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Apartment-level electric vehicle charging coordination: peak load reduction and charging payment minimization

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ABSTRACT

In future apartment complexes, high penetration of electric vehicles (EVs) may cause to significantly increase electricity load at certain times, and the demand for uncoordinated EV charging power may significantly affect the stability of the apartment-level power grid. In order to efficiently accommodate the significant charging demand from a large number of EVs in apartment complexes, we propose an apartment-level EV charging coordination scheme to not only reduce the peak EV charging load but also minimize the apartment-level EV charging payment, and then we validate it through various case studies. To be specific, we compare the performance of the proposed EV charging coordination scheme with that of a typical as-soon-as-possible (ASAP) charging scheme and a random charging scheme in terms of peak-to-average power ratio (PAPR), relative charging duration (RCD), and total charging payment. It is observed that the proposed coordination scheme manages the apartment-level power grid more stable, and EV owners in this apartment-level power grid can obtain economic benefits by participating in the EV charging coordination.

1. Introduction

Recently, we have faced serious climate changes and greenhouse gas emission problems due to overuse of fossil fuels. One of promising solutions for mitigating such climate changes and reducing greenhouse gas emissions is to use eco-friendly vehicles such as hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and battery electric vehicles (BEVs) using clean energy [1]. In the near future, such EVs are expected to gradually replace the existing gasoline/diesel-based vehicles, and the penetration of EVs is expected to be accelerated with approximately 60% per year [2,3].

However, another technical challenge due to a significant charging demand of EVs (i.e., 497 W (level 1 charging) and 856 W (level 2 charging) of average per-household incremental peak demand for an EV penetration of 50% [4]) is also expected to be required in the existing power grid, and, thus, a number of related studies on the effect of increasing EV charging loads and demands on the existing power grid have been investigated in the literature [5–11]. Mu et al. [7] investigated the impact of large scale deployment of plug-in EVs on urban distribution networks based on the developed a spatial-temporal model. They validated the effectiveness of the spatial–temporal model by comparing 'dumb' charging and 'smart' charging schemes under different EV penetration levels. Neaimeh et al. [8] focused on the impact of uncontrolled and clustered charging of EVs on the electricity distribution networks, where it was shown that the substantial collaboration between distribution network operators and charging infrastructure operators can provide more opportunities for demand-side management, and the distribution networks can accommodate higher EV penetrations accordingly. Munkhammar et al. [9] considered on the impact of the electricity demand and generation patterns combined with household electricity consumption, EV charging and photovoltaic (PV) power generation under a future environment in Westminster, UK, where it was shown that the EV home-charging increases the electricity use by between 14% and 61% depending on the number of occupants.

On the other hand, more than half of people live in apartment complexes in South Korea, which exhibits a unique feature compared with the life style in other countries [12]. In addition, many people living in cities do not have their dedicated parking lots and personal EV chargers. EV owners in cities (apartment complexes) may need to share both parking lots and EV chargers. In addition, the apartment complex needs to manage the electricity power

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usage under a certain power capacity limit since each apartment complex generally contracts with an electric power company to set a power capacity limit. If the electricity usage exceeds the contracted power limit, the apartment complex should pay extra penalty charge [13]. Thus, it becomes very difficult to manage and control the power usage of the apartment complex as the number of EVs and the corresponding charging demand increases in the near future.

Meanwhile, Korea Electric Power Corporation (KEPCO) announced a plan to install 30000 EV chargers in 4000 apartment complexes to improve the EV charging infrastructure across the country in South Korea [14]. Through this project, it is expected that the access to EV chargers is more convenient in apartment complexes. However, the related EV charging management and coordination technologies are still immature and the relevant techniques based on information and communication technologies (ICTs) are needed in apartment complex environments with a large number of EVs.

Studies on EV charging coordination are in general categorized into centralized coordination schemes [15–18], and decentralized coordination schemes [19–22] according to operation method. In the centralized coordination schemes, the charging operation center controls each EV to optimize EV charging load profile in a centralized manner. Wang et al. [23] investigated a multi-agent system with particle swarm optimization and a fuzzy controller for the integration of the PHEVs in smart buildings. Yagcitekin and Uzunoglu [24] also proposed a centralized charging management algorithm which routes the EVs to a suitable charging point, decreases the charging costs, and prevents transformers from overloading. Xu et al. [15] proposed a centralized hierarchical coordinated charging framework for the PHEVs across multiple aggregators, which not only minimizes the electricity cost but also effectively control the system peak load. Majidpour et al. [25] proposed EV charging load forecasting schemes based on customer profiles or station measurements, and it was shown that the forecasted EV charging load information is useful for the charging coordination schemes. Wu et al. [18] proposed a hierarchical charging scheduling and control framework to enable EVs for grid services while satisfying vehicle owners' travel needs. In short, the central coordinator determines the optimal power allocation for a look-ahead time window based on grid services to be provided, and helps to reduce computational complexity and communication requirement compared with existing methods.

On the other hand, in the decentralized coordination schemes, each EV determines its charging rate based on the control signal broadcast by the operation center in a decentralized manner. Zhou and Cai [19] proposed a decentralized random access framework in order to avoid both bus load congestion and a voltage drop problem in the distribution power grid, where each EV adjusts its charging rate based on the proposed access probability. Ma et al. [22] proposed a decentralized charging control scheme and proved the optimality of the proposed scheme in limited cases where all EVs have identical arrival time, departure time, required amount of charging, and charging rate. Latifi et al. [26] proposed a game-theoretic decentralized EV charging coordination scheme to minimize EV owners' payments while maximizing potential capacity for ancillary services.

In the literature, there exist studies on optimal EV charging performances in which the charging rate of each EV is optimally adjusted [16,27,20,28,29]. Richardson et al. [16] demonstrated how the charging rate of EV can improve the utilization of existing networks, where an optimal centralized charging algorithm was proposed to maximize total delivered energy with a weighted objective function according to the location and the current state-of-charge of EVs. However, it did not provide economical charging service since they did not consider time-of-use (TOU) electricity price in the charging algorithm. Gan et al. [20] proposed an optimal decentralized protocol for EV charging, which EVs choose their own charging profile based on control signal instead of being instructed by a centralized infrastructure. However, each EV experiences a large number of iterations with a center in order to determine the charging profile. Moreover, it was assumed that the center exactly knows all parameters of EVs for solving the optimization problem at the beginning of the scheduling algorithm. They proposed a real-time operation scheme when the number of EVs is equal to 20, but it is not guaranteed that the proposed protocol operate well with a large number of EVs. Sedding et al. [29] compared three different approaches (heuristic, optimization, and stochastic programming) to schedule the charging process of three different electric vehicles fleets (commuters, opportunity, and commercial fleets) at a common charging infrastructure under uncertainty.

The conventional charging optimization algorithms have limitations for practical deployment scenarios because the practical EV chargers cannot control their charging rates dynamically. Instead of the charging rate control, on–off charging control schemes [17,21,22] seem to be more feasible for practically deploying coordination mechanisms with a large number of EVs. For instance, Google developed a smart charging system, in which the charging power is turned on or off remotely by the aggregator [30].

