Electric Vehicle Charging Navigation Strategy Considering Multiple Customer Concerns

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***Abstract*—This paper proposes a platform that supports the electric vehicle (EV) to navigate to a proper station for charging. This platform considers several important factors, concerns, that influence the selection of a suitable charging station. These factors are the energy consumption in driving to reach the charging station from the EV location, the demanded charging energy, the parking time to start charging at the charging station, the extra time in charging due to lowering the charging power rate at the charging station pole, and the energy consumption in driving to reach the EV target destination after charging at the charging station. These factors are represented by their costs and formulated as a cost function for charging the EV. This formulation is constructed for each EV to facilitate the distributed implementation of this charging navigation platform. The problem is then solved in an optimal way for selecting the charging station. Several comparison methods are introduced and the advantage of the proposed strategy is demonstrated to lower the cost paid by the customer to charge the EV during his/her travel mobility plan.**

***Index Terms*—Charging navigation, electric vehicle, charging station, customer concerns, customer behavior, travel mobility.**

I. Introduction

Electrification transportation has obtained an increasing attention due to the growing demand in environmental concerns and energy. Electric vehicles (EVs) are considered to be promising automobiles and developing them is an integral part of future transportation [1]. Therefore, EVs have notably received a big attraction by industry and government and the number of EVs on roads is potentially going to increase. Yet, the limited capacity of their on-board batteries remains a challenging issue for their spreads. This limitation requires the EV customers to frequently charge their EVs to satisfy their charging energy demands [2]. The time for charging the EV relies on its remaining energy and its customer behavior, i.e., EV customers charge the EVs periodically or when the state-of-charge (SoC) of EV is low [3]. Whereas, the place for charging the EV, i.e., selecting the charging station (CS), depends on several aspects, including the EV SoC, EV customer behavior and travel mobility plan, the status of the CS, and status of the power grid.

Several works in the literature were proposed to address the selection of CSs for charging, i.e., EV charging navigation, on the basis of different aspects [4]–[11]. Ref. [4] proposed route selection and charging navigation model to the EV users', customers', travel costs with care about the load on the distribution system. Ref. [5] introduced a charging navigation framework to benefit the power grid and transportation system. Ref. [6] presented an optimal route scheduling model for charging EVs during navigation considering specific locations of CSs as well as features of roads and battery electric vehicles (BEVs). Ref. [7] applied a joint charging and routing optimization into the EV charging navigation systems. Ref. [8] implemented a distributed strategy for EV charging navigation with consideration of power grid and traffic network interactions. Ref. [9] developed a deep reinforcement learning strategy for the EV charging navigation. Ref. [10] solved the EVs' charging decisions by a price incentive-based charging navigation strategy. Ref. [11] formulated a coordinated spatial EV charging navigation on the basis of user behavior.

The above literature tried to handle the preferences of both the EVs and the power grid from a big picture. However, this led to a distraction on the detailed concerns of each individual, particularly the EV and its customer. Unlike these works, this paper investigates in the EV customer perspective and encompasses his/her own interests once demanding to navigate to CS. The proposed strategy here studies the factors of the EV energy consumption in driving for both reaching the CS from the current EV location, i.e., before the charging process, and for reaching the target EV customer destination from the CS, i.e., after the charging process is completed. These two factors are mainly related with the EV customer travel mobility plan, i.e., travel trips. The strategy also tackles the cost of the demanded amount of charging energy as well as it includes the parking time before the start of charging at the CS. Moreover, it addresses the extra time in charging due to the reduction in the power rate at the CS pole.

The rest of this paper is organized as follows. Section II models the charging navigation system, whereas section III formulates this charging navigation problem for each EV and proposes the solution technique. Simulation analysis and comparisons are discussed in section IV and the conclusion is presented in section V.

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II. System Model

The charging navigation system (CNS) of EVs is a actually a cyber-physical energy system after considering the focus is on the charging aspects of EVs, i.e., the scope of this paper, and the interactions between different located components in the system. The configuration of the main components in this CNS along with their features are shown in Fig. 1. These components are assumed to be geographically distributed and connected by proper communication infrastructure, such as Internet, as well as some components are connected by power lines. The upper part of Fig. 1 consists of traffic, weather, and power grid centers that are necessary to operate the lower part by supporting and exchanging information with its components. The lower part includes the CSs and the EVs, which are the main focused components in this paper.

