bar{p}_k is a weighted average of historical price:

$$\bar{p}_k = (1 - \eta)\bar{p}_{k-1} + \eta p_k,$$
 (14)

where η is a smoothing parameter to encode moving average [14]. To prevent energy waste caused by unbalanced charging and discharging, we add a penalty for remaining energy in every testing episode:

$$r_{SESS,K} = (\bar{p}_k - p_k) c_k - \beta SOC_K, \tag{15}$$

where β is a negative penalty factor.

B. MADDPG algorithm

The main idea of Multi-Agent Deep Deterministic Policy Gradient (MADDPG) algorithm is adopting centralized training with decentralized execution. Each agent has both actor and critic neural network. Given the states and actions of all agents defined in the previous subsection, the critic network is a value function to estimate expected discounted returns. It is demonstrated in [10] that given the actions of other agents when training critic network, the environment is stationary even as the policies change: $P_r(s' \mid s, a_1, \dots, a_N, \pi_1, \dots, \pi_N) =$ $P_r(s' \mid s, a_1, \dots, a_N) = P_r(s' \mid s, a_1, \dots, a_N, \pi'_1, \dots, \pi'_N),$ where P_r denotes the state transition probability. With a welltrained value function, the actor network, which is utilized to map states to actions, updates its parameter by policy gradient method under the critic's guidance.

At every time step k, each agent takes actions based on its own states. Without loss of generality, we use i as the index of building agents and SESS agent: $\mathbf{a}_{i,k} = \pi_{\theta_i}(\mathbf{s}_{i,k})$, where π_{θ_i} represents the actor network's policy with model parameters θ_i , and θ_i will be omitted in the following statement. Given the actions of all agents and their current state, the environment will feedback reward and next state for all agents. Thus we can obtain a tuple (s, a, s', r) and store it in the replay buffer \mathcal{D} , where s' denotes the full state in next time step. (Here we omit the time index without loss of generality.)

With the tuples sampled from experience replay buffer, the value function is updated by minimizing the following loss:

$$\mathcal{L}(\mu_i) = \mathbb{E}_{\mathbf{s}, \mathbf{a}, r, \mathbf{s}'} \left[\left(Q_i \left(\mathbf{s}, \mathbf{a} \right) - y \right)^2 \right], \tag{16}$$

where $y = r_i + \gamma Q_i'(\mathbf{s}', \mathbf{a}')|_{\mathbf{a}_i' = \pi_i'(\mathbf{s}_j)}; \ \mu$ is the model parameters of critic network; Q_i and Q_i' represent critic network and target critic network. j is the index of minibatch samples sampled from \mathcal{D} in each episode, which will be further introduced in Algorithm 1.

The policy gradient method used to update actor network is given as follows:

$$\nabla_{\theta_{i}} J\left(\pi_{i}\right) = E_{\mathbf{s}, \mathbf{a} \sim \mathcal{D}} \left[\nabla_{\theta_{i}} \pi_{i} \left(\mathbf{a}_{i} \mid \mathbf{s}_{i}\right) \nabla_{\mathbf{a}_{i}} Q_{i} \left(\mathbf{s}, \mathbf{a}\right) \big|_{\mathbf{a}_{i} = \pi_{i}(\mathbf{s}_{i})} \right]. \tag{17}$$

Algorithm 1 Learning to schedule coupled SESS and HVAC

```
Require: The number of buildings N; p_k, T_k^{out}, k \in [1, K]
 1: Initialize experience replay buffer \mathcal{D} and environment;
```

- 2: **for** episode = 1, 2, ..., M **do**
- Reset environment;
- **for** step = 1, 2, ..., K **do** 4:
- Each agent select actions $\mathbf{a}_{i,k} = \pi_{\theta_i} \left(\mathbf{s}_{i,k} \right)$ 5:
- 6: Execute $\mathbf{a}_{i,k}$; observe $\mathbf{s}_{i,k+1}$ and reward $r_{i,k+1}$;
- 7: Store tuple (s_k, a_k, s_{k+1}, r_k) in \mathcal{D} ;
- Update state: $\mathbf{s_k} \leftarrow \mathbf{s_{k+1}}$ 8:
 - for agent = 1, 2, ..., N + 1 do
- Sample mini-batch **B** with B_{size} 10: $(\mathbf{s_k}, \mathbf{a_k}, \mathbf{s_{k+1}}, \mathbf{r_k})$ from \mathcal{D} ;
- Calculate actions with target actor network: $\mathbf{a}'_i =$ 11:
- $\pi'_i(\mathbf{s}_i)$ for j in mini-batch **B**;
- Calculate $Q'_i(\mathbf{s}_i, \mathbf{a}_i)$ for j in mini-batch \mathcal{B} ; 12:
- Update critic network by minimizing (16); 13:
- Calculate $Q_i(\mathbf{s}_i, \mathbf{a}_i)$ for j; 14:
- 15: Update actor network with (17); Update target network
- 16: end for
- end for 17:
- 18: end for

