Optimal Operation of Virtual Charging Systems for Plug-In Electric Vehicles

Mohamed Mokhtar, *Member*, *IEEE*, M. F. Shaaban, *Senior Member*, *IEEE*, Hatem Zeineldin, *Senior Member*, IEEE, and E. F El-Saadany, *fellow*, IEEE

***Abstract*— This paper proposes a novel concept, denoted as Virtual Charging System (VCS), for electric vehicles' (EVs). In a conventional charging system (CCS) with a competitive environment, the competition between charging stations can utilize game theory as a price competition game model. On contrary, charging stations with different ownerships under the VCS umbrella will cooperate to act as one charging station for EV drivers in order to increase customer satisfaction and obtain more profits collectively and individually. The proposed VCS consists of three parts: participating charging stations, EVs contracting with the VCS, and finally the VCS operator. The operator is responsible for optimally routing the EVs to a suitable charging station within the VCS. A new formulation for implementing this novel concept is presented to allow interaction between various VCSs to maximize the profit gained by each VCS as well as minimize the transit charging time and cost for each customer as a measure representing customer satisfaction. Different case studies are introduced to evaluate the significance of the VCS concept. The performance of the VCS is compared to CCS, and the results show that VCS provides superior customer satisfaction and higher profit.**

***Index Terms*—Charging stations, electric vehicles, virtual charging system, game theory, price competition.**

I. Introduction

Electric vehicles (EVs) play a vital role in the future of transportation systems. Vehicle electrification is considered as an essential trend to reduce global warming. Various countries have announced roadmaps for electric vehicles (for example Scotland will dispose internal combustion engine (ICE) vehicles by 2032) [1]-[3]. Moreover, EVs became cost-competitive with ICE vehicles, mainly due to the drop in battery price in the last few years. This has led to a continuous increase in EVs' share in the vehicle market [4]. Although EVs are an emerging trend, they suffer from long charging times, limited driving miles, and the insufficiency of infrastructure as well as their negative impact on the distribution network [5]-[7].

EVs' drivers can charge their battery at either home, in parking lots, or at the charging stations. Both dc and ac chargers can be used to charge the EVs. The dc charger can be found mainly at the fast-charging stations and this is due to the high currents used in the charging process and high capital cost. On the contrary, ac chargers are installed at homes or in parking lots [8]-[10].

In this context, charging of EVs at public charging stations becomes more attractive for several different reasons. The first is that the charging stations, as a commercial entity, purchase the electricity from the gird at a lower price compared to the EVs' owners charging at home. The second reason is that the charge of the battery may run out during the trip and the need for a charging station will be inevitable [11]. Therefore, it is a necessity to install an optimal number of charging stations and minimize the time of the charging process to encourage customers to utilize EVs and to minimize the use of diesel or gas vehicles [12].

The relevant existing research considers the time of the charging process to be a major challenge and options are being explored to aminimize this time. The authors, in [12], considered smart charging options like ac charger, dc fast charger, and battery exchange in a specific charging station. Furthermore, they considered different prices for each option at the same charging station, and the charging option was selected aiming to minimize the waiting time and charging cost. The authors, in [13], suggested a framework to use the communication to share information such as electricity price, and time of arrival between the competing charging stations and EVs ' drivers for optimal power flow and EVs routing. The work, in [14], presented an approach for allocating the EVs charging stations on the highways. The approach utilized the coordination between the charging stations and EVs to reduce the travel time of PEVs using the A* search technique. The authors, in [1], presented a dynamic pricing strategy for charging stations to utilize renewable energy generation. It was assumed that the EV's driver will select the charging station based on the distance to each charging station as well as the charging price. Charging network operators (CNOs) were introduced in [15] to set a charging price mechanism for the charging stations. This price mechanism aimed to minimize the charging costs incurred by EV's driver, the travel time, and the waiting cost. Moreover, it was assumed that CNO was aware of the travel plans of all EVs. The authors in [16] introduced the EV routing problem based on the time of use (TOU) electricity price. This problem was formulated in a similar manner to the travel salesman problem to minimize the charging cost and cost of reducing battery life due to fast charging. The authors in [17] introduced the Stackelberg game, formulated as a single leader and multi follower where the charging network operator was considered as the leader and the EVs were considered as the followers. This game aimed to set the charging price to maximize the profit gained by the charging stations and then the follower selects the charging station to charge at. The work in [18] presented a price competition method between charging stations. Furthermore, the charging station demand was considered to decrease linearly with the price increase. In [11], a price competitive game between different charging station was proposed. In this game, the EV's driver selected the charging station based on the charging price and the distance to

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the charging station. Furthermore, the authors of [11] assumed that the EVs were uniformly distributed, and all batteries have the same capacity. However, the impact of customers' selection on the waiting time at each charging station for the upcoming customers and the characteristics of battery charging weren't considered. In this context, the authors in [19] considered the effect of waiting time on customer selection in the price competitive game. They assumed that the customers selected the charging station based on the charging price, the distance to the charging stations, and the waiting time at the charging stations. The waiting time was determined based on $M/G/K$ queue model although the authors assumed that the customers weren't aware of other customers' behavior due to a lack of communication between them. The authors of [20] assumed that there is Charging Network Operator (CNO) owned EV public charging stations. This CNO is responsible for determining optimal charging prices and routing EVs drivers to a certain charging station. However, they assumed that EVs drivers cannot directly select the station to charge at it. The authors of [21] proposed a charging strategy based on price incentives for EVs while considering the spatial and temporal impact of EVs decisions. The work in [22] proposed a platform to route EVs drivers that considered the required energy to reach the station, the waiting time, the charging time, and the required energy to reach the required destination after the charging. However, these factors were considered as an extra cost for the charging process. The authors is [23] proposed a strategy to route EVs drivers to the charging station through minimizing the cost of the traveling distance and the charging cost while considering time-of-use energy prices, and EVs' energy consumption.

