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# A Customer-Centered Smart Charging Strategy Considering Virtual Charging System

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**ABSTRACT** Electric vehicle (EV) charging is considered as one of the main issues that face EV drivers. Thus, there should be a facility to suggest the best charging station based on the customer requirements. However, the routing process of EVs in most of the literature was generally implemented centrally based on the charging station/operator perspective. On contrary, this paper proposes a smart charging strategy that routes EVs drivers to the best charging station based on their priorities. In the proposed smart strategy, various charging stations will cooperate through a virtual charging system (VCS) to serve all EVs charging requests with a high satisfaction level. The drivers' requirements are achieved through a new scoring criterion which ranks the participating charging stations based on EV driver's perspective. Then, the EV driver will select individually the charging station based on his priorities. The data required for the scoring criterion are computed through two stages: offline (day-ahead) and online stages. The expected waiting time at each charging station within the VCS is computed during the offline stage based on the forecasted arrivals. The integration between offline and online stages aims to reduce the data flow, calculated data, and finally the communication bandwidth during the online stage. Different case studies are introduced to evaluate the significance of the proposed strategy. The results demonstrate the superiority of the proposed strategy in achieving EVs requirements.

**INDEX TERMS** Smart Charging Strategy, Virtual Charging System (VCS), Customer Perspective, Operator Perspective, routing of EVs.

## NOMENCLATURE

### SETS AND INDICES

$\mathcal{J}$  The set of all participating charging stations.  
 $j$  The index of charging stations.  
 $\mathcal{T}$  The set of time segments.  
 $t$  The index of time segments.  
 $\mathcal{V}$  The set of customers.  
 $v$  The index of customers.

$N_v$  The total number of EVs' requests.  
 $w_{f(j)}, w_{c(j)}, w_{i(j)}$  The weight matrices for charging station  $j$  used in LSTM network.  
 $b_{f(j)}, b_{c(j)}, b_{i(j)}$  The bias vectors used in LSTM network.  
 $\mu$  The average service rate at each charging station.  
 $s$  The specific number of servers (bays) in each charging station.  
 $k$  The total station occupancy.  
 $l_{(j,v)}$  The percentage of customer  $v$  loyalty to charging station  $j$ .  
 $SOC_v$  The current/present SOC of the customer  $v$  at request time.  
 $\varepsilon_1$  The price score offset value.

### PARAMETERS

$N_{cs}$  The total number of participating charging stations in VCS.  
 $N_t$  The total number of time segments throughout the day.

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$\varphi_1$	A constant related to the price score.
$d_{(j,v,t)}$	The distance from the current location of the customer $v$ to the charging station $j$ during time segment $t$ .
$\varepsilon_2$	The traveling score offset value.
$\varphi_2$	A constant related to the traveling score.
$\varepsilon_3$	The waiting score offset value.
$\varphi_3$	A constant related to the waiting score.
$\alpha_1, \alpha_2, \alpha_3$	constants.

**VARIABLES**

$x_{(t,i)}$	The actual historical EVs' arrivals at charging station $j$ during time segment $t$ .
$y_{a(t,j)}$	The actual EVs' arrivals at charging station $j$ during time segment $t$ .
$y_p(t,j)$	The working memory of LSTM neural network which represents the predicted EV arrivals.
$c_{(t,j)}$	The memory cells of long short-term memory (LSTM) neural network.
$\rho$	The occupancy rate at each charging station.
$P_0$	The probability that the system is ideal.
$L_q$	The expected number of customers on the queue.
$L_s$	The expected number of EVs in the system.
$T_w$	The expected whole waiting time.
$P_{(v)}^{V2V}$	The probability that the customer $v$ selects the V2V charging criteria.
$S_r(j,v,t)$	The price score obtained by charging station $j$ for the customer $v$ during time segment $t$ .
$r_{(j,t)}$	The charging price offered by the charging station $j$ during this time segment $t$ in \$/kWh.
$\bar{r}(t)$	The average price during this time segment $t$ .
$S_T(j,v,t)$	The travel score obtained by charging station $j$ for the customer $v$ during time segment $t$ .
$A_j(t)$	The average speed from the current location of customer $v$ to the charging station $j$ considering the road conditions.
$T_{ir}(j,v,t)$	The traveling time from the current location of the customer $v$ to the charging station $j$ during time segment $t$ .
$\bar{T}_{ir}(t)$	The expected average traveling time during request time segment $t$ .
$S_w(j,v,t)$	The waiting score obtained by charging station $j$ for the customer $v$ during time segment $t$ .
$T_w(j,v,t)$	The expected waiting time of customer $v$ at charging station $j$ during this time segment $t$ .
$\bar{T}_w(t)$	The expected average waiting time during request time segment $t$ .
$u_{(j,v)}$	A binary variable indicating serve customer $v$ at charging station $j$ .

**I. INTRODUCTION**

Electric vehicles (EVs) are the emerging trend for the future of transportation systems. They play a vital role in reducing greenhouse gas emissions. Roadmaps have been published by many countries to promote the adoption of EVs on the road [1], [2]. In addition, EVs have become cost-competitive with conventional vehicles due to the decline in the price of batteries in the last few years [3]. Despite the explosive growth of EVs, they suffer from long charging periods and limited infrastructure, where existing charging facilities can't satisfy the enormous demands of a significantly growing number of EVs [4]. Moreover, they have many negative consequences on the distribution network like increasing peak demand, thermal overloading, voltage deviations, and power imbalance [5]–[9].

EVs' drivers can charge their vehicles at parking lots at either homes or workplaces where they stay for long hours [10], [11]. Furthermore, they can charge their vehicles at charging stations, which are becoming more attractive for EVs' drivers. Commercial charging stations purchase electricity from the wholesale power market at a lower rate compared to residential homes (e.g., the electricity rate for a commercial entity is 30 % less compared to residential) [12], [13]. Thus, charging stations can offer lower charging prices after adding their profit. Moreover, batteries of EVs may run out of charge during the trip, and hence, this will make charging at public stations inevitable. Charging infrastructure are divided into three classes, which are level 1, 2, and 3. Level 1 and 2 chargers are mainly ac charging while level 3 is dc charging [14], [15]. Nowadays, utilities focus on installing sufficient numbers of charging stations with lower charging time to encourage customers to use EVs [7].