9:

IV. CASE STUDY

A. Experiment Setup

The real-world weather and pricing dataset is from Hourly energy demand generation and weather², a dataset in Kaggle. It contains Spain's 4 years of electrical consumption, generation, pricing, and weather data. Each episode contains 96 time steps (i.e. 4 days) and the time interval is 1 hour. To test the framework's performance in different situations, we show 3 typical cases here: (1) Winter (case 1): the HVAC systems need to heat all the time; (2) Spring (case 2): the HVAC system should both heat and cool; (3) Summer (case 3): the HVAC system needs to cool to keep comfort temperature.

²https://www.kaggle.com/datasets/nicholasjhana/energy-consumptiongeneration-prices-and-weather?select=energy_dataset.csv

TABLE I PARAMETERS USED FOR SESS, HVAC, AND RL SIMULATIONS.

T_{target} (°C)	20	w_2^g	1	λ	0.3
$R_1({}^{\circ}C/kW)$	8	$P_1^{max}(kW)$	5	$S\bar{O}C(kWh)$	10
$R_2 (\circ C/kW)$	6	$P_1^{min}(kW)$	-5	$\bar{d}_i(kW)$	5
$C_1(kWh/^{\circ}C)$	15	$P_2^{max}(kW)$	5	$\bar{c}(kW)$	5
$C_2\left(kWh/^{\circ}C\right)$	14	$P_2^{min}(kW)$	-5	γ	0.9
w_1^d	0.9	δ_c	0.9	$ \tau $	0.01
w_1^{b}	1.1	δ_d	1.1	N	2
$w_2^{\bar{d}}$	1	η	0.2	Episode	500

Other parameters we use are given in Table I. In this section, we show the results of 3 cases in Table II and visualize some typical results of case 2 with $\alpha_{temp}/\alpha_{energy}=10$ in Proposed of the most interest.

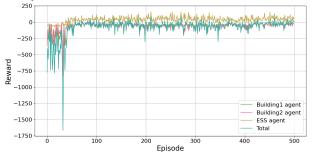


Fig. 2. Training reward evolution of Proposed in case 2.

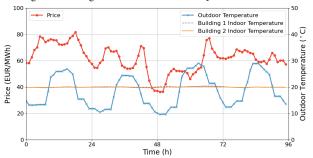


Fig. 3. The external inputs of price and outdoor temperature, along with the indoor temperature under Proposed.

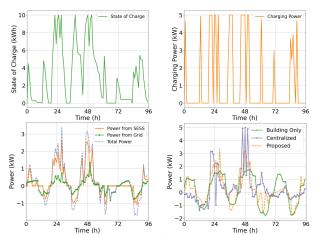


Fig. 4. Simulation results in case 2. (a) State-of-charge of SESS under Proposed; (b) charging power c_k of SESS under Proposed; (c) power injection of building 1 from grid $P_{1,k}^g$, SESS $P_{1,k}^d$, and total power injection $P_{1,k}^g + P_{1,k}^d$ under Proposed; (d) total power injection of building 1 under Building Only, Centralized, and Proposed.

Here we choose 3 baselines to compare with our proposed method (Proposed):

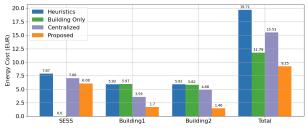


Fig. 5. Energy Cost comparison.

Heuristic Scheme (Heuristics): Heuristics uses some rules based on SOC, price, and outdoor temperature to control the power rate. The charging power of SESS $c_k = 5kW$ if $p_k < \bar{p}_k$, otherwise $c_k = 0$. The power injection of HVAC systems from grid and SESS $P_{i,k}^d = 1$ and $P_{i,k}^g = 1$ if outdoor temperature $T_k^{out} < 0$, otherwise $P_{i,k}^d = -1$ and $P_{i,k}^g = -1$. The charging rate should not obey the constraint of SESS's capacity (7).