In this paper, hence, we propose a novel apartment-level EV charging coordination scheme for a large-scale apartment complex, in which residents participate in EV charging coordination for pursuing the common profit since the total power usage from both normal electricity power and EV charging power are required to be managed under the contracted power capacity. In addition, EVs in general have sufficient sojourn (slack) time to be fully charged before their departure. By exploiting the time flexibility, our proposed charging coordination schemes control charging actions of a large number of EVs, and effectively shift or distribute EV charging load to the off-peak period while achieving economical benefits. This is a main difference of this paper, compared with [17,21,22], in which each EV owner in a single house pursues an individual profit (e.g., minimizes individual charging payment and maximizes individual user-convenience). The proposed apartment-level EV charging coordination scheme operates based on the on–off charging control and a charging operation center (COC) schedules a number of EVs to be charged on each time slot based on coordination objectives. The proposed scheme requires a small amount of information exchanges and deals with a less-complex optimization problem, which enables a real-time charging coordination even in a large number of EVs. As a result, the proposed EV charging coordination system can manage the apartment-level power grid more stable, and EV owners in the apartment can obtain economic benefits by participating in the EV charging coordination as well. The performance of the proposed scheme is evaluated in terms of peak load reduction and charging payment minimization over various cases.

The rest of this paper is organized as follows. In Section 2, we present a system model considered in this work. In Sections 3, we propose an apartment-level charging coordination scheme. In particular, SubSection 3.1 provides a peak load reduction mechanism with a flat electricity price, and SubSection 3.2 provides a charging payment minimization mechanism with a time-of-use (TOU) electricity price. We also present case studies in Section 4. Finally, we draw conclusive remarks in Section 5.

2. System model

Fig. 1 shows an exemplary model of an apartment-level EV charging system. Electricity in this huge apartment complex is

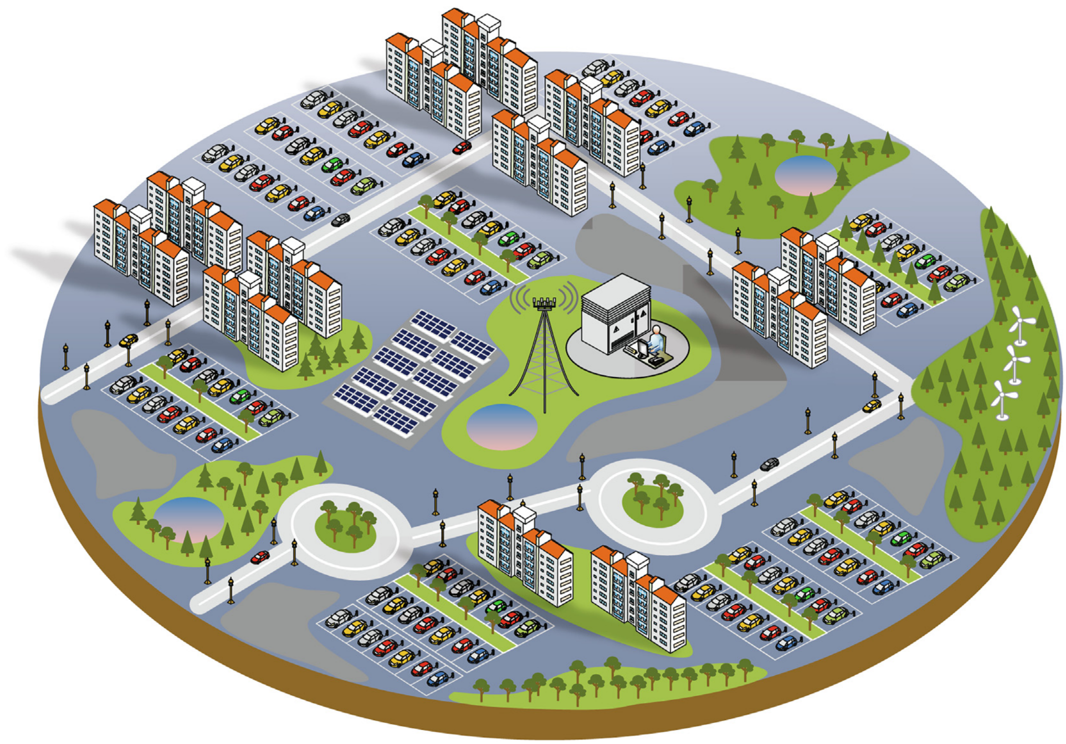


Fig. 1. An exemplary model of apartment-level EV charging system.

supplied through a transformer with a maximum capacity of L_{tx}. Even though the maximum power capacity supplied to the apartment complex is L_{tx}, the apartment complex generally contracts with an electric power company to set a power capacity limit called the contracted power capacity $L_{contract} < L_{tx}$, which is less than the maximum transformer capacity. Therefore, the apartment complex needs to manage the electricity power usage under the contracted power capacity limit.

We consider a total of K EVs with a set of EV indices or identifications (IDs), $\mathbb{K} = \{1, \ldots, K\}$, and they can be coordinated by a charging operation center (COC). The COC controls and manages the total electricity load $L_{total}(i)$, which consists of the normal electricity load $L_{normal}(i)$ and the EV charging load $L_{ev}(i)$, i.e., $L_{total}(i) = L_{normal}(i) + L_{ev}(i)$ on the i-th time slot. It is worth noting that the total electricity load $L_{total}(i)$ should be controlled under the contracted power level of $L_{contract}$, i.e., $L_{total}(i) \leqslant L_{contract}$.

In the apartment-level EV charging system, each EV charger is assumed to communicate with the COC through a communication network in order to exchange EV charging parameter values. The proposed EV charging coordination scheme utilizes a slotted time and on–off based charging mechanism. The on–off based charging mechanism operates by turning the charging power on or off for each EV charging station during a time slot [30]. Let N_{slot} denote the number of time slots per hour (unit: slots/hour), and there exists $24N_{slot}$ time slots in a day, with an index $i \in \mathbb{I} = \{1, 2, \ldots, 24N_{slot}\}$. For the next day, the time slot index is added by $24N_{slot}$. One time slot occupies $T_{slot} = 60/N_{slot}$ (unit: minutes/slot), and T_{slot} is called the slot interval time.

The k-th EV in $\mathbb{K} = \{1, \ldots, K\}$ has the following charging parameters:

- i_k^{in} : Arrival time slot of the k-th EV,
- i_k^{out} : Departure time slot of the k-th EV (set by the owner),
- $i_k^{comp.}$: Charging completion time slot of the k-th EV,
- $S_k = i_k^{out} - i_k^{in}$: The number of sojourn time slots of the k-th EV,
- μ_k : Charging priority (preference) level of the k-th EV (set by the owner),
- SoC_k^{in} : State-of-charge (SoC) level at the arrival of the k-th EV (unit: $0 \sim 1$),
- SoC_k^{out} : SoC level at the departure of the k-th EV (unit: $0 \sim 1$),
- SoC_k^{i} : SoC level at the i-th time slot of the k-th EV (unit: $0 \sim 1$),
- SoC_k^{target} : Target SoC level at the departure of the k-th EV (set by the owner and unit: $0 \sim 1$),
- E_k : Battery energy capacity of the k-th EV (unit: kWh),
- r_k : Charging power rate of the k-th EV (unit: kW),
- $N_k(i)$: The required number of charging time slots of the k-th EV at the i-th time slot, which is calculated as

$$N_k(i) = \left\lceil \frac{N_{slot} \cdot E_k\left(SoC_k^{target} - SoC_k^{i}\right)}{r_k} \right\rceil,$$

where $\lceil \cdot \rceil$ is the ceiling function.