The power grid center interacts with the CSs center to exchange information about the power status and market, such as electricity prices and power capacity and demand. The weather center provides weather forecasts to traffic centner, EVs, and CSs center, which can be utilized if CSs have renewable energy resources. The traffic center takes place in communicating with EVs to support them with information, such as traffic congestion and road conditions. The models of the lower part two components are described in the below.

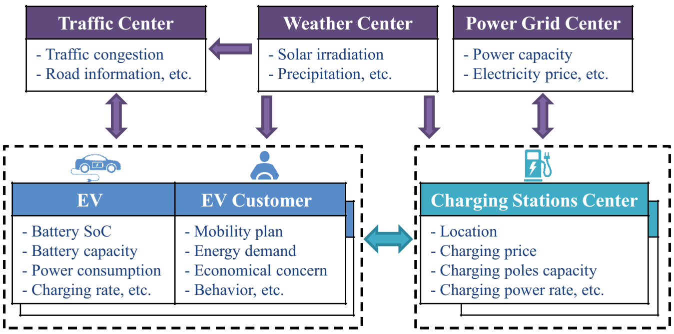

Fig. 1. Component configuration of the EV charging navigation system.

A. Charging Stations Center Model

This center is assumed to have information about a number of CSs $\mathcal{I} := \{1, 2, \ldots, I\}$; $i \in \mathcal{I}$. Given that x refers to the altitude and y to the latitude, the fixed locations of these CSs are in $\mathcal{L}_i := \{L_i \in \mathcal{L}_i \mid L_i(x_i, y_i)\}$. These CSs are the places for charging the EVs within the travel mobility multitime interval $\mathcal{T} := \{1, 2, \ldots, T\}$. At any time $t \in \mathcal{T}$, the ith CS, i.e., CS$_i$, is supplied by the grid power at its point $p^g_{i,t}$ and may also by the power of its renewable and storage energy resources $p^r_{i,t}$. Therefore, the total available power of this CS at time t for charging EVs, i.e., $p_{i,t}$, can be written as [12],

$$p_{i,t} = p^g_{i,t} + p^r_{i,t}, \quad \forall t \in \mathcal{T}. \tag{1}$$

By considering the maximum loading capacity of CS P^{max}_i and its overload control threshold $\eta_i (\leq 1)$ [13], the announced available power has to held the following,

$$p_{i,t} \leq \eta_i P^{max}_i, \quad \forall t \in \mathcal{T}. \tag{2}$$

It is assumed that every ith CS has a number of charging poles (CPs) $\mathcal{K}^c_i := \{1, 2, \ldots, K^c_i\}$; $k^c \in \mathcal{K}^c_i$ and a number of parking slots (PSs) $\mathcal{K}^p_i := \{1, 2, \ldots, K^p_i\}$; $k^p \in \mathcal{K}^p_i$. Given that the charging power rate of CP is $P^r_{i,c} \in \mathcal{P}^r_c$, if all CPs in the ith CS are occupied by EVs, the maximum applied power rate, i.e., charing capacity, that can be supported by this CP is

$$P^{r,max}_{i,c} \in \mathcal{P}^{r,max}_i = min(P^r_{i,c}, \frac{p_{i,t}}{K^c_i}), \quad \forall t \in \mathcal{T}. \tag{3}$$

At any time t, each CS offers a specific charging price for EVs $\theta^c_{i,t} \in \theta^c_t$ (\$/(kWh)) on the basis of electricity market and charging power demand. It also offers a specific parking price, fee, $\theta^p_{i,t} \in \theta^p_t$ (\$/h). These two prices are considered to be fixed according to time-of-use rate plan.

B. EV Model

The term EV refers to the BEV itself and also to its customer, i.e., user/driver, in which they are interchangeably used. It is assumed to have in the CNS a number of EVs $\mathcal{N} := \{1, 2, \ldots, N\}$; $n \in \mathcal{N}$. Unlike CSs, these EVs have dynamic geographical locations $\mathcal{L}_n := \{L_n \in \mathcal{L}_n \mid L_n(x_n, y_n)\}$, which are determined by the travel mobility plans of EV customers. This mobility plan indicates to the cycle of the daily travel activities that can be represented by the three main statuses of EVs as illustrated in Fig. 2, namely moving, parking, and charging.