Electric vehicles are an emerging trend, therefore, most of existing research focuses on facilitating the charging process of EVs to incentivize customers toward EVs through introducing new charging strategies to reduce the entire time of the charging process. The strategies presented in most of the literature focus either on satisfying customers' requirements or increasing profits of charging stations as there is a competition between the profit obtained by the charging station and the customer satisfaction. Most of these strategies were based on the competition between charging stations and thus, the charging station may offer lower charging price to attract more customers. The main solution to the previous issue is to consider the cooperation between charging stations through an organized system to fulfills both the stations and customers' requirements. However, limited research considered the cooperation between charging stations. The cooperation between the charging stations will allow them to only think about serving all customers, and hence, obtaining more profits.

This paper proposes a new concept called virtual charging system (VCS). The new concept of VCS takes into consideration the cooperation between charging stations under different ownership in the same VCS. However, there is a competition between different VCSs. Furthermore, the charging stations contributing in VCS aim to maximize customer satisfaction through minimizing the entire time of charging process as well as their profit through serving all charging requests. We assume that this procedure is implemented centrally through a centralized operator. Through combined competition and cooperation, we will reach to the optimal solution that not only maximizes the profit but will also maximize customer satisfaction by reducing the entire time of the charging process. To realize this novel concept, a new formulation is introduced to optimally route EVs to suitable charging stations participating in VCS in the case of single VCS as well as multiple VCSs. The problem proposes a real-time solution for routing of EVs to optimal charging station participating in VCS. The main contributions of this paper can be summarized as follows:

- We introduce the concept of VCS that takes into consideration the cooperation between charging stations under different ownerships in the same VCS.
- The main role of VCS is to route the EV to the most suitable charging through computing all parameters based on deterministic models and the collected data from participating charging stations which share their information due to the absence of competition as they work under one umbrella.
- A model for conventional charging system (CCS) is introduced in this paper to be used as a base case for a comparison with VCS.
- Finally, we investigate the importance of coordination between various VCSs in order to increase the customer satisfaction and profit gained by each VCS.

The rest of the paper is organized as follows: CCS is presented in Section II. The VCS and proposed methodology are explained in Section III and Section IV, respectively. The proposed methodology for coordination between different VCSs is explained in Section V. Results and multiple case studies are presented and discussed in Section VI. Finally, the conclusions are presented in Section VII.

II. Conventional Charging System (CCS)

In this section, the model of CCS is presented to be used as a base case for comparison with VCS. Each charging station in CCS competes with neighboring charging stations under different ownerships to attract more EVs by offering a lower price than the other stations. Therefore, we assume that there is price competition between different charging stations in order to set its price which maximizes the revenue. The price competition between different charging stations is formulated as an N-player non-cooperative game [11], [19]. This procedure can be implemented through two stages which run iteratively until convergence:

- Stage 1: each charging station will determine its charging price at the beginning of each time segment independent of the behavior of the other charging stations. Each station will focus on achieving the highest profit based on the predicted EVs' requests during this time segment while considering the impact of the price variations offered by the other stations on the EV's decision. Moreover, each charging station will broadcast the variable day-ahead charging price.
- Stage 2: every EV driver will select independently the charging station according to the EV location from different charging stations and the quoted charging price of each station.

As mentioned before, each charging station will set its charging price independently to attract more EVs and hence, maximize its profit. Thus, the competition includes:

- Players: different charging stations in competition.
- Strategies: set the charging price for EVs.
- Payoff: the profit which the charging station will obtain.
- Nash equilibrium: optimal stable charging price of each charging station.

The payoff of charging station i to maximize its profit R_i can be expressed as follows:

$$\max\ R_i(\rho_i, \rho_{-i}) \quad \forall\ i \in \mathcal{I} \qquad \rho_i \in \{\rho_i^{min}, \rho_i^{max}\} \tag{1}$$

where i and $\mathcal{I} = \{1,2, \dots, N_{cs}\}$ are the index and the set of charging stations respectively, ρ_i is the charging price of charging station i, ρ_{-i} refers to the price of all charging stations except the charging station i, N_{cs} is the total number of charging stations in competition, and $\rho_i^{min}, \rho_i^{max}$ are the lower and upper limit of the charging price of charging station i.

R_i depends not only on the charging price of charging station i but also it depends on the prices offered by the other charging stations as these prices affect the EVs' decisions. The solution of the previous equation for each charging station will determine the Nash equilibrium which expresses the optimal charging price of each charging station ρ_i^* during each time segment $t \in \mathcal{T}$, where t and $\mathcal{T} = \{1,2, \dots, N_t\}$ are the index and the set of time segments respectively. N_t is the total number of time segments throughout the day. The optimal charging price offered by a charging station will be affected by the charging prices offered by the other charging stations during this time segment, expected EVs' requests during this time segment, the electricity price from the grid, and the distance from the current location of each EV to this charging station compared to the distances from the current locations of the EVs to the other charging stations where the charging station may reduce the cost to compensate the farthest distance of the customer. Therefore, ρ_i^* is determined numerically each time segment. The profit of the charging station each time segment can be expressed as follows:

$$R_i(t) = \sum_{c \in \mathcal{C}} E_{req(c)} * \rho_i(t) \tag{2}$$

where c and $\mathcal{C} = \{1,2, \dots, N_c\}$ are the index and the set of customers respectively, N_c is the total EVs select to charge at the charging station i during time segment t, $E_{req(c)}$ is the required charging energy by customer c, and $\rho_i(t)$ is the price offered by charging station i during time segment t.

