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Electric Vehicle Recharging Allocation Problem with Electricity Price Fluctuation using Decomposition Approach

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ABSTRACT

The usage of electric vehicles (EVs) is widely considered because of their contribution to environmental preservation. In an EV system, each EV must undergo recharging after use to ensure its battery has sufficient capacity for subsequent trips. This study examines an EV recharging problem, focusing on the allocation of EVs to be recharged at some stations. The primary objective is to minimize the overall electricity costs associated with recharging. The variation in electricity prices at each station plays an important role in influencing the selection of recharging stations. The problem is formulated mathematically in the form of integer programming. A decomposition-based method is proposed for solving larger-sized instances, and then various data sets are solved to test the applicability of the proposed solution methods. The results show that the performance gap is, in average, 7.02% using decomposition method in comparison to the integer programming. This study addresses a specific problem to obtain a solution within a short computational time.

Keywords: Electric Vehicle, Recharging, Mathematical Model, Electricity Price Fluctuation

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1. INTRODUCTION

Electric vehicle (EV) systems have been deployed in various countries due to the crucial role in addressing climate changes while reducing nonrenewable fuel source dependency worldwide. By 2024, the majority of Japanese and Westerners will have chosen to utilize electric vehicles for public transportation, including cars and buses (Da Silva *et al.*, 2020). Despite having the benefit of being environmentally friendly, it is necessary to ensure that EVs are recharged appropriately during their operations (Agrali and Lee, 2023).

In the context of sustainable mobility, the Electric Vehicle Recharging Allocation Problem assumes great importance, especially when combined with the dynamic environment of electricity price variations. The electricity price variations can be seen in three different perspectives: real-time electricity price (Zhou *et al.*, 2020; Yu *et al.*, 2020), time-of-use tariff (Gong *et al.*, 2020; Zheng *et al.*, 2020), and dynamic electricity price (Fang *et al.*, 2021; Dante *et al.*, 2022). The dynamic electricity pricing is more flexible than the time-of-use tariff and can guarantee appropriate overall scheduling when compared to the real-time power price.

There are numerous research works on dynamic electricity pricing for EV recharging allocation problem due to its benefits. Lai *et al.* (2023) presented a dynamic pricing model with competitive effects that accomplishes the goals of protecting aggregator interests and balancing grid load and traffic congestion. Nevertheless, the technique of dynamic electricity price fixing fails to include the stochastic nature of electric vehicles and so it cannot provide overall optimality. Integrating a large number of various EVs has a number of negative impacts, including peak load control, reactive power injection, frequency disruption, and voltage fluctuation (Mahfouz and Iravani, 2020). Dynamic pricing makes it possible to schedule EV charging, set variable rates for charging, and profit from extra energy by feeding it back into the grid. Furthermore, a number of characteristics have also been suggested for the fast-charging scheduling, including EV arrival time, energy availability, battery full charging capacity, and departure time in relation to traffic and customer behavior. An EV should charge during a period of low electricity market price and discharge to the grid during a period of high electricity market price to implement a dynamic pricing system. As a result, there is a contradiction when it comes to charging and discharging EVs when prices are high or low.

The transportation mode that contributes mainly the emissions of roadside pollutants and greenhouse gases is taxi. Electrifying the taxi fleet is an effective solution strategy (Zhou *et al.*, 2021). Many cities around the world have utilized electric taxis, such as in New York City in USA (Hu *et al.*, 2018), Tokyo in Japan (Palmer *et al.*, 2018), Stockholm in Sweden (Hagman and Langbroek, 2019), Seoul in South Korea (Kang and Lee, 2019), and Beijing (Zhou *et al.*, 2021) and Shenzhen in China (Zhang and Zhao, 2018). Parking lots and charging stations are two crucial aspects that affect how comfortable drivers are using electric cars (Wolbertus *et al.*, 2018). In addition, taxi drivers' working hours and daily earnings are significantly impacted by charging times (Zhang *et al.*, 2020). Despite the negative consequences of charging times for electric taxis, the government of Sweden has implemented laws that can offset these costs, allowing electric taxi drivers to earn more money (Hagman and Langbroek, 2019).

1.1 Research Status

EV charging stations and related equipment can be broadly categorized into two groups as of 2020. The first division is level 1-2, which uses alternating current and may be utilized for up to 150 miles. It takes 3-5 hours to fully charge. The second category consists of level 3-5 cars, which can travel up to 200 miles and require 1-2 hours and 15-45 minutes, respectively, to fully charge. Direct Current Fast Chargers (DCFC) are used by Tesla, Hyundai, and Tata Motors for level 3 and 4 divisions electric vehicle charging.