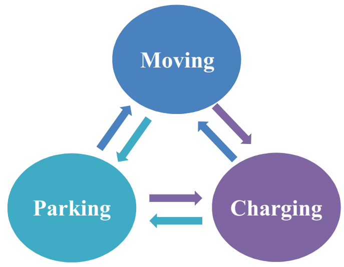

Fig. 2. Travel mobility statuses of EVs.

While EV is moving on road from the origin to the destination, i.e., EV in the moving status, it consumes energy from its battery. Once the EV arrives at the destination, it will park for some time, i.e., EV in the parking status. At any of these two statuses, if the remaining energy of EV battery becomes low, its EV customer may decide to navigate to a specific CS to plug in the EV for charging, i.e., EV in the charging status. Therefore, the term of EV charging navigation refers to the state when EV customer demands to select a proper CS to charge the EV. Once the EV is charged by the demanded energy, it will continue to move on road to its planned destination.

When EV runs on road, it consumes (discharges) power $p^d_{n,t}$ which is related to its speed $v_{n,t}$ by an approximated quadratic form with proper coefficients a_1, a_2, and a_3 [11],

$$p^d_{n,t} = a_1 v^2_{n,t} + a_2 v_{n,t} + a_3, \quad \forall t \in \mathcal{T}. \tag{4}$$

The actual speed of EV on road $v_{n,t}$ between two locations, such as $L_i(x_i, y_i)$ and $L_n(x_n, y_n)$, depends on the expected speed of EV between the two locations $v_{n,i}$ and also on the EV customer behavior factor $b_{n,t}$, as defined in (5). The expected speed can be substituted by the distance between the two locations $D_{n,i}$ (simply equals $\sqrt{(x_n - x_i)^2 + (y_n - y_i)^2}$) and the expected time to travel between them $T_{n,i}$. It is assumed that the EV customer can access the values of the distance $D_{n,i} \in \mathcal{D}$ and the expected time $T'_{n,i} \in \mathcal{T}'$ from the information supported by the traffic center. Whereas, the factor $b_{n,t}$ is related to the EV customer behavior. This behavioral factor could rely on several issues, such as the weather and traffic conditions, therefore, it is reasonably assumed to be in the range [0,3].

$$v_{n,t} = v_{n,i} \times b_{n,t} = \frac{D_{n,i}}{T'_{n,i}} \times b_{n,t}, \quad \forall t \in \mathcal{T}. \tag{5}$$

The SoC dynamics of EV battery depends on the battery capacity (size) S_n as well as on the EV status, i.e., moving or charging here. However, at any time t the SoC of EV, $SoC_{n,t}$, should be within the maximum and minimum limits, SoC_n^{max} and SoC_n^{min}, respectively, as follows,

$$SoC_n^{min} \leq SoC_{n,t} \leq SoC_n^{max}. \tag{6}$$

Once the EV is moving on the road, the SoC dynamics can be written by the following linear model,

$$SoC_{n,t+1} = SoC_{n,t} - \frac{\eta_d \Delta t p_{n,t}^d}{S_n}, \tag{7}$$

with $\eta_d \in (0, 1]$ is the discharging efficiency and Δt is the time step. Similarly, given that $\eta_c \in (0, 1]$ is the charging efficiency and $p_{n,t}^c$ is the charging power delivered to the EV battery at the CS, the SoC dynamics of EV while it is plugged in and charged at the CS is [14],

$$SoC_{n,t+1} = SoC_{n,t} + \frac{\eta_c \Delta t p_{n,t}^c}{S_n}. \tag{8}$$

It should be noted that the charging power delivered to the EV battery has also to be no smaller than zero, i.e., unidirectional charging of EV, and also no bigger than the charing power rate that can be supported by the cth CP in the ith CS as written in (9).

$$0 \leq p_{n,t}^c \leq P_{i,c}^{r,max}, \quad \forall t \in \mathcal{T}. \tag{9}$$

It is assumed that EV arrives at the ith CS at time $T_{n,i}^a$ with SoC of $SoC_{n,i}^a$ and departs, leaves, CS at time $T_{n,i}^l$ with SoC of $SoC_{n,i}^l$. Therefore, the demanded (requested) charging energy of EV in its charging time interval $\mathcal{T}_{n,i}^c := \{T_{n,i}^a, \ldots, T_{n,i}^l\}$ can be written as follows [15],

$$E_n^r = (SoC_{n,i}^l - SoC_{n,i}^a) S_n = \sum_{t \in \mathcal{T}_{n,i}^c} \Delta t p_{n,t}^c. \tag{10}$$

It has to be noted that only the focused models are presented here which will be used in the following sections.

