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Decentralized Electric Vehicle Supply Stations (D-EVSSs): A Realistic Scenario for Smart Cities

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ABSTRACT In this paper, we consider the decentralization of power generation and management problems in electric vehicle supply equipment (D-EVSE). We propose two algorithms to manage the interaction between electric vehicles (EVs) and D-EVSEs while maximizing EV drivers' satisfaction in terms of reducing the waiting time for charging or discharging services and minimizing the stress level for D-EVSEs. The first algorithm is used to schedule charging or discharging service for EVs. The second algorithm is used to manage unscheduled EV needs at D-EVSEs. The simulation results using realistic scenarios are conducted to validate the proposed schemes and demonstrate their efficiency and effectiveness while satisfying the defined constraints. Furthermore, we apply both D-EVSE scheduled and unscheduled schemes to Ontario highways 174, 416, and 417 in the city of Ottawa as a case study.

INDEX TERMS Electric vehicle, EVs charging, EVs discharging, EVSE, EV driver's satisfaction, D-ESS, waiting time, D-EVSE, D-EVSS, stochastic model.

I. INTRODUCTION

Reducing greenhouse gas (GHG) emissions and energy consumption are very important and challenging issues for smart cities. However, the existing structures of energy consumption are no longer able to adapt the dynamic conditions. New communication systems expected to be used in smart grid for energy infrastructure devices should be dynamically adaptable because static conditions will no longer be applicable in the near future. Therefore, new infrastructure and communication must be flexible in the smart city to enable the achievement of efficiency and sustainability. The carbon footprint has impacted the global environment with CO2 emissions reaching more than 9% of all emissions between 2008 and 2017. Furthermore, the global CO2 footprint is estimated to become more than 11% by 2020 [1], [2]. For example, the Canadian government has announced that 100% of electricity use will be from renewable energy sources by 2025. The federal government aims to reduce GHG emissions by 40% by 2025 [3].

EV, as part of the electrification of transportation in a smart city, is an important challenging issue due to its power demand. Although EVs come with zero emissions and low noise [4]–[7], EVs' charging demand as a new power consumer will add more stress to the power grid and may cause in some cases power outages due to the overloading of regional transformers.

Nowadays, centralized energy storage system (CESS) architecture is used as a solution for peak power demand [8], [9]. However, the CESS architecture does not provide power scalability nor reliability, and it is a one-point failure. Furthermore, CESS is classified as having high maintenance cost and cost of degradation as well as high delayed response to power outage issues.

The decentralized energy storage system (D-ESS) has the ability to resolve these problems while giving more scalability, battery energy quality (less line loss), and very fast reaction to demand. Moreover, as a multi-point failure it is easy to maintain with low risk of power outage in the macro-grid as well as a more secure grid.

In this work, we consider the installation of D-EVSEs in power supply stations. The D-EVSEs are based on renewable energy sources such as photovoltaic or wind power. We resolve the problem of EV charging or discharging scheduled services when EVs need to know the best available supply station before the plug-in phase, as well as the

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EV charging or discharging unscheduled services when EVs decide to participate in unscheduled services.

Our contributions are as following: 1) To the best of our knowledge, we are the first to consider the decentralization of the power generation and management in smart cities. 2) We propose a system model to minimize the D-EVSEs' stress level. 3) We design a scheduling algorithm which helps the EVs to determine and select the best supply station so as to maximize the drivers' satisfaction. 4) We propose a system model to minimize the charging and discharging waiting time. 5) Finally, we compare the D-EVSE algorithms with three other algorithms: random algorithm, Dijkstra's shortest path algorithm, and EV smart-guidance algorithm.

The rest of the paper is organized as follows: Section II presents some related works. Section III introduces D-EVSE system model and problem formulation for EV charge scheduling process. In Section IV, performance evaluations are presented. The conclusions and future work are provided in Section V.

II. RELATED WORKS

Operations of micro-grid and EV charging and discharging at supply stations based on D-ESSs have attracted extensive research. Authors in [10] proposed a decentralized micro-grid management system (MGMS) framework which showed more control functionality than the centralized MGMS. The authors concluded that the decentralized MGMS present greater flexibility, reliability, and scalability. Also, the decentralized MGMSs are well-recognized and enhance the reliability of the system. The authors of [11] presented two-sided Hospital/Residents (HR) schemes aiming to reduce the complexity of the charging process. However, the proposed architecture did not consider the EV discharging service and EV preferences. The authors of [12] proposed a centralized charging controller based on EV satisfaction and the power stability requirement in parking lots. One study [5] presented two optimization objectives: maximizing the number of charged EVs and minimizing the losses in the distribution network. In [13] and [14], several schemes are proposed to aggregate the power and manage the EV charging loads. In [15], a control scheme is considered to show the benefits of V2G technology in the context of renewable energy sources (RESs). In [16], a new scheme for EV trip planning is introduced. The initial EV State of Charge (SoC), the final destination, and the available charging EVSEs are considered while EVs are on the road. The authors of [7] proposed a new metric to describe the EV driver's satisfaction with fairness and cost using a centralized charging algorithm. However, these last two works did not investigate the power grid stress level.