The required energy to be charged at each charging station depends on the charging price of the other charging stations as the price of the other stations affects the decision of EVs. We assume that each EV's driver will select the charging station independent of the behavior of other EVs' drivers and according to the distance from its current location to each charging station's location which represents the travel time in addition to the charging price announced by each charging station. The waiting time at each charging station will not be considered in the driver's decision as we assume that the customers aren't aware of the choices or decisions of the other customers during this time step. Therefore, the EV's driver will select the charging station i which minimizes the following function:

$$\arg\min_{i \in \mathcal{I}} \left[w_1 * \bar{d}_{(c,i)} + w_2 * \bar{\rho}_i(t) \right] \tag{3}$$

$$\bar{d}_{(c,i)} = \frac{d_{(c,i)}}{d_{max}} \tag{4}$$

$$\overline{\rho_i}(t) = \frac{\rho_i(t)}{\rho_{max}(t)} \tag{5}$$

where, $\bar{d}_{(c,i)}$ is the normalized distance, $\overline{\rho_i}(t)$ is the normalized price, $d_{(c,i)}$is the distance from the current location of EV and the charging station i, w_1, w_2 are the weighting coefficients for distance and price respectively which are assumed equally in this paper, d_{max} is the distance from the current location of the EV to the farthest station, and $\rho_{max}(t)$ is the highest charging price among all charging stations during this time segment.

III. Proposed Virtual Charging System

This section will introduce the new concept of VCS. As mentioned earlier, there is no need for competition between charging stations participating in the same VCS. However, these charging stations under different ownership can cooperate together to serve the customers with a high level of customer satisfaction. This concept is similar to a virtual power plant where a set of distributed generators (DGs) and energy storage devices act together in the market as one power plant with defined hourly output. Hence, the charging stations under VCS will act as one station with respect to the customers as shown in Fig. 1. Furthermore, all charging stations participating in the same VCS will offer the same charging price as there is no need to vary the price to attract more customers due to the absence of competition between them as they work under one umbrella. The main objective of VCS is the optimal routing of the EVs to the suitable charging stations to increase the customer satisfaction and the profit obtained by VCS and hence the profit obtained by each charging station participating in the VCS. The VCS consists of three major parts which are the EVs' drivers that are contracted with this VCS to charge their batteries, the charging stations participate in VCS, and finally the centralized operator as shown in Fig. 2.

A. *Electric Vehicles' Drivers*

The EV driver will send a request through a mobile app when needed to charge the battery. This request will contain all required information to optimally route this EV to the most suitable charging station, which satisfies the customer's requirements. This request contains the current SOC of the battery, battery's capacity, and finally, the current location of EV to determine the driving time needed to reach each charging station while considering the traffic flow at this time segment.

B. *Charging Stations*

The second part of the VCS is the contributing charging stations. Each charging station will share its information with the centralized operator as there is no competition between these charging stations. Therefore, serving customers efficiently will benefit all stations. Moreover, increasing customer satisfaction and revenue are vital priorities for all charging stations. The shared information includes the number

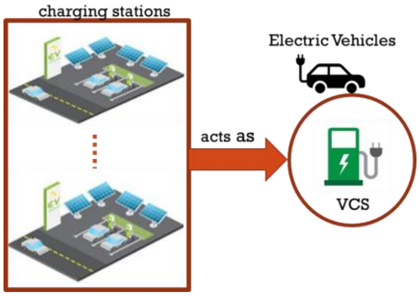

Fig. 1. The proposed VCS concept.

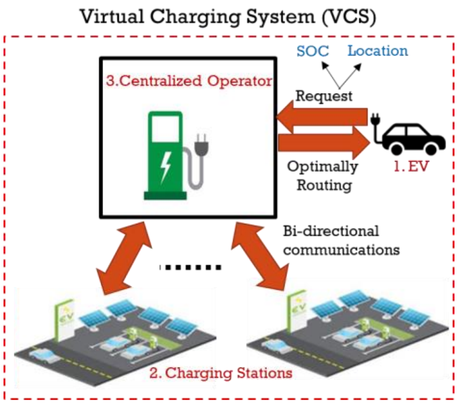

Fig. 2. The proposed framework of VCS.

of bays available at the charging station, the type of chargers in this station and the number of occupied bays. However, the process of selecting the charging station to be used to charge an EV is not the responsibility of the charging stations rather it's the centralized operator responsibility which will be explained in the next subsection.

C. Centralized Operator

The centralized operator is the vital link between the EVs' drivers and the charging stations. Further, it is responsible for the communication between the EVs and VCS. This operator will be set by agreement between the participating charging station. The procedure implemented by the centralized operator is shown in Fig.3. Bi-directional communication between the centralized operator and EVs are needed. It receives a request from the EV owner including the current SOC, the location of the EV, and the battery capacity. Then, it calculates the travel time from the current location of EV to each charging station while considering the traffic flow and the maximum distance that the EV can travel before its battery runs out of charge. Moreover, there is another communication channel between the centralized operator and the charging stations participating in the VCS. The centralized operator of VCS receives information from the charging stations about the status of each charging station including the number of occupied bays. Then, it will implement the decision-making process to calculate the expected waiting time and the expected charging time at each charging station and finally, optimally route the EV to a suitable charging station based on the collected and calculated data. Finally, it will send the optimal route to the EV driver to the best charging station along with the expected waiting, charging durations and expected departure time if the battery is charged to the required SOC. If the EV owner approves the route, the process ends with the operator reserving a place for this EV in the queue for this specific bay and identifies the selected charging station to devote a bay for this EV. It is worth mentioning that the signals sent to the EVs drivers should be secured to avoid the possible cyber-attacks that may be applied to these signals, which may aim to cause traffic jams at certain places.