It has been observed that numerous private businesses, like Echo, Tesla, KIA, ChargePoint, etc., are developing their infrastructure in order to install ultra-fast charging stations. To find a charging station, many businesses have provided maps of charging stations. As of June 2016, there were around 43,000 charging stations in the US. Even though there are more charging stations available, range anxiety is still a significant issue when it comes to EV scheduling (Liu and Liang, 2021).

There are some previous works dealing with recharging cost reduction with considerations such as peak reduction of electricity grid load (Ren *et al.*, 2023), uncertainty on demand and charging time (Liang *et al.*, 2023), and idle rate (Zhong *et al.*, 2023). Some works emphasized a specific EV such as logistics fleet (Deng *et al.*, 2022) or even the recharging type such as smart grid (Lin *et al.*, 2021). While those works have similarity with our works in terms of dynamic electricity prices, there is none of the works focusing on taxi. One of the most similar works with this study is Aljafari *et al.* (2023). It considered minimum waiting time for the scheduling using Markov decision process. Even though it observed queues of EVs at recharging stations, it limits the real-time issues on which the queues may exceed the number of available slots at the EV recharging stations. To the best of our knowledge, there are none of previous studies which attempt to consecutively consider dynamic electricity prices along with real-time capacity of EV recharging stations. The summary of the latest works on EV recharging allocation problem, contrasted to the proposed method is shown at Table 1.

Previous studies on electric vehicle recharging used decomposition approaches. Bruglieri *et al.* (2018) produced alternatives of worker routes and schedules for the EV relocations in the first phase and then found non-dominated solutions in the second phase. Wang and Thompson (2019) solved the EV admission problem in the first phase, then schedule the EV recharging in the second phase. Wu and Sioshansi (2017) discussed an EV recharging problem at one station in the first phase and then dealt with uncertain parameters in the second phase. All of these studies show the effectiveness of the decomposition method to solve EV recharging problems. These studies differ from our study because they solve different EV recharging problems.

1.2 Paper Contribution

Referring to the above problems, this study discusses a problem of determining the location and schedule for recharging EVs that considers real problem situations, e.g., electricity price fluctuation (Mahyari *et al.*, 2023), a limited available number of recharging slots, and different remaining EV battery levels (Singgih and Kim, 2020). An existing work focused on one dataset with an integer programming that solely solved the NP-hard optimization problem using a complex mathematical model that requires a long computational time (Singgih *et al.*, 2023).

Decomposition-based algorithms have been successfully applied to solve NP-hard optimization problem (Beheshti Asl *et al.*, 2022; Arslan and Detienne, 2022). For this reason, this study proposes two-phase decomposition approach to handle NP-hard optimization problems. To show the effectiveness and the efficiency of the proposed approach, extensive experiments are performed with various datasets. The experiments have been conducted by looking at schedules which are generated in real-time, considering a short look-ahead period. This EV recharging problem is faced by the taxi operating companies that use EVs and EV rental operators.

Different from Aljafari *et al.* (2023), who considered queues of EVs at recharging stations, this study solves the EV recharging allocation problem in a more real-time fashion by ensuring that the number EVs does not exceed the number of available slots at the EV recharging stations.

The structure of this study is as follows. Section 2 defines the problem considered in this study. Section 3 provides the mathematical model for the problem. Section 4 explains the proposed decomposition algorithm. Section 5 shows the numerical experiment results. Section 6 concludes the study.

2. PROBLEM DEFINITION

This study considers a complete graph with a number of EV stations, a number of EVs, and a planning horizon (consisting of a set of time slots). Each EV *e* requires a certain number of time slots to recharge its battery level to allow its use by the next customers. Each EV *e* is located at its initial station, the ending station of its previous use, and can be recharged at any EV station. When an EV is recharged at a station that is different from its initial station, the EV must be transported first during a predefined transportation time. The EV cannot be recharged before it arrives at its recharging station. Also, the EV recharging must be completed before the planning horizon. Each recharging station has its own electricity price fluctuation, which highly depends on the behavior of the people living in the area, e.g., the electricity price is higher during working hours in the area with many companies, and the price is higher during the night in the residential area. Setting a high electricity price during the electricity usage peak-hour times is common to influence people to shift their electricity use from those peak-hour times. The recharging duration for each EV must satisfy its required recharging time slots; however, the EV recharging decisions must minimize the total required recharging costs when possible. Each recharging station has a number of available recharging slots, which limits the number of EVs that can be recharged at the station.