Most of the existing research focuses on reducing the charging time and offering different charging options for EVs' drivers to facilitate their charging process. The authors in [4] presented a price strategy for charging EVs to utilize renewable energy generation while considering the traffic flow. The authors in [7] proposed a routing strategy for EVs' drivers to the most suitable charging station that satisfies the minimum charging time, traveling distance, and charging cost. However, this routing process was based on the operator's perspective, which didn't ensure satisfying the customer requirements. The work in [14] introduced a dynamic pricing model that aimed at reducing the demand of EVs during peak load hours by shifting the charging of EVs during this period, which can be enforced by setting different tariffs. The work in [16] studied the impact of charging/ discharging price variations on the operation cost of microgrid. Furthermore, an optimization technique is presented in order to find the optimal price such that minimizing the operation cost. The Authors of [17] proposed charging scheduling strategy for both private EVs and taxis in order to determine the optimal load charging profile and thus, to reduce their charging impacts on the power system. In [18], the routing problem of the integrated electric and transportation systems based

**TABLE 1.** The advantages of the proposed strategy over the other strategies.

		Proposed Strategy
Advantages regarding	Charging stations	Cooperation will increase the profit gained by each participating charging station by serving all EV charging requests.
	EV driver	Achieving customer/driver's requirements through selecting the charging station based on his priorities.
	Communications	Communication bandwidth is reduced through integrating offline and online stages. The required communicating data through the online stage: <ul style="list-style-type: none"> <li>• The charging request: SOC, weighting coefficients regarding waiting time, charging price, and traveling distance.</li> <li>• The selected charging station.</li> </ul>

on the social coordinator perspective to optimize the driving route for EVs' drivers was analyzed. A strategy for routing EV drivers to the fast-charging station that minimizes the charging cost and the whole time of the charging process was proposed in [19]. Furthermore, the traffic flow and level of distribution network loading were considered in the proposed strategy where they were reflected on both the traveling time and the charging price offered by each fast-charging station, respectively. A routing process based on time of use (TOU) electricity price was presented in [20], which was formulated similar to the traveling salesman problem. The introduced strategy aimed to minimize the charging cost and the cost of battery degradation due to the fast-charging process. The work in [21] considered the impact of waiting time on the drivers' decisions in the price competitive game where EVs' drivers select the charging station based on the charging price, the traveling distance, and finally the waiting time. Queueing theory was used to compute the waiting time at each charging station despite it is assumed that the EV drivers weren't aware of other drivers' decisions as a result of the absence of communication between them. The authors of [22] solved the routing process by considering multiple options such as partial charging (there is no need for battery full charging) and battery swapping option for EVs drivers. The work in [23] proposed a list of options for customers, where optimal pricing and routing schemes were presented with a focus on motivating EV drivers to charge at the specific charging stations. On the other hand, the authors assumed that the EVs drivers cannot select the charging station; instead, the Charging Network Operator (CNO) is responsible for routing EV drivers to the charging station. In the same context, the work in [24] presented an optimization framework to determine the optimal charging prices and charge scheduling considering the EVs drivers' behavior through offering multiple options for EVs drivers: Charging-Flex, Charging ASAP, and leave. In the first option, EV drivers can control the charging schedule and charging rate. However, in the second option, EV driver has no access to set the charging rate or schedule (uncoordinated charging). Finally, if the EV driver did not accept the charging price, he will select the third option.

From the aforementioned discussion, most of the existing research focuses on routing EVs to the most suitable charging

station centrally based on the charging station/system operator perspective without considering customers' priorities. However, routing the EV from an operator's perspective does not guarantee that customer satisfaction is achieved. For example, The EV may be routed to the nearest charging station for achieving less time in the charging process despite the high charging price. However, the priority for this customer may be the price, even if he waits longer. Thus, the EV routing criterion should be modified to consider customer requirements which increase customers satisfaction and motivate customers toward EVs. Table 1 summarizes the advantages of the proposed strategy.

In this paper, with the customer's needs in mind, we propose a smart charging strategy by offering multiple charging options including different charging prices and different waiting times. We assume that different charging stations with different chargers' ratings will cooperate through a virtual charging system (VCS) to offer these charging options for EV drivers to opt between them. Moreover, the routing of EVs in the proposed strategy is implemented centrally based on the EV driver's perspective, not the operator's perspective. Therefore, the proposed strategy, based on the EV driver's perspective, guarantees a high level of customer satisfaction. The required data for the proposed strategy are computed through two stages, which are the online stage and offline stage. The suggested framework aims to reduce the data needed to be transferred, as well as computational effort, and to eliminate the need for communications with the charging stations during the routing process. This leads to reducing the required communications bandwidth and thus the capital cost. The main contributions of the paper can be summarized as follows:

- Multiple charging options for EV drivers including charging prices, charging times, and traveling distances are taken into consideration, which are decided through cooperation between different charging stations through a VCS.
- A new scoring criterion is proposed to route EV drivers to the suitable charging station based on the customers' priorities.
- The framework of the proposed strategy focuses on reducing the communication data during the routing process.