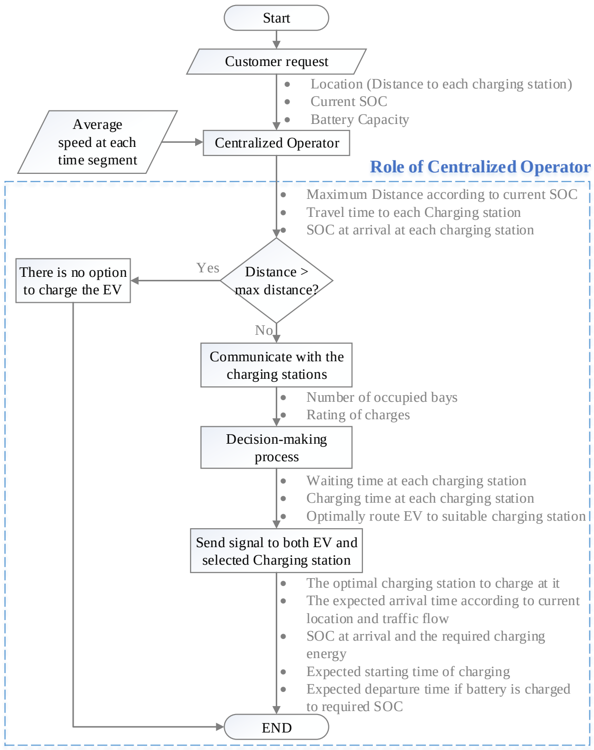

Fig. 3. Flow chart of VCS Framework.

IV. Mathematical Model of Routing Problem through VCS

As mentioned before, we assume that there is no competition between the charging stations contributing in the VCS and they will cooperate. Hence, the charging stations will offer the same charging price. Furthermore, we assume that there is no coordination between different VCSs in this section. The optimal decisions include the EV route to the suitable charging station, which satisfies the requirements of the EV's driver. Therefore, for the central operator to develop the optimal route for each EV, we develop a mixed-integer nonlinear programming (MINLP) formulation with the objective of maximizing the EV drivers' satisfaction. The charging cost at each charging station isn't considered in this decision-making process as the charging price is the same at all charging stations in the same VCS. The MINLP can be expressed as follow:

$$\min \sum_{i\in \mathcal{I}} \left(T_{tr(c,i)} + T_{wa(c,i)} + T_{ch(c,i)}\right) * x_{(c,i)}\,, \qquad \forall c \in \mathcal{C} \tag{6}$$

$$x_{(c,i)} \in \{0,1\} \tag{7}$$

$$\sum_{i\in \mathcal{I}} x_{(c,i)} \le 1, \qquad \forall c \in \mathcal{C} \tag{8}$$

$$b_i(t) \le N_{bays(i)} \quad \forall i \in \mathcal{I}, \qquad \forall t \in \mathcal{T} \tag{9}$$

$$b_i(\mathrm{t}+1) = b_i(\mathrm{t}) + \sum_{c\in \mathcal{C}} x_{(i,c)}\ , \ \ \forall t \in \{t_{ch(c)}^{start} : t_{ch\,(c)}^{end}\} \tag{10}$$

where, $T_{tr(c,i)}$ is the travel time from the current location of customer c to the charging station i, $T_{wa(c,i)}$ is the waiting time of customer c at charging station i, $T_{ch(c,i)}$ is the charging time of customer c at charging station i, $x_{(c,i)}$ is a binary variable indicating serve customer c at charging station i, $b_i(\mathrm{t})$ is the number of occupied bays at any time segment t at charging station i, $N_{bays\,(i)}$ is the total number of bays available at charging station i, and $t_{ch\,(c)}^{start}$, $t_{ch\,(c)}^{end}$ are the start time and end time of the charging process of customer c, respectively.

In the objective function (6), the summation of travel, waiting, and charging times of each customer is minimized. $x_{(c,i)}$ is a binary variable as expressed in (7). For, $x_{(c,i)} = 1$, the customer c is assigned to charging station i. In (8), each customer will be assigned to only one station if it will be served. Constraint (9) shows that the number of occupied bays should be less than or equal to the total number of bays available in the charging station i. Constraint (10) shows that if the customer c is assigned to the charging station i, so, the number of occupied bays at this charging station i will increase by one during the charging period of customer c.

A. *Travel Time*

Travel time or driving time depends on the distance from the current location to the destination and traffic flow currently. The distance can be converted to time by dividing the distance by the average speed. The traffic flow can be considered in the average speed. The average speed is affected by the speed limit of the roads, traffic, and road conditions. This time can be expressed as follow:

$$T_{tr(c,i)} = \frac{d_{(c,i)}}{v_i(t)|_{t=T_{req(c)}}} \tag{11}$$

where $v_i(t)|_{t=T_{req(c)}}$is the average speed from the current location of the customer to the charging station i at request time of this customer $T_{req(c)}$.