The dynamic pricing scheme proposed in [17] aimed to increase the profit of an EV parking deck. However, in this model the author did not consider EV driver's satisfaction nor smart grid overloading. Likewise, the dynamic pricing protocol proposed in [18] and [9] aimed to minimize the peak EV power demand for the power providers; however, home charging was proposed. Additionally, the time-of-use pricing (TOUP) was considered in their work to increase the EV satisfaction for charging demand. However, [18] only considered the charging service while [9] considered both the charging and discharging services. In [4], most issues regarding cost of EV charging and energy management are considered. However, market-level customer satisfaction is the only parameter in this study. The authors of [19] proposed a simulated annealing algorithm for EV charging in smart grid based on mathematical optimization to choose the best charge stations. The goal of this work is to minimize the EV driver's cost and reduce the peak demand in these stations. The authors in [20] discussed a travel aware scheduling scheme while considering the benefits of EVSEs and increasing EV satisfaction. In all previous works described above, a centralized approach has been considered for the power and management system.

The authors in [21] presented a system-guidance model to minimize the waiting times for an EV which has requested charging service. Also, this model assumes that the algorithm called SMART-EV-Guidance for directing vehicles to charging stations has minimized the search time. The authors of [22] presented two models for EV charging at public stations. The first model considered the charging waiting times while the second model considered the cut-off priority protocol and a TOUP strategy. However, the proposed models assumed that the power came from the power grids. The authors of [23], proposed a model aiming to manage and control charging and discharging services at EVSEs. Two algorithms were proposed in this model: peak load management (PLM) and guidance algorithm (GA). PLM algorithm was used to schedule EV charging or discharging service according to power demand while taking into account the time and location for each EV's requested service. GA was used to guide every EV to the appropriate EVSE for the purpose of reducing its waiting time before plug-in. The proposed model considered the mobility of vehicles in an urban scenario and TOUP. The authors concluded that the PLM efficiently used unused EV batteries' storage to store energy and thereby support the power grid at all times, especially during peak time. In addition, GA minimized the waiting times for each EV before the plug-in phase. Yet none of these works considered realistic scenarios.

The authors of [9], [22], and [24] studied the impact of EV charging to the power grid and concluded that EV charging demand will affect the power demand by drastically increasing the demand for power from the power generation providers. The authors of [25] presented a fast-charging station placement with the flexible demand to determine the optimal location and capacity of the charging stations. However, there is no mention of the power source nor of how many vehicles were considered in this work.

The authors of [26] presented an EV charging and discharging queuing model at public supply stations aiming to manage EV charging and discharging requests in a real-time way as well as to reduce the EV charging and discharging waiting times. All of the EVs send their charging and discharging requests to the provider through a cloud computing network. A mathematical model has been proposed to compute the waiting times for EVs' requests. Two classifications identified each EV as high or low priority and as high or low class. However, this model is used as centralized management, which is not recommended if the system has been shut down or attacked.

The authors of [27] proposed an EV charging service model located at a workplace station based on TOUP. Two parts are presented in that work: an admission control approach to increase the charging quality service, and a joint searching scheme to maximize the charging station's revenue based on TOUP. Likewise, an EV charging service model located at an intelligent parking garage based on real TOUP is proposed in [28]. The proposed model used the [27] model and added an adaptive utility-oriented scheduling scheme aiming to optimize the total utility for the charging operator.

The authors of [29] proposed a dynamic charging scheduling scheme in a workplace parking lot aiming to manage and control EV charging services in a real-time manner. The proposed scheme used the photovoltaic power system with the power grid as the main resources to guarantee the EV charging service at all times. Furthermore, all of the EVs' charging requests are collected in a central controller to obtain the optimal decision for each EV request. However, this work did not consider the discharging services or identify how to gain the most benefits from the ESS to save the generated energy from the solar panel.

III. SYSTEM MODEL AND PROBLEM FORMULATION

To develop our detailed problem formulation, we will develop our system model on a case study of city of Ottawa's highways in Ontario, Canada, and we have selected 12 gas stations in the city of Ottawa, Ontario in which we propose D-EVSE model (see Fig.1). We consider that all D-EVSEs are equipped by EVSEs, and that all EVSEs operate a set of charging and discharging sockets [22]. The D-EVSEs are powered by renewable energy (photovoltaic or wind turbines). The power is stored in a very big battery or ultra-capacitor (see Fig.2). With the city of Ottawa having three highways (417, 416, and 174 as shown in Fig. 3a, 3b and 3c), we selected Hunt Club Road to connect 417 and 416 in both directions as shown in Fig. 3d. Moreover, we assumed that each EV considered by D-EVSE model has at least 20% of its maximum battery capacity.

Each EV on the highway requests the D-EVES' availability that are on its route as well as each D-EVSE's waiting time status. If the EV SoC is not enough for its trip, then the EV has the ability to stop more than once at different D-EVSEs. For each EV, we define the SoC requested to reach the destination expected by Eq. 1:

$$SoC_{req}^{(i)} = Trip^{(i)} \times D_{rat} + SoC_{mini} \tag{1}$$

- $Trip^{(i)}$: distance,
- D_{rat}: EV consumption rate per mile,

TABLE 1. Distance between EVs and D-EVSEs.