- $R_k = N_k\left(i_k^{out}\right)$: The remaining (uncompleted) number of charging time slots of the k-th EV at the departure time slot i_k^{out}, which is calculated as

$$R_k = N_k\left(i_k^{out}\right) = \left\lceil \frac{N_{slot} \cdot E_k(SoC_k^{target} - SoC_k^{out})}{r_k} \right\rceil.$$

The charging priority (preference) level μ_k is simply classified into three fixed levels, i.e., $\mu_k \in \left\{\mu_{low}, \mu_{mid}, \mu_{high}\right\}$, and the unit of μ_k is set in terms of the number of time slots. Thus, each EV owner chooses an EV's charging priority level among the three levels. Throughout this paper, we utilize the same index k for the EV charger, which the k-th EV is plugged in.

3. Proposed apartment-level EV charging coordination scheme

In this section, we propose an apartment-level EV charging coordination scheme, in which the COC explicitly notifies the EVs of the charging schedule information in a centralized manner using a charging schedule vector $\mathbb{V}(i)$ for the i-th time slot. We assume that all EV chargers have the same charging rate[1], i.e., $r_k = \eta, \forall k \in \mathbb{K}$. Before providing the detailed explanation, Fig. 2 summarizes the overall steps of the proposed apartment-level EV charging coordination scheme.

When the k-th EV charger starts a charging service, it sends its charging parameters to the COC. Then, before the i-th time slot, the COC calculates the number of EVs to require charging services on the i-th time slot as follows:

$$C_{\text{req}}(i) = \sum_{k \in \left\{k \mid \left(i_k^{\text{out}} - i\right) > 0\right\}} \mathrm{I}_{N_k(i) > 0}, \tag{1}$$

where $\mathrm{I}_{N_k(i)>0}$ represents an indicator function to set to 1 if $N_k(i) > 0$, 0 otherwise. For each of $C_{\text{req}}(i)$ EVs, the COC calculates the charging time margin:

$$M_k(i) = \left(i_k^{\text{out}} - i\right) - N_k(i) - \mu_k, \tag{2}$$

where $\left(i_k^{\text{out}} - i\right)$ represents the remaining number of sojourn time slots, $N_k(i)$ denotes the required number of charging time slots and μ_k denotes the charging priority level. Then, the COC sorts the charging time margins in ascending order in order to give faster charging opportunities for EVs with smaller charging time margins, and makes the set of sorted charging time margins, $\mathbb{M}(i)$, which has the cardinality of $|\mathbb{M}(i)| = C_{\text{req}}(i)$ for the i-th time slot. Thereafter, $\mathbb{M}(i)$ is categorized into two subsets $\mathbb{M}_{\text{urgent}}(i)$ and $\mathbb{M}_{\text{normal}}(i)$ as follows:

- A set of charging time margins for urgent EVs: $\mathbb{M}_{\text{urgent}}(i) = \left\{M_k(i) \mid M_k(i) \le 0, \left(i_k^{\text{out}} - i\right) > 0, N_k(i) > 0, \forall k\right\}$,
- A set of charging time margins for normal EVs: $\mathbb{M}_{\text{normal}}(i) = \left\{M_k(i) \mid M_k(i) > 0, \left(i_k^{\text{out}} - i\right) > 0, N_k(i) > 0, \forall k\right\}$,

which have cardinalities of $|\mathbb{M}_{\text{urgent}}(i)| = U(i)$ and $|\mathbb{M}_{\text{normal}}(i)| = X(i) = C_{\text{req}}(i) - U(i)$, respectively. For the i-th time slot, the COC effectively schedules EVs based on two subsets $\mathbb{M}_{\text{urgent}}(i)$ and $\mathbb{M}_{\text{normal}}(i)$ and the corresponding EV IDs, and it generates a set of charging-scheduled EVs $\mathbb{S}(i)$. We will describe the detailed EV charging scheduling algorithms with a flat electricity price in the SubSection 3.1 and with a time-of-use (TOU) electricity price in SubSection 3.2, respectively.

If the k-th EV belongs to $\mathbb{S}(i)$, i.e., $k \in \mathbb{S}(i)$, the COC updates $N_k(i) = N_k(i-1) - 1$, otherwise, it keeps $N_k(i) = N_k(i-1)$. Then, it broadcasts a K-bits charging schedule vector $\mathbb{V}(i) = [v_1, \ldots, v_K]$ obtained by $\mathbb{S}(i)$, in which the k-th bit v_k indicates the charging schedule of the k-th EV (0: unscheduled, 1: scheduled), to all EV chargers before the i-th time slot. Upon reception of the charging schedule vector $\mathbb{V}(i)$, EV chargers with $\left(i_k^{\text{out}} - i\right) > 0$ and $N_k(i) > 0$ check whether their schedule indicator bits are 0 or 1. If $v_k = 1$, the k-th EV charger provides a charging service during the i-th time slot, otherwise, it does not provide the charging service.

[1] In reality, EV chargers may have several charging rates. The COC can configure multiple EV charger groups based on distinct charging rates such as slow charging rate η_1, medium charging rate η_2, and fast charging rate η_3. Thus, the COC independently coordinates each group of EVs with the same charging rate η_n by the corresponding charging schedule vector $\mathbb{V}_n$.

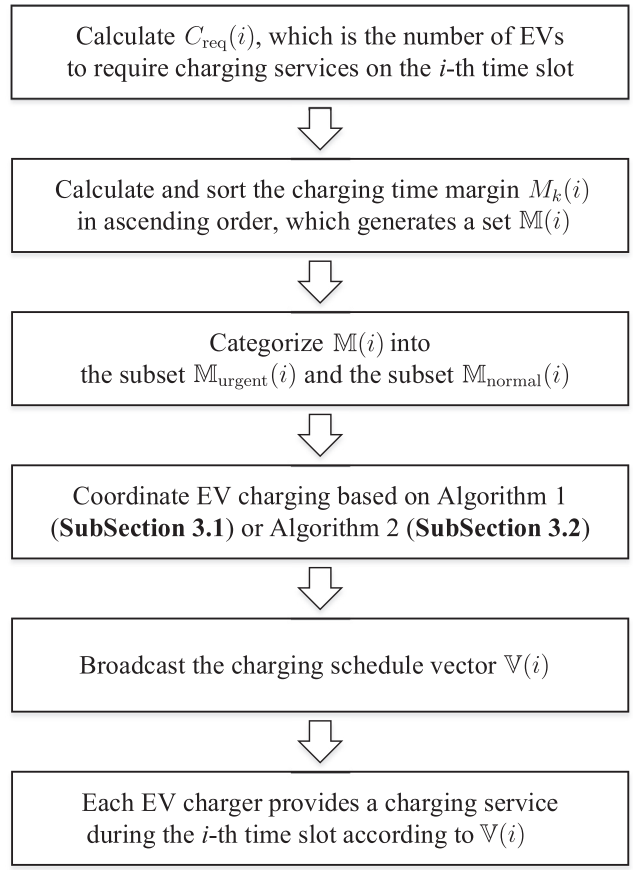


Fig. 2. A diagram to summarize the overall steps of the proposed apartment-level EV charging coordination scheme.