The distance to a specific charging station must be less than or equal to the maximum distance that the EV can travel $D_{(c)}^{max}$. This distance is based on the current SOC at the request time in order to make sure that the battery of EV will not run out of charge before arriving at the charging station. The maximum distance that the EV can travel according to its current SOC can be expressed as follow:

$$d_{(c,i)} * x_{(c,i)} \le D_{(c)}^{max} \tag{12}$$

$$D_{(c)}^{max} = \frac{\left[SOC_{req} - SOC_{min}\right] * E_{cap}}{E_{con}} \tag{13}$$

$$SOC_{min} = 1 - MOD \tag{14}$$

where, SOC_{req} is the current SOC of battery in EV at request time, SOC_{min} is the minimum acceptable SOC, E_{cap} is the total battery capacities in this EV, and E_{con} is the energy consumption per unit distance in (kWh/km). This energy depends on several parameters as the distance between the current location of the customer and the charging stations, the traffic conditions to each charging station which reflects on the average speed, the ambient temperature, the current SOC of the battery, and driver habits. However, it is assumed to be constant in this paper just for validation the proposed concept [24].

Constraint (12) illustrates that the distance from the current location of customer c to charging station i must be less than or equal to the maximum distance that the customer can travel. Hence, if this distance is higher than the maximum distance, so $x_{(c,i)}$ must be 0 and this means that this customer c can't be assigned to this charging station i; otherwise, $x_{(c,i)}$ may take a value of 1 or 0. In constraint (13), the maximum distance is determined based on the current SOC and minimum SOC, which depends on the maximum depth of discharge (MOD), as in (14).

B. Waiting Time

The waiting time is determined based on the difference between the arrival time of customer c at the charging station i and when there is an available bay. The availability of a bay is investigated when the number of occupied bays becomes less than the total number of bays available at this charging station. Therefore, this time can be formulated as follows:

$$T_{wa\,(c,i)} = \begin{cases} 0 & b_i(t_{arr(c,i)}) < N_{bays(i)} \\ (t|_{b_i<N_{bays(i)}} - t|_{arr(c,i)}) & b_i(t_{arr(c,i)}) \geq N_{bays(i)} \end{cases} \quad (15)$$

$$T_{wa\,(c,i)} * x_{(c,i)} \leq T_{wa}^{max} \quad (16)$$

In (15), the waiting time of customer c at charging station i will be zero if the number of occupied bays $b_i(t_{arr(c,i)})$ at the instant of customer c arrival at the charging station i $(t|_{arr(c,i)})$, is less than the total number of available bays at this charging station ($N_{bays(i)}$). Otherwise, the customer c will wait at this charging station until there is an available charging bay at this charging station $(t|_{b_i<N_{bays(i)}})$ which is investigated when the number of occupied bays (b_i) is less than the total number of bays ($N_{bays(i)}$) and thus, the waiting time of this customer is the difference between two times. In (16), the waiting time of customer c at charging station i should be less than or equal to the maximum allowable waiting time T_{wa}^{max}. If the waiting time at a certain charging station is higher than the maximum waiting time, the customer can't be served at this station and hence $x_{(c,i)}$ must be zero; otherwise, $x_{(c,i)}$ may be 1 or 0.

C. Charging Time

The charging time is the time needed to fully or partially charge the battery in EV. This time depends on the battery characteristics and the rating of chargers available at the charging station. The lithium-ion battery is the most employed battery in the majority of the EVs. This battery type distinguished by higher performance, efficiency, safety operation and moderate cost compared with the other types like the lead-acid battery. The major charging characteristics used to charge lithium-ion batteries divide the charging region into two regions, which are constant current and constant voltage regions. In the first region, the charger varies its voltage to maintain the constant current used to charge the battery. Then, the charger switches to a constant voltage region if the voltage reaches the rated voltage [25]. In the constant voltage region, the current decreases rapidly with increasing of SOC due to internal electrochemical characteristics of the battery. The relation between the maximum allowable charging power of the battery and the SOC of the battery can be approximated as follows [25]:

$$p(SOC) = \begin{cases} P_{rated} & SOC \leq SOC_{tr} \\ \dfrac{1-SOC}{1-SOC_{tr}} * P_{rated} & SOC > SOC_{tr} \end{cases} \quad (17)$$

where, P_{rated} is the rated power of charger, SOC is the current state of charge of the battery, and SOC_{tr} is the transition SOC between constant current and constant voltage regions. In (17), the power is assumed to be constant in the constant current region as the voltage varies not obviously while the power is assumed to reduce almost linearly during the constant voltage region.

For the charging power consumption, there are three scenarios depending on the SOC at arrival and the desired SOC at departure with respect to SOC_{tr}. In this paper, we consider only one scenario where the initial SOC at arrival (SOC_{arr}) is less than SOC_{tr}, while the desired SOC is higher SOC_{tr}. Therefore, the battery will be charged through two regions which are constant current and constant voltage regions. Thus, the SOC at any time instant can be expressed as follow:

$$SOC(t) = \begin{cases} SOC_{arr} + \dfrac{P_{rated}\,t}{E_{cap}} & t \leq t_{cc} \\ (SOC_{tr}-1)\exp\left(\dfrac{-P_{rated}}{(1-SOC_{tr})E_{cap}}(t-t_{cc})\right)+1 & t > t_{cc} \end{cases} \quad (18)$$

where t_{cc} is the required time to reach SOC_{tr} from SOC_{arr} in the constant current (cc) region. It can be calculated as follow:

$$t_{cc} = \frac{(SOC_{tr}-SOC_{arr}) * E_{cap}}{P_{rated}} \quad (19)$$

The charging power of the battery can be obtained as a function of time by substituting equation (18) into equation (17) and can be written as follow:

$$p(t) = \begin{cases} P_{rated} & t \leq t_{cc} \\ P_{rated} * \exp\left(\dfrac{-P_{rated}}{(1-SOC_{tr}) * E_{cap}}(t-t_{cc})\right) & t > t_{cc} \end{cases} \quad (20)$$