The assumptions used in this study are:

1. The transportation resources required for transporting the EVs between stations are sufficient and not discussed in this study.
2. The recharging speeds at all EV stations are the same.
3. The EV recharging decisions are made in real-time, any time necessary. Therefore, the study only considers one look-ahead EV recharging process

Table 1. Differences between this study and previous studies

Study	Decisions	Objective
Ren *et al.* (2023)	EV recharging cost	Minimizing total recharging costs and recharging load fluctuation
Liang *et al.* (2023)	EV recharging cost	Minimizing total recharging costs for all users
Zhong *et al.* (2023)	EV charging decisions based on their battery levels	Minimizing total costs for the EVs to travel to the recharging stations, the total queuing costs, and the total recharging costs
Deng *et al.* (2022)	EV routing and recharging schedule	Minimizing total EV energy consumption
Lin *et al.* (2021)	EV recharging cost	Minimizing recharging load fluctuation and maximizing total profits for the EV company
Aljafari *et al.* (2023)	Allocations of EVs to recharging stations (allowing queues at recharging stations)	Minimizing the total EV recharging costs
Our study	Allocations of EVs to recharging stations (exact number EVs to be allocated based on the number of available recharging slots)	Minimizing the total EV recharging costs

for each EV.

The EV recharging problem is stated as follows:
1. Input (given parameters):
   a. A set of EVs to be recharged. Each EV's initial position and required recharging time slots are given.
   b. A set of EV recharging stations. Each station has its remaining recharging slots and time-dependent electricity price information.
   c. The required time to transport an EV from any pair of recharging stations.
2. Output (decisions):
   a. Allocation of each EV to a recharging station.
   b. The first and last time slots when each EV is recharged at its recharging station.
3. Objective:
The total costs required to recharge all EVs.

3. MATHEMATICAL MODEL

In this section, the mathematical model of EV recharging mechanism under dynamic electricity prices with limited number of recharging slots is described in detail. The first subsection describes the overall mathematical model. In addition, we propose two-phase decomposition to solve the computational complexity of the firstly proposed mathematical model.

3.1 Mathematical Model for The Electric Vehicle Recharging Problem

The math models account for the EV for vehicle capacity, battery capacity, charging time, time-dependent electricity prices, and the number of available recharging slots in the system. The mathematical model is presented as follows.

Sets
- E : Set of electric vehicles to recharge (e = 1, 2, …, $|E|$)
- E : Set of recharging stations (s = 1, 2, …, $|S|$)
- T : Set of time slots (each time slot could refer to 30 minutes, 1 hour, etc.) (t = 1, 2, …, $|T|$)

Parameters
- C_{st} : Recharging cost per time slot at station s during time slot t
- D_{su} : Required EV transportation time from station s to station u
- O_e : Station where EV e is initially located
- P_s : Number of available recharging slots at station s
- R_e : Number of required time slots to recharge EV e and reach its minimum battery level

Decision variables
- w_e : The first time slot during when EV e is recharged at a station
- x_{est} : 1, if EV e is recharged at station s during time slot t; otherwise, 0
- y_{es} : 1, if EV e is recharged at station s; otherwise, 0
- z_e : The last time slot during when EV e is recharged at a station

$$\min z = \sum_e \sum_s \sum_t x_{est} C_{st} \tag{1}$$

$$x_{est} \le y_{es} \qquad \forall e \in E,\ s \in S, t \in T \tag{2}$$

$$\sum_s y_{es} = 1 \qquad \forall e \in E \tag{3}$$

$$\sum_e x_{est} \le P_s \qquad \forall s \in S, t \in T \tag{4}$$

$$x_{est} = 0 \qquad \forall e \in E, s \in S, t \in \{1,2,\ldots,D_{O_e s}\} \tag{5}$$

$$z_e \le |T| \qquad \forall e \in E \tag{6}$$

$$w_e \le |T|(1 - x_{est}) + t x_{est} \quad \forall e \in E, s \in S\ t \in T \tag{7}$$

$$z_e \ge t x_{est} \qquad \forall e \in E, s \in S\ t \in T \tag{8}$$

$$z_e - w_e + 1 = R_e \quad \forall e \in E \tag{9}$$

$$\sum_s \sum_t x_{est} = R_e \qquad \forall e \in E \tag{10}$$

$$x_{est} = \{0,1\} \qquad \forall e \in E, s \in S\ t \in T \tag{11}$$

Objective (1) minimizes the total costs required to recharge all EVs, considering the electricity price fluctuation and the EV recharging decisions (during which time slots and at which EV recharging station). Constraints (2) and (3) guarantee that each EV e is recharged at a station s. Constraints (4) limit the number of recharged EVs with the number of available recharging slots at station s. Constraints (5) do not allow EV e to be recharged at station s if it cannot be transported and arrive at the station on time slot t. Constraints (6) restrict EV e to not be recharged if the recharging cannot be completed before the time horizon ends. Constraints (7) and (8) define the time slot when EV e starts and finishes its recharging, respectively. Constraints (9) and (10) ensure that EV e is recharged as long as its required time slots. Constraints (11) are binary constraints.

3.2 Mathematical Model for The Two-Phase Decomposition Approach

Since the above problem is computationally complex, it is solved in a two-phase decomposition method that deals with a mathematical model for each subproblem. The first subproblem is a variant of the knapsack problem, in which the EVs are classified into recharging stations while minimizing the estimated total recharging costs.