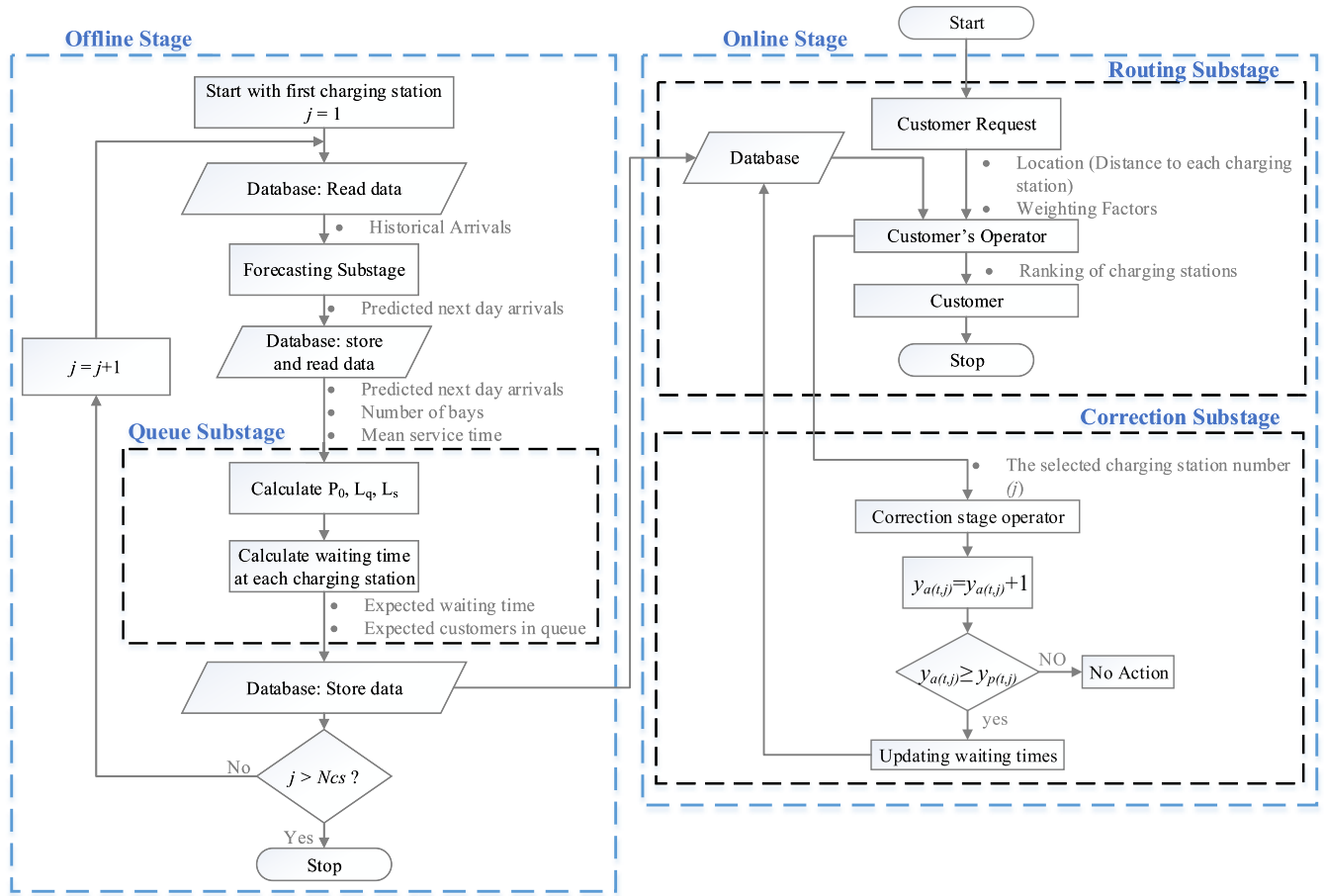


FIGURE 1. Structure of the proposed strategy.

The rest of the paper is organized as follows: a smart charging strategy is presented in Section II. The details of the offline stage and online stage are explained in Section III and Section IV, respectively. Results and multiple case studies are presented and discussed in Section V. Finally, the conclusions are presented in Section VI.

**II. SMART CHARGING STRATEGY**

Charging stations with different ownerships participating in VCS will cooperate rather than compete in a conventional charging system to act as one charging station for EV drivers. This cooperation will benefit both participating charging stations by increasing their profit through serving all EVs' requests and EV drivers by satisfying their requirements. However, coordination between multiple VCSs can be existed to maximize the profit gained by each VCS as well as minimize the cost incurred by the customer besides the whole charging time. In this paper, different charging stations with different chargers' ratings will cooperate through a VCS to offer various charging options for EV drivers including: different charging prices, different traveling times and various waiting times at these charging stations. The VCS will route the EV centrally to the most suitable charging station by

ranking the participating charging stations based on the driver's priorities. This allows the EVs to select individually the most suitable charging stations according to their requirements. Therefore, the proposed strategy guarantees a high level of customer satisfaction compared to the methods introduced in the literature since the routing process in the proposed strategy is based on customer's perspective and not based on the operator's perspective. Moreover, the smart charging strategy proposes another option for EVs, which is Vehicle-to-Vehicle (V2V) charging mode at their location with a higher charging price. This option will be inevitable if the current state of charge (SOC) isn't sufficient to reach the nearest charging station. The required data for the routing process is computed through two stages: offline stage and online stage as shown in Fig. 1. The offline stage is implemented day ahead by the virtual charging system (VCS) operator while the online stage is occurred for each customer once the EV driver sends a charging request. The details of the two stages are explained in the following sections.

**A. ASSUMPTIONS**

It is assumed that various charging stations with different owners are cooperated together to offer different charging

options for EVs drivers to facilitate the charging process from the EV driver's perspective. The participated charging station will form a system called VCS and it is responsible for routing EV drivers based on their priorities. These stations are assumed to be fast-charging stations with different charger rates so that they offer different charging prices.

### III. PROPOSED OFFLINE STAGE

The offline stage is a day-ahead stage that is responsible for computing the expected waiting time at each charging station within the VCS during the next day. This stage is integrated with the online stage to reduce both the communications and the required data to be collected or calculated during the online stage. Furthermore, it eliminates the need to communicate with the participating charging stations during the online stage by transferring waiting time calculations from the online stage after receiving EV requests to the offline stage. This will result in reducing the running time of the routing process starting with receiving EV requests until selecting the proper charging station. Further, it will aid in reducing the investment for the bandwidth communications incurred by the charging stations. On contrary, in case of the absence of an offline stage, the operator will communicate with all participating charging stations during the online stage after receiving the charging request to collect the vital data regarding the status of bays at each charging station. Moreover, the waiting time and the charging time at each charging station will be computed online after receiving the vital data. Finally, the operator will communicate with both the EV's driver to inform him of the selected charging station as well as the selected station to devote a bay for this customer. The offline stage consists of two substages: a forecasting substage and a queueing substage. The forecasting substage is responsible for predicting the expected arrivals at each charging station during the next day. Then, the outcomes from the forecasting substage are fed to the queueing substage to determine the expected waiting times at each charging station participating in the VCS during each time segment. Finally, the outcome of the queueing substage is stored in the database to be used during the online stage. The required data to be used during the offline stage are stored in the database, which includes the number of bays available at each charging station, the mean service time, and the total occupancy/capacity of the charging stations. Each charging station shares its information due to the absence of competition between the charging stations participating in VCS.