3.1. Peak load reduction mechanism with a flat electricity rate

In this subsection, we propose a peak load reduction mechanism to reduce or flatten the aggregated peak load of EVs with a flat electricity price. Here, the flat electricity price represents the same electricity price on every time slot. Let L_{contract} denote the contracted power capacity (kW) of the apartment complex and $L_{\text{normal}}(i)$ denote the predicted normal electricity load (kW) without EV loads on the i-th time slot [31–33]. Thus, we can obtain the time-varying charging capacity limit on the the i-th time slot as follows:

$$C_{\text{limit}}(i) = \left\lfloor \frac{L_{\text{contract}} - L_{\text{normal}}(i)}{\eta} \right\rfloor, \tag{3}$$

where $\lfloor \cdot \rfloor$ is the floor function, and η is the EV charging power rate.

Since the number of charging-scheduled EVs is limited by $C_{\text{limit}}(i)$ on the i-th time slot, the COC should effectively select EVs among $C_{\text{req}}(i)$ EVs that need to be charged on the i-th time slot. To this end, we can consider two cases with $|\mathbb{M}_{\text{urgent}}(i)| = U(i), |\mathbb{M}_{\text{normal}}(i)| = C_{\text{req}}(i) - U(i)$, and $C_{\text{limit}}(i)$ for the peak load reduction mechanism. If $U(i) \geqslant C_{\text{limit}}(i)$, i.e., the number of urgent EVs is greater than the charging capacity limit, the COC schedules only first $C_{\text{limit}}(i)$ EVs from $\mathbb{M}_{\text{urgent}}(i)$ and yields a set of charging-scheduled EVs, $\mathbb{S}(i) = \{\mathrm{ID}_1, \mathrm{ID}_2, \ldots, \mathrm{ID}_{C_{\text{limit}}(i)}\}$. On the other hand, if $U(i) < C_{\text{limit}}(i)$, i.e., the number of urgent EVs is smaller than the charging capacity limit, the COC schedules all $U(i)$ EVs from $\mathbb{M}_{\text{urgent}}(i)$ and first $(\min[C_{\text{limit}}(i), C_{\text{req}}(i)] - U(i))$ EVs from $\mathbb{M}_{\text{normal}}(i)$, and yields a set of charging-scheduled EVs,

$\mathbb{S}(i) = \left\{ \mathrm{ID}_1, \mathrm{ID}_2, \ldots, \mathrm{ID}_{\min\left[C_{\mathrm{limit}}(i), C_{\mathrm{req}}(i)\right]} \right\}$. Algorithm 1 summarizes this scheduling algorithm for peak load reduction.

Algorithm 1 EV charging scheduling algorithm for peak load reduction

Generate two subsets $\mathbb{M}_{\mathrm{urgent}}(i)$ and $\mathbb{M}_{\mathrm{normal}}(i)$.
Calculate $C_{\mathrm{limit}}(i)$ by Eq. (3)
if $U(i) \geqslant C_{\mathrm{limit}}(i)$
  Schedule first $C_{\mathrm{limit}}(i)$ EVs from $\mathbb{M}_{\mathrm{urgent}}(i)$
  $\mathbb{S}(i) = \{\mathrm{ID}_1, \mathrm{ID}_2, \ldots, \mathrm{ID}_{C_{\mathrm{limit}}(i)}\}$.
else
  Schedule all $U(i)$ EVs from $\mathbb{M}_{\mathrm{urgent}}(i)$
  Schedule first $\left(\min\left[C_{\mathrm{limit}}(i), C_{\mathrm{req}}(i)\right] - U(i)\right)$ EVs from $\mathbb{M}_{\mathrm{normal}}(i)$
  $\mathbb{S}(i) = \left\{ \mathrm{ID}_1, \mathrm{ID}_2, \ldots, \mathrm{ID}_{\min\left[C_{\mathrm{limit}}(i), C_{\mathrm{req}}(i)\right]} \right\}$.
end if

3.2. Charging payment minimization mechanism with a TOU electricity rate

In this subsection, we assume a TOU electricity price available in a power grid. The time-varying charging capacity limit on the i-th time slot $C_{\mathrm{limit}}(i)$ is calculated as Eq. (3). In the proposed charging payment minimization mechanism, urgent EVs in the subset $\mathbb{M}_{\mathrm{urgent}}(i)$ are always considered to be first charged on the i-th time slot. Thus, in case of $U(i) \geqslant C_{\mathrm{limit}}(i)$, the COC always schedules first $C_{\mathrm{limit}}(i)$ EVs from $\mathbb{M}_{\mathrm{urgent}}(i)$ and yields a set of charging-scheduled EVs, $\mathbb{S}(i) = \{\mathrm{ID}_1, \mathrm{ID}_2, \ldots, \mathrm{ID}_{C_{\mathrm{limit}}(i)}\}$. However, in case of $U(i) < C_{\mathrm{limit}}(i)$, the COC can optimally determine the number of charging-scheduled EVs $C(i)$ in a range of $U(i) \leqslant C(i) \leqslant \min\left[C_{\mathrm{req}}(i), C_{\mathrm{limit}}(i)\right]$ based on the TOU electricity price in order to minimize the total apartment-level charging payment. From the determined result of $C(i)$, the COC schedules charging for all $U(i)$ EVs from $\mathbb{M}_{\mathrm{urgent}}(i)$ and first $(C(i) - U(i))$ EVs from $\mathbb{M}_{\mathrm{normal}}(i)$, which yields $\mathbb{S}(i) = \{\mathrm{ID}_1, \mathrm{ID}_2, \ldots, \mathrm{ID}_{C(i)}\}$. For the EV scheduling algorithm, let us first define the predicted charging load profile on the future $(i+j)$-th time slot as:

$$\widehat{C}(i+j) \triangleq \sum_{k \in \left\{k \mid \left(i_k^{\mathrm{out}} - i\right) > 0, N_k(i) > 0\right\}} \mathrm{I}_{\left(N_k(i) + \mathrm{I}_{k \notin \mathbb{S}(i)}\right) > j}, \tag{4}$$

where $j \geqslant 1, \mathrm{I}_{\left(N_k(i) + \mathrm{I}_{k \notin \mathbb{S}(i)}\right) > j}$ is an indicator function to set to 1 if $\left(N_k(i) + \mathrm{I}_{k \notin \mathbb{S}(i)}\right) > j$, 0, otherwise, and $\mathrm{I}_{k \notin \mathbb{S}(i)}$ is an indicator function to set to 1 if $k \notin \mathbb{S}(i)$, 0, otherwise. Especially, $\mathrm{I}_{\left(N_k(i) + \mathrm{I}_{k \notin \mathbb{S}(i)}\right) > j}$ is used to determine whether the charging demand of the k-th EV continues until the future $(i+j)$-th time slot or not. In addition, $\widehat{C}(i+j)$ depends on the determined set of charging-scheduled EVs $\mathbb{S}(i)$ whose cardinality is $|\mathbb{S}(i)| = C(i)$. Using the predicted EV charging load profile $\widehat{C}(i+j)$, the predicted charging payment on the i-th time slot with a variable $C(i)$ is calculated as

$$\mathrm{Payment}(C(i)) = \sum_{j \geqslant 1} \$(i+j)\widehat{C}(i+j) + \$(i)C(i), \tag{5}$$

where $\$(i)$ denotes the TOU electricity price per EV on the i-th time slot. Consequently, Algorithm 2 summarizes the EV scheduling algorithm for minimizing total apartment-level charging payment. For each $C \in \left[U(i) + 1, \min\left[C_{\mathrm{req}}(i), C_{\mathrm{limit}}(i)\right]\right]$, the COC yields a set of charging-scheduled EVs $\mathbb{S}_C = \{\mathrm{ID}_1, \mathrm{ID}_2, \ldots, \mathrm{ID}_C\}$. According to $\mathbb{S}_C$, the COC calculates $\mathrm{Payment}(C)$ and obtains $\left\{\mathrm{Payment}(C) \mid C = U(i) + 1, \ldots, \min\left[C_{\mathrm{req}}(i), C_{\mathrm{limit}}(i)\right]\right\}$. Finally, the COC finds C^* with the lowest charging payment $\mathrm{Payment}(C^*)$ and determines $\mathbb{S}^*(i) = \mathbb{S}_{C^*}$, and then, the COC generates the charging schedule vector $\mathbb{V}(i)$ from $\mathbb{S}^*(i)$ for the i-th time slot. Especially, on the off-peak TOU period, the COC does not perform the charging payment minimization mechanism since, but the peak load reduction mechanism.