Finally, the charged time utilized in the proposed model considers the actual characteristics of lithium-ion batteries. Therefore, the charging time composes of two components. The first term is the time required to charge SOC from SOC_{arr} to SOC_{tr} while the second term Δt is the time required to charge the battery from SOC_{tr} to desired SOC (SOC_{ds}). The charging time can be expressed as follow:

$$T_{ch(c,i)} = t_{cc} + \Delta t \quad (21)$$

$$\Delta t = \frac{(1-SOC_{tr}) * E_{cap}}{P_{rated}} * \ln\left(\frac{1-SOC_{tr}}{1-SOC_{ds}}\right) \quad (22)$$

For fairness, we assume that the customer will continue charging its battery to the desired SOC if there are no waiting customers at this charging station. However, the customer with SOC higher than or equal SOC_{tr} will have the choice to continue charging to the desired SOC with a higher price or stop charging in case of existence of other customers in the waiting. Charging in this region will utilize the charging station's facilities without a significant income to the charging station due to the low charging rate. This will encourage customers to opt for partial charging and leave early. Therefore, this procedure can provide an effective solution to the problem of long waiting times. Hence, the following constraints will be added to our model.

$$\rho_{(c,i)} = \begin{cases} \rho & SOC(t) \leq SOC_{tr} \\ \rho + w_i * \Delta\rho & SOC(t) > SOC_{tr} \end{cases} \quad (23)$$

$$w_i \in \{0,1\} \quad (24)$$

where, $\rho_{(c,i)}$ is the charging price of customer c at charging station i, ρ is the price offered by the charging stations, w_i is binary value represents the waiting index at charging station i which is 0 when no customers are waiting at this charging station and 1 otherwise, $\Delta\rho$ is the price increase when there are waiting customers at this charging station and the SOC of the customer charging at this charging station is higher than SOC_{tr}.

Finally, if the customer selects to stop charging due to the increase in the price, the SOC of this customer will be updated according to (25) and the waiting time of the customers in the queue will be updated according to (15):

$$SOC_{dp} = (SOC_{tr} - 1) * \exp\left(\frac{-P_{rated}}{(1 - SOC_{tr}) * E_{cap}}(t_{dr} - t_{cc})\right) + 1 \qquad (25)$$

where, SOC_{dp} is SOC when the customer will leave the charging station, and t_{dr} is the charging duration of this customer.

V. Coordination between VCSs

In this section, we assume that there is a competition/ coordination between different VCS with neighboring charging stations. This coordination can be represented by routing customer in a contract with a certain VCS to another VCS in exchange for a fraction γ of the profit. Therefore, the objective function in (6) should be modified to include both the profit gained by the VSC and customer satisfaction. Hence, the objective function can be rewritten as in (26) to increase the profit gained by VCS such that minimizes the travel, waiting, and charging times of customers. The VCS will take the whole profit if the customer is assigned to a charging station participating in this VCS. However, the VCS will take a portion of this profit if the customer is assigned to a charging station not participating in this VCS, as in (27). Constraint (28) indicates that the travel penalty factor of charging station i regarding customer c depends on the travel time of this customer to this charging station and the minimum travel time of this customer to the nearest charging station. Therefore, the penalty factor of travel time is zero, if the customer is assigned to the nearest station; otherwise, it will be more than zero. Similarly, the penalty factors regarding the waiting time and charging time are determined according to constraints (29)-(30).

$$\max \sum_{i \in \mathcal{I}} [E_{req(c)} * \rho_{(c,i)} * r_{(c,i)} - (\varphi_{tr\,(c,i)} + \varphi_{wa\,(c,i)} + \varphi_{ch\,(c,i)})] * x_{(c,i)}, \qquad \forall c \in \mathcal{C} \qquad (26)$$

$$r_{(c,i)} = \begin{cases} 1 & i \in VCS \\ \gamma & i \notin VCS \end{cases} \qquad (27)$$

$$\varphi_{tr\,(c,i)} = \alpha * (T_{tr(c,i)} - T_{tr\,(c)}^{min}) \qquad (28)$$

$$\varphi_{wa\,(c,i)} = \alpha * (T_{wa(c,i)} - T_{wa\,(c)}^{min}) \qquad (29)$$

$$\varphi_{ch\,(c,i)} = \alpha * (T_{ch\,(c,i)} - T_{ch\,(c)}^{min}) \qquad (30)$$

where, $E_{req(c)}$ is the requested energy by customer c, $\varphi_{tr\,(c,i)}$, $\varphi_{wa\,(c,i)}$, $\varphi_{ch\,(c,i)}$ are the penalty factors due to travel, waiting and charging times, respectively, α is a penalty constant in \$/hr, $T_{tr(c)}^{min}$ is the travel time from the current location of customer c to the nearest charging station to its location, and $T_{wa\,(c)}^{min}$ and $T_{ch\,(c)}^{min}$ are the minimum waiting time and minimum charging time for a customer c among all the charging stations.