	D-EVSE $^{(1)}$	D-EVSE $^{(2)}$	D-EVSE $^{(3)}$	D-EVSE $^{(j)}$
EV_1	$d^{(1,1)}$	$d^{(1,2)}$	$d^{(1,3)}$	$d^{(1,j)}$
EV_2	$d^{(2,1)}$	$d^{(2,2}$	$d^{(2,3)}$	$d^{(2,j)}$
EV_3	$d^{(3,1)}$	$d^{(3,2)}$	$d^{(3,3)}$	$d^{(3,j)}$
$EV_{(i)}$	$d^{(i,1)}$	$d^{(i,2)}$	$d^{(i,3)}$	$d^{(i,j)}$

- SoC_{mini}: minimum SoC requirement,
- $^{(i)}$: EV number.

Also, the difference between initial SoC and requested SoC is given by Eq.2:

$$\delta SoC^{(i)} = SoC_{ini}^{(i)} - SoC_{req}^{(i)} \tag{2}$$

- $SoC_{ini}^{(i)}$: initial SoC.

We also suppose that all EVs are randomly distributed on the city streets as shown in Fig. 2. As well, we assume that all EVs are occupied with a GPS and are randomly assigned (C/D, SoC_{ini} and *speed*). The EV C/D in Algorithm 1 is used to manage the EV driver's preference about charging or discharging participation. We assume that EVs and D-EVSEs are able to communicate for requesting and reservation processes while the EVs are on the road. Furthermore, we assume that all of the D-EVSEs are communicating with each other. The EV arrival time is given by Eq.3:

$$t_{Arrival}^{(i,j)} = \frac{d^{(i,j)})}{Sp^{(i)}} + \beta \tag{3}$$

- $d^{(i,j)}$: Distance between EV & D-EVSE,
- $Sp^{(i)}$: EV speed,
- β: Weather and driver behaviour,
- $^{(j)}$: D-EVSE number.

As shown in Table 2, we consider three types of vehicles (Tesla, Nissan Leaf, and BMW i3). We choose the maximum charging level to be 80% of the EV battery's capacity because we are trying to avoid the non-linear charging behaviour which starts after 80% of the EV battery's charging capacity. However, all EVs can participate in the discharging process if they have more than 20% in their batteries. Each vehicle type has its own capacity as well as its required minimum SoC and maximum SoC.

In the following equation (Eq. 4), we give the distance between EVs and D-EVSEs.

$$D_{IJ} = \begin{bmatrix} \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \\ \cdot & \cdot & \cdot & d_{(i,j)} & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \end{bmatrix} \tag{4}$$

- $I := 1, \ldots\ldots\ldots\ldots, i$,
- $J := 1, \ldots\ldots\ldots\ldots, j$.

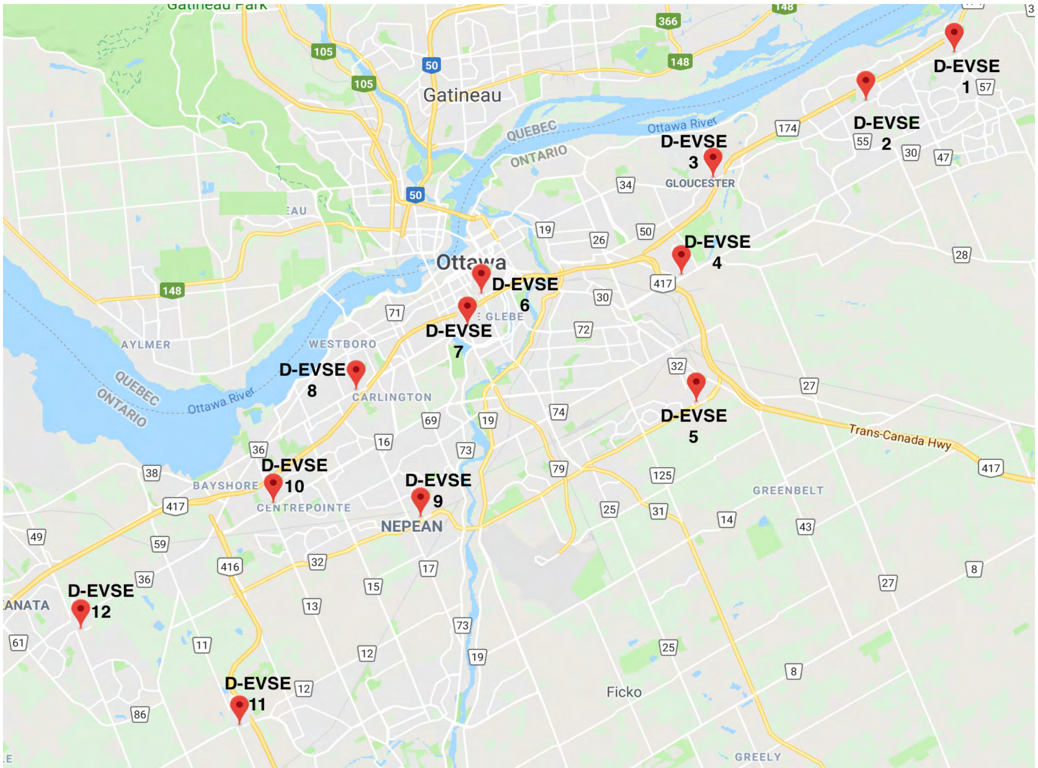

FIGURE 1. Overview of D-EVSE system model.