III. EV Charging Navigation

Again, the EV charging navigation refers to the condition when the EV customer demands to charge his/her EV at the nearby/available CS. In other words, guiding the specific EV to properly selecting the target CS. The problem formulation and the technique to reach the solution are described in the follows.

A. Problem Formulation

The focus in this paper is on the practical implementation of EV charging navigation in a large scale of geographical distribution of EVs with consideration of economical objectives and behavioral concerns of EV customers. It is known that the timely move of EV over the designated destinations is the main principle of the EV customer travel mobility plan. Therefore, charging EV is assumed to be the mission that needs to be done as fast and cheaper as possible. Therefore, the cost function of each EV customer, in minimizing the monetary value to finish this charging mission, is reasonably constructed in this paper as the focused problem of this EV charging navigation. At this point, several concerns, i.e., criteria, have to be considered when formulating the EV customer decision to select, navigate to, a proper CS, as described in the below.

Intuitively, each EV customer concerns about selecting the closest CS to his/her location for charging the EV. This is because the EV customer needs to avoid the useless power consumption running on the road to reach the CS. Therefore, the EV customer cares about the cost of energy consumption (i.e., discharging) to reach the ith CS $C_{n,i}^d \in \mathcal{C}_n^d$ from the current time ($t = 1$). This cost can be defined as in (11) after assuming that the running time on road to reach the CS is in the interval $\mathcal{T}_{n,i}^d := \{1, 2, \ldots, T_{n,i}^{a\prime} \in \mathcal{T}_n^{a\prime}\}$ and the unit cost of the energy consumption is θ^d (\$/kWh). This cost can also be approximated to have relation with the EV driving efficiency η_n^d (kWh/km) and the distance between the nth EV and the ith CS, $D_{n,i}$ (km).

$$C_{n,i}^d = \theta^d \sum_{t \in \mathcal{T}_{n,i}^d} \Delta t p_{n,t}^d = \theta^d \eta_n^d D_{n,i}. \tag{11}$$

The second concern for the EV customer is about the cost $C_{n,i}^p \in \mathcal{C}_n^p$ of EV parking, i.e., waiting at the PS of the ith CS before start charging when all its CPs are occupied. If the waiting time is in the interval $\mathcal{T}_{n,i}^p := \{T_{n,i}^{a\prime}, \ldots, T_{n,i}^a \in \mathcal{T}_n^a\}$, this cost can be written as follows,

$$C_{n,i}^p = \sum_{t \in \mathcal{T}_{n,i}^p} \theta_{i,t}^p \Delta t. \tag{12}$$

The time to fully charge the EV by its demanded energy at the CS can be basically calculated by $E_n^r / P_{i,c}^r$, as can be derived from (10). However, the charging power capacity from the CP at the CS could be lower than its charging power rate CP due to the lack of available power in the CS, as discussed in the section II-A. This will result in an extra time $\Delta T_{n,i}$ in charging the EV. Therefore, a newly discussed concern of EV customer in this paper is about the cost of this extra charing time $C^w_{n,i} \in \mathcal{C}^w_n$ that is defined by (13). Here, θ^b_n is the unit cost (\$/h) for the extra charing time, which is defined by the EV customer behavior and his/her own estimation for the monetary influences tied with this extra time.

$$C^w_{n,i} = \Delta T_{n,i}\theta^b_n = \left(\frac{E^r_n}{P^{r,max}_{i,c}} - \frac{E^r_n}{P^r_{i,c}}\right)\theta^b_n. \tag{13}$$

It is known that the charging energy cost $C^c_{n,i} \in \mathcal{C}^c_n$, paid by the EV customer to the CS, is an important concern while selecting the CS for charging the EV, which is defined as,

$$C^c_{n,i} = \sum_{t \in \mathcal{T}^c_{n,i}} \theta^c_{i,t}\Delta t p^c_{n,t}. \tag{14}$$