Algorithm 2 EV charging scheduling algorithm for minimizing total apartment-level charging payment

Generate two subsets $\mathbb{M}_{\mathrm{urgent}}(i)$ and $\mathbb{M}_{\mathrm{normal}}(i)$.
Calculate $C_{\mathrm{limit}}(i)$ by Eq. (3)
if $U(i) \geqslant C_{\mathrm{limit}}(i)$
  Schedule first $C_{\mathrm{limit}}(i)$ EVs from $\mathbb{M}_{\mathrm{urgent}}(i)$
  $\mathbb{S}^*(i) = \{\mathrm{ID}_1, \mathrm{ID}_2, \ldots, \mathrm{ID}_{C_{\mathrm{limit}}(i)}\}$
else
  for $C = U(i) + 1 : \min\left[C_{\mathrm{req}}(i), C_{\mathrm{limit}}(i)\right]$
    Schedule all $U(i)$ EVs from $\mathbb{M}_{\mathrm{urgent}}(i)$
    Schedule first $(C - U(i))$ EVs from $\mathbb{M}_{\mathrm{normal}}(i)$
    $\mathbb{S}_C = \{\mathrm{ID}_1, \mathrm{ID}_2, \ldots, \mathrm{ID}_C\}$
    $\widehat{C}(i+j) = \sum_{k \in \left\{k \mid \left(i_k^{\mathrm{out}} - i\right) > 0\right\}} \mathrm{I}_{\left(N_k(i) + \mathrm{I}_{k \in \mathbb{S}_C}\right) > j}$
    $\mathrm{Payment}\ (C) = \sum_{j \geqslant 1} \$(i+j)\widehat{C}(i+j) + \$(i)C$
  end for
  Obtain $\left\{\mathrm{Payment}(C) \mid C = U(i) + 1, \ldots, \min\left[C_{\mathrm{req}}(i), C_{\mathrm{limit}}(i)\right]\right\}$
  Find $C^* = \arg\min_C \mathrm{Payment}(C)$
  $\mathbb{S}^*(i) = \mathbb{S}_{C^*} = \{\mathrm{ID}_1, \mathrm{ID}_2, \ldots, \mathrm{ID}_{C^*}\}$
end if

4. Case studies

Table 1 lists the parameters utilized in case studies. We utilize a time slot interval of 15 min, which corresponds to $N_{\mathrm{slot}} = 4$ (slots per hour) [34]. $\mathcal{N}\left(a, b^2\right)$ denotes the normal (or Gaussian) distribution with a mean of a and a standard deviation of b. First of all, we assume that an apartment complex has total 1500 units, and each unit has approximately 1.33 cars [35]. Then, assuming an EV penetration rate of 50%, approximately 1000 EVs exist in the apartment complex. In addition, their arrival times at the EV chargers are distributed as shown in Fig. 3 [36]. Around 6 pm, it shows the highest number of EV arrivals. Low-, mid-, and high-charging priority levels are set to $\mu_{\mathrm{low}} = 0, \mu_{\mathrm{mid}} = 2N_{\mathrm{slot}}$, and $\mu_{\mathrm{high}} = 4N_{\mathrm{slot}}$, respectively, and EVs with $\mu_{\mathrm{low}}, \mu_{\mathrm{mid}}$, and μ_{high} are randomly selected with proportions of 20%, 60%, and 20%, respectively, among 1000 EVs.

Fig. 4 shows the normal load profile $L_{\mathrm{normal}}(i)$ [37] corresponding to the aggregated electricity loads from approximately 1500 house units in the apartment complex. We assume that this profile is estimated by a load estimation scheme with significantly high accuracy. It also shows the contracted power capacity L_{contract}, which is calculated by the fact that each of 1500 units uses 3 kW electricity on average [38], and a common electricity of 500 kW is reserved for elevators, lightnings, and so on. Thus, approximately 5000 kW (4500 W + 500 W) is set for the contracted power capacity in the apartment complex being considered. As described in Eq. (3), $L_{\mathrm{normal}}(i)$ and L_{contract} determine a time-varying charging capacity limit $C_{\mathrm{limit}}(i)$.

We evaluate the performance of the proposed apartment-level EV charging coordination scheme in terms of peak load reduction and apartment-level charging payment minimization, compared

Table 1
Simulation parameters and values.

Parameters	Values
Transformer capacity (L_{tx})	6000 kW
Contracted capacity ($L_{contract}$)	5000 kW
Total number of EVs (K)	1000
EV battery capacity (E_k)	20 ∼ 30 kWh
EV charging rate (r_k)	3.5 kW
SoC at the arrival (SoC_k^{in})	$\mathcal{N}\left(0.5, 0.2^2\right)$
Target SoC at the departure (SoC_k^{target})	1
# of time slots per hour (N_{slot})	4
# of sojourn time slots ($i_k^{in} - i_k^{out}$)	$N_{slot} \times \mathcal{N}\left(13, 3.8^2\right)$
Priority levels ($\mu_{low}, \mu_{mid}, \mu_{high}$)	$0, 2N_{slot}, 4N_{slot}$
EV proportions with $\mu_{low}, \mu_{mid}, \mu_{high}$	20%, 60%, 20%
Flat electricity price per kWh	$0.226

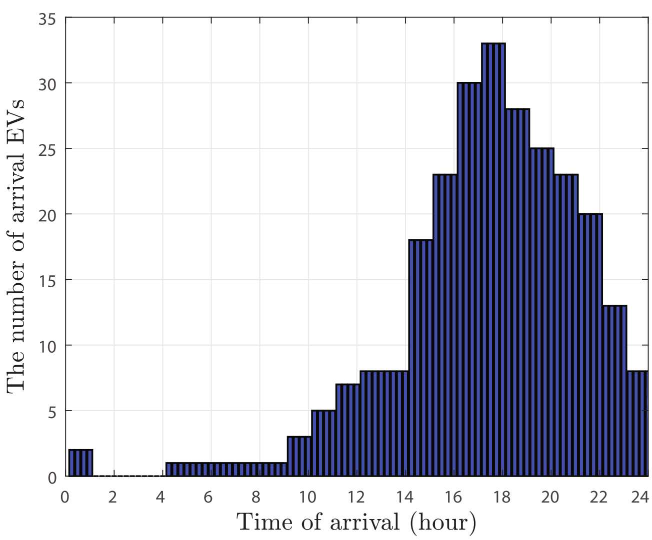


Fig. 3. The number of EV arrivals during a single day.