#### A. FORECASTING SUBSTAGE

The forecasting substage is the first step during the offline stage. This substage is fed by historical arrivals to the charging stations participating in VCS. The outcome from this substage is the predicted EV arrivals at each charging station. Time series forecasting method based on long short-term memory (LSTM) neural network is proposed to predict the EVs arrivals at a certain charging station. LSTM is a

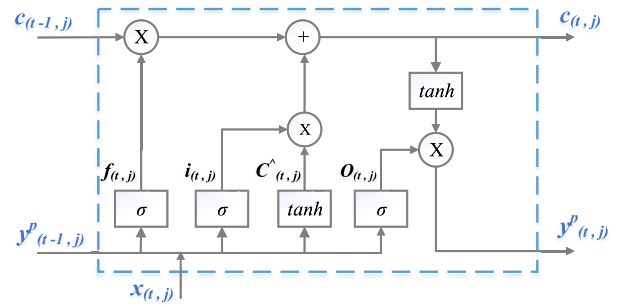


FIGURE 2. Structure of LSTM neural time series used for forecasting.

sequence-based model, capable of establishing the temporal correlations between past and present information [25], [26]. The LSTM consists of three parts: memory cells  $c_{(t,j)}$  which represents the candidate output, working memory  $y_{p(t,j)}$  which represents the predicted EV arrivals at charging station  $j \in \mathcal{J}$  during time segment  $t \in \mathcal{T}$ , and three gates as shown in Fig. 2. The parameter  $t$ ,  $\mathcal{T} = \{1, 2, \dots, N_t\}$  are the indices and the set of time segments respectively, and  $j$ ,  $\mathcal{J} = \{1, 2, \dots, N_{CS}\}$  are the indices and the set of charging stations respectively.

The three gates are input, output, and forgetting gates, which are not static and act as binary gate. These gates are used to determine whether the data will be updated or ignored. This will make the network converge faster and overcomes the main disadvantage of recurrent neural network (RNN), which mainly relies on the gradient [25], [26]. First, the forgetting gate will determine which part of information of the memory cell at the previous time step ( $c_{(t-1,j)}$ ) will be discarded (reset to zero) in the current cell state  $c_{(t,j)}$ . This data will be determined according to the current input  $x_{(t,i)}$  and the predicted output at the previous time step  $y_{p(t-1,j)}$  which can be expressed as follows [25], [26]:

$$f_{(t,j)} = \sigma(w_{f(j)}[y_{p(t-1,j)}, x_{(t,j)}] + b_{f(j)}) \quad (1)$$

where  $\sigma()$  is the Sigmoid activation function.

After discarding part of the information, the current state should learn to predict new information using the current input, which is achieved through the input gate. This gate consists of two layers: tanh and sigmoid layers. The first layer is utilized to create new candidate values  $\hat{c}_{(t,j)}$  while the second layer is used to determine which information from the first layer will be updated and added to the current cell state, which can be expressed as follows:

$$\hat{c}_{(t,j)} = \tanh(w_{c(j)}[y_{p(t-1,j)}, x_{(t,j)}] + b_{c(j)}) \quad (2)$$

$$i_{(t,j)} = \sigma(w_{i(j)}[y_{p(t-1,j)}, x_{(t,j)}] + b_{i(j)}) \quad (3)$$

$$c_{(t,j)} = f_{(t,j)} \cdot c_{(t-1,j)} + i_{(t,j)} \cdot \hat{c}_{(t,j)} \quad (4)$$

where  $\tanh()$  is the hyperbolic tangent activation function and it is used here as it distributes the gradients and hence, prevents vanishing or exploding.

Finally, the updated memory cell  $c_{(t,j)}$  is used to determine the output value at the current time segment. The working

memory  $y_{p(t,j)}$  is used as the output and the output gate  $o_{(t,j)}$  is used to determine the portion of the current memory cell state  $c_{(t,j)}$  to be written to the output as follows:

$$o_{(t,j)} = \sigma(w_{o(j)} [y_{p(t-1,j)}, x_{(t,j)}] + b_{o(j)}) \quad (5)$$

$$y_{p(t,j)} = o_{(t,j)} \cdot \tanh(c_{(t,j)}) \quad (6)$$

To assess the accuracy of the prediction, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) can be determined. RMSE is the residuals between the actual data and the predicted data while MAE is the average of absolute residuals. MAPE is the ratio of error to the true value in percentage. These indices can be expressed as follows:

$$RMSE = \sqrt{\frac{1}{N_t N_{cs}} \sum_{j \in \mathcal{J}} \sum_{t \in \mathcal{T}} (y_{p(t,j)} - y_{a(t,j)})^2} \quad (7)$$

$$MAE = \frac{\sum_{j \in \mathcal{J}} \sum_{t \in \mathcal{T}} |y_{p(t,j)} - y_{a(t,j)}|}{N_t N_{cs}} \quad (8)$$

$$MAPE = \frac{1}{N_t N_{cs}} \sum_{j \in \mathcal{J}} \sum_{t \in \mathcal{T}} \frac{|y_{p(t,j)} - y_{a(t,j)}|}{y_{a(t,j)}} \times 100\% \quad (9)$$

### B. QUEUEING SUBSTAGE

The outcomes from the forecasting substage are fed to the queueing substage to determine the expected waiting time at each charging station during the next day. However, these times are determined based on the predicted arrivals, which may differ from the actual arrivals. Therefore, to provide a reliable operation that can lead to a higher level of customer satisfaction, the waiting times under a percentage increase in EVs' arrivals than the predicted arrivals are determined during queueing substage and stored in the offline database. These times will be used during the online stage based on an updating signal triggered by the correction stage, which is explained in the following sections when the actual arrivals at a certain charging station during this time segment reach the predicted arrivals at this station. The queueing theory is used in the queueing substage to estimate the waiting time. We use  $M/M/s/k/FCFS$  model where [7]:

- The first  $M$  refers to Markov where the EVs' arrivals are assumed to follow Markovian or exponential distribution.
- The second  $M$  refers also to Markov where the charging time is assumed also to follow Markovian or exponential distribution.
- $s$  indicates that there is a specific number of servers (bays) in each charging station.
- $k$  refers to the total station occupancy (the total number of EVs that the charging station can accommodate at one time segment).
- $FCFS$  refers to first come first served.

