Electric Vehicle Charging Allocation Considering Electricity Price Fluctuation

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Abstract. Charging decisions on electric vehicles is an important aspect to consider for ensuring the continuity of the electric vehicle demand satisfaction. An electric vehicle system could not operate well without sufficient resources for charging each vehicle's battery after its use. In this study, we propose an allocation problem of electric vehicles to battery recharging stations. We discuss a real-time electric vehicle charging problem, in which the decision to allocate the vehicles to the charging stations must be made fast. Such a situation occurs when we need to charge the vehicles within the operational time of the electric vehicle system. We consider the required charging time and the number of recharging slots available at each station to ensure the recharging demand satisfaction. To allocate the vehicles efficiently, we consider the charging price at each station and minimize the total costs for the recharging. We formulate the problem mathematically. Important cases to be considered in the problem are listed.

Keywords: Electric Vehicle Recharging, Price Fluctuation, Allocation Problem.

1 Introduction

The usage of electric vehicles (EVs) for various purposes (e.g., car sharing, public transportation, etc.) has become clearly important nowadays [1, 2]. EV sales have been reported to increase every year, as shown in Fig. 1 [3]. Many studies have discussed various optimization problems in the EV system, including the EV station location problem [4, 5], EV routing problem [6, 7], EV recharging problem [1, 8], etc. In this study, we address the EV recharging allocation problem, in which the EVs to be recharged are allocated to one of many recharging stations, as illustrated in Fig. 2 [9].

M. Hartono et al. (eds.), *Proceedings of the 4th International Conference on Informatics, Technology and Engineering 2023 (InCITE 2023)*, Atlantis Highlights in Engineering 21,
https://doi.org/10.2991/978-94-6463-288-0_33

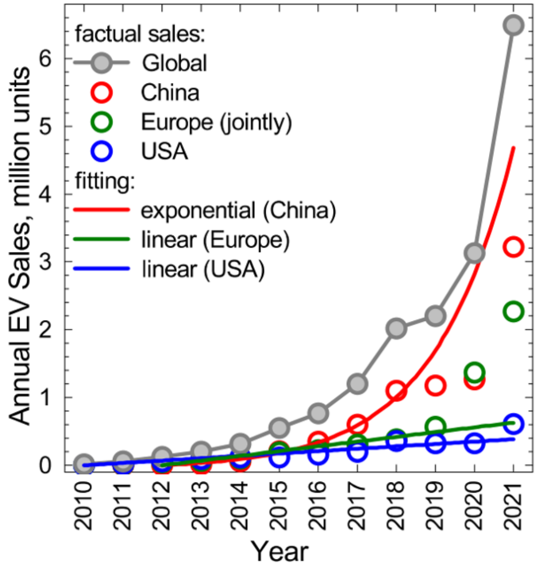

Fig. 1. Increased global EV sales.

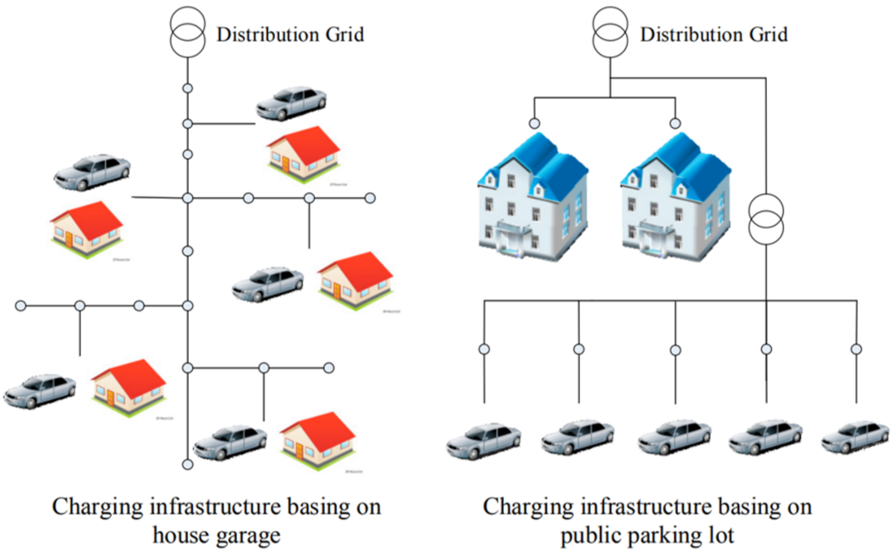

Fig. 2. Alternative of EV recharging stations.

