Smart Energy Scheduling of B2V-enabled Prosumer Community as EVSE Based on SDN Network: A Deep Reinforcement Learning Approach

Luyao Zou, and Choong Seon Hong
Department of Computer Science and Engineering, Kyung Hee University, South Korea
Email: {zouluyao, cshong}@khu.ac.kr

Abstract

With the increasing penetration of the electric vehicle (EV) in the smart city, the demand for public EV charging infrastructure is highly required. Therefore, the prosumer community with Building-to-Vehicle (B2V) systems can serve as EV support equipment (EVSE) is introduced to provide energy to public EVs. However, the dynamic change of the energy demand of prosumers and the EVs tends to increase the difficulty of network management. Further, the mismatching problem between the demand and renewable energy generation of the entire prosumer community leads to the low efficiency of renewable energy adoption and the high requirement of the power grid support. Thus, to address these issues, firstly, we leverage the software-defined network (SDN) to reduce network management hardness. Secondly, we introduce a battery storage system and energy sharing to investigate the energy scheduling problem for the B2V-enabled prosumer community as EVSE, which aims to minimize the aggregated cost of purchasing energy from the power grid, while fulfilling the energy demand of EVs and prosumer buildings. Besides, deep reinforcement learning method with experience replay is proposed for the energy scheduling problem. Finally, the evaluation results indicate the proposed method can significantly diminish the energy trading cost with the power grid.

1. Introduction

In recent years, with the rising number of electric vehicle (EV), demand for EV supply equipment (EVSE) is increased. Buildings have the potential to provide energy to EVs with the Building-to-Vehicle (B2V) system. Hence, we consider the B2V system installed prosumer community as the EVSE (PCEVSE) to offer the energy to EVs. However, renewable energy generation and energy demand exist the unbalance phenomenon [1], and both prosumer buildings and EV users' energy demands are uncertain. Besides, the dynamic energy demand causes the hardness of managing the network. Therefore, it is urgent to introduce an effective energy scheduling mechanism to address such issues.

Recently, research on energy scheduling has become popular such as scheduling energy within a smart city with considering battery storage system for minimizing renewable energy usage is studied in [2]. In [3], energy scheduling of a prosumer community that consists of various types of buildings is proposed to minimize the renewable energy utilization. Different from previous studies, we focus on software-defined network (SDN) based energy scheduling for PCEVSE to reduce the hardness of managing the network, and minimize the overall power grid cost while satisfying the demand of EVs and buildings.

The main contributions are listed as follows:

- An energy scheduling problem is formulated for minimizing the PCEVSE trading cost with the power grid. The public EVs' charging process, scheduling of battery storage system of PCEVSE (PCBSS), and energy sharing within the PCEVSE is considered. However, it is hard to obtain the optimal PCBSS charging/discharging and energy sharing. And the dynamic demand for EVs causes difficulty in managing the network.
- To address such problems, we introduce SDN network and propose deep reinforcement learning method with experience replay in SDN application layer to get the best values.
- Finally, we show the proposed approach can significantly minimize the power grid cost.

2. System Model and Problem Formulation

This section shows the system model with the related SDN framework as well as the formulation. The system model composes of roadside unit (RSU), macro base

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*Dr. CS Hong is the corresponding author.

station (MBS), power grid, distributed system operator (DSO), and multiple prosumers $P = \{1,2,\ldots,P\}$, shown in Fig.1. Each prosumer connects with the DSO equips with the cloud that is responsible for making the energy scheduling decision. Besides, each prosumer performs as the EVSE, which can provide the energy to public EVs. And it is possible to share energy within the PCEVSE. Discrete-time slots $T = \{1,2,\ldots,T\}$ and each time interval $t \in T$ as an hour duration are considered [4].

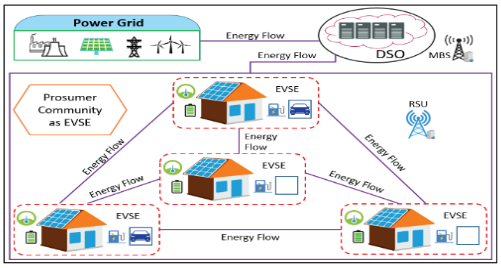

Fig. 1 System Model

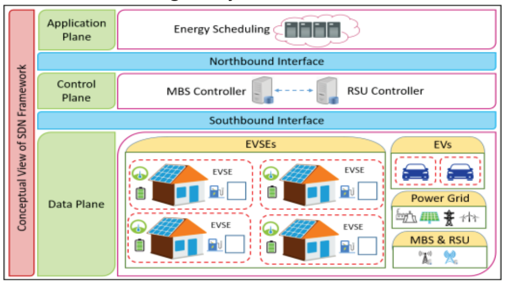

Fig. 2 Conceptual View of SDN Framework

Fig. 2 introduce the conceptual view of the underlying SDN framework of the proposed system model. The data plane consists of physical components: EVSE, public EVs, power grid, MBS and RSU [5]. The control plane includes the MBS controller and RSU controller that performs the management of MBS and RSU. The application plane is responsible for energy scheduling.

