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Charging Station Placement Optimization Using Queueing Model with Time-varying Arrival Rate

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Executive Summary

Inappropriate electric vehicle (EV) charging station (CS) placement inevitably increases operator's costs and decrease Quality of Service (QoS). This paper proposes a CS placement optimization model, which aims to minimize the installation cost with the constraints related to QoS, i.e., maximum waiting time and CS reachability. To reach these targets, firstly, the driving uncertain parameters are modeled by the probability distributions. Next, based on the EV's driving routes, the charging behavior, including where, when to charge, and charging demand are predicted. Then, the waiting time is calculated based on the queueing model with time-varying arrival rate, i.e., *M(t)/M/s* system. The model is optimized based on the genetic algorithm (GA). Both theoretical analysis and computational simulation are given to verify the feasibility of proposed optimization algorithm.

Keywords: battery electric vehicle, charging infrastructure, infrastructure deployment, quality of service, optimization algorithm

1 Introduction

Recently, the global transportation system has seen a transition from traditional gasoline-powered vehicles to EVs, and EVs' production and market share have been expanded to an unprecedented level [1-3]. The mainly reasons for the prosperity of EV industry are the increasingly awareness in reducing the reply on oil, utilizing the renewable sources, and combating environmental crises [4-7]. Boarder and more ambitious policies have been set in more than 20 countries to accelerate this transition, and the number of EV fleet is expected to reach 230 million in 2030 [8].

However, limited battery capacity requires drivers charge frequently [9, 10]. If there is a serious mismatch between enormous EVs and limited CSs, EV owners would suffer from severe driving anxiety, which is deemed as one of the dominant obstacles for ongoing EV adoption [11]. Therefore, an appropriate CS placement scheme with high QoS is needed to ensure a satisfactory trip [12-14]. Generally, QoS is evaluated by waiting time, since long waiting time brings uncomfortable charging experience. In the recent years, numerous researchers have delved into the CS deployment problem [15-20]. Average waiting time has attracted great attentions, which is regarded as the minimizing objective or considered into constraints [21-

23]. Usually, it is calculated based on the *M/M/s* model in queueing theory, which assumes that the EVs' arrival rate is a constant value in the time duration [24]. However, on the one hand, the average value cannot reflect waiting situation during the busiest period accurately. On the other hand, the traffic flow soars in peak hours and drops in midnight in the real world, so there is a great difference of arrival rate during one day. Using a constant arrival rate to calculate the average waiting time as the QoS indicator might bring errors in estimating, thus degrading the optimization performance of the final decision scheme.

To tackle with above problems, this paper proposed a CS deployment optimization model using the *M*(*t*)/*M*/*s* model [25]. Firstly, the probability distributions are used to model the drivers' behaviors, and hence the EV charging profile could be obtained. Secondly, the *M*(*t*)/*M*/s model with a time-varying arrival rate is utilized to estimate the waiting time throughout 24 hours. Thirdly, the CS placement scheme is decided based on GA algorithm. The main contributions of this paper are concluded as followed:

(1) A charging behavior model is proposed. The randomness of drivers' behavior is considered based on probability distributions, such as average travelling distance, arrival time, and departure time, etc. Whether or not to charge is determined by the State of Charge (SOC) of battery. If there is a charging demand but no CS along the route, the route would be re-scheduled to reach the nearest CS.

(2) A CS placement optimization framework is designed. The model aims to minimize the installation cost, with the constraints of maximum waiting time, CS reachability and the limited number of servers.

(3) The impact of using *M/M/s* or *M(t)/M/s* model on placement decisions are studied. A result of tolerable difference would lead to a preference using *M/M/s* model due to its relatively low computational burden, otherwise using *M(t)/M/s* model for a more accurate QoS indicator.

The remainder of the paper is organized as follow. Section II introduces the methodology. The simulation results are presented in Section III. The conclusion is given in Section IV.