The difference between our study and previous studies are listed in Table 1. While most studies discussed how to determine the EV charging price, our study deals with the EV allocation to the charging stations to minimize the total charging costs. Even though [10] also discussed an EV allocation problem, our study differs from theirs because we consider the limited number of charging slots available at each station, while Aljafari et al. [10] allowed each EV to wait in queue at its allocated station.

Table 1. The novelty of our study.

Study	Decision variables	Objective
Ren et al. [11]	EV charging price	Minimizing charging load fluctuation and total charging costs
Liang et al. [12]	EV charging price	Minimizing charging costs of all users
Zhong et al. [13]	Whether to charge each electric taxi or not based on its level (state of charge)	Minimizing travel costs to the recharging station, the queuing cost, and the recharging cost
Deng et al. [14]	EV routing and charging schedule	EV energy consumption
Lin et al. [15]	EV charging price	Minimizing charging load fluctuation and maximizing profits for the company
Aljafari et al. [10]	EV allocation to charging stations (allowing queue at each station)	Minimizing total costs for EV recharging
Our study	EV allocation to charging stations (no queue, considering an exact number of empty charging slots at each station)	Minimizing total costs for EV recharging

Section 2 introduces a simplified EV allocation problem that does not consider the transportation time required for the EV from its initial location to the recharging station. Section 3 discusses the EV allocation problem considering the required EV transportation time. Section 4 shows the numerical experiment result. Section 5 discussed some important aspects of the defined problems and possible extensions of the problems to be considered by the next researchers. Section 6 concludes the study.

2 Electric Vehicle Allocation Problem without Transportation Time Consideration

In the first problem, we consider the problem of allocating EVs to recharging stations. We define time slots (e.g., 30 minutes) and consider that each EV requires a number of time slots to recharge its battery to reach a minimum battery level for its next use. At the moment of such real-time decision-making, each recharging station has a limited number of empty recharging slots. The mathematical model is presented as follows.

Sets

E : Set of electric vehicles to recharge ($e = 1, 2, \ldots, |E|$)

S : Set of recharging stations ($s = 1, 2, \ldots, |S|$)

Parameters

c_s : Recharging cost per time slot at station s

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

x_{es} : 1, if EV e is recharged at station s; otherwise, 0

$$\sum_e \sum_s x_{es} c_s r_e \tag{1}$$

$$\sum_s x_{es} = 1 \qquad \forall e \in E \tag{2}$$

$$\sum_e x_{es} \leq p_s \qquad \forall s \in S \tag{3}$$

$$x_{es} = \{0,1\} \qquad \forall e \in E, s \in S \tag{4}$$

Objective (1) minimizes the total charging costs considering the allocation of EVs to recharging stations. Constraints (2) ensure each EV e to be recharged at exactly one station. Constraints (3) limit the number of recharged EVs with the number of available slots at each station s. Constraints (4) are binary constraints.

This first problem can easily be solved by using the transportation (mathematical) model. The supply nodes are the slots available at the recharging stations, and the demand nodes are the EVs. Considering that the number of EVs to be recharged is less than the number of recharging slots, we introduce dummy nodes at the demand side of the transportation model. Matrix representing the transportation problem is shown in Fig. 3. A similar way to convert the allocation problem into the transportation model was considered by [1].

3 Electric Vehicle Allocation Problem with Transportation Time Consideration

In the second problem, we consider a more realistic problem. We consider the EV allocation problem to the recharging slots while considering the required transportation time for each EV from its initial location to its recharging station. To consider the required transportation time, we introduce the time slot index, and to deal with a more realistic setting, we consider the changes (fluctuation) in recharging prices at different time slots. Time slots with a higher demand have a higher price [16, 17]. The mathematical model is presented as follows.