The second sub-problem determines the EV recharging schedule at each station separately. This decomposition method is contrasted with the simultaneous allocation and recharging scheduling problem, as shown in Figure 1.

The decomposition-based method is conducted based on Algorithm 1. In Algorithm 1, the value of α is set equal to 0.1.

Algorithm 1

1 : For each station s, set an initial percentage of available recharging time slots (of the total available time), $\theta_s = 100\%$.

2 : Solve the EV allocation model (Submodel 1) and obtain the EV allocations to the recharging stations.

3 : Given the EV allocation results, for each station s, solve the EV recharging scheduling model (Submodel 2) and observe whether a feasible schedule can be obtained at each station with EV allocations. If the recharging scheduling at any station is infeasible, go to Step 4. Otherwise, obtain the EV recharging schedules and stop.

4 : For each station s on which no feasible solution could be found, reduce the θ_s value by a percentage of available recharging time (α), go to Step 2.

In this first subproblem (Submodel 1), EVs are allocated to the stations. The EVs can be allocated to a station if the total required EV recharging times is less than the total available recharging time slots at all recharging slots in the station. Because the allocation of EVs to the stations is based on the total times, the EV recharging might be infeasible at one or more slots of a station (e.g. station s). To deal with such infeasibility, less number of EVs are allocated to such station s by reducing the available recharging time slots (θ_s) when necessary until any feasible recharging schedule can be generated.

Mathematical model, additional sets, parameters, and decision variables for the first EV allocation subproblem are described as follows (the unexplained sets, parameters, and decision variables have been presented with the previous mathematical model in Section 3.1):

Sets

G_s : Set of available recharging slots at station s ($g = 1, 2, \ldots, |G_s|$)

K : Set of possible consecutive time slots used for recharging EVs ($k = 1, 2, \ldots, |K|$)

Parameters

A_{ks} : Total recharging costs when k simultaneous time slots are required at station s

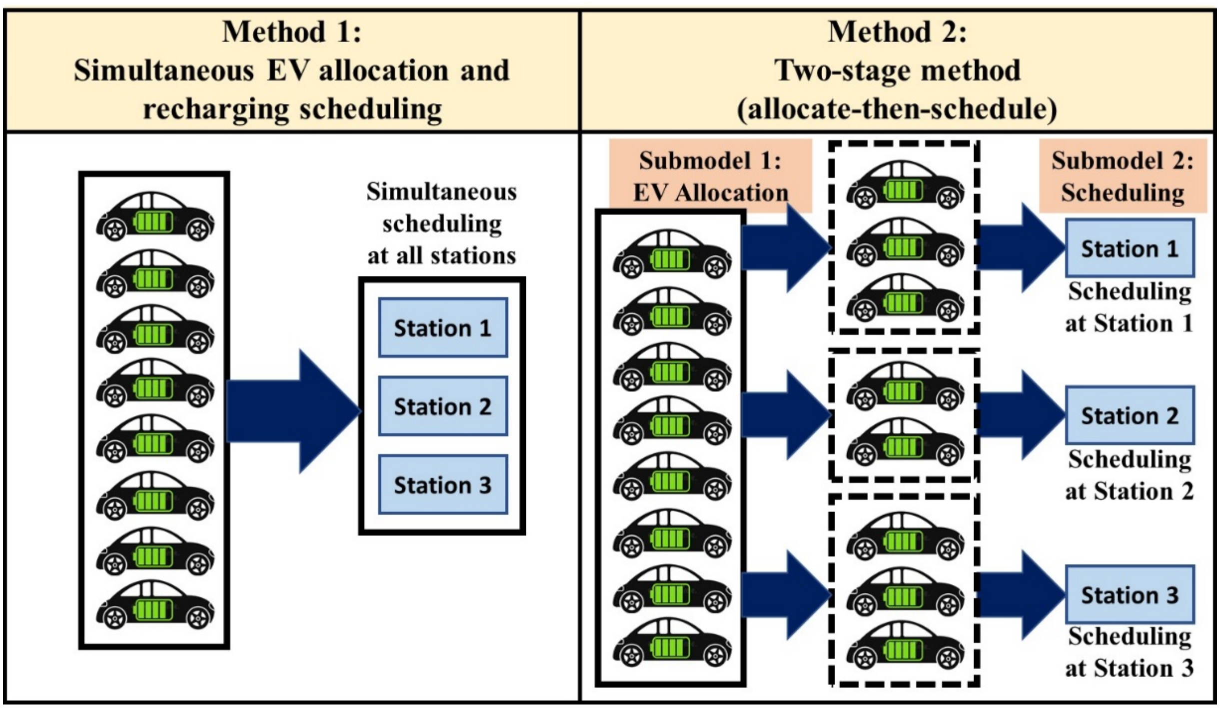

Figure 1. Comparison between the simultaneous model (Method 1) and the decomposition method (Method 2).