For the PCBSS, the capacity $\Phi_p^{BSS}(t+1)$ at the next time slot can be denoted as follows [6]:

$$\Phi_p^{BSS}(t+1) = \Phi_p^{BSS}(t) + \xi_c \Phi_p^{bc}(t) - \frac{\Phi_p^{bd}(t)}{\xi_d}, \forall t \in \mathrm{T}, \tag{1}$$

where ξ_c and ξ_d represents the PCBSS charge and discharge efficiency, respectively. $\Phi_p^{BSS}(t)$ denotes the PCBSS capacity at time slot t. $\Phi_p^{bc}(t)$ shows the energy charge amount, while $\Phi_p^{bd}(t)$ indicates the discharge quantity.

For an EV, the charging period is denoted as τ. In practice, there exists EV charging loss. Thus, we denote the EV charging efficiency as η. The actual charging Ψ_{EV}^c can be defined by $\Psi_{EV}^c = \int_0^\tau \eta * P_\tau d\tau$ [7]. Here P_τ is the charging power of the EV. We define the time that the EV starts to charge is t_s and finish charging is t_{end}. Therefore, the EV battery (VBSS) capacity $\Phi_{EV}^{BSS}(t_{end})$ after charge can be obtained as below:

$$\Phi_{EV}^{BSS}(t_{end}) = \Phi_{EV}^{BSS}(t_s) + \int_{t_s}^{t_s+\tau} \eta * P_\tau d\tau, \tag{2}$$

where $\Phi_{EV}^{BSS}(t_s)$ means the VBSS capacity before charge and τ is the charging period.

For prosumer p, the load $\Phi_p^l(t)$ can be represented as,

$$\Phi_p^l(t) = \Phi_p^d(t) + \Phi_p^{bc}(t) + \Phi_p^s(t) + \Phi_p^{vc}(t), \tag{3}$$

where $\Phi_p^d(t)$ defines the demand of each prosumers, $\Phi_p^s(t)$ represents the sharing quantity, $\Phi_p^{vc}(t)$ denotes the energy used for charging the EVs at time slot t. The sharing loss within same community can be ignored [4]. Hence, the suppliable energy $\Phi_p^e(t)$ can be denoted by,

$$\Phi_p^e(t) = \Phi_p^g(t) + \Phi_p^{bd}(t) + \Phi_p^r(t), \tag{4}$$

where $\Phi_p^g(t)$ denotes the renewable energy generation, $\Phi_p^r(t)$ indicates the energy received from neighborhood.

Accordingly, for the prosumer p, the purchasing energy from the power grid, $\Phi_p^{grid}(t)$, at time slot t can be denoted by,

$$\Phi_p^{grid}(t) = \begin{cases} \Phi_p^l(t) - \Phi_p^e(t), & \text{if } \Phi_p^l(t) \geq \Phi_p^e(t), \\ 0, & otherwise. \end{cases} \tag{5}$$

Therefore, the energy cost of buying energy from the power grid $Cost^{grid}(t)$ can be defined as below [8]:

$$Cost^{grid}(t) = \int_{t-1}^{t} \Phi_p^{grid}(t) * \delta(t) dt, \tag{6}$$

where $\delta(t)$ denotes the unit buying price from the grid.

The objective of this research is to reduce the hardness of network management and minimize the total energy trading cost with the power grid through scheduling PCBSS charging/discharging operation and energy sharing while fulfilling the energy demand of EVs and prosumers. The problem formulation is as follows:

$$\min_{\Phi_p^s(t), \Phi_p^{bc}(t), \Phi_p^{bd}} \sum_{\forall p \in P} \sum_{\forall t \in T} Cost^{grid}(t) \tag{7}$$

s.t.

$$\sum_{\forall p \in P} \Phi_{PCBSS}^{min} \leq \sum_{\forall p \in P} \Phi_p^{BSS}(t) \leq \sum_{\forall p \in P} \Phi_{PCBSS}^{max} \tag{8}$$

$$\Phi_{VBSS}^{min} \leq \Phi_p^{BSS}(t) \leq \Phi_{VBSS}^{max} \tag{9}$$

$$\sum_{\forall p \in P} \Phi_p^s(t) \leq \sum_{\forall p \in P} \Phi_p^g(t) + \sum_{\forall p \in P} \xi_d * \Phi_p^{BSS}(t) \tag{10}$$

$$0 < \xi_c, \ \xi_d < 1, \ t \in T. \tag{11}$$

In problem (7), constraint (8) indicates the limitation of the total PCBSS of the PCEVSE, while constraint (9) shows the VBSS capacity requires not more than the maximum capacity Φ_{VBSS}^{max} and not less than the minimum capacity Φ_{VBSS}^{min}. The constraint for the total energy sharing of PCEVSE at time slot t is shown in (10), which guarantees the quantity of energy sharing needs not to exceed the summation of total generation and PCBSS capacity. PCBSS charge/discharge efficiency range is denoted in the constraint (11).