HVAC system operates without SESS (User Only): This scheme only considers independent HVAC operators. In other words, we trained building agents separately.

Centralized Reinforcement learning (Centralized): Centralized trains a single agent with combined states for SESS and HVAC systems.

B. Performance Analysis

We introduce performance metrics to analyze performance numerically the Average Temperature Deviation (ATD) ATD $\frac{1}{KN}\sum_{k=1}^{K}\sum_{i=1}^{N}|T_{i,k}-T_{target}|;$ Total Energy Cost (TEC) $TEC = \sum_{k=1}^{K} \sum_{i=1}^{N} \left(\left| P_{i,k}^{g} \right| + d_{i,k} \right);$ and Comprehensive **Performance (CP)** $CP = 0.5 \frac{ATD'}{ATD_{max}} + 0.5 \frac{TEC}{TEC_{max}}$, where ATD_{max} and TEC_{max} are the maximum ATD and TEC among each case, respectively.

In TABLE II, we present the simulation results of all cases with all baseline algorithms and Proposed. The TEC of Proposed is the smallest in all 3 cases; although the ATD is not the smallest, it is smaller than $0.4^{\circ}C$, which is a relatively small value in the real world. The performance on metric CE indicates that Proposed with user-tunable weighting parameter α_{temp} and α_{energy} can achieve the heterogeneous users' control objectives and always has the potential to obtain the best comprehensive temperature control and energy cost saving performance once we carefully set the α_{temp} and α_{energy} .

Fig. 2 suggests that the reward of all 3 agents converge after around 50 episodes with Proposed. Recall in Equation (13), the SESS is encouraged to charge when real-time price p_k is lower than weighted average price \bar{p}_k and keeps $c_k=0$ to avoid the negative reward (penalty) when $p_k < \bar{p}_k$. It can be observed in Fig. 4(b) that the SESS actively charges to take advantage of the price signal shown in Fig. 3 with the encouragement of our well-designed reward. In our proposed method, the 3 agents tend to maximize their own reward to achieve the greater total reward. In other words, the real-time power injection of Fig. 4(c) shows that the building agent determines the heating or cooling power according to the

TABLE II
COMPARISON OF EXPERIMENT RESULTS.

Methods	Case1		Case2			Case3			
Methods	ATD	TEC	CP	ATD	TEC	CP	ATD	TEC	CP
Heuristics	0.113	21.260	0.613	0.109	19.793	0.605	0.107	22.200	0.558
User Only	0.491	14.574	0.833	0.098	11.791	0.392	0.181	14.280	0.420
Centralized	0.501	20.277	0.977	0.520	15.531	0.892	0.917	22.045	0.997
Proposed ($\alpha_{temp} / \alpha_{energy} = 10$)	0.256	14.237	0.590	0.117	9.247	0.346	0.377	12.698	0.492
Proposed ($\alpha_{temp} / \alpha_{energy} = 20$)	0.184	16.576	0.573	0.076	11.438	0.362	0.189	13.985	0.418
Proposed ($\alpha_{temp}/\alpha_{energy}$ =25)	0.088	17.746	0.505	0.081	9.752	0.324	0.147	14.645	0.410

temperature situation and determines the source of energy based on the real-time SOC and price to take advantage of the SESS. For instance, from Fig. 3 and Fig. 4 we can see that at the 24^{th} hour and the 48^{th} hour, due to the lower temperature, the HVAC needs a larger heating power to maintain the temperature to reduce the negative reward in (11) regarding the temperature difference.

We observe that our well-designed settings ensure the balance of battery charge and discharge as shown in Fig. 4(a), and use the energy storage of the battery as much as possible to minimize energy costs. One of the settings is that the discharge (corresponding to $P_{i,k}^d$) of the SESS is controlled by the building agent, which can not only avoid complex communication problems but also enable the building to perform power dispatch according to its real-time energy demand as illustrated in Fig. 4(c). Another unique design is to avoid excessive energy storage of the SESS by using Equation (15).

As shown in Table II, Heuristics has an energy cost about 2 times that of Proposed in case 2. This is because the Heuristics is only based on the current state, and it cannot learn some complex strategies. As for User Only, from Fig. 4(d), its power curve is similar to that of Proposed. However, the energy consumption in each case is still about 2% to 28% higher than that of Proposed. Although the rewards of RL in User Only can converge well, due to the lack of SESS, as illustrated in Fig. 5, the energy cost of building 1 and building 2 of Proposed is much lower than that of User Only. Speaking of Centralized, it can be seen from Table II that it is not as good at maintaining temperature and saving energy as Proposed. This is because the convergence of RL is difficult due to the increased dimension of the state and action spaces. In addition, due to the existence of multiple rewards in centralized training, it is difficult for the agent to learn to trade off among multiple rewards to maximize return.