θ_s : Percentage of available recharging time slots for station s

Decision variables

q_s : 1, if recharging station s is used; otherwise, 0

v_{kgs} : 1, if k time slots are required when recharging EVs at recharging slot g of station s; otherwise, 0

$$minz = \sum_k \sum_g \sum_s A_{ks} v_{kgs} \tag{12}$$

$$\sum_s y_{es} = 1 \quad \forall e \in E \tag{13}$$

$$y_{es} \le q_s \quad \forall e \in E, s \in S \tag{14}$$

$$\sum_k v_{kgs} \le 1 \quad \forall s \in S, g \in G_s \tag{15}$$

$$\sum_e R_e y_{es} \le \sum_k \sum_g \theta_k k v_{kgs} + |T| P_s (1 - q_s) \quad \forall s \in S \tag{16}$$

$$\sum_e R_e y_{es} \ge \sum_k \sum_g \theta_k k v_{kgs} - |T| P_s (1 - q_s) \quad \forall s \in S \tag{17}$$

$$\sum_k \sum_g v_{kgs} \le \sum_e y_{es} \quad \forall s \in S \tag{18}$$

$$q_s, v_{kgs}, y_{es} = \{0,1\} \quad \forall e \in E, k \in K, s \in S, g \in G_s \tag{19}$$

Objective (12) minimizes the estimated total costs required to recharge all EVs based on their selected stations. Please note that each recharging slot is located at a station. In this subproblem, it is assumed that the EVs are recharged consecutively at their recharging slots, to reduce the complexity of the model. Constraints (13) guarantee that each EV e is recharged at a recharging slot g. Constraints (14)–(17) observe the number of time slots required to recharge the EVs allocated to each recharging slot g. The range defined for the total number of recharging slots ensures that the only feasible recharging schedules are generated. Constraints (18) ensure that the number of accumulated time slot sets does not exceed the number of EVs recharged at each station. Constraints (18) encourage a more appropriate recharging cost estimation. Constraints (19) are binary constraints. This first subproblem ignores the required times for the EVs to be transported from their origin stations.

The mathematical model for the second subproblem (Submodel 2) utilizes the information of EV allocation to the recharging stations and is formulated as follows:

Sets

E^s : Set of allocated electric vehicles to the station ($e = 1, 2, \ldots, |E|$)

T : Set of time slots (each time slot could refer to 30 minutes, 1 hour, etc.) ($t = 1, 2, \ldots, |T|$)

Parameters

C_t^s : Recharging cost per time slot at the station during time slot t

P^s : Number of available recharging slots at the station

R_e : Number of required time slots to recharge EV e and reach its minimum battery level

Decision variables

w_e : The first time slot during when EV e is recharged at the station

x_{et}^s : 1, if EV e is recharged at the station during time slot t; otherwise, 0

z_e : The last time slot during when EV e is recharged at the station

$$minz = \sum_e \sum_t x_{et}^s C_t^s \tag{20}$$

$$\sum_e x_{et}^s \le P^s \quad \forall t \in T \tag{21}$$

$$x_{et}^s = 0 \quad \forall e \in E,\ t \in \{1, 2, \ldots, D_{O_e s}\} \tag{22}$$

$$z_e \le |T| \quad \forall e \in E \tag{23}$$

$$w_e \le |T| \left(1 - x_{et}^s\right) + t x_{et}^s \quad \forall e \in E, t \in T \tag{24}$$

$$z_e \ge t x_{et}^s \quad \forall e \in E, t \in T \tag{25}$$

$$z_e - w_e + 1 = R_e \quad \forall e \in E \tag{26}$$

$$\sum_t x_{et}^s = R_e \quad \forall e \in E \tag{27}$$

$$x_{et}^s = \{0,1\} \quad \forall e \in E, t \in T \tag{28}$$

Objective (20) minimizes the total costs required to recharge all EVs, considering the electricity price fluctuation and the EV recharging decisions (during which time slots at the specified EV recharging station). Constraints (21) limit the number of recharged EVs with the number of available recharging slots at the station. Constraints (22) do not allow EV e to be recharged at the station if it cannot be transported and arrive at the station on time slot t. Constraints (23) restrict EV e to be recharged at the station at time slot t if the recharging cannot be completed before the time horizon ends. Constraints (24) and (25) define the time slot when EV e starts and finishes its recharging, respectively. Constraints (26) and (27) ensure that EV e is recharged as long as its required time slots.

Constraints (28) are binary constraints.