2 Methodology

2.1 Overview of The CS Placement Optimization Framework

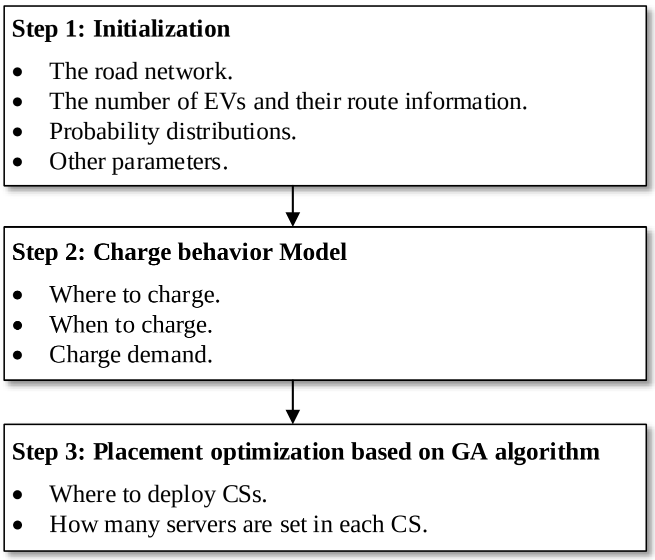

Figure 1: Main procedures of proposed optimization scheme

Fig. 1 depicts the main procedures of the proposed optimization scheme, which mainly comprising three steps. The first step is the initialization. The road network, the number of EV, and their route information should be generated. Several probability distributions should be set. Also, some other parameters are required, including: driving speed, energy consume per km, battery capacity, and etc.

Secondly, the charging behavior of each EV is modeled. Based on the given route and the battery SOC, the model predicts where, when, and how much the EV will charge. The EV load profile of each CS could be formed based on these predictions.

Thirdly, the waiting time during 24 hours could be calculated based on *M(t)/M/s* model. Based on GA, minimizing installation costs is the object of the model, while the maximum waiting time, CS reachability and capacity constraint are taken into account. The final CS placement decisions could be obtained, including where to deploy CSs and how many servers are installed in each CS. For a better understanding of the following part, the notations are defined and listed in Table 1 for easy retrieval.

Table 1: Notations used in the model

Name	Definition
$G(V,A)$	A graph G represents the road network. V and A indicates nodes and edges respectively
v_i	i-th node
$neighbours_i$	A set of nodes that are neighbours of v_i
x_i	A binary variable indicating whether the v_i should be deployed a CS or not
n_i	The number of charging servers at v_i
$n_{\max}$	The maximum number of servers of one CS
$\text{cost}^{installation}$	The total cost of installation
cost^{CS}	The cost for one CS
cost^{server}	The cost for one charging server
cost^{basic}	The basic cost used in the fitness calculation
$waiting\_time_i^{\max}$	The maximum waiting time of v_i during 24 hours
R_k	The route of k-th EV
SoC_k^{ini}	The initial SOC of k-th EV
t_k^{start}	The start time of the R_k
t_k^{charge}	The time to start charging of the k-th EV
t_k^{dep}	The time to depart CS of k-th EV
CS_k^{access}	The accessible CS along the R_k.
CS_k^{decide}	The decided CS of k-th EV to charge.
e_k^{demand}	The charging demand of k-th EV
e_k^{prob}	The charging demand formed based on probability distribution.
e_k^{remain}	The remaining energy of k-th EV at the destination.
d_k^i	The distance between start node and node v_i of R_k
d_k^{sd}	The distance between start and destination node of R_k.
d_k^{decide}	The distance between start node and decided CS to charge.
$d_k^{\max}$	The maximum distance that k-th EV can travel based on initial SOC
cap_k	The battery capacity of k-th EV
$threshold^{\text{charge}}$	The charging threshold
$threshold^{waitingtime}$	The waiting time threshold
$e^{consume}$	Energy consumed per unit distance
r^{charge}	Charging rate
v	Velocity of the vehicles
$\lambda(t)$	The arrival rate at time t
μ	The service rate
$p_m(t)$	The probability that m customer in the system at time t
$W(t)$	The delay of a customer at the start of time segment t
s	The number of servers in the system
m	The number of customers in the system
M	The maximum customer in the system
α, β	The weights used in the fitness calculation

2.2 Initialization

This part mainly introduces the initialization of probability distributions.