We assume that each EV arriving at the charging station will be served immediately according to  $FCFS$  if there is an available bay in this charging station; otherwise, the EV will wait in a queue until there is an available bay. All EVs

arriving at the charging station will be served by  $s$  servers or bays. The service time is assumed to be exponential with an average service rate  $\mu$ . Furthermore, the arrivals pattern at a specific charging station is assumed to follow a poison distribution with an average arrival rate  $\lambda$ . The service rate is set based on the chargers' rating available at each charging station. Whereas, the average arrival rate during each time segment through the day is set according to the outcomes from the previous forecasting substage. Assuming that the occupancy rate is  $\rho = \lambda/(s\mu)$ , then the stationary probability of  $n$  EVs in the system ( $P_n$ ) can be determined as follows [7]:

$$P_n = \begin{cases} \frac{1}{n!} \left(\frac{\lambda}{\mu}\right)^n P_0 & n < s \\ \frac{1}{s!s^{n-s}} \left(\frac{\lambda}{\mu}\right)^n P_0 & s \leq n \leq k \end{cases} \quad (10)$$

$$P_0 = \left[ \sum_{n=0}^{s-1} \frac{1}{n!} \left(\frac{\lambda}{\mu}\right)^n + \sum_{n=s}^k \frac{1}{s!s^{n-s}} \left(\frac{\lambda}{\mu}\right)^n \right]^{-1} \quad (11)$$

$P_0$  can be rewritten using the occupancy rate as follows:

$$P_0 = \left[ \sum_{n=0}^{s-1} \frac{(s\rho)^n}{n!} + \frac{1}{s!} \left(\frac{\lambda}{\mu}\right)^s \frac{1 - \rho^{k-s+1}}{1 - \rho} \right]^{-1} \quad (12)$$

Based on the probability function, the expected number of customers on the queue  $L_q$  and the expected number of EVs in the system  $L_s$  can be determined as follows:

$$L_q = \sum_{n=s}^k (n-s) P_n \quad (13)$$

$$L_s = L_q + \frac{\lambda(1 - P_k)}{\mu} \quad (14)$$

$L_q$  and  $L_s$  can be rewritten using the probability in (10) and occupancy rate as follows:

$$L_q = \frac{\rho(s\rho)^s}{s!(1-\rho)^2} \left( 1 - \rho^{k-s+1} - (1-\rho)(k-s+1)\rho^{k-s} \right) P_0 \quad (15)$$

$$L_s = L_q + s - P_0 \sum_{n=0}^{s-1} \frac{(s-n)}{n!} \left(\frac{\lambda}{\mu}\right)^n \quad (16)$$

Finally, based on little law, the expected whole waiting time spent at the charging station during this time segment based on average arrival rate can be determined as follows:

$$T_w = \frac{L_s}{\lambda(1 - P_k)} \quad (17)$$

### IV. PROPOSED ONLINE STAGE

The second stage in smart charging strategy is the online stage, which is responsible for routing EVs to the most suitable charging station within the VCS based on customer-centered decision perspective. It consists mainly of two substages: routing substage and correction substage. The routing substage focuses on routing each EV in contract with the VCS individually based on its priorities. On the other hand, the correction substage starts after selecting the charging station through the routing substage and it aims to provide corrective action when the actual EVs' arrivals at a certain charging station exceed the predicted arrivals at this station.

**A. ROUTING SUBSTAGE BASED ON THE CUSTOMER PERSPECTIVE**

The routing substage is responsible for routing EVs to the most suitable charging station according to EV’s perspective. It starts when the EV sends a request to the operator. This request includes the current location, weighting coefficients regarding the charging price, the traveling time, and the waiting time. Then, the operator will read the data from the offline database, which includes mainly the average waiting time, and the broadcasted charging price. Finally, the operator of the routing substage will introduce two optimal charging options for each EV, which include: 1) rank the charging stations according to the EV priorities and 2) charging the EV at its location through V2V mode. The EV will opt for a suitable option according to the current SOC of the battery. The formulations of the two options are explained in the following subsections.

**1) V2V OPTION**

In this subsection, we propose a V2V option for EVs with a higher charging price. The distance to a specific charging station must be less than or equal to the maximum distance that the EV can travel based on the current SOC to make sure that the battery of the EV will not run out of charge before arriving at the charging station. Therefore, if the distances to all charging stations are higher than this maximum distance, no charging station can be selected for the routing process and this option will be inevitable. In this case, we assume that the charging stations participating in VCS offer a V2V charging option. Where the nearest charging station will send a vehicle owned by this station equipped with a fully charged battery to the location of the EV to be used to charge the depleted battery with a higher charging price. The probability that the customer is forced to select V2V charging criteria can be expressed as follows:

$$P_{(v)}^{V2V} = \begin{cases} 1 & SOC_v \leq SOC_{c1} \\ \exp\left(\frac{SOC_v - SOC_{c1}}{SOC_v - SOC_{c2}}\right) & SOC_{c1} \leq SOC_v \leq SOC_{c2} \\ 0 & SOC_v > SOC_{c2} \end{cases} \quad (18)$$

There are two critical SOC in (18), the first SOC ( $SOC_{c1}$ ) represents the minimum SOC that is sufficient to reach the nearest charging station. If the current SOC is less than this value, this means that the distance is higher than the maximum distance and thus the battery will run out of charge before reaching the charging station. Therefore, in this case, selecting the V2V option will be inevitable. The second SOC ( $SOC_{c2}$ ) represents a higher SOC compared to ( $SOC_{c1}$ ), which means there is no probability that the EV’s driver will select the V2V charging option.

**2) NEW SCORING CRITERION**

We propose a new scoring criterion during the online stage. The scoring stage aims to rank the charging stations according to weighting coefficients (set by the driver) regarding charging price, traveling time, and waiting time. Each EV

will send a charging request to the operator associated with his weighting coefficients according to his priorities. For example, a customer may prefer charging at a station that offers the highest charging price to minimize the entire time of the charging process. On the contrary, another customer may choose to charge at a charging station that offers the lowest charging price and wait more time. The scoring criterion used to rank the charging stations is composed of three scores determined independently: price score, traveling score, and waiting score. Then, the three scores are combined together according to the weighting coefficients set by each individual EV’ driver to determine the final score obtained by each charging station.

The first vital parameter that has a great impact on the EV’s decision is the charging price offered by each charging station participating in VCS. The following nonlinear model is considered to determine the price score for each charging station [4]. This nonlinear model is selected to represent the EVs drivers’ behavior in the real world where the EV does not select another charging station to charge at it due to a small difference in the charging price.

$$S_{r(j,v,t)} = l_{(j,v)} - \frac{1}{\exp(-f(r_{(j,t)} - \bar{r}_{(t)}))} + \varepsilon_1 \quad (19)$$

$$f(r_{(j,t)} - \bar{r}_{(t)}) = \varphi_1 \left( \frac{r_{(j,t)} - \bar{r}_{(t)}}{\bar{r}_{(t)}} \right) \quad (20)$$

The second parameter that affects the driver’s decision is the travel time to the charging station. This time depends on the distance from the current EV location to the charging station and the traffic flow at the request time. This time can be computed by dividing the distance by the average speed. The travel score obtained by each charging station can be determined as follows:

$$T_{tr(j,v,t)} = \frac{d_{(j,v,t)}}{A_j(t)} \quad (21)$$

$$S_{T(j,v,t)} = l_{(j,v)} - \frac{1}{\exp(-f(T_{tr(j,v,t)} - \bar{T}_{tr(t)}))} + \varepsilon_2 \quad (22)$$

$$f(T_{tr(j,v,t)} - \bar{T}_{tr(t)}) = \varphi_2 \left( \frac{T_{tr(j,v,t)} - \bar{T}_{tr(t)}}{\bar{T}_{tr(t)}} \right) \quad (23)$$