4. NUMERICAL EXPERIMENTS

The mathematical model for this study is written in Python on a Visual Studio Community 2022 platform. The models are solved using GUROBI 9.5.2. The computation environment is an 8192MB RAM Intel(R) Core (TM) i7-5500U CPU at 2.40GHz (4 CPUs). To test the model, twenty instances are generated with the characteristics shown in Tables 2 and 3 (please refer to the explanations of the parameters in Section 3). Area width is used to define a square area, on which the depot and customers are located. The width is measured by the time required to travel it. Travel time required between any pair of nodes would be defined based on the depot and customer locations. The instances are generated while ensuring the expected station utilization is around 0.4 to 0.8. The value is below one to allow the possibility of obtaining feasible solutions. Meanwhile, the value is not too low to avoid recharging all EVs in a single station and allow a more proper evaluation of the proposed method by distributing the EVs among stations. The data are accessible at https://ubaya.id/evrecharging_pricefluctuation. The results are shown in Table 4. When generating the required transportation time, the triangular inequality requirement between each set of three stations is preserved. The presolving heuristic is activated in GUROBI.

Table 4 shows the effectiveness of the proposed decomposition method, which obtains less than 10% difference in the objective value when compared with the best solution of the simultaneous model. When solving the larger instances (instances 11–20), the proposed decomposition method obtains good solutions within a short computational time, while in most instances the simultaneous model could not obtain any feasible solution.

An example of the results is presented using Instance 1 in Figures 2 and 3. Figure 2 shows that some EVs are recharged at their initial stations, but some are transported to other stations, which have less recharging costs, without violating the required transportation time before starting the recharging process. The recharging schedule of the EVs is shown in Figure 3. In Figure 3, the available recharging slots are presented as well. It can be seen that the number of recharged EVs at each station and time slot does not exceed the available number of recharging slots.

In Instance 1, the average recharging cost per time slot in Station 1, 2, 3, 4, and 5 are 56.8, 39, 35.4, 51.5, and 60, respectively. Based on the average recharging cost per time slot, most EVs must be recharged to Stations 2 and 3. Such results are represented well in Figure 3 that shows that almost all time slots at Stations 2 and 3 are used for the recharging. Given the remaining stations (Stations 1, 4, and 5), most EVs are recharged at consecutive time slots on those stations that cost the least among all remaining possible time slots at all stations. The consecutive time slots with the least cost among the remaining ones are time slots 11-15 and 18-24 at Station 1, and time slots 20-24 at Station 5. Such results prove the quality of the proposed method.

Table 2. Value ranges of parameters in the data sets

Parameter	Range of values
C_{st}	[1,100] cost unit
area width	10 time slots
P_s	[2,4] recharging slots
R_e	[5,9] time slots
O_e	[1,number of stations]

Table 3. Characteristics of each data set

Instances	# of electric vehicles	# of recharging stations	# of time slots	Expected station utilization
1–5	25	5	24	[0.43, 0.5]
6–10	40	7	24	[0.61, 0.65]
11–15	60	8	24	[0.66, 0.87]
16–20	80	10	24	[0.72, 0.78]

Table 4. Numerical experiment results

Instances	Integer Programming			Decomposition Method			Gap = (B-A(UB))/B (%)
	Objective* (A)	Gap = (UB-LB)/UB (%)	Solving time (s)	Best objective (B)	Solving time (s)**	Final available recharging capacity (per station)	
1	6,208	0	1,063	6,557	1+1=2	[1, 1, 1, 1, 1]	5.32
2	6,045	0	128	6,591	1+2=3	[1, 1, 1, 1, 1]	8.28
3	5,907	0	162	6,150	1+1=2	[1, 1, 1, 1, 1]	3.95
4	6,579	0	982	7,214	1+2=3	[1, 1, 1, 1, 1]	8.80
5	7,168	0	852	7,725	1+1=2	[1, 1, 1, 1, 1]	7.21
6	(11,240) 11,425	1.62	1,800	12,629	1+2=3	[1, 1, 1, 1, 1, 1, 1]	9.53
7	(9,463) 9,761	3.05	1,800	10,707	1+2=3	[1, 1, 1, 1, 1, 1, 1]	8.84
8	(11,942) 12,028	0.71	1,800	13,254	1+2=3	[1, 1, 1, 1, 1, 1, 1]	9.25
9	(11,833) 11,963	1.09	1,800	12,870	1+4=5	[1, 1, 1, 0.9, 1, 1, 1]	7.05
10	(10,420) 10,666	2.31	1,800	11,206	1+4=5	[1, 1, 1, 0.9, 1, 1, 1]	4.82
11	(14,290) -	-	1,800	16,273	1+5=6	[1, 1, 1, 1, 1, 1, 1, 1]	-
12	(15,758) -	-	1,800	17,744	6+7=13	[1, 0.9, 0.9, 1, 1, 1, 1, 1]	-
13	(19,177) -	-	1,800	21,196	62+12=74	[0.9, 0.9, 0.9, 0.9, 0.9, 0.9, 1, 0.9]	-
14	(17,467) -	-	1,800	19,284	3+8=11	[1, 0.9, 1, 1, 1, 1, 1, 1]	-
15	(18,032) 18,894	4.56	1,800	19,707	3+8=11	[1, 0.9, 1, 1, 1, 1, 1, 1]	4.13
16	(22,026) -	-	1,800	26,677	133+12=145	[0.9, 1, 1, 0.8, 1, 0.9, 0.9, 1, 0.9, 0.9]	-
17	(18,661) -	-	1,800	22,714	21+15=36	[1, 1, 1, 1, 0.9, 0.9, 1, 1, 1, 1]	-
18	(20,453) -	-	1,800	23,191	453+26=479	[0.9, 0.9, 0.9, 1, 1, 1, 0.9, 0.9, 0.9, 0.9]	-
19	(22,418) -	-	1,800	26,648	629+30=659	[0.9, 0.9, 0.9, 0.9, 1, 1, 0.9, 0.9, 0.9, 0.8]	-
20	(19,971) -	-	1,800	23,870	11+8=19	[1, 1, 1, 1, 1, 1, 1, 1, 0.9, 0.9]	-
	Average		1,509		66+8=74		7.02