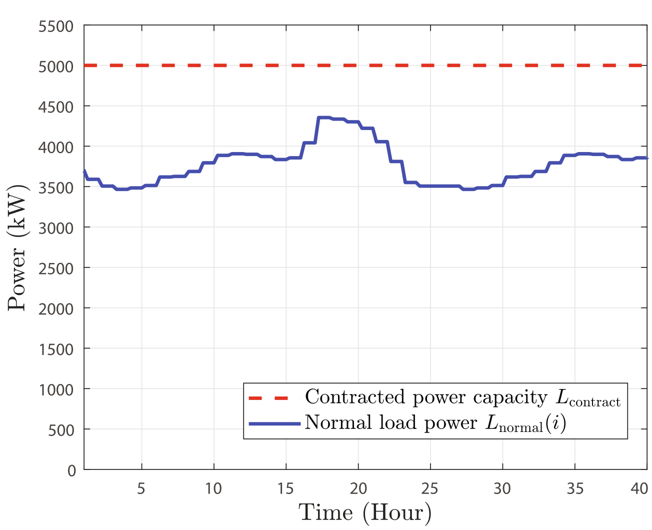


Fig. 4. Contracted power capacity and normal load power profile.

with those of two schemes: the first one is an '*as-soon-as-possible (ASAP)*' scheme, in which each EV is charged up to the required SoC level as soon as possible, and the second scheme is a '*random distribution*' scheme, in which the k-th EV charger randomly selects $N_k\left(i_k^{in}\right)$ time slots over $\left[i_k^{in}, i_k^{out}\right]$, and it charges the k-th EV on each of the selected time slots.

4.1. Charging coordination for peak load reduction with a flat electricity price

Fig. 5 shows the load profile of the proposed coordination scheme for an objective of peak load reduction with a contracted power capacity of $L_{contract} = 5000$ kW. Since the COC determines a set of charging-scheduled EVs $\mathbb{S}(i)$ on every time slot i, the proposed coordination scheme shows the perfect peak load reduction to satisfy the contracted power capacity. On the other hand, the ASAP scheme may not satisfy the contracted power capacity between 5 pm and 10 pm due to the uncoordinated EV charging load. Peak load is slightly over the contracted power capacity at 8 pm in the random distribution scheme, but, it shows the effect to satisfy the contracted power capacity by randomly distributing EV charging load.

For quantitative evaluation of the peak load reduction, we utilize a metric of peak-to-average power ratio (PAPR), which is measured by the proportion of the maximum aggregate load power to the average aggregate load power. Fig. 6 shows the PAPR of the proposed coordination scheme, compared with that of the other schemes as the contracted power capacity $L_{contract}$ increases. The PAPR value of the proposed scheme slightly increases as $L_{contract}$ increases, while the ASAP and random distribution schemes show fixed PAPR values of 1.41 and 1.23, respectively, since they do not control EV charging load according to the contracted power capacity. This result implies that the proposed coordination scheme is quite effective for reducing peak load level, compared to the other schemes.

In another way, we can estimate the number of EVs accommodated without exceeding contracted power capacity. As shown in Fig. 7, the proposed coordination scheme shows the significantly higher number of EVs accommodated without exceeding the contracted power capacity, compared to other schemes. With a contracted power capacity of 4550 kW, the proposed coordination scheme can accommodate all 1000 EVs in the apartment complex.

However, when the COC coordinates all 1000 EVs with a smaller contracted power capacity (e.g. 4400 kW–4500 kW), it may be more difficult to satisfy all of the SoC requirements of all 1000 EVs. To measure this dissatisfied SoC level, let us define the SoC dissatisfaction level of k-th EV as

$$\varphi_k \triangleq \mathrm{SoC}_k^{target} - \mathrm{SoC}_k^{out}, \tag{6}$$

where SoC_k^{target} and SoC_k^{out} represent the target SoC level ($0 \sim 1$) and the SoC level ($0 \sim 1$) at the departure of the k-th EV, respectively. It is worth noting that the PAPR and the SoC dissatisfaction level have a trade-off relationship with each other in the proposed coordination scheme. In other words, a smaller PAPR value may cause a larger SoC dissatisfaction level in the proposed scheme. On the other hand, in ASAP and random distribution schemes, even though they exceed the contracted power capacity with 1000 EVs, there is no SoC dissatisfaction since they allow to charge all EVs regardless of the contracted power capacity.

Fig. 8 shows the average SoC dissatisfaction level of all 1000 EVs of the proposed coordination scheme as the contracted power capacity $L_{contract}$ increases. The average SoC dissatisfaction level linearly decreases as $L_{contract}$ increases, and the proposed scheme achieves a zero SoC dissatisfaction level over $L_{contract} = 4550$ kW. For an $L_{contract}$ value of 4550 kW, the PAPR of the proposed scheme in Fig. 6 is 1.11, which is reduced by 0.30 and 0.12, compared with that of the ASAP scheme and the random distribution scheme, respectively. In addition, Fig. 7 shows that the proposed scheme can accommodate 1000 EVs, which is significantly higher than

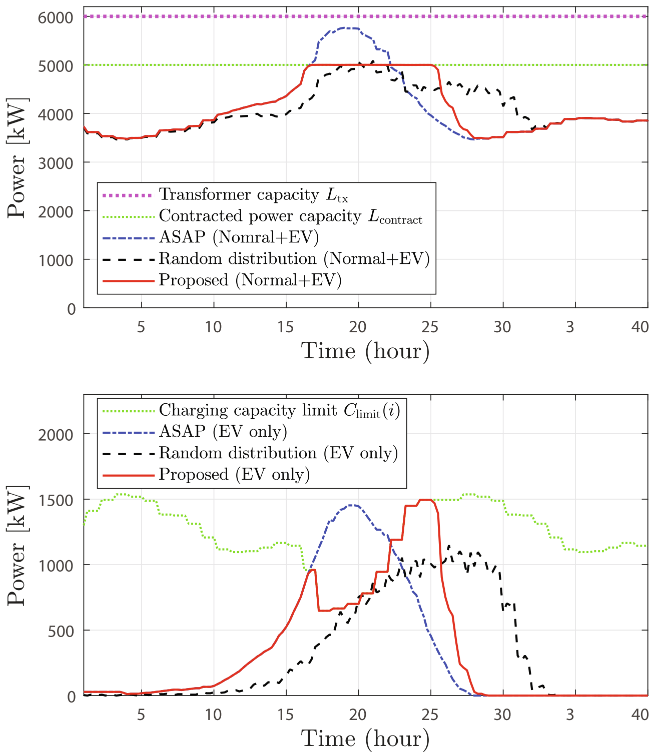


Fig. 5. Load profiles with the flat electricity price.

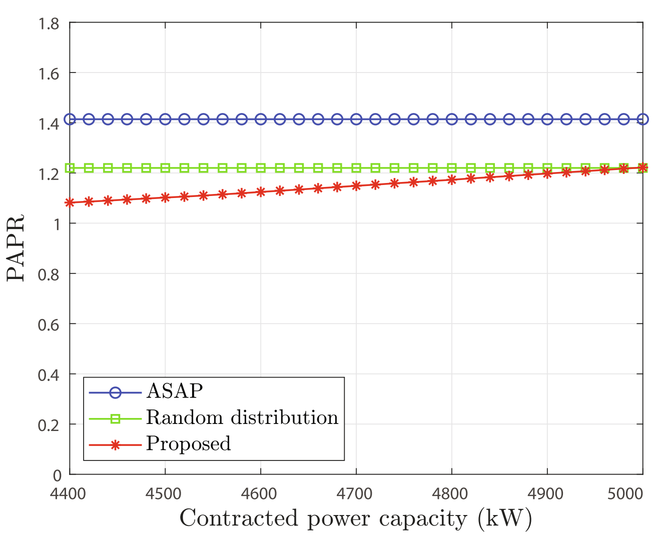


Fig. 6. Peak-to-average power ratio (PAPR) in the apartment complex.