The final discussed concern of EV customer here is about the cost of energy consumption $C^r_{n,i} \in \mathcal{C}^r_n$ to resume running on the road from the ith CS, after finishing the charging process, to the target destination $L_{n,d}$. This concern is worthy to be included in the cost function of EV customer once selecting the CS for charging the EV. Similar to (11), this cost can be defined as in (15), given that $\mathcal{T}^r_{n,i} := \{T^l_{n,i} \in \mathcal{T}^l_n, \ldots, T^r_{n,i} \in \mathcal{T}^r_n\}$ is the time interval to leave the ith CS and to reach the destination. This cost can also be approximated given that the distance between the ith CS and the target destination is $D_{i,d}$ (km) as follows,

$$C^r_{n,i} = \theta^d \sum_{t \in \mathcal{T}^r_{n,i}} \Delta t p^d_{n,t} = \theta^d \eta^d_n D_{i,d}. \tag{15}$$

After considering all the above concerns, the cost function of the nth EV customer can be then represented in the following optimization problem,

$$\min_{f_{n,i}} \sum_{i \in \mathcal{I}} f_{n,i}\left(C^d_{n,i} + C^p_{n,i} + C^w_{n,i} + C^c_{n,i} + C^r_{n,i}\right), \tag{16}$$

where $f_{n,i}$ is a binary number that indicates to the selection status of the ith CS by the nth EV as defined by,

$$f_{n,i} = \begin{cases} 1 & EV_n \ selects \ CS_i, \\ 0 & Otherwise. \end{cases} \tag{17}$$

B. Solution Technique

The solution of the above problem by selecting the proper CS for charging the EV is made locally by the EV side. Therefore, each EV is assumed to have a local controller that makes the CS selection decision. Once the EV customer asks to select a CS at time t, the EV local controller calls the proposed EV charging navigation strategy (EVCNS), i.e., algorithm 1. This EVCNS is divided into four stages, namely initializing EV information, collecting information from charging stations center, collecting information from traffic center, and selecting the charging station.

At the first stage of EVCNS, the local parameters of EV have to initialized. Some of these parameters are time-based, therefore, they need to be updated at the beginning of executing EVCNS, as in line 1 of algorithm 1.

Algorithm 1 EV Charging Navigation Strategy

I. Initializing EV Parameters

1: Update L_n, $b_{n,t}$, $L_{n,d}$, $SoC_{n,t}$, $D^m_{n,t}$, B_n, θ^b_n,

II. Collecting Data From Charging Stations Center

2: Fetch $\mathcal{I}_n$, $\mathcal{L}_i$, $\mathcal{T}^a_n$, θ^p_t, $\mathcal{P}^r_c$, $\mathcal{P}^{r,max}_c$, θ^c_t, $\mathcal{T}^l_n$,

III. Exchanging Information with Traffic Center

3: Receive $\mathcal{T}^{a\prime}_n$, $\mathcal{D}$, $\mathcal{T}'$, $\mathcal{T}^r_n$,

IV. Selecting The Charging Station

4: Calculate $\mathcal{C}^d_n$ by (11),
5: Calculate $\mathcal{C}^p_n$ by (12),
6: Calculate $\mathcal{C}^w_n$ by (13),
7: Calculate $\mathcal{C}^c_n$ by (14),
8: Calculate $\mathcal{C}^r_n$ by (15),
9: Solve (16),
10: Navigate to the ith CS of $f_{n,i} = 1$.

After that the EV controller collects data from the charging stations center, as in line 2. This data is important to get knowledge about the available CSs and their charging schedules, capacities, and prices. However, only some nearby CSs to the EV location $\mathcal{I}_n$ are of interest to the EV customer, as defined in (18). These interested CSs are located inside a geographical circle that its center is the EV location. The radius of this circle is defined by the accepted distance of EV customer D^a_n, which depends on two factors as written in (19). The first factor is the maximum driving distance $D^m_{n,t}$ that can be supported by the EV. This maximum distance is related to the amount of energy in the EV battery, which can be accessed by the battery management system of EV battery and can be read from the EV dashboard. The second factor is the driving range anxiety of EV customer A_n [16]. This factor is related to the EV customer behavior, in which an increase in its value will to lead to a decrease in the geographical circle radius, i.e., focus on closer CSs. The value of this range anxiety is defined to be in the range [0,1] and to follow a Poisson distribution.

$$\mathcal{I}_n = \{i \in \mathcal{I} \mid D_{n,i} \leq D^{max}_n\}, \quad \forall n \in \mathcal{N}. \tag{18}$$

$$D^a_n = D^m_{n,t} \times (1 - A_n), \quad \forall n \in \mathcal{N}. \tag{19}$$

The EV controller also exchanges information with the traffic center. It sends the locations of the EV, target destination, and CSs to the traffic center. Then, it receives from the traffic center the distances and the expected arrival times to these areas, as listed in line 3.