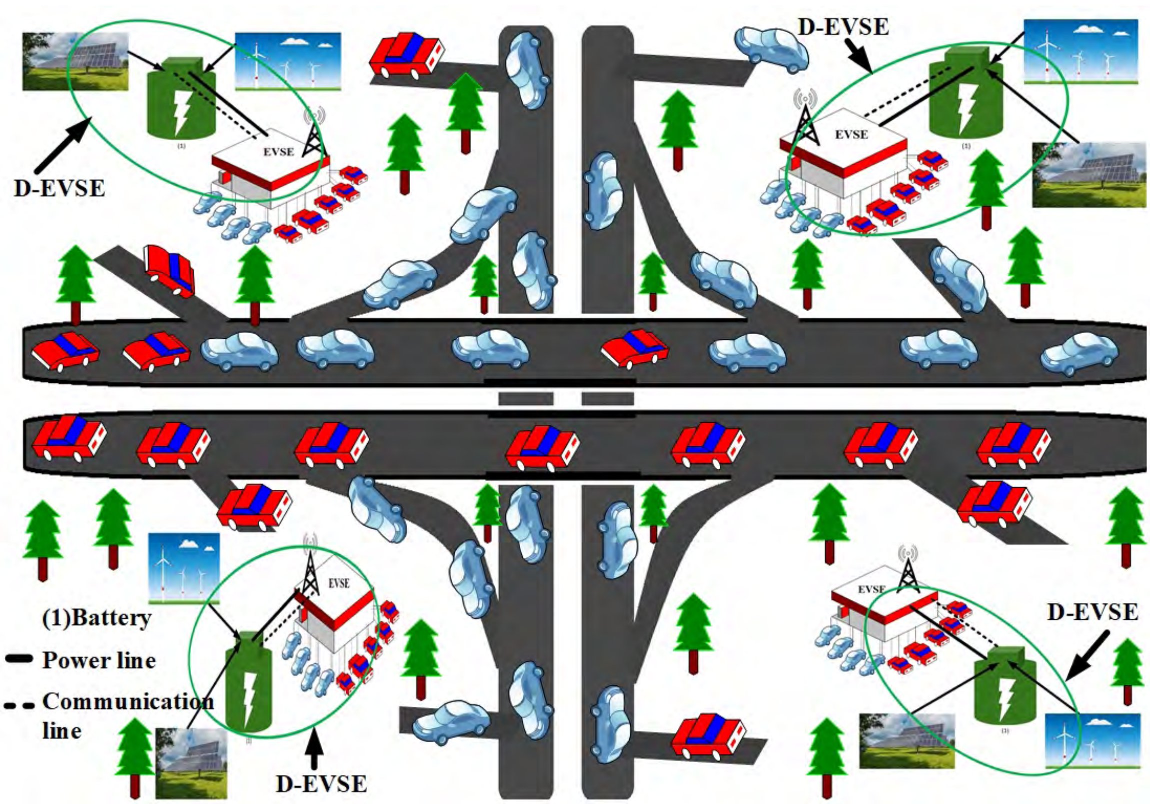

FIGURE 2. Street overview.

(a)

(b)

(c)

(d)

FIGURE 3. Ottawa's highways 417, 416, and 174. (a) 174 and 417 highways in Ottawa, Ontario. (b) 417 highway in Ottawa, Ontario. (c) 174, 417, and 416 highways in Ottawa, Ontario. (d) 417 and 416 highways via Hunt Club Road in Ottawa, Ontario.

In D-EVSE model, EVs can choose to participate or not participate in the charging service. Also, EVs can choose to not participate in the discharging service. Each EV can compute its ability to reach the destination by using Eqs. 1 and 2. If the current EV's SoC is positive, then the EV can use the discharging service. If not, then the EV cannot use the discharging service. Thus, when the EV is in need of power, it can request the charging service. Subsequently, any EVs which want to charge, or discharge will send a request message containing the SoC request (Eq.2) to D-EVSEs directly asking for the time slot availability and the charging or discharging service. The D-EVSEs will reply to the EV and attach the information requested as well as the current waiting time status. The charging time for each EV needing electricity power is given by Eq.5:

$$t_{Ch}^{(i,\varepsilon)} = \frac{SoC^{(i)}}{Ch^{(\varepsilon)}} \tag{5}$$

- $Ch^{(\varepsilon)}$: Charging rate,
- (ε): Type of the charging (fast or ultra-fast) for scheduled and (Level 2) for unscheduled Algorithms.

The discharging time for each EV that agrees to sell its surplus electricity power to help the D-EVSE stabilization is given by Eq. 6. Eventually, the discharging process can lead to a new upcoming energy market

$$t_{Disch}^{(i,\varepsilon)} = \frac{SoC^{(i)}}{Disch^{(\varepsilon)}} \tag{6}$$

- *Disch*: Discharging rate.