The third vital parameter is the waiting time at each charging station. The outcome from the offline stage is used to determine the waiting score. The nonlinear model used in computing both the price score and traveling score is used here to determine the waiting score. This score depends on the deviation of the waiting time at a certain charging station from the average waiting time at all charging stations as follows:

$$S_{w(j,v,t)} = l_{(j,v)} - \frac{1}{\exp(-f(T_{w(j,v,t)} - \bar{T}_{w(t)}))} + \varepsilon_3 \quad (24)$$

$$f(T_{w(j,v,t)} - \bar{T}_{w(t)}) = \varphi_3 \left( \frac{T_{w(j,v,t)} - \bar{T}_{w(t)}}{\bar{T}_{w(t)}} \right) \quad (25)$$

Finally, the three scores are combined to determine the total score obtained by each charging station  $S_{(j,v,t)}$  based on weighting coefficients as expressed in (26). The weighting coefficients ( $w_r, w_T, w_w$ ) are set individually by each customer according to his priorities. All scoring factors are normalized to unify the range of different scoring factors as shown in (26).

$$S_{(j,v,t)} = w_r \frac{S_{r(j,v,t)}}{\sum_{j \in \mathcal{J}} S_{r(j,v,t)}} + w_T \frac{S_{T(j,v,t)}}{\sum_{j \in \mathcal{J}} S_{T(j,v,t)}} + w_w \frac{S_{w(j,v,t)}}{\sum_{j \in \mathcal{J}} S_{w(j,v,t)}} \tag{26}$$

**B. CORRECTION SUBSTAGE**

As mentioned earlier, the waiting time in the proposed strategy is computed offline based on the predicted EVs’ arrivals at the charging station, not based on the actual arrivals. In the real world, the EV drivers’ real-time behavior can’t be predicted. This could result in an error in the expected waiting times that are utilized in the routing process where the number of EVs’ drivers who select a certain charging station may be higher than the predicted number. Therefore, a correction action should be applied during this substage to ensure that the data is reliable as shown in Fig. 1. We assume that each customer’s operator will send a signal to the operator of the correction substage. This signal includes only the charging station number, which is selected by the EV’s driver. If the number of EVs who select a certain charging station  $y_{a(t,j)}$  is less than the predicted arrivals at this station  $y_{p(t,j)}$ , no action is triggered where the worst waiting times based on the forecasted arrivals are utilized as shown in Fig. 1. Otherwise, an updating signal will be triggered by the operator of the correction substage to the offline database to use the updated waiting times. The updated waiting times are determined during the offline stage while considering an increase in EV requests with a specific percentage as mentioned in section III. This procedure is repeated during each time segment.

**V. RESULTS AND DISCUSSIONS**

In this section, two case studies are presented and discussed. These cases are formulated and solved using MATLAB software. The first case study is dedicated to evaluating the performance of each stage of the smart charging strategy based on the customer perspective. Whereas the second case study represents a comparison between results of the routing process obtained from the smart charging strategy based on the customer-centered decision perspective proposed in this paper and the same charging strategy but based on operator perspective. This comparison aims to assess the superiority of the proposed strategy in satisfying the customers’ requirements. In all the case studies, we consider an hourly time segment during the offline stage as it is the day-ahead stage while both online and correction stages are executed instantly once an EV request is received. In all the case studies, we consider an hourly time segment.

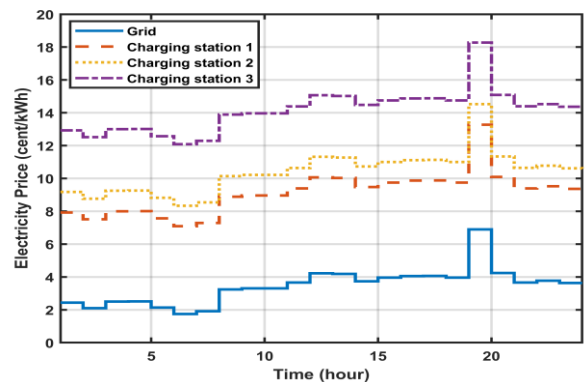
In the smart charging strategy, three charging stations under different ownership will cooperate through a VCS to act as one charging station for EVs. The participating charging stations will offer different charging prices due to different chargers’ ratings available at each charging station as shown in Table 2. Thus, the VCS will offer different charging options for EVs: different charging prices as well as different waiting times.

**TABLE 2. Charging stations specifications [27]–[29].**

Charging Stations	Mean Service time (Min)	AC/DC	Charger Rating
Charging station 1	36	DC	50 kW
Charging station 2	28	DC	62.5 kW
Charging station 3	18	DC	100 kW

The charging price offered by each charging station  $j$  during the time segment  $t$  is composed of two components which are a fixed price due to charging service ( $z_{(j)}$ ) and a time-varying price due to purchasing the electricity from the grid as illustrated in (27). The fixed price differs from one charging station to another according to the rating of the charger available at this station which is assumed (5, 6.25, 10 cent/kWh for each charging station, respectively). Whereas the time-varying component is assumed to be fixed for all charging stations participating in VCS with an increase  $\delta$  over the grid price offered during this time segment ( $G_{(t)}$ ). The Hourly Ontario Energy Price (HOEP) [30] is used for real-time pricing in this work. Fig.3 illustrates the charging price offered by each charging station and the grid.

$$r_{(i,t)} = z_{(i)} + \delta G_{(t)} \tag{27}$$



**FIGURE 3. Hourly-based charging price offered by participating charging stations.**

**A. CASE STUDY 1: SMART CHARGING STRATEGY BASED ON CUSTOMER-CENTERED DECISION PERSPECTIVE**

In this section, the outcomes from the proposed smart charging strategy based on the customer’s perspective will be discussed to assess its performance. Hence, this section is dedicated to illustrate the outcomes of the two stages.