After gathering all the above data, the EV local controller can then processes the necessary information to select the suitable CS. It first calculates the costs that concern the EV customer, as in lines 4-8. Then, it solves the optimization problem (16) and suggests to navigate to the optimal CS, as in lines 9 and 10, respectively.

It should be noted that the proposed EVCNS has several advantages in the modern implementation of the cyber-physical systems. At the large-scale network application, the proposed EVCNS works in a distributed manner. Therefore, it only needs to collect some information and applies the solution for a single EV in the specified interval comparing with the centralized approach that has one global controller who requires to gather all the information of EVs and finds the solutions for all EVs. Another issue is that the proposed EVCNS runs by sharing/collecting general (public) information to/from the connected centers with no need to reveal private information of EV customers. This concern is important to protect and to secure the privacy of the EV customers in the cyber-physical systems network.

IV. Simulation results and analysis

The performance of the proposed algorithm is evaluated here by the following described simulation setup. It is assumed to have EV customer, who demands to charge his/her EV by $E_n^r = 50$ (kWh) at a time of the day with unit of charging price $\theta^c = 0.16$ (\$/kWh) at all CSs [17]. The model of this example EV is BMW iX3 with driving efficiency $\eta_n^d = 0.206$ (kWh/km) [18], [19]. The unit cost of energy consumption θ^d is considered to be the same of θ^c, because the consumed energy in EV in driving will be compensated by the charged energy at the CS. It is assumed also to have four CSs and all are located within the circle of the accepted distance of EV customer. The distances between the example EV and these CSs, i.e., CS_1, CS_2, CS_3, and CS_4, are 7.5, 15, 20, and 23.5 (km), respectively. Whereas, the distances between the CS_1, CS_2, CS_3, and CS_4 and the target destination of EV customer are 23, 18, 15.5, and 6 (km), respectively. All the four CSs have available CPs at the time of charging demand by the example EV except CS_1, which needs $\mathcal{T}_{n,1}^p = 0.5$ (h) to have a vacant CP and it offers a parking fee $\theta^p = 0.5$ (\$/h). Out of the four CSs, CS_1 and CS_2 have extra charging time $\Delta T_{n,1} = \Delta T_{n,2} = 1$ (h), due the lack of power and the example EV customer estimates the unit cost for this extra charing time to be $\theta^b = 0.2$ (\$/h).

Three methods in this paper are adopted, i.e., Method-1, Method-2, and Method-3, and compared with the proposed one, i.e., method-4. The addressed issues by each method are summarised in Table I and described as follows:

1) *Method-1:* Minimizes the costs of energy consumption to reach the CS and charging energy.
2) *Method-2:* Minimizes the costs of energy consumption to reach the CS, charging energy, and parking time.
3) *Method-3:* Minimizes the costs of energy consumption to reach the CS, charging energy, parking time, and extra charing time.
4) *Method-4:* Minimizes the costs of energy consumption to reach the CS, charging energy, parking time, extra charing time, and energy consumption to reach the target destination.

Therefore, Method-1 is actually seeking for the nearest CS that supports the lowest charging price while dropping the other criteria. As shown in Table II, The lowest calculated cost is for CS_1, i.e., 8.247 (\$) and this method chooses CS_1 to navigate for charging, as illustrated by the arrow from the EV location to this CS in Fig. 1(a).

TABLE I
Concerned Criteria of The Comparison Methods

Criterion	$\mathcal{C}_n^d$	$\mathcal{C}_n^c$	$\mathcal{C}_n^p$	$\mathcal{C}_n^w$	$\mathcal{C}_n^r$
Method-1	✓	✓	✗	✗	✗
Method-2	✓	✓	✓	✗	✗
Method-3	✓	✓	✓	✓	✗
Method-4	✓	✓	✓	✓	✓

Method-2 is similar to Method-1 but with ability to tackle the case of unavailable CPs at the CSs for the current time. Therefore, since in the described simulation setup all CPs at CS_1 are occupied and it needs $\mathcal{T}_{n,1}^p = 0.5$ (h) to have a vacant CP, it will apply a parking cost of 0.25 (\$). Therefore, the lowest calculated cost by Method-2 is supported by CS_2, i.e., 8.494 (\$), as listed in Table II. This means Method-2 chooses CS_2 to navigate, as depicted in Fig. 1(b).