Algorithm 1 D-EVSE Immediate Scheduling Algorithm (ISA)

Input 1 EV [N_{EV},C/D, SoCs, speed, location, destination].
Input 2 D-EVSE [Availability].

```
for each EV 1 (1..N_EV) do
    Calculate SoC_req
    Calculate SoC_req^(i) (Eq. 1)
    Calculate δSoC^(i) (Eq. 2)
    if δSoC^(i) > 0 and EV(C/D) = 2 then
        select [{nearest, available}] D-EVSEs
        Schedule: Discharging process
    end if
    if δSoC^(i) ≤ 0 and EV(C/D) = 1 then
        select [{nearest, available}] D-EVSEs
        Schedule: charging process
    end if
    if no D-EVSE immediate available then
        go to algorithm 2
    end if
end for
```

Additionally, each EV has its decision made based on the information received from D-EVSEs. In ISA Algorithm 1, once the EV receives the information from the D-EVSEs which contain the time slot availability, charging, or discharging type, then the EV will compute its arrival time using Eq. 3 based on its location as shown in Eq.4 and Table 1. Also, the EV will compute the charging or discharging time period based on the availability of D-EVSEs (see Eqs. 5 and 6). Afterward, the EV will select the optimal D-EVSE that fits with its requirements and constraints. Finally, a conformation message will be sent from D-EVSE to the EV if the EV has selected to participate in the immediate service. In this algorithm, the EV's preference is met regarding the EV charging and discharging services.

$$W_{time}^{j} = \frac{\lambda_u{}^{(j)}}{\mu_u} \tag{7}$$

- $^{(j)}$: D-EVSE number.
- $\lambda_u{}^{(j)}$: Average unscheduled EV arrivals rate,
- μ_u: Average unscheduled EV services rate. We suppose that this parameter is the same for all D-EVSEs.

Each D-EVSE will compute its service waiting times using Eq. 7 based on the number of EV arrivals rate and services rate. All of the D-EVSEs are equipped with fast and ultra-fast charging services as well as discharging services. However, for unscheduled services there are only two services which are based on level 2 charging and discharging services. Each

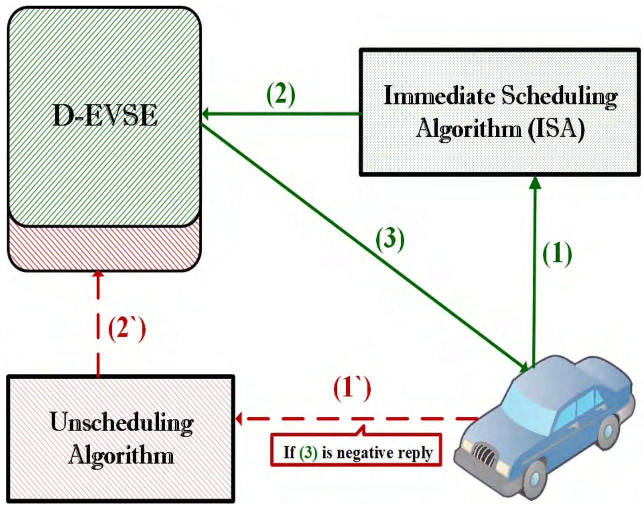

FIGURE 4. EV and D-EVSE interaction flow chart.

EV that selects to not participate in scheduled charging and discharging services can participate in unscheduled service at the selected D-EVSEs considering the charging and discharging waiting time. Consequently, each EV has access to information about all D-EVSEs' service waiting time.

We use the proposed Algorithm 1 and Algorithm 2 to test the D-EVSE system model

Algorithm 2 D-EVSE Unscheduling Algorithm

Input 1 EV [N_{EV}, $\delta SoC^{(i)}$, $SoC_{req}^{(i)}$, location, destination].
Input 2 D-EVSEs [W_{time}^{j}].

```
for each EV 1 (1..N_EV) do
    Each D-EVSE Calculate W_time^j (Eq. 7) //* but NO immediate D-EVSEs available
    select {[nearest, least {W_time^j}]} D-EVSEs
    if δSoC^(i) > 0 then
        EV reserves plug-in socket for discharging service
    else
        EV reserves plug-in socket for charging service
    end if
end for
```

Fig 4 summarizes EV interaction with D-EVSE. There are two states for the EV:

- First: EV is on the road.
  (1) EV sends a request to D-EVSE scheme.
  (2)&(3) D-EVSE scheme uses ISA to reply to EV.
- Second: if the response from the D-EVSE is negative, then EV goes to {nearest D-EVSE, least waiting time}. (1′) & (2′) D-EVSE uses the unscheduling algorithm to manage EV requests.

IV. PERFORMANCE EVALUATION

In this section, we discuss the performance of the proposed D-EVSE schemes described by D-EVSE ISA and unscheduling algorithms. We used MATLAB to simulate the D-EVSE

TABLE 2. Simulation parameters.

EV Type	Tesla (75 - 100 kWh) [30] Nissan Leaf (45 kWh) [31] BMW i3 (46 kWh) [32]
Number of EVs $(NoEV)$	1000
EVs SoC (SoC_{ini}) %	20 - 90 %
EVs stop	0 - 2 times
EV stop durations	0, 15, or 30 mins
EVs' trip $(Trip)$	Random 30 - 200 km
EVs' speed on highway	60 - 120 km/h
Number of D-EVSEs	12
D-EVSE's Capacity	10000 kW
Duration of a time slot	10 min
Maximum duration of a time slot (unscheduled arrival)	2 hours
EV SoC requirement (SoC_{mini})	20 %
Fast charging rate Discharging rate	60 kW DC [23]
Max fast charging time Max discharging time	20 min [23]
Ultra-fast charging	150 kW DC
Max ultra-fast charging time	15 min [33]
SoC_{max} charging level	80 %
Level 2 charging $(unscheduled)$	7 kW Power
Number of sockets $(scheduled)$	16 / D-EVSE
Number of sockets $(unscheduled)$	4 / D-EVSE
λ_u	Random {3/1 and 2/1}
μ_u	2/10
EVs discharging mini level SoC	mini 20%
Tesla Nissan Leaf BMW i3	1%/km (0.204 kWh/km) [30] 1%/km(0.187 kWh/km) [31] 1%/km (0.187 kWh/km) [32]