For initial SOC, arrival and departure time are described based on truncated Gaussian distributions. The parameters of these distributions refer [26]. The log-normal distribution function is employed to modelling travelling distance [27]. According to the daily travelling distance, the charging demand probability distribution can be obtained refers [28].

2.3 Charging Behavior Model

Algorithm 1 Charging behavior model of k-th route

Input: CS placement, route R_k, initial SOC SOC_k^{int}, start time of the route t_k^{start}, the battery capacity cap_k, the charging threshold $threshold^{charge}$, energy consumed per unit distance $e^{consume}$,charging rate r^{charge}, velocity v.

Output: Connect time t_k^{charge}, CS to charge CS_k^{decide}, charging demand e_k^{demand}

1: Calculate the remaining energy e_k^{remain} at the destination node based on (1)
2: **if** $e_k^{remain}/cap_k>threshold^{charge}$ **then**
3:     The k-th EV would not charge.
4: **else**
5:     Calculate the maximum allowable travel distance d_k^{max} by (2).
6:     Obtain a set of accessible CSs CS_k^{access} along the route by $d_k^i<d_k^{max}$.
7:     **if** CS_k^{access} is not empty **then**
8:         Calculate the arrival time t_k^i in node v_i by (3), where $v_i \in \mathrm{CS}_k^{access}$. obtain the corresponding probability value by the arrival time probability distribution. CS_k^{decide} would be CS with highest probability value.
9:     **else**
10:         calculate the extra distance to each CS
11:         **if** number of CSs with minimum extra distance>1 **then**
12:             CS_k^{decide} would determined following line 8.
13:         **else**
14:             CS_k^{decide} is the CS with minimum extra distance.
15:         **end if**
16:     **end if**
17: **end if**
18: The charging demand could be calculated by (4).

The charging behavior model for one route is presented in algorithm 1. There are some assumptions of this model. (a) The EV can be charged immediately when arriving at the CS, regardless of the queueing situation. (b) The EV could travel at a constant speed, regardless of the traffic jam. (c) Only one charge for one route. The detailed processes of charging behavior model are described as following.

Firstly, the remaining energy at the destination node is calculated based on (1)

$$e_k^{remain} = SOC_k^{\mathrm{int}} \cdot cap_k - d_k^{sd} \cdot e^{consume} \tag{1}$$

If $e_k^{remain} / cap_k > threshold^{\mathrm{charge}}$, indicating that the battery energy is considered sufficiently and does not require to be charged. For those EVs which are needed to charge, the maximum allowable travel distance can be calculated by (2). Then, a set of accessible CSs CS_k^{access} along the route can be obtained if $d_k^i < d_k^{\max}$, where $v_i \in R_k$ and $x_i = 1$.

$$d_k^{\max} = SOC_k^{\mathrm{int}} \cdot cap_k / e^{consume} \tag{2}$$

One situation is that CS_k^{access} is not empty, meaning the k-th EV could be charged along the route before the energy is running out. Then, the arrival time could be calculated by (3). After obtaining a set of arrival time of CS_k^{access}, the probability value could be obtained according to the arrival time probability distribution, and the CS with higher probability would be selected to charge, and t_k^{charge} is equal to the corresponding arrival time.

$$t_k^i = t_k^{start} + d_k^i / v \tag{3}$$

Another situation is that CS_k^{access} is empty, meaning there is no available CS along the route, hence the driver has to travel extra distance to charge their EV. Based on the route and the placement of CSs, the extra distance could be calculated based on the shortest path method, and the CS with least extra distance would be choose to charge. Specially, if there are several CSs with same extra distance, the CS selection would be decided by the arrival time probability value, which is introduced before.