3. Solution with Deep Reinforcement Learning Method

This section shows the detailed process of the proposed approach: DQN with experience replay, shown in Algorithm 1. In this method, the state space is defined as $S = \{1,2,\ldots,S\}$, where a state $s_t \in S$ is the tuple composed of four elements $<\Xi_t^{dem}, \Xi_t^{ren}, \Xi_t^{sto}, \Xi_t^{grid}>$. In detail, $\Xi_t^{dem}, \Xi_t^{ren}, \Xi_t^{sto}$ and Ξ_t^{grid} represent the total energy demand requirement of the entire prosumer community, the total renewable energy generation, storage energy, and the energy buying from the grid at time slot t. We define each action $a_t \in < \alpha_t^b, \alpha_t^s >$, where α_t^b is the decision of buying energy from the power grid, α_t^s is the decision of saving energy into PCBSS. The goal of this work is to minimize the energy purchasing cost from the grid. Therefore, we define the immediate reward as $r_t = -\sum_{\forall p \in P} \Phi_p^{grid}(t)$. In this work, deep neural network (DNN) is used to approximate the Q network, where the loss function is defined as,

$$\mathcal{L}(\theta) = \mathbb{E}_{(s,a)\sim\rho(\cdot)}[(r + \gamma max_{a'} Q(s', a'; \theta^i) - Q(s, a; \theta))^2]. \quad (12)$$

Here, s', a' and θ^i denote the next state, next action and parameter of DNN training in i^{th} iteration, respectively. The probability distribution over the sequences s and actions a is defined as $\rho(s, a)$. After DNN training, the optimal policy can be obtained by,

$$\pi^{opt}(s) = argmax_{a'} Q^{opt}(s_t, a_t'; \theta). \quad (13)$$

Here, $Q^{opt}(s_t, a_t'; \theta)$ is the optimal Q-value via DNN.

Algorithm 1: DQN With Experience Replay for Smart Energy Scheduling

```
Input: ξ_c, ξ_d, Φ_PCBSS^min, Φ_PCBSS^max, Φ_VBSS^min, Φ_VBSS^max, demand, energy_generation
Output: Cost*
  Step 1: DRL with experience reply learning stage
  Randomly initialize the PCBSS capacity s.t (8)
  Generate EV demand according to uniform distribution s.t (9)
  Initialize experience replay memory M, Q(s,a,θ) with the random
  for each episode do
      Get initial state s
      for t=1,2,⋯,T do
          Select random action a_t with probability ϵ,
          Observe the reward r_t and the next state s_t'
          Store the experience (s_t, a_t, r_t, s_t') into M
          Randomly sample the minibatch of the experience from M
          Update parameter θ and Q(s,a,θ) by minimizing L(θ)
          Update the policy π(s_t) = argmax_a' Q(s_t, a_t'; θ)
  Step 2: Obtain the minimize power grid cost
  Using eq. (6) – (7) get the minimal grid cost: Cost*
  return Cost*
```

4. Performance Evaluation

In this research, we use the one-year energy demand dataset from [9] and solar generation dataset from [10]. The related parameters are $\xi_c = 0.958$, $\xi_d = 0.958$, $\Phi_{VBSS}^{max} = 16kWh$, $\Phi_{VBSS}^{min} = 4.8kWh$, $\Phi_{PCBSS}^{min} = 0kWh$, $\Phi_{PCBSS}^{max} = 13.5kWh$[2].

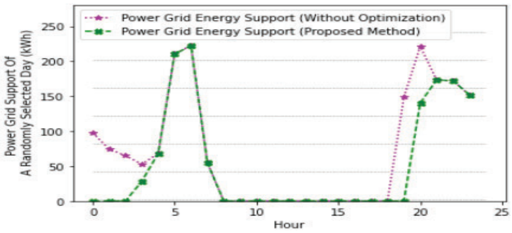

Fig. 3 Power Grid Energy Support of a Randomly Selected Day

Fig. 3 shows the hourly energy support from the power grid of a randomly selected day in the one-year dataset. Through this figure, it can be seen that the proposed method can significantly reduce the energy buying from the power grid. Fig. 4 illustrates the energy trading cost with the power grid of the selected day. Particularly, with the proposed method, the energy cost can be reduced from $174.84 to $124.76.

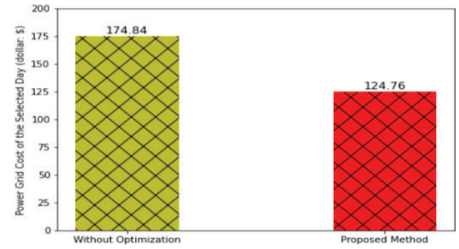

Fig. 4 Energy Trading Cost with Power Grid of the Selected Day

5. Conclusion

This paper introduced SDN to diminish the hardness of managing the network of the PCEVSE and proposed DQN with experience replay approach to minimize the total energy trading cost with the power grid while fulfilling the energy demand of EVs and prosumers. The evaluation results show the proposed method can significantly reduce the energy cost of buying from the power grid by $50.08 of the randomly selected day.

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