Comparing with Method-2, Method-3 handles the extra charging time due the lack of power, such as the extra 1 (h) at CS_1 and CS_2. This will result in an extra cost of 0.2 (\$) at these two CS. Thus, CS_3 will be offering the lowest calculated cost of 8.659 (\$) in Method-3, and then it will be chosen for navigation, as seen in Table II and Fig. 1(d).

Beyond to the concerned issues in Method-3, Method-4 addresses also the traveling cost after charging from the potential selected CS to the target destination of EV customer. Therefore, including this cost of traveling will make the calculated cost of CS_4, i.e., 8.972 (\$), as the lowest among others. Thus, Method-4 will indicate to navigate to CS_4 for charging, as pointed out in Table II and Fig. 1(d).

It is worthy to observe from the costs of CSs in proposed Method-4 that it saves, i.e., reduces the cost by, 0.483 (\$) comparing with Method-1 for a single charging navigation of the EV customer. This means a monetary saving by 5.108 (%). By extending this saving for multiple charging navigation demands due to the travel mobility activities of EV customer over time, i.e., monthly and yearly, the resulted monetary saving will be worthy to adopt the usage of the proposed method.

TABLE II
Costs and Charging Station Selections by The Comparison Methods

Target CS	CS_1	CS_2	CS_3	CS_4	Selected CS
Method-1 (\$)	8.247	8.494	8.659	8.774	CS_1
Method-2 (\$)	8.497	8.494	8.659	8.774	CS_2
Method-3 (\$)	8.697	8.694	8.659	8.774	CS_3
Method-4 (\$)	9.455	9.287	9.169	8.972	CS_4

V. Conclusion

Once the EV customer demands to charge his/her EV at a charging station, multiple important factors need to be considered for a better selection. These factors are related to the stages before, during, and after charging. This paper introduced a strategy that addressed these factors in the selection problem of the charging station. The strategy was structured to be suitable for the distributed large-scale implementation

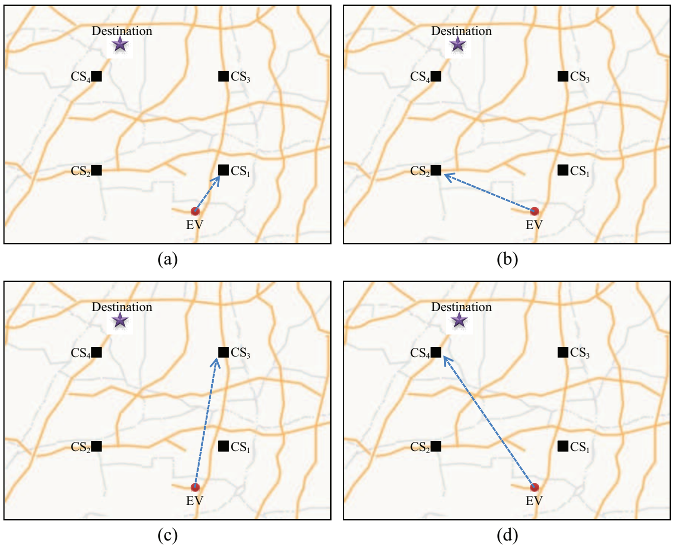

Fig. 3. Illustrative example of CS selection by the comparison methods. (a) Method-1. (b) Method-2. (c) Method-3. (d) Method-4.

of the EV charging navigation. This navigation problem was formulated as a cost function for each EV/customer which included the costs of energy consumption in driving to reach the charging station and the EV destination after charging, parking time, extra time due to the uncertainty in the charging power rate, and the demanded charging energy. The solution of choosing the charging station was reached in an optimal way. The simulation analysis proofed the performance of the proposed strategy over several comparison methods for lowering the overall cost to finish the charing of EV within the travel mobility of EV customer. The work in this paper could be extended to show the economical improvements at a large-scale charging of EVs over a long time interval.

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