After decide where and when to charge, the next step is to obtain the charging demand. First, the energy demand e_k^{prob} should be formed randomly based on charging demand probability distribution. Then, considering t_k^{charge}, the departure time t_k^{dep} should also be generated, and notice that t_k^{dep} should be later than t_k^{charge}. Therefore, the final desired charging demand should be calculated as (4). e_k^{demand} should be the minimum value of these components: e_k^{prob}, the energy calculated based on the start and departure time, the energy limited by battery capacity.

$$e_k^{demand} = Min\left\{\left[e_k^{prob}\right], \left[r^{charge} \cdot \left(t_k^{dep} - t_k^{charge}\right)\right], \left[cap_k - SOC_k^{ini} \cdot cap_k + d_k^{decide} e^{consume}\right]\right\} \tag{4}$$

Based on above steps, the charging time, location, and amount are obtained, and hence the EV load profile of each CS could be calculated.

2.4 Optimization Problem Formulation

The objective is minimizing the CS installation cost, which is defined is as (5). It contains cost for building stations and the cost for installing charging servers in the station. The constraints can be expressed as (6)~(8), where (6) indicates that maximum waiting time during 24 hours at node *i* should be less than the corresponding threshold; (7) means that, if node *i* is for a CS, the number of servers should be larger than 1 but less than the maximum server capacity n_{max}; and (8) ensures the CS reachability. It shows that for each R_k, it must pass through more than one CS in its route, or CSs are located at neighbour nodes that drivers travel through.

$$F = \min\left(\cos t^{installation}\right) = \min\left(\left(cost^{CS} \sum_{i \in V} x_i + \sum_{i \in V} x_i n_i cost^{server}\right)\right) \tag{5}$$

subject to

$$waiting\_time_i^{\max} \le threshold^{waitingtime} \tag{6}$$

$$1 \le n_i \le n_{\max}, \ if \ x_i = 1 \tag{7}$$

$$\sum_{v_i \in R_k} \left(x_i + \sum_{v_j \in neighbors_i} x_j \right) \ge 1 \tag{8}$$

According to *M(t)/M/s* model [25], the probability $p_n(t)$ can be calculated by solving (9). The delay *W(t)* could be calculated by (10). In the CS placement task, one customer is equal as unit energy demand; arrival rate indicates the energy demand per unit time; service rate means the energy that a server can provide per unit time.

$$\begin{cases} p_0'(t) = -\lambda(t) p_0(t) + \mu p_1(t) \\ p_m'(t) = \lambda(t) p_{m-1}(t) + (m+1)\mu p_{m+1}(t) - (\lambda(t) + m\mu) p_m(t), \quad 1 \le m < s \\ p_m'(t) = \lambda(t) p_{m-1}(t) + s\mu p_{m+1}(t) - (\lambda(t) + s\mu) p_m(t), \quad m \ge s \end{cases} \tag{9}$$

$$W(t) = \sum_{m=s}^{M} \left((m - s + 1)\, p_m(t) \right) \Big/ s\mu \tag{10}$$

The proposed model is optimized based on GA algorithm. Firstly, a certain number of individuals are formed. The chromosomes of individual are the decision variables, i.e., x_i and n_i. Secondly, revise each individual to meet the constraint in (7) and (8). Specially, the waiting time constraint is realized by penalty method. The fitness function is (11). The first part is related to the installation cost. The real $cost^{installation}$ is divided by a basic value $cost^{basic}$, so that when installation cost is smaller, the cost fitness score is higher. The second part is related to the waiting time. When threshold is smaller than the calculated maximum waiting time, it would be negative, so the total fitness score would be decreased. When the waiting time constraint is satisfied, the second part is 0. The weight α and β are positive. Thirdly, Calculate the fitness score of each individual, and reserve the individuals with high fitness. Based on fitness, select parents to cross and mutate, and then update the population to next cycle. The optimization stops when converge or at the end of iterations.