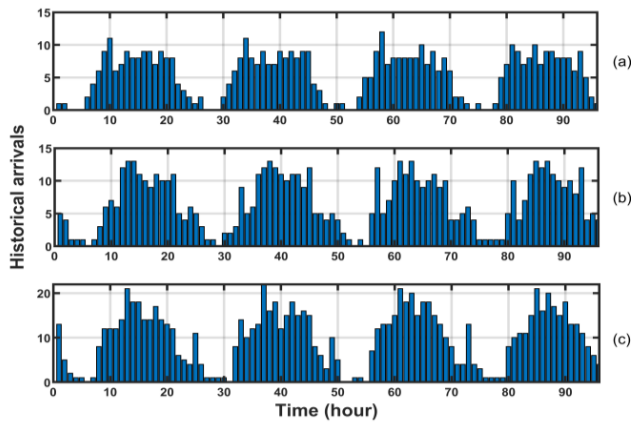


FIGURE 4. Hourly-based input to forecasting substage for charging station # a)1 b)2 c)3.

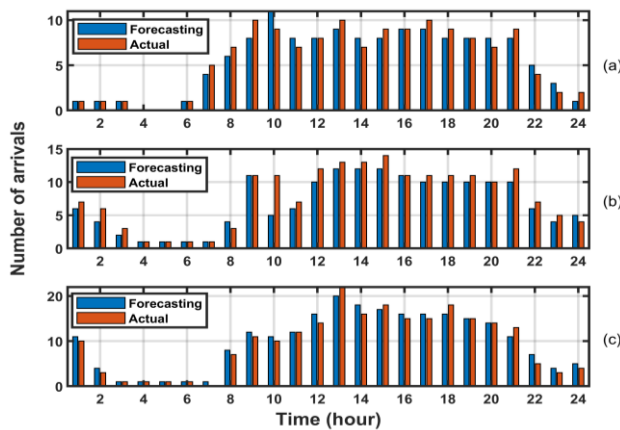


FIGURE 5. The outcomes from forecasting substage and routing substage for scenario (A) for charging station # a)1 b)2 c)3.

First, the actual arrivals to parking lots in Toronto, Canada, obtained from Toronto Parking Authority (TPA) for a period of four days is shown in Fig. 4. These data are used as an input (historical data) to the forecasting substage/offline stage to predict the EVs’ arrivals at each charging station during the next day. Fig. 5 illustrates the predicted arrivals at the three charging stations participating in the VCS obtained by the forecasting substage. Then, the outcomes from the forecasting substage are fed to the queueing substage to compute the expected waiting time during each time segment based on the predicted arrivals as well as a 30% increase in hourly-based arrivals for the next day as an example. Fig. 6 shows the expected waiting time for the next day during each time segment. The expected waiting time at each charging station varies due to the different arrivals at each charging station during each time segment computed by the forecasting substage. The outcomes from the queueing substage will be stored in the offline database to be used by the EV’s operator for the routing process during the next day.

The actual/real arrivals hourly based time segment to the same parking lots for the next day are used as the actual

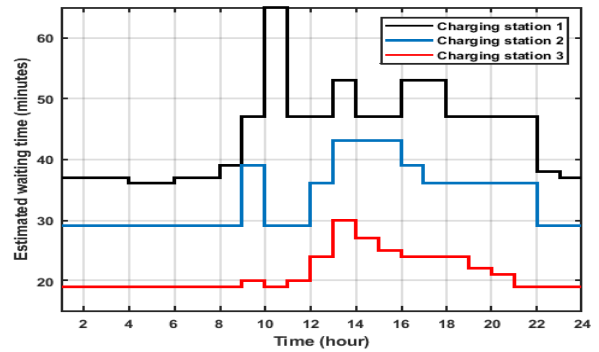


FIGURE 6. The outcomes from queue substage based on predicted arrivals.

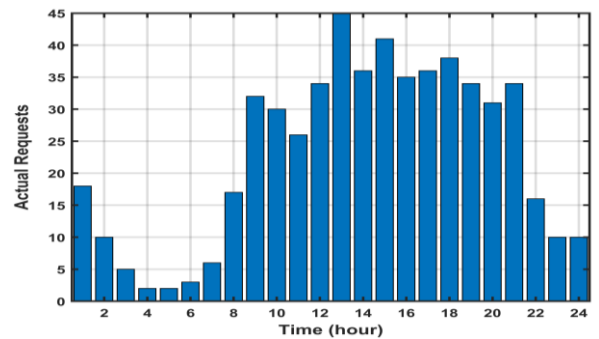


FIGURE 7. The actual requests to customers’ operators.

EV requests during the online stage/ running day, which are shown in Fig. 7. The hourly-based arrivals are distributed over the hour using the Poisson distribution. When the EV sends a charging request to the operator associated with its weighting coefficients regarding the charging price, traveling time, and the waiting time, the operator will read the day-ahead stored data. Then, it will rank the participating charging stations based on EV driver’s priorities. In this case study, we consider only one scenario. We assume that all EV requests to their operators have equal weighting coefficients as described as follows:

- Scenario (A): all EVs’ drivers are assumed to set equal weighting coefficients ( $w_r = w_T = w_w = 33.33\%$ ).

The outcomes from the routing substage considering equal weighting coefficients are illustrated in Fig. 3. The percentages of EVs requests selecting to be charged from the three charging stations are 24.29%, 33.21%, 40.89%, respectively. Whereas 1.61% of EVs’ drivers are forced to select V2V mode due to SOC’s status. An example of the signal sent by the operator to a specific EV is shown in Table 3. The three scores obtained by each charging station are combined using weighting coefficients set by this EV to rank the charging stations according to their priorities as shown in Table 3.

To assess the performance of the forecasting substage, the outcome of the routing substage which represents the actual EVs’ arrivals at each charging station will be compared

**TABLE 3.** An example of the outcome from the routing substage.

	Price score	Traveling score	Waiting score	Total score
Charging station 3	26.13 %	42.64 %	37.32 %	35.32 %
Charging station 1	38.09 %	32.22 %	27.9 %	32.7%
Charging station 2	35.79 %	25.14 %	34.79 %	31.87 %

with the predicted arrivals to compute the performance indices of the LSTM forecasting technique. LSTM succeeds to achieve accurate estimation for EVs’ arrivals at the three participating charging stations with an average  $RMSE = 1.291$ ,  $MAE = 0.917$ , and  $MAPE = 12.32\%$ .

It is worth mentioning that the number of EVs who select to charge at each charging station will vary depending on the values of weighting coefficients that are individually set by each EV’s driver according to his priorities for charging price, the traveling time, and the waiting time. The impact of weighting coefficients’ variations will be illustrated in the next case study to show the superiority of the proposed strategy based on the customer’s perspective to satisfy EV requirements compared to the methods used in the literature.