proposed models. We considered twelve D-EVSEs in known locations as shown Fig. 1, and we distributed 1000 EVs randomly on the roads as shown in Fig.2. Simulation parameters are shown in Table 2. All EVs have travelling trip (30 – 200 km) and speed (60 – 120 km/h) as well as initial SoC (20 – 90%).

Moreover, we assumed that each D-EVSE has a capacity of approximately 10MW. The D-EVSEs are powered by renewable energy sources such as photovoltaic and wind power. Additionally, each D-EVSE is composed of fast and ultra-fast charging services as well as discharging service. Each D-EVSE offers two services for each EV that needs a service: immediate scheduled service and unscheduled arrival service. Also, each D-EVSE is equipped with 16 plug-in sockets for the scheduled services and 4 plug-in sockets for the unscheduled services. This means that the total of plug-in sockets are 240 sockets. 192 sockets are for scheduled services and the rest of the sockets are for the unscheduled services in all D-EVSEs.

Another consideration in unscheduled services is service waiting time. The waiting time is considered only for the second algorithm to encourage the EV drivers to participate in scheduled services. For the same reason, we used level 2 charging sockets for unscheduled service. Each EV will receive a conformation including reservation time and the plug-in socket number if the request is for an immediate scheduled service. However, if the request is for an unscheduled service, then the EV will receive the plug-in socket number only at the D-EVSE location.

We assume that the remaining SoC of EV can reach any D-EVSE. We also suppose that the λ_u for all D-EVSEs is flowing the random distribution between 3/1min and 2/1min. This means that some D-EVSEs' arrival rate is three EVs every minute while other D-EVSEs' arrival rate is two EVs every minute. We considered that the μ_u is the same in all of the D-EVSEs. The μ_u equals 2/10 which means that two EVs depart every 10 minutes.

We have considered three cases. We present case one, in which we compare the D-EVSE algorithms and the random algorithm, followed by case two, in which we compare the D-EVSE algorithms and the Dijkstra's shortest path algorithm [34]. Finally, we compare the D-EVSE and the EV smart guidance algorithm [21]. The random algorithm selects the nearest D-EVES for EV services while the Dijkstra's shortest path algorithm selects the D-EVES for EV services based on the shortest path between its current location to the target destination. The EV smart-guidance algorithm selects the nearest D-EVSE for EV services so as to minimize the EV charging waiting time. In addition, those algorithms are based on centralized power generation systems.

In D-EVSE scheduling algorithm, the satisfaction level is measured based on the number of EVs which sent a charging or discharging request and received charging or discharging conformation from the D-EVSEs. Also, the dissatisfaction level is measured based on the EVs which sent a charging or discharging request and received charging or discharging rejection from the D-EVSEs. However, the EVs which have received either charging or discharging rejection from the D-EVSE can go to the nearest D-EVSE to participate in unscheduled services to either sell the power to D-EVSE or buy the power from D-EVSE.

In D-EVSE scheduling algorithm, the satisfaction level is measured based on the number of EVs that received charging or discharging conformation from the D-EVSEs divided by the number of EVs that sent a charging or discharging request. Also, the dissatisfaction level is measured based on the EVs that received charging or discharging rejection from the D-EVSEs divided by the number of EVs sent a charging or discharging request. However, the EVs which have received either charging or discharging rejection from the D-EVSE can go to the nearest D-EVSE to participate in unscheduled services to either sell the power to D-EVSE or buy the power from D-EVSE.

The driver's satisfaction level indicates how satisfied the driver is with the services that he has requested. In other words, the satisfaction level for each EV driver is kept high. Also, the D-EVSE stress level measures how stressed the D-EVSE is. In other words, the stress level for each D-EVSE is kept low. Fig. 5 shows a comparison of the D-EVSEs' stress level with the D-EVSE algorithm and the other three algorithms. As shown in Fig. 5, the D-EVSE algorithm minimizes the stress level between D-EVSEs and shows better performance in terms of managing the EV charging and

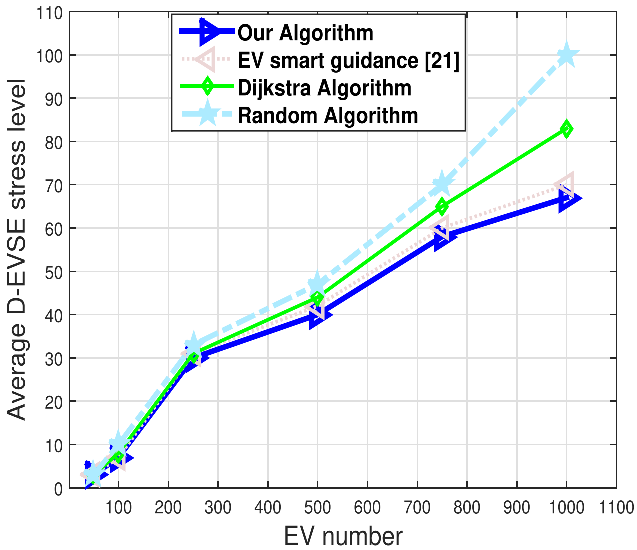

FIGURE 5. D-EVSEs' stress level.