*(Lower bound/LB) Upper bound/UB. The lower bound is presented separately, when no optimal solution is found.
**a+b=c, with a = total computational times of the first EV allocation subproblem, b = total computational times of the second EV recharging scheduling subproblem. The computational time for each subproblem is limited to 10 minutes.

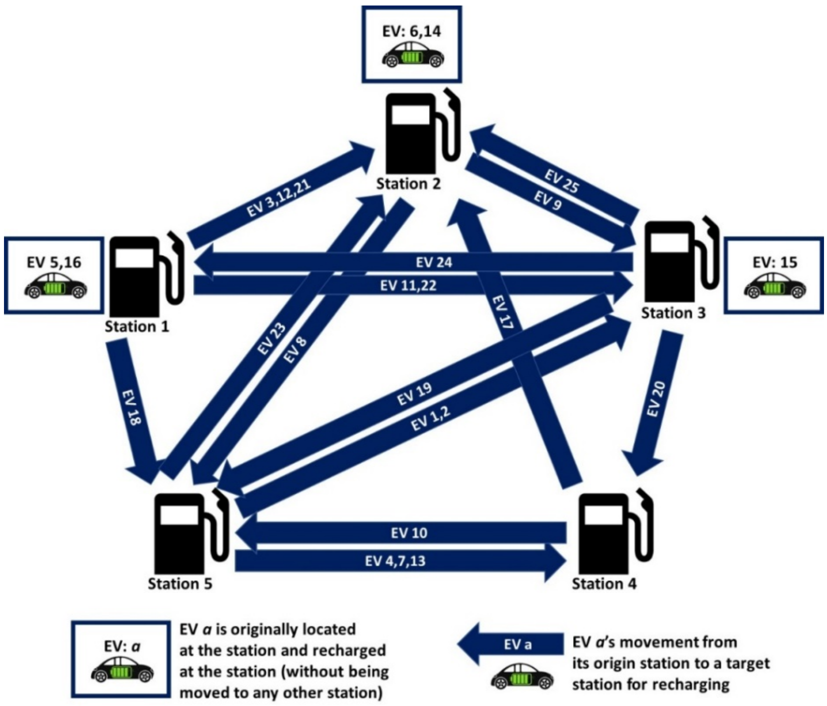

Figure 2. EV recharging locations and EV movements in Instance 1.

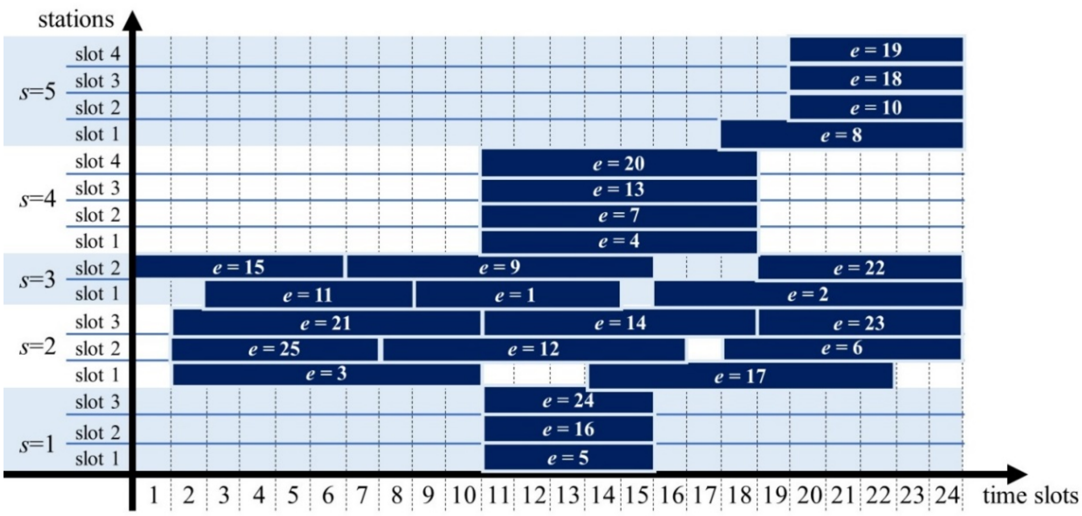

Figure 3. EV recharging schedules at their designated stations.