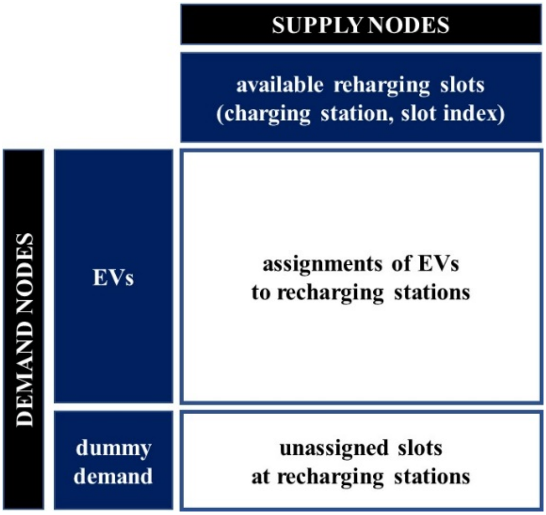

Fig. 3. Alternative of EV recharging stations.

Sets

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

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

$$\sum_e \sum_s \sum_t x_{est} c_{st} \quad (5)$$

$$x_{est} \leq y_{es} \quad \forall e \in E,\, s \in S,\, t \in T \quad (6)$$

$$\sum_{s} y_{es} = 1 \qquad \forall e \in E \tag{7}$$

$$\sum_{e} x_{est} \le p_s \qquad \forall s \in S, t \in T \tag{8}$$

$$x_{est} = 0 \qquad \forall e \in E, s \in S, t \in \{1,2,\ldots,d_{o_e s}\} \tag{9}$$

$$x_{est} = 0 \qquad \forall e \in E, s \in S, t \in \{|T| - d_{o_e s} - r_e, |T| - d_{o_e s} - r_e + 1, \ldots, T\} \tag{10}$$

$$w_e \le |T|(1 - x_{est}) + t x_{est} \qquad \forall e \in E, s \in S, t \in T \tag{11}$$

$$z_e \ge t x_{est} \qquad \forall e \in E, s \in S, t \in T \tag{12}$$

$$z_e - w_e + 1 = r_e \qquad \forall e \in E \tag{13}$$

$$\sum_{s} \sum_{t} x_{est} = r_e \qquad \forall e \in E \tag{14}$$

$$x_{est} = \{0,1\} \qquad \forall e \in E, s \in S, t \in T \tag{15}$$

Objective (5) minimizes the total charging costs considering the allocation of EVs to recharging stations. Constraints (6)–(7) ensure that each EV e must be recharged at exactly one station. Constraints (8) limit the number of recharged EVs with the number of available slots at each station s during each time slot t. Constraints (9) ensure that each EV e cannot be recharged before it has been transported to the target station. Constraints (10) limit the EV recharging decision at recharging station u if the EVs cannot arrive at station u and complete the recharging before the planning horizon ends. Constraints (11) and (12) calculate the first and last time slots when the EV e is recharged. Constraints (13) and (14) ensure each EV e is recharged as long as it is required. Constraints (15) are binary constraints.

4 Numerical Experiment

A numerical experiment was used to verify the mathematical model in Section 3 that represents the more realistic situation. The solutions were obtained using GUROBI 10.0.2. The experiment was conducted on an Intel(R) Xeon(R) CPU at 2.20GHz on the Google Colab platform. The input data are shown in Tables 2-6. The optimal solution was obtained in less than 1 second and is shown in Fig. 4. It shows the recharging schedule at each station s on each time slot t. As an example, electric vehicles 1 and 4 are recharged at station 1 during time slots 3-4, while electric vehicle 5 is recharged at station during time slots 3-5. The number of electric vehicles recharged at each time slot at station 1 does not violate the station's number of available recharging slots (3).