TABLE 3. Stress level performance between D-EVSE ISA and random algorithm.

Number of EVs	Random Algorithm	D-EVSE ISA	Savings rate
0 - 250	15%	12.3%	17.8%
251- 500	46%	40%	13%
501 - 750	70%	57%	18%
751-1000	100%	70%	30%

TABLE 4. Stress level performance between D-EVSE ISA and Dijkstra's algorithm.

Number of EVs	Dijkstra's shortest path Algorithm	D-EVSE ISA	Savings rate
0 - 250	14%	12,3%	11.9%
251- 500	45%	40%	11.1%
501 - 750	65%	57%	12.3%
751-1000	83%	70%	15.7%

discharging services. In summary, Fig. 5 shows the average of all D-EVSEs' stress levels.

According to Table 3, a comparison between the random and D-EVSE ISA algorithms shows that the D-EVSEs' stress levels in random algorithm in some cases are fully stressed. The random algorithm is the worst case in terms of the stress level because there is no consideration for the distance between EVs and D-EVSEs and the EV's charging or discharging request preference when the decision is about to be made. Table 3 also presents the stress level using the D-EVSE ISA algorithms and shows that the D-EVSE ISA algorithms have increased the system performance and reliability whenever the number of EVs is increased. For example, when the number of EVs is 250, the savings rate is 17.8%. When the number of EVs is 1000, then the savings rate is 30%. This is a significant improvement.

TABLE 5. Stress level performance between D-EVSE ISA and EV smart-guidance algorithm.

Number of EVs	EV Smart-guidance Algorithm	D-EVSE ISA	Savings rate
0 - 250	13%	12.3%	5.1%
251- 500	43%	40%	6.9%
501 - 750	61%	57%	6.6%
751-1000	75%	70%	6.7%

TABLE 6. Comparison of the average performance for D-EVSEs' stress level.

	Average D-EVSEs' Stress level %	Savings rate %
Random Algorithm \	57.8	22.4
D-EVSE ISA	44.8	
Dijkstra's shortest path Algorithm \	51.75	13.4
D-EVSE ISA	44.8	
EV smart-guidance Algorithm \	48	6.6
D-EVSE ISA	44.8	

Table 4 compares the D-EVSEs' stress level with the Dijkstra's shortest path algorithm as well as with the D-EVSE ISA algorithms. The Dijkstra's shortest path algorithm shows better performance than the random algorithm in terms of minimizing the stress level between D-EVSEs. However, the D-EVSE ISA algorithms show a savings rate of approximately 15.7% when compared to the Dijkstra's shortest path algorithm performance when the number of EVs are 1000.

The D-EVSEs' stress level using EV smart-guidance and D-EVSE ISA algorithms are shown on Table 5. The EV smart-guidance algorithm shows much better performance in terms of minimizing the stress level between D-EVSEs compared to the Dijkstra's shortest path and random algorithms. The D-EVSE ISA algorithm shows better performance than the EV smart-guidance algorithm and has achieved a savings rate of approximately 6% in most cases.

Table 6 presents a comparison of the average stress levels between all of the algorithms. As shown in Table 6, it is clear that D-EVSE ISA minimized the D-EVSE average stress level with a savings rate of more than 22.4% compared to the D-EVSE stress level based on the random algorithm, and a savings rate of 13.4% when the D-EVSE average stress level used the Dijkstra's shortest path algorithm. However, when the D-EVSE average stress level is managed by the EV smart-guidance algorithm, the D-EVSE ISA algorithm minimized the D-EVSE average stress level in comparison to the D-EVSE ISA algorithm with a savings rate of 6.6%. This result proves the robustness of D-EVSE ISA in terms of minimizing the D-EVES stress level.

The average level of EV drivers' satisfaction with the D-EVSE ISA in comparison to the other three algorithms is shown in Fig. 6. Table 7 shows the savings rate of the D-EVSE ISA compared to the savings rate of the other three algorithms. The average savings rate in terms of the EV drivers'

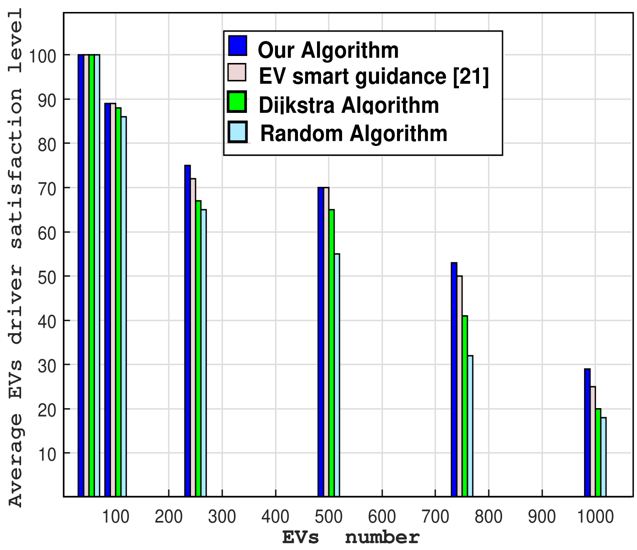

FIGURE 6. EV drivers' satisfaction.