VI. Results and Discussions

In this section, three case studies are presented and discussed to evaluate the performance of the proposed VCS concept. In the first case study, the results obtained from the price competition game model are presented to be utilized as a base case to compare the CCS with the VCS. The results obtained from the proposed single VCS are illustrated in the second case study. Finally, the interaction between several VSCs is demonstrated in the third case study. Different classes of EVs with various capacities are considered in these case studies according to the actual classes in the electric vehicles market as illustrated in Table I. These classes are selected to cope with the rating of chargers shown in Table II. In all the case studies, we consider a time segment of 5 minutes, which corresponds to a total of $N_t = 288$ time segments representing the day. The prediction of the EV arrivals to the parking lots is assumed to be an input to the study and is out of the scope of this paper. The problem is solved using MATLAB software and the General Algebraic Modeling Software (GAMS). GAMS has different solvers, the Branch-And-Reduce Optimization Navigator (BARON) is used to solve the proposed optimization problem.

A. *Case study 1: CCS*

In this case, we assume that there are three charging stations in competition to attract more EVs to gain more profit. First, the actual arrivals to a parking lot in Toronto, Canada obtained from Toronto Parking Authority (TPA) shown in Fig. 4 is used to solve the game model, which generates the charging price of each charging station, where we assumed that the charging stations may reduce charging price up to 25% to attract more customers. The total customers' requests during this day are 721 customers. Furthermore, we assume that each charging station has to keep its electricity price fixed for at least a half-hour. The three charging stations are equipped with type three chargers as illustrated in Table II. The charging price for the next day obtained from the game model is broadcasted to customers through a Mobile application as shown in Fig. 5. Then, the customers will select the charging station according to the quoted charging price and the distance to the charging station. Table III illustrates the number of served customers, average waiting time, the maximum waiting time, and finally the profit obtained by all charging stations.

B. *Case study 2: single VCS*

This case study represents the cooperation of the charging stations under a single VCS based on the same assumptions in the first case study. First, the constraint related to the maximum waiting time in (16) will be disabled to compare the results obtained from both cases to have a fair comparison as the maximum waiting time isn't considered in CCS.

The decision-making process of the proposed VCS involves three stages collecting the requests from the customers, information from the charging stations, and then decides the optimal decision. The simulation results in Table III indicate that the average waiting time in the case of VCS is reduced by 7.8% compared to that in CCS. In addition, the total profit obtained by VCS is increased by 13.93% while serving 100% of total customers. This indicates the superiority of VCS over the CCS as the coordination between the charging stations contributing in VCS leads to increased revenue while satisfying the customers' requirements by decreasing the overall time of charging process for each customer including travel, waiting, and charging times. Therefore, compared to the competition, cooperation between charging stations can be useful for both charging stations owners and customers.

TABLE I
DIFFERENT EV CLASSES [26]-[29]

Class	Battery Capacity (kWh)	EV Range (miles)
Nissan LEAF	40	149
Nissan LEAF PLUS	62	226
Chevrolet Bolt	66	238
Ford Focus	33.5	115
BMW i3	42	153
Mercedes-Benz B-Class	28	87

TABLE II
RATING OF RAPID CHARGER IN CHARGING STATIONS [30]-[31]

Supply Type	AC/DC	Charger Rating
3 phase, 60 A per phase	AC	43 kW
3 phase, 120 A	DC	50 kW
3 phase, 125 A	DC	62.5 kW

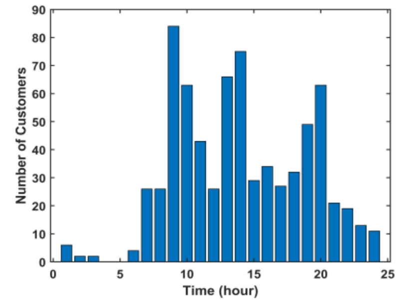

Fig. 4. Hourly-based Customers' requests during the next day.

TABLE III
RESULTS OBTAINED IN CASE OF CCS AND SINGLE VCS

Parameters	CCS			Single VCS: Disable T_{wa}^{max} constraint			Single VCS: Enable T_{wa}^{max} constraint		
	Station 1	Station 2	Station 3	Station 1	Station 2	Station 3	Station 1	Station 2	Station 3
Number of served customers	227	250	244	271	226	224	258	216	202
Customers not served	——			——			45		
Average waiting time (minutes)	23.87			22			10.3		
Maximum waiting time (minutes)	70	50	60	55	55	50	15	15	15
Total Profit ($/day)	2466.44			2809.9			2762.7		

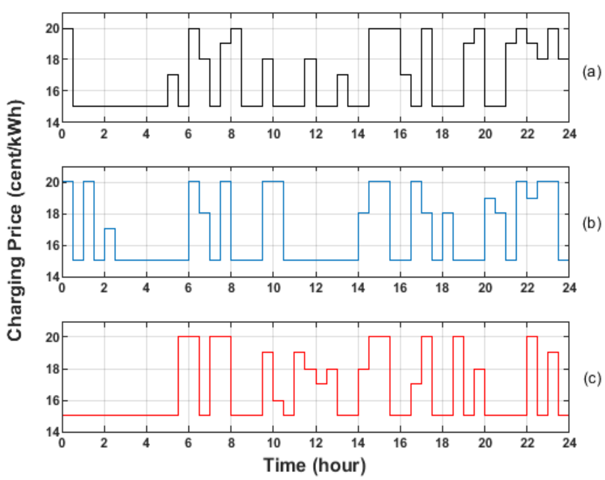

Fig. 5. The quoted charging price by charging station # a) 1 b) 2 c) 3 in case of CCS.