$$fitness = \alpha \cdot \left(1 - cost^{installation} \,/\, cost^{basic}\right) + \beta \cdot Min\left\{0, 1 - waiting\_time_i^{\max} \,/\, threshold^{waitingtime}\right\} \tag{11}$$

3 Simulation Results

3.1 Simulation Setup

4 Table 2: Parameter settings in simulation

Parameter	Value	Parameter	Value
Number of vehicles	2500	Charging rate	10 kW
Velocity	60 km/h	Interval of distance probability distributions	1.6 km
Energy consumption per km	0.6 kWh	Interval of arrival/departure time probability distributions	1/6 h
Max number of servers n_{max}	300	α	100
Cost of installing a server	0.2 k$	β	80
Cost of building one CS	5.0 k$	$threshold^{charge}$	0.9
Battery capacity	60 kWh	$threshold^{waitingtime}$	0.5 h

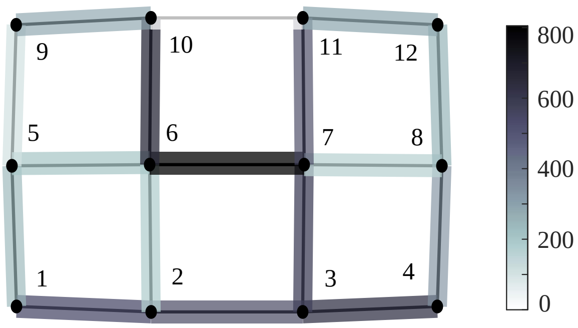

Figure 2: Road network and traffic flow among 24 hours

In order to validate the proposed method, computational simulation is performed by MATLAB. The related parameters are set as Table 2. The road network is a 3×4 grid. The routes of EVs are formed by several steps. Firstly, the start node and destination node are randomly selected from *G*. Secondly, the routes are generated based on the shortest path method. Thirdly, the peak hours are defined. The morning peak hours and evening peak hours are 7:00 to 9:00 am and 17:00 to 19:00 pm, respectively. The start time of the route is 31.5%, 31.5% and 37% generated from the morning, evening peak, and other hours. The traffic pattern is shown in Fig. 2. The color of each road segment represents the cumulative traffic flow during 24 hours. Namely, the darker lines have a higher traffic flow. It is assumed that the potential CS locations are nodes in the road networks. Fig. 3 depicts the probability distributions [26, 28], which are used to calculate the charging demand of CSs.

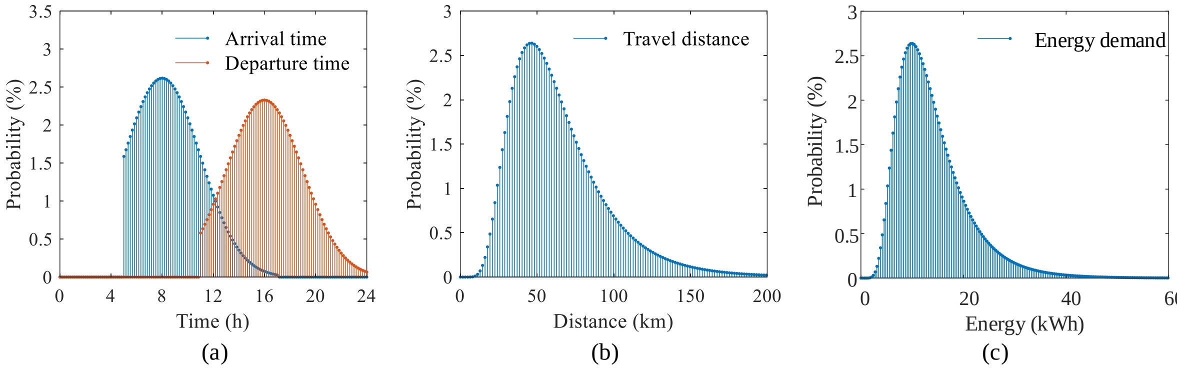

Figure 3: Probability distributions. (a) Arrival and departure time. (b) Daily travel distance. (c) Energy demand calculated based on daily travel distance.