V. CONCLUSION AND FUTURE WORKS

In this paper, we design a multi-agent, distributed power dispatch and information exchange framework for SESS and a group of users in the community. With the multi-agent reinforcement learning algorithm, each SESS and user agent can decide the power dispatch based on its own states to meet the energy demand of HVAC system and SESS's charging/discharging balance without additional communication. The well-designed reward functions help the agents to decide

energy demand based on temperature deviation and take advantage of the capacity of SESS and price signals to save energy costs. Numerical experiments with real-world weather and electricity prices data show that the agents achieve great energy cost savings and energy demand satisfaction in all simulation cases. We will consider a more scalable framework and algorithm in our future work.

REFERENCES

- [1] K. Divya and J. Østergaard, "Battery energy storage technology for power systems—an overview," *Electric power systems research*, vol. 79, no. 4, pp. 511–520, 2009.
- [2] R. Dai, R. Esmaeilbeigi, and H. Charkhgard, "The utilization of shared energy storage in energy systems: a comprehensive review," *IEEE Transactions on Smart Grid*, vol. 12, no. 4, pp. 3163–3174, 2021.
 [3] N. Bhusal, M. Abdelmalak, and M. Benidris, "Optimum locations of
- [3] N. Bhusal, M. Abdelmalak, and M. Benidris, "Optimum locations of utility-scale shared energy storage systems," in 2019 8th International Conference on Power Systems (ICPS). IEEE, 2019, pp. 1–6.
- [4] C. E. C. E. Division, "New residential zero net energy action plan 2015-2020 executive summary," *California Public Utilities Commis*sion Energy Division, 2016.
- [5] A. Walker and S. Kwon, "Analysis on impact of shared energy storage in residential community: Individual versus shared energy storage," *Applied Energy*, vol. 282, p. 116172, 2021.
- [6] Y. Yang, G. Hu, and C. J. Spanos, "Optimal sharing and fair cost allocation of community energy storage," *IEEE Transactions on Smart Grid*, vol. 12, no. 5, pp. 4185–4194, 2021.
- [7] H. Zhu and K. Ouahada, "A distributed real-time control algorithm for energy storage sharing," *Energy and Buildings*, vol. 230, p. 110478, 2021.
- [8] P. Odonkor and K. Lewis, "Control of shared energy storage assets within building clusters using reinforcement learning," in *International Design Engineering Technical Conferences and Computers and Infor*mation in Engineering Conference, vol. 51753. American Society of Mechanical Engineers, 2018, p. V02AT03A028.
- [9] J. Hu, M. P. Wellman *et al.*, "Multiagent reinforcement learning: theoretical framework and an algorithm." in *ICML*, vol. 98, 1998, pp. 242–250.
- [10] R. Lowe, Y. I. Wu, A. Tamar, J. Harb, O. Pieter Abbeel, and I. Mordatch, "Multi-agent actor-critic for mixed cooperative-competitive environments," *Advances in neural information processing systems*, vol. 30, 2017.
- [11] K. Paridari, A. Parisio, H. Sandberg, and K. H. Johansson, "Demand response for aggregated residential consumers with energy storage sharing," in 2015 54th IEEE conference on decision and control (CDC). IEEE, 2015, pp. 2024–2030.
- [12] T. Wei, Y. Wang, and Q. Zhu, "Deep reinforcement learning for building hvac control," in *Proceedings of the 54th annual design* automation conference 2017, 2017, pp. 1–6.
- [13] Z. Wang, Y. Chen, and Y. Li, "Development of rc model for thermal dynamic analysis of buildings through model structure simplification," *Energy and Buildings*, vol. 195, pp. 51–67, 2019.
- [14] H. Wang and B. Zhang, "Energy storage arbitrage in real-time markets via reinforcement learning," in 2018 IEEE Power & Energy Society General Meeting (PESGM). IEEE, 2018, pp. 1–5.
- [15] L. Yu, Y. Sun, Z. Xu, C. Shen, D. Yue, T. Jiang, and X. Guan, "Multiagent deep reinforcement learning for hvac control in commercial buildings," *IEEE Transactions on Smart Grid*, vol. 12, no. 1, pp. 407–419, 2020.