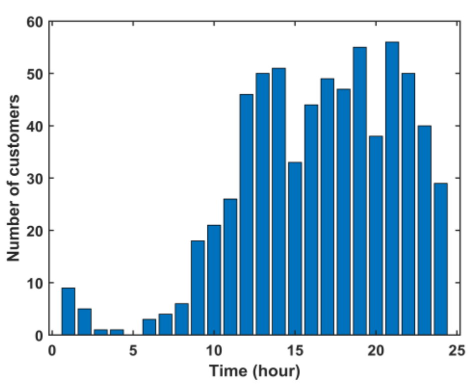

Fig. 6. Hourly-based Customers' requests for the second VCS.

After comparing the results with CCS, the constraint related to maximum waiting time in (16) will be enabled as it is not rational for a customer to wait a long time (55 minutes) at fast-charging stations. The maximum allowable waiting time at any charging station is limited to be 15 minutes. The new results obtained from the proposed model are dedicated in Table III. The results show that the average waiting time for all customers is reduced by 56.85% compared to that in CCS, while the total profit is increased by 12.01%. However, this will result in some customers not served (6.24% of total customers). On the other hand, increasing the maximum allowable waiting time will increase the served customers and will also increase the waiting time and thus, decreasing customer satisfaction. Therefore, the existence of non-served customers and the necessity of decreasing waiting time show the need for coordination between various VCSs to serve all customers with a high satisfaction level which is described in the next subsection.

C. Case study 3: Interaction between several VCSs

This case study represents the coordination of several VCS based on the same assumptions used in CCS as well as enabling the constraint regarding the maximum waiting time. Furthermore, we assume that the centralized operator belonging to a specific VCS can assign a customer to a charging station belonging to another VCS in exchange for a proportion of the profit. Furthermore, the actual arrival to the same parking lot in Toronto, Canada for another day shown in Fig. 6, is used as the customers' requests for the second VCS2. The total customers' requests during this day for the second VCS are 682 requests. The main aims are to reduce the whole time of the charging process and increase the profit of VCS1. The modified proposed model presented in section V which allows coordination between various VCSs is applied. The results for VCS1 with and without coordination with the second VCS are shown in Table IV. The results demonstrate that all customers belonging to each VCS are served due to coordination between two VCS despites the maximum allowable waiting time restriction. Moreover, the average waiting time is reduced by 43.78% which have a great impact on motivating customers toward EVs, while the revenue obtained by the first VCS is increased by 15.1% compared to that in CCS. In this case, the profit gained by a specific VCS composed of three components as illustrated in Table IV. The first component (*A*) is the profit gained through serving its customers which represents 96.21% of total profit, while the second component (*B*) is the portion of the profit gained by assigning some of its customers to be served by the other VCS (1.33% of total profit), and finally, the third component (*C*) is the profit gained through serving customers belonging to the other VCS after deducting the profit portion granted to the other VCS (2.46% of total profit). The results indicate that the coordination between VCSs leads to more profit for both VCS and serve all customers with high customer satisfaction. Therefore, these results show the importance of coordination between various VCSs.

VII. Conclusions

This paper proposes a new concept of VCS, which is similar to VPP in the power system. The charging stations contributing in VCS cooperate rather than compete with high customer satisfaction by minimizing the entire time of the charging process. A formulation based on the new concept is proposed with the aim of optimally routing the customers to a suitable charging station that satisfies the customer requirements. Furthermore, we propose coordination between various VCSs, where the VCS can assign its customers to another VCS in exchange for a percentage of the profit. Therefore, a new formulation based on the interactions between various VCSs is presented to reduce the waiting time for each customer, which is a vital concern in the fast-charging stations while achieving more profit by each VCS. Several case studies are investigated to evaluate the performance of the proposed model. The competition between various charging systems in CCS is simulated and utilized as a base case for comparison with other case studies which are single VCS and interaction between various VCSs. The results show that profit obtained by a single VCS is increased by 12.01% compared to the profit obtained in the case of CCS with a reduction in the average waiting time by 56.85% while serving 93.76% of total customers. Whereas the interaction between various VCSs allows to serve all customer with a high level of customer satisfaction. The results indicate that the coordination between various VCSs leads to an increase in the profit obtained by each VCS by 15.1% and reduction in the waiting time by 43.78% compared to that in CCS while serving all customers' requests.

TABLE IV
RESULTS OBTAINED IN CASE OF COORDINATION BETWEEN TWO VCSS

Parameters		Case 2: No coordination between different VCSs			Case 3: Coordination between different VCSs					
		VCS1: Enable T_{wa}^{max} constraint			VCS 1: Enable T_{wa}^{max} constraint			VCS 2: Enable T_{wa}^{max} constraint		
		Station 1	Station 2	Station 3	Station 1	Station 2	Station 3	Station 1	Station 2	Station 3
Number of served customers belonging to	VCS 1	258	216	202	251	217	206	19	18	10
	VCS 2	NA			13	2	10	211	236	210
Customers not served		45			-------			-------		
Average waiting time (minutes)		10.3			10.45			9.24		
Total profit due to	Serve its customers (*A*)	2762.7			2731.4			2384.76		
	Assign its customers to another VCS (*B*)	NA			34.88			18.18		
	Serve customers from another VCS (*C*)	NA			72.712			139.52		
	Total Profit	**2762.7**			**2839**			**2542.46**		

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