4.1 Result of The Proposed Model

By using the GA algorithm, the installation cost and waiting time of 100 cycles are shown in Fig. 4. It is clear the installation cost decreases at the cost of increasing of waiting time within constraint of 30 min. The final placement decisions are listed as Table 3. It can be found that the locations of CSs and the number of servers have a directly relationship with traffic flow. The total cost is 52.0 k$, and the maximum waiting time is around 25.3 min. The charging demand and related waiting time of CSs are shown in Fig. 5. It can be observed that the waiting time occurs when the charging demand accumulates to a certain level. Drivers require to wait for a certain time to charge during the peak hours, but less than 25.3 min, which is considered acceptable.

Table 3: Decisions based on the proposed model

Node of CS	6	7	10
Number of servers	51	101	33
Total cost (k$)		52.0	
Maximum waiting time (min)		25.3	

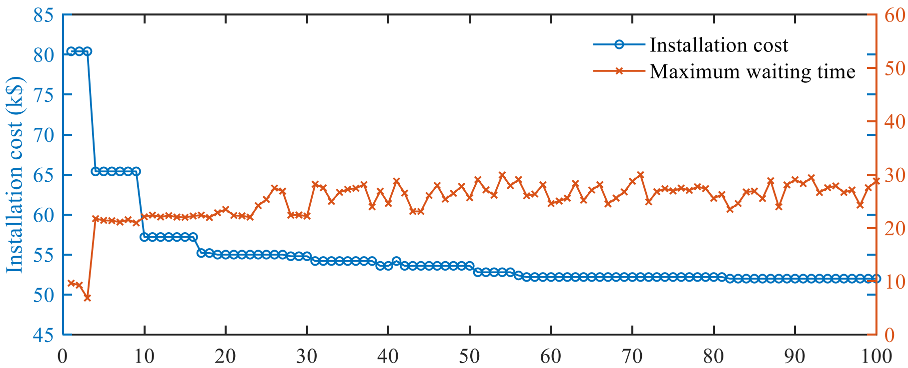

Figure 4: Installation cost and maximum waiting time of all CSs during 24 hours based on GA algorithm with iteration of 100

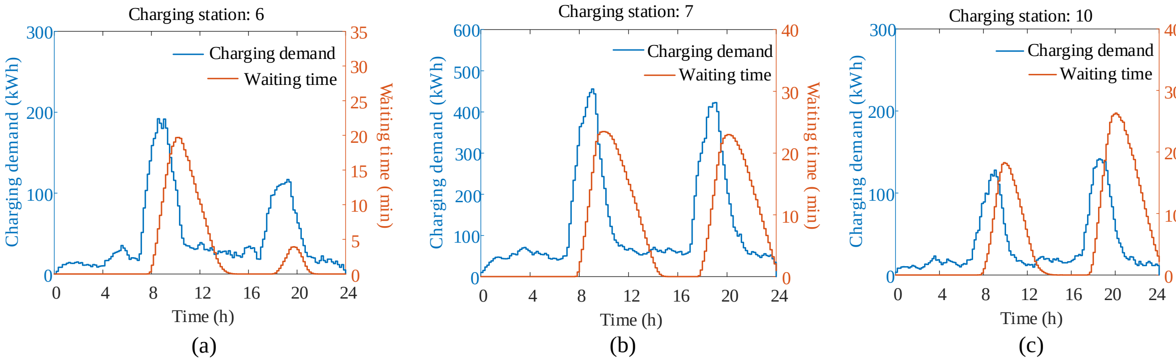

Figure 5: Charging demand and waiting time during 24 hours in different CSs. (a) CS 6. (b) CS 7. (c) CS 10.