Table 2. Values for *c* parameter.

	t											
	1	2	3	4	5	6	7	8	9	10	11	12
s = 1	20	50	13	31	81	62	54	97	13	47	65	19
s = 2	96	86	65	62	46	97	63	82	44	31	51	31
s = 3	8	26	64	56	71	42	10	10	9	30	10	19
s = 4	79	50	3	20	94	85	46	28	50	73	57	93

Table 3. Values for *d* parameter.

	u			
	1	2	3	4
s = 1	0	3	6	4
s = 2	3	0	5	7
s = 3	6	5	0	2
s = 4	4	7	2	0

Table 4. Values for *o* parameter.

t					
1	2	3	4	5	6
1	1	3	2	2	1

Table 5. Values for *p* parameter.

s			
1	2	3	4
3	4	3	2

Table 6. Values for *r* parameter.

e					
1	2	3	4	5	6
2	2	3	2	3	1

5 Discussions

The problems above are still simplified versions of what happens in reality. To ensure more realistic cases, we could consider the following additional aspects:

1. A relaxation of the time slot concept. It will allow more effective use of available charging times but require more computational time.

2. Availability of the relocation vehicles, e.g., trucks transporting the EVs [1] or vehicles driven by the relocation operators [18].
3. A longer planning horizon that considers the recharging operation of multiple EVs at every single slot. It optimizes the relocation system better considering more look-ahead periods.
4. A strong use of big data for understanding relationships between data and allowing a better prediction that could increase the efficiency of the EV relocation process [19, 20]. An example of how big data could be considered to optimize the EV system operation is shown in Fig. 5 [21].

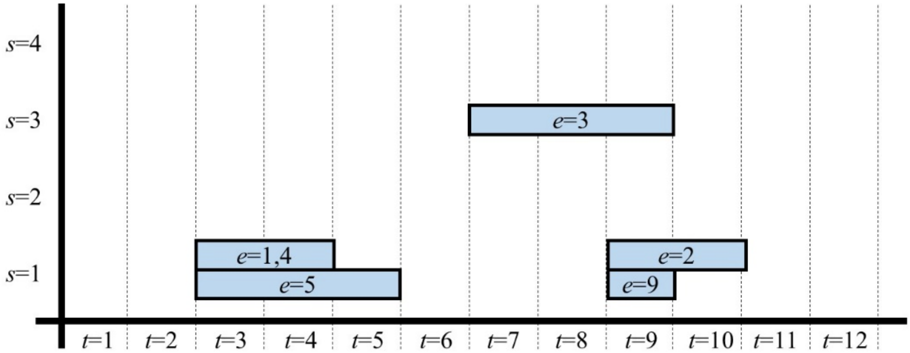

Fig. 4. The obtained optimal solution.

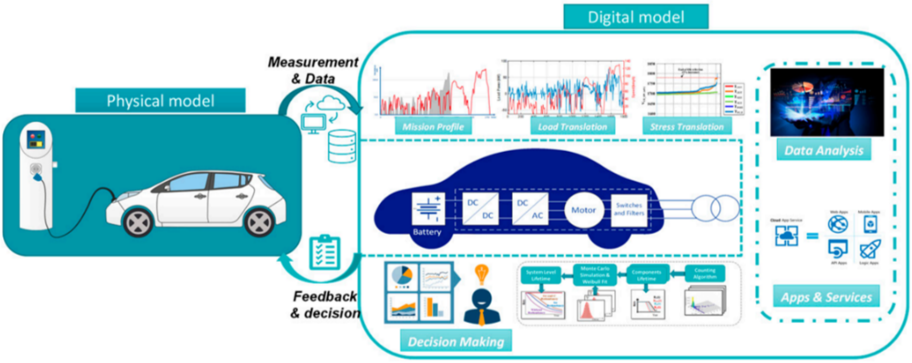

Fig. 5. Optimization framework for the EV system based on big data.

6 Conclusions

In our study, we introduced problems of allocating EVs to recharging stations. We proposed two models: (1) when the transportation times of EVs from their initial locations to the recharging stations are not considered, and (2) when the transportation times are taken into account. We provide the mathematical formulation for both cases. At the end of our study, we list some important aspects to be additionally considered in the models to ensure considering more realistic scenarios. For further studies, it is also necessary to conduct more experiments with realistic data to observe the proposed models' behavior and assess the model's strengths and weaknesses.

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