120 and 240 EVs of the ASAP scheme and the random distribution scheme, respectively. On the other hand, in order to transform the SoC dissatisfaction level into the reduced driving range, we should consider a specific EV model. For example, Hyundai Ioniq electric car has a battery of 28 kWh, and the expected total driving range is 169 km [39]. For this EV model, approximately a driving range of 1.69 km is reduced by 1% SoC dissatisfaction level. In a general form, the reduced driving range of the *k*-th EV due to a degradation in the SoC dissatisfaction level is estimated as

$$D^k_{\text{reduced}} \triangleq \varphi_k \times T_k, \tag{7}$$

where φ_k and T_k denote the SoC dissatisfaction level ($0 \sim 1$) and the expected total driving range (km) of the *k*-th EV, respectively. Fig. 8 also shows the reduced driving range due to a degradation in the SoC dissatisfaction level. Here, we assume the expected total driving range is 169 km with a battery capacity of 25 kWh on average. Specifically, we can observe that an average SoC dissatisfaction of 4.65 % reduces the driving range by 7.86 km for a contracted power capacity of 4500 kW.

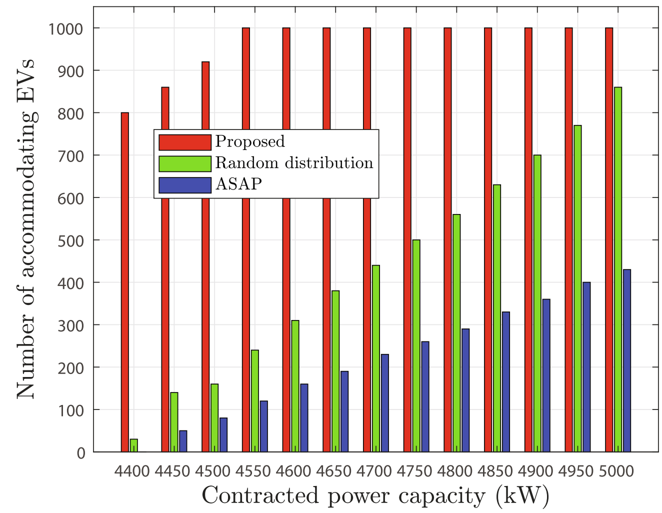


Fig. 7. Number of EVs accommodated without exceeding the contracted power capacity.

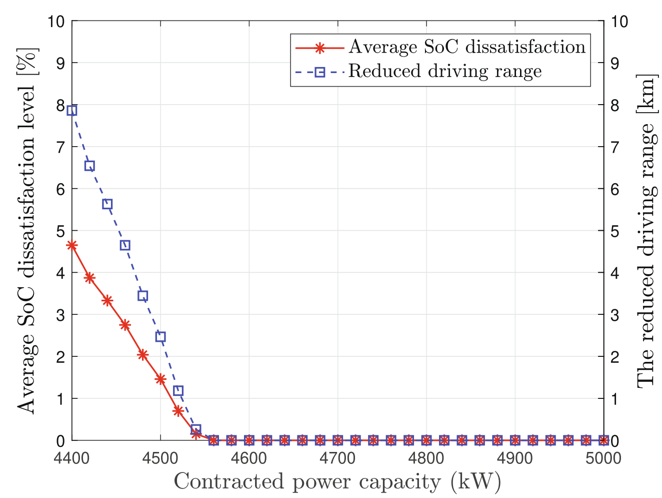
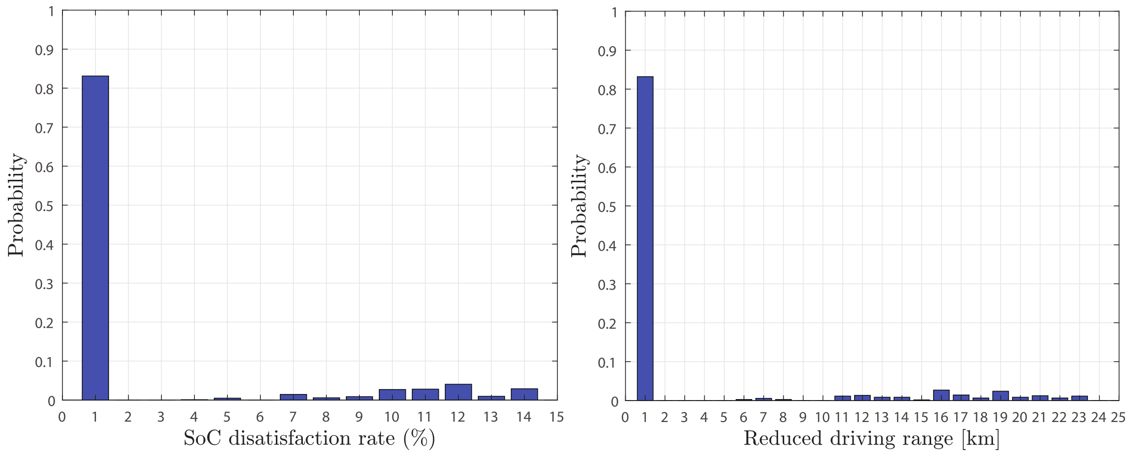


Fig. 8. Average SoC dissatisfaction level of all EVs and the reduced driving range for varying the contracted power capacity.

Fig. 9 (a) and (b) show the distribution of the SoC dissatisfaction levels and the distribution of the reduced driving ranges of all EVs, respectively, when $L_{\text{contract}} = 4500$ kW. The worst SoC dissatisfaction level is 14% (the reduced driving range: 23 km) with a probability of 0.025, but most of SoC dissatisfaction levels are lower than 1% (the reduced driving range: 1 km) with a probability of higher than 0.8. It is worth noting that contracted power capacity of $L_{\text{contract}} = 4500$ kW is a rather small value for the apartment complex being considered. Thus, in practice, $L_{\text{contract}} = 5000$ kw could be set in the apartment complex being considered, which does not cause any SoC dissatisfaction or reduce the driving range. If any SoC dissatisfaction level is caused by the charging coordination, the COC may provide EV with the remaining (incomplete) charging time slots ($R_k > 0$) for some compensation in charging payment.



(a) Distribution of SoC dissatisfaction levels.

(b) Distribution of the reduced driving ranges.

Fig. 9. Distribution of SoC dissatisfaction levels and distribution of the reduced driving ranges when $L_{\text{contract}} = 4500$ kW.

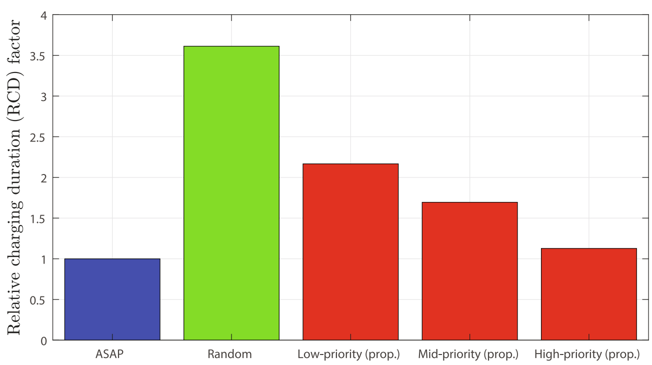


Fig. 10. Average relative charging duration (RCD) factor values under the flat electricity rate.