4.2 Comparison Between *M/M/s* and *M(t)/M/s* Model

Also, the decision results using *M/M/s* model are shown in Table 4. The constant arrival rate is the mean value of time-varying arrival rate. Compared with the results in Table 3, Using *M/M/s* model can offer a significant drop in the numbers of servers, so the total installation cost can be reduced. However, when using the decisions in Table 4 to calculate the waiting time, there is a significant difference between the constant and time-varying arrival rate models. The waiting time is less than 2.7 min when using the *M/M/s* model but the maximum value actually higher than 50 min when cross-checking with the *M(t)/M/s* model as shown in Fig. 6, which is an unacceptable error. Therefore, it can be concluded that the waiting time is seriously underestimated based on the constant arrival rate model, and the corresponding decision results are overly optimistic.

Table 4: Decisions based on *M/M/s* model

Node of CS	6	7	10
Number of servers	52	80	0
Total cost (k$)		36.4	
Maximum waiting time (min)		2.7	

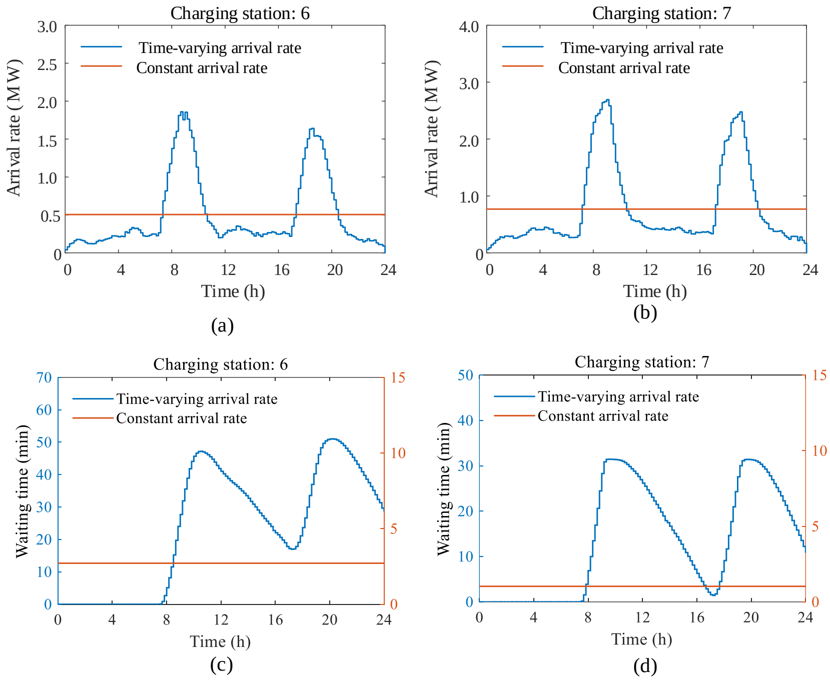

Figure 6: Comparison of results using decisions based on *M/M/s* model. (a) Arrival rate in CS 6. (b) Arrival rate in CS 7. (c) Waiting time in CS 6. (d) Waiting time in CS 7.

5 Conclusion

The problem of CS placement optimization is studied in this paper. The charging behavior model is developed, which utilize probability distributions to capture the uncertainties. Based on GA, the optimization aims to minimizing the total installation cost with the consideration of QoS, which is indicated by maximum waiting time and CS reachability. The simulation results show that the CS deployment decisions are highly related to the traffic condition. Without considering traffic jam, the CS is more likely to build in the places with high traffic flow. Also, the decisions using *M/M/s* and *M(t)/M/s* model are compared. The total cost of *M/M/s* model is much lower because fewer charging servers are set. However, when using the *M(t)/M/s* model to crosscheck the waiting time, it is much higher than the result in *M/M/s* model. Therefore, the decisions based on *M/M/s* model are overly optimistic. It demonstrates that the proposed optimization model is effective and practical for the CS placement task.

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Presenter Biography

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