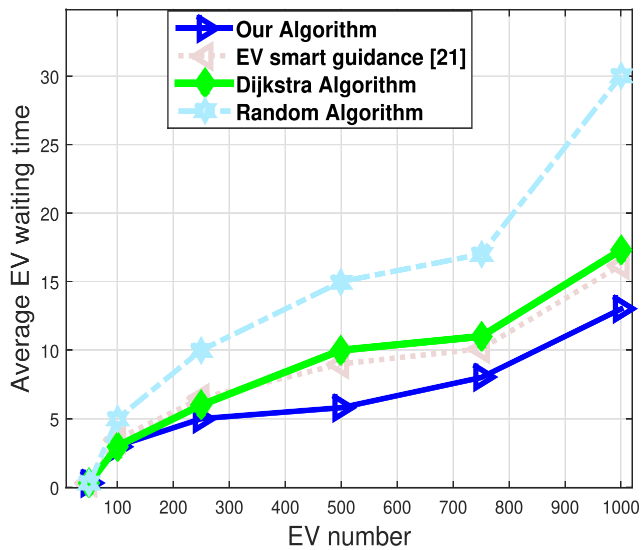

FIGURE 7. Waiting times comparison for EVs by using D-EVSE scheduling algorithm.

TABLE 7. Comparison of average performance for EV drivers' satisfaction level.

	Average EV drivers' Satisfaction level %	Savings rate %
Random Algorithm \ D-EVSE ISA	52.8 / 40.5	23.3
Dijkstra's shortest path Algorithm \ D-EVSE ISA	47.25 / 40.5	14.3
EV Smart-guidance Algorithm \ D-EVSE ISA	43 / 40.5	5.8

TABLE 8. Comparison of average waiting time for EV services.

	Average Waiting Time (minutes)	Savings rate %
Random Algorithm \ D-EVSE Unscheduling Algorithm	18 / 8	55.6
Dijkstra's shortest path Algorithm \ D-EVSE Unscheduling Algorithm	11.5 / 8	30.4
EV smart-guidance Algorithm \ D-EVSE Unscheduling Algorithm	10.5 / 8	23.8

satisfaction using the random algorithms compared to the D-EVSE ISA is more than 23%, while the average savings rate using the Dijkstra's shortest path algorithm when compared to D-EVSE ISA is more than 14%. Moreover, the EV smart-guidance algorithm is superior than the last two algorithms. However, when compared to the D-EVSE ISA, the D-EVSE ISA's average savings rate is approximately 5.8%. According to Fig. 6 and Table 7, in a comparison between D-EVSE ISA and the other three algorithms the D-EVSE ISA is robust and has the ability to maximize the EV driver's satisfaction.

Fig. 7 shows waiting time for EV services by comparing the D-EVSE unscheduling algorithm and the other three algorithms. As shown in Fig. 7, the D-EVSE unscheduling algorithm minimized the waiting time for EV services and showed much better performance in terms of managing the EVs' unscheduled arrival services. Moreover, Fig. 7, shows the average waiting time for EV service in all cases. By observing the EV waiting times in Table 8, the D-EVSE ISA savings rate is more than 23.8% compared to the EV smart-guidance algorithm which is the best among those three algorithms. In contrast, the worst savings rate is more than 55% with random algorithm. Consequently, D-EVSE algorithms have the ability to manage most of the waiting time accordingly for charging and discharging service requests while minimizing the waiting time for services in all scenarios as shown in Table 8.

In summary of these results, D-EVSE scheduled and unscheduled schemes are able to manage D-EVSE stress level while maximizing EV satisfaction as well as minimizing the EV charging and discharging waiting time. Consequently, the D-EVSE algorithms are robust and have the ability to manage immediate scheduled and unscheduled services.

V. CONCLUSIONS

In this paper, we have proposed a model to manage the interaction between EV and D-EVES. We present two algorithms: ISA and unscheduling algorithm. The ISA is used to minimize the D-EVSEs' stress level, maximize the EV drivers' satisfaction, and take in account the EV's preference for charging or discharging service. Also, we considered the D-EVSE availability to be reserved as well as the distance for each EV to reach the selected supply station. The unscheduling algorithm is used to manage the unscheduled EV arrivals aimed to minimize the EV waiting time for the services. D-EVSE algorithms are tested through simulations considering realistic scenarios with EV and D-EVSE constraints.

We obtained results from different scenarios to investigate the EV drivers' satisfaction as well as the D-EVSEs' stress level. We have also proved that the D-EVSE system model far outperforms the random, Dijkstra's shortest path, and EV smart-guidance approaches. Simulations showed that the proposed protocol manages the EVs' charge and discharge services in an effective way. Our future plans are to extend this work by considering the trading energy between EVs.

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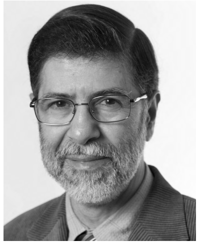

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