5. CONCLUSIONS

This study discussed an EV recharging problem that considered a limited number of recharging slots and the electricity price fluctuation at each recharging station. The problem was formulated mathematically, and a decomposition-based method was proposed to solve larger instances effectively. It is shown that the proposed decomposition method obtains good solutions (that has an average gap of less than 10% when compared with the complete mathematical model) and solved the instances in less than 2 minutes for problems up to 80 EVs, 10 stations (with 2–4 recharging slots), and 24 time slots.

The limitation of this study is not considering the EV movement costs. Such a situation caused more EV movements between stations to minimize the recharging costs. EV movement decisions are considered in EV relocation problem (Singgih and Kim, 2020), which could be performed using various ways, e.g., trucks moving multiple EVs, operators driving each individual EV, etc. EV allocations obtained in this study could be used as a recommendation for such EV relocation decisions. When movement costs are considered in the EV relocation problem, inefficient EV movements between stations could be removed when solving the EV allocation model in this study iteratively while setting the values of related EV movement variables equal to 0. Future research topics could also propose (1) more effective solution methods and (2) an integrated framework that combines the data collection and analysis using machine learning techniques, which improves the results of the optimization.

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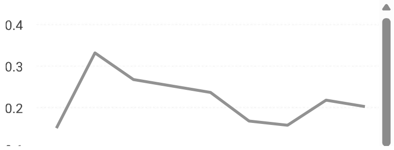

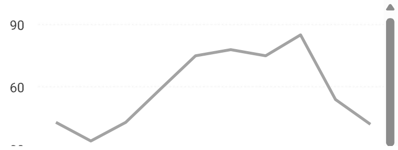

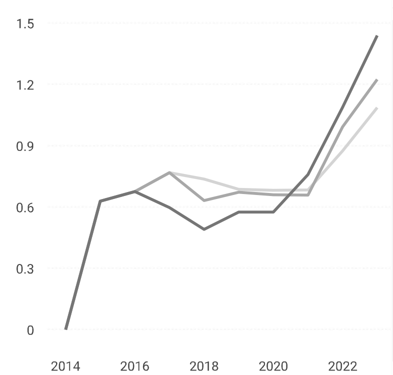

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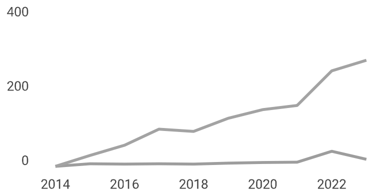

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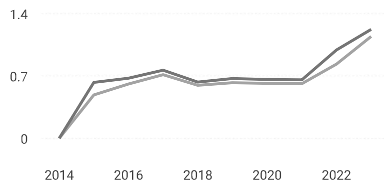

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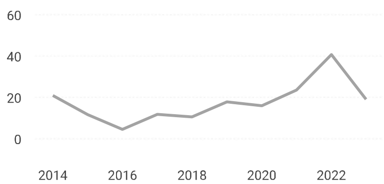

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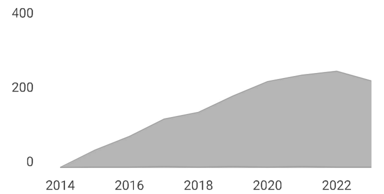

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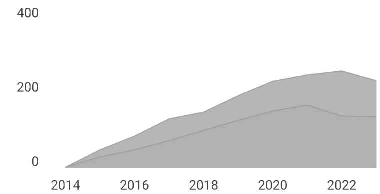

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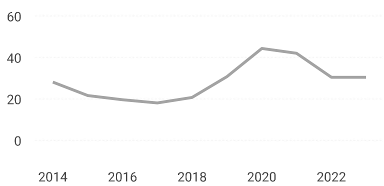

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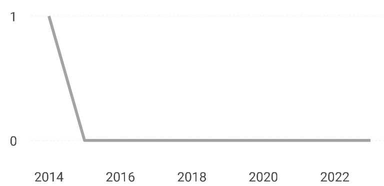

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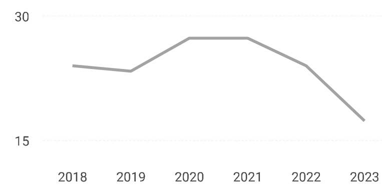

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