**B. CASE STUDY 2: ROUTING BASED ON OPERATOR’S PERSPECTIVE (CENTRALIZED OPERATOR)**

Most of the methods introduced in the literature for routing EVs’ drivers are based on the operator’s/charging station’s perspective. The operator may route the EV without considering customers’ priorities. For example, the operator may route the EV to the nearest charging station with the lowest charging price, however; the EV owner may prefer to charge at a farther charging station with a higher charging price to wait less time. Thus, this section is devoted to compare the results obtained from the proposed smart strategy based on the customer’s perspective and those obtained from the same strategy with the same framework but based on the operator’s perspective. The same assumptions/data used in the first case study are considered here to have a fair comparison.

In this case study, the routing process of EVs’ drivers to the most suitable charging stations within VCS is implemented centrally to minimize the charging price  $r_{(j,t)}$ , traveling time  $T_{tr(j,v,t)}$ , and waiting time  $T_{w(j,v,t)}$ . The routing process starts with receiving the EV driver’s charging request, then the centralized operator will implement the decision-making process to route the EV’s driver to the most suitable charging station which minimizes the following objective function:

$$\min \sum_{j \in J} (\alpha_1 r_{(j,t)} + \alpha_2 T_{tr(j,v,t)} + \alpha_3 T_{w(j,v,t)}) u_{(j,v)}, \forall v \in \mathbb{V} \tag{28}$$

$$u_{(j,v)} \in \{0, 1\} \tag{29}$$

$$\sum_{j \in J} u_{(j,v)} \leq 1, \quad \forall v \in \mathbb{V} \tag{30}$$

$u_{(j,v)}$  is a binary variable as expressed in (29).  $u_{(j,v)} = 1$  means that the EV’s driver  $v$  will be routed to the charging station  $j$ .

In (30), each EV will be assigned to only one station, if it will be served.

The same EVs’ requests in the first case study are considered here. The centralized operator will route the EV driver to the suitable charging station from its perspective to minimize (28). The percentages of the EVs charging at the three stations participating in VCS based on centrally routing based on the operator’s perspective are 24.11%, 31.79%, 42.5%, respectively compared to 24.29%, 33.21%, 40.89% based on the customer’s perspective under equal weighting coefficients for scenario (A). The scoring criterion is based on customers’ priorities which vary from one customer to another. Where some customers may care about time and the other customers may be interested more in the cost. Therefore, we consider different scenarios. The results obtained by the smart charging strategy based on the customer’s perspective are replicated with different weighting coefficients to demonstrate the superiority of the proposed strategy in satisfying customers’ requirements. These scenarios can be described as follows:

- Scenario (B): all EVs’ drivers are assumed to set a higher weighting coefficient for the price ( $w_r = 50\%$ ,  $w_T = w_w = 25\%$ )
- Scenario (C): all EVs’ drivers are assumed to set a higher weighting coefficient for the traveling time ( $w_T = 50\%$ ,  $w_r = w_w = 25\%$ )
- Scenario (D): all EVs’ drivers are assumed to set a higher weighting coefficient for the waiting time ( $w_w = 50\%$ ,  $w_r = w_T = 25\%$ ).
- Scenario (E): the weighting coefficients are generated randomly.

**TABLE 4.** Comparison between results obtained based on customer’s and operator’s perspective.

Different scenarios	Number of EVs arrivals at			Time (hours)	Cost (\$)	
	Charging station 1	Charging station 2	Charging station 3			
Customer perspective	A	136	186	229	311.7	2013.4
	B	176	230	145	349	1903.9
	C	137	169	245	309.7	2031
	D	112	185	254	297.5	2050.5
	E	143	181	227	313.5	2008.5
Operator perspective	135	178	238	310.13	2023.9	

Time: total waiting time spent by all EVs in all charging stations  
 Cost: Total charging costs paid by all EVs

The results for all previous scenarios are illustrated in Table 4. The results show that the proposed smart charging strategy based on customer’s perspective allows EVs’ drivers to opt between the participating charging stations by ranking these charging stations based on the EV’s priorities. Thus, the customer will select the suitable charging station for his priorities with full cognizance of all the data. For example, if EV’s driver sends a request with 80%, 10%, 10% weighting coefficient regarding the charging cost, the traveling time, and the waiting time, respectively, the operator will rank

the charging stations according to the obtained score. The charging station which ranked first, may not have the cheapest price but it has the highest overall score compared to the station with the cheapest price. Where, the cheapest station may be far from this customer and has a high waiting time. Therefore, the number of EVs charging at each charging station varies at each scenario. As illustrated in Table 4, when the weighting coefficient regarding the price is higher than the other weighting coefficients as in scenario (B), the total charging cost paid by all EVs is reduced through routing EVs to the available cheapest charging station. However, if the priority of customers is adjusted to be the waiting time as in scenario (D), the EVs are routed to the available charging station with less waiting time and thus the total waiting time spent by all EVs is reduced. On contrary, the routing process based on operator's perspective doesn't consider customer's priorities and thus, the number of EVs charging at each charging station didn't change with variations of EVs' priorities.

## VI. CONCLUSION

This paper proposes a smart charging strategy where various charging stations can cooperate through a VCS to serve all EVs' charging requests and thus, obtaining more profit. This cooperation offers multiple charging options for EVs' drivers to opt between them. Moreover, the routing process through the proposed strategy is based on the customer's perspective, not the operator's perspective. This will ensure routing the EV's driver to the most suitable charging station which satisfies his requirements. The expected waiting time at each charging station during each time segment is determined day-ahead through the offline stage based on the forecasted EVs' arrivals. The online stage is dedicated to routing EVs' drivers to the most suitable charging station via ranking the participating charging stations according to the obtained scores regarding price, traveling time, and charging time as well as the EV driver's priorities. Two case studies are simulated and discussed to assess the performance of the proposed strategy in satisfying customers' requirements. The results show the superiority of the proposed strategy based on the customer's perspective in satisfying the customers' requirements compared to the results obtained by a similar strategy but based on the operator's perspective. In the proposed strategy based on the customer's perspective, the number of EVs' arrivals at each charging station varies with variations of customers' priorities. On contrary, the proposed strategy based on the operator's perspective doesn't depend on the customers' priorities. Finally, the structure of VCS, the criterion of computing both the waiting time as well as the charging time using deterministic model considering full and partial charging, the benefits of cooperation between the participating charging stations through VCS rather than the competition between them, the methodology of sharing the profit between the participating charging stations are considered as future work.

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