Table 2
Time-of-use (TOU) electricity price.

Price ($/kWh)	Time
$0.428	14:00 ~ 21:00
$0.226	07:00 ~ 14:00 and 21:00 ~ 23:00
$0.099	23:00 ~ 07:00

Next, let us define a relative charging duration (RCD) factor in order to measure how fast each EV charging is done. The RCD factor of the k-th EV is defined as follows:

$$\tau_k \triangleq \frac{i_k^{\text{comp.}} - i_k^{\text{in}}}{N_k\left(i_k^{\text{in}}\right)}, \tag{8}$$

where $i_k^{\text{in}}, i_k^{\text{comp.}}$, and $N_k\left(i_k^{\text{in}}\right)$ denote the arrival time slot, the charging completion time slot, and the required number of charging time slots at the arrival, respectively.

Fig. 10 shows the average RCD factor of three priority groups in the proposed coordination scheme, compared with the other schemes. The ASAP scheme shows an average RCD factor of 1, and the average RCD factor of the random distribution scheme is the highest value of 3.61. In the proposed coordination scheme, from the low-priority group to the high-priority group, the average RCD factor decreases. Especially, the high-priority group achieves an average RCD factor of approximately 1.13, which implies that the EVs belonging to the high-priority group can complete their charging services 1.13 times slower than the ASAP scheme, and the mid- and low-priority groups achieve average RCD factor of 1.70 and 2.17, which implies that the charging completion times of EVs in the mid- and low-priority groups are longer delayed for more active participation in the charging coordination.

4.2. Charging coordination for minimizing the total apartment-level charging payment with a TOU electricity rate

In this case, we utilize the same parameter values in Table 1 and the same EV arrival distribution in SubSection 4.1. In addition to those, Table 2 lists the TOU electricity price [40]. It is classified into three different periods: peak load period, mid-load period, and off-

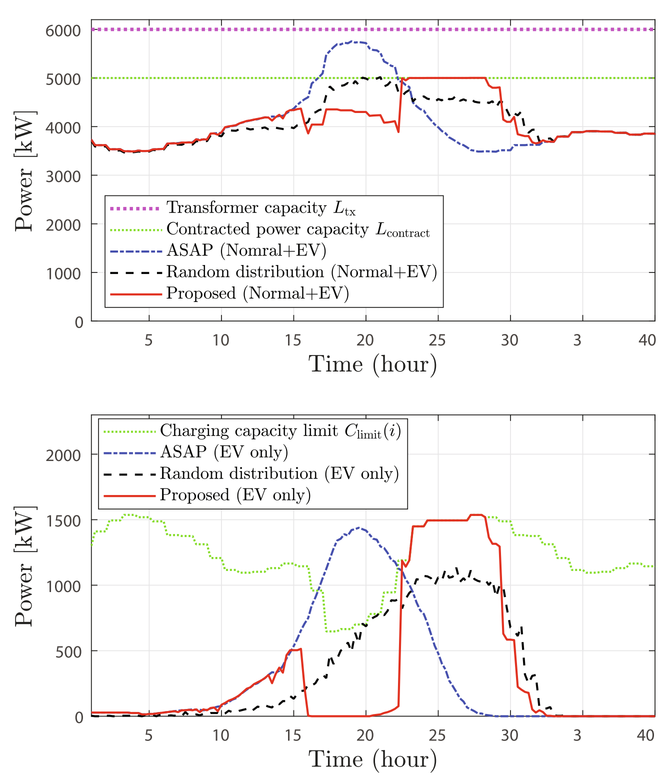


Fig. 11. Load profiles under the TOU electricity rate.

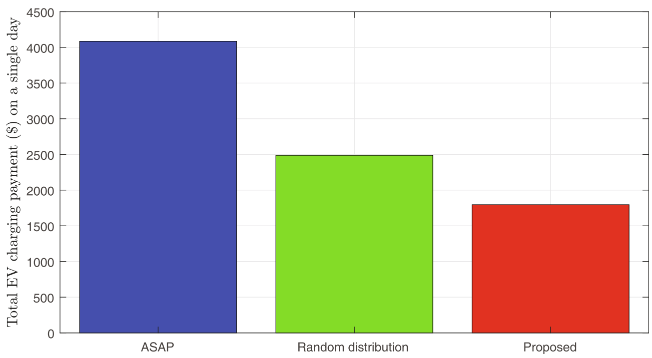


Fig. 12. Per-day total EV charging payment in the apartment complex.

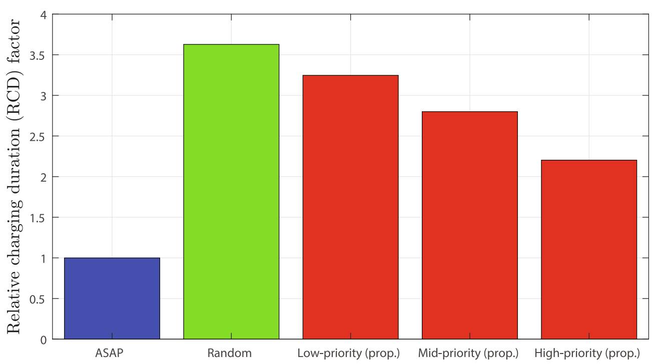


Fig. 13. Average relative charging duration (RCD) factor values under the TOU rate.

peak load period. We evaluate the performance of the proposed EV charging coordination mechanism in terms of the total apartment-level charging payment.

Fig. 11 shows the load profile of the proposed apartment-level EV charging coordination scheme for minimizing the total charging payment under the TOU electricity price. The proposed coordination scheme significantly restricts EV charging load during the peak load period ($16:00 \sim 21:00$) in order to minimize the total EV charging payment, and the restricted EV charging load is shifted to the mid-load period and the off-peak load period.

Fig. 12 compares the per-day total apartment-level charging payment, which is the result from the EV load profile in Fig. 11. The total charging payment of the proposed scheme amounts to be $1796 with the SoC dissatisfaction level of 0%. This result shows that the proposed coordination scheme can save approximately $2290 and $692 on a single day, compared to those of the ASAP scheme and the random distribution scheme, respectively.

Fig. 13 shows the average RCD factor of three priority groups in the proposed coordination scheme for minimizing the charging payment, compared with those of the other schemes. The ASAP and random distribution schemes show the same average RCD factor values as the cases with the flat electricity rate. However, the RCD factor of the high-, mid-, and low-priority groups of the proposed coordination scheme with TOU electricity price increase by 195%, 165%, and 150%, respectively, compared with the RCD factor values with the flat electricity rate in Fig. 10,

5. Conclusion

In this paper, we proposed an apartment-level EV charging coordination scheme, in which the charging operation center (COC) effectively coordinates a large group of EVs in an apartment complex. As case studies, we showed the advantages of the proposed EV charging coordination scheme in terms of peak load reduction and apartment-level charging payment minimization. As a result, the proposed EV charging coordination system can be used to manage an apartment-level power grid more stable, and EV owners in this apartment complex can obtain more economic benefits by participating in the EV charging coordination.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, athttps://doi.org/10.1016/j.enbuild.2020.110155.

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