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Decentralized Game-Theoretic Scheme for D-EVSE Based on Renewable Energy in Smart Cities: A Realistic Scenario

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ABSTRACT In this paper, we address a decentralized power production and management system based on Game Theory (GT) for Electric Vehicles' (EVs') interplay with a Decentralized Electric Vehicle Supply Equipment (D-EVSE) located at the public supply station. Renewable energy production such as solar energy (PV) is considered as the main power source for our D-EVSE and we consider the connection to the grid when the solar renewable energy system is failing to respond to the demand. We propose a decentralized GT (D-GT) scheme aiming to optimize the EVs' interaction with the D-EVSE considering both EVs' satisfaction as well as the D-EVSEs' stability. Also, the D-GT model is used to choose the optimal available solution for EV charging or discharging services that fulfill predefined constraints. A realistic scenario is considered as a testbed for our D-GT optimization model. Simulation results indicate that the proposed model can manage and control the interaction between EVs and D-EVSEs efficiently.

INDEX TERMS Electric vehicles, electric vehicles charging, electric vehicles discharging, decentralized-energy storage system, decentralized-electric vehicle supply equipment, decentralized game theory, renewable energy, smart cities.

NOMENCLATURE

Parameter	Description
N_{ch}	number of EV in charging service not plugged in yet
N_{dis}	number of EV in discharging service not plugged in yet
N_{ch}^{j}	number of EV in charging service plugged in D-EVSE$_j$
N_{dis}^{j}	number of EV in discharging service plugged in D-EVSE$_j$
i	EV number dedicated for charging
j	D-EVSE number, $j = 1..\,M$
h	EV number dedicated for discharging
R_{ch}	charging rate
R_{dic}	discharging rate
$SoC_{\min}$	minimum EV SoC
$SoC_{ch}^{EV_i}$	initial EV SoC (charging services)
$SoC_{\max}$	maximum EV SoC
SoC_{need}^{i}	SoC needed by EV
SoC_{trip}^{i}	SoC requirement to reach the final destination
SoC_{j}^{i}	SoC requirement to reach the D-EVSE
$Trip(i,j)$	distance between EV^i and D-EVSE$_j$
D_{rat}	EV consumption rate
$t_{ch}^{EV_i}$	EV charging time
$t_{1}^{EV_i}$	EV arrival time (charging services)
$t_{2}^{EV_i}$	EV departure time (charging services)
Sp^{EV_i}	EV's speed
SoC_{ch}^{j}	total EVs charging power requested
T	slot time number
M	number of D-EVSE station
D-ESS(t)	current battery storage for D-EVSE
b_{Max}^{EV}	Max battery power for EV

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t	time variation, t = 1 .. T
P_{PV}	Photovoltaic power
$SoC_{dis}^{EV_h}$	initial EV SoC (discharging service)
d_0	EV battery Deep of discharge (DoD)
SoC_{trip}^{h}	SoC requirement to reach the final destination
SoC_{j}^{h}	SoC requirement to reach the D-EVSE
$Trip^h$	distance between EV^h and final destination
$Trip(h, j)$	distance between EV^h and D-EVSE$_j$
SoC_{Av}^{h}	available power offered by EV
$t_{dis}^{EV_h}$	EV discharging time
$t_1^{EV_h}$	EV arrival time (discharging services)
$t_2^{EV_h}$	EV departure time (discharging services)
SoC_{dis}^{j}	total EVs discharging power offered
D-ESS$_0$	DoD for D-ESS battery
D-ESS$_{\min}^{j}$	minimum D-ESS power level

I. INTRODUCTION

With the growth in the Electric vehicle (EV) market due to its releasing of zero air pollution and reduction of greenhouse gas (GHG) emissions in smart cities, the power demand will increase accordingly. By 2030, the number of EVs will be more than 100 million globally [1]. While this will create a huge power charging demand which must be managed, EVs have the potential to provide a good opportunity for power storage by supporting the power grid as Vehicle to Grid (V2G) service [2], [3]. As well, EVs provide many advantages for EV owners such as minimizing travel expenses and providing revenue to EV owners by selling their surplus power.

In our model, the optimization of EV charging and discharging is modelled based on a Decentralized Game Theory (D-GT). The D-GT approach is proposed to select and determine the optimal solution for both EV services and the Decentralized EV Supply Equipment (D-EVSE). The optimal solution would increase the D-EVSE stability while also maximizing EVs' satisfaction level. The D-GT is the most important aspect of our model, as it allows each EV to manage its charging and discharging service demands based on the concept of win-win while taking into account the defined constraints.

Nowadays, the necessity of adopting Renewable Energy Sources (RES) with an Energy Storage System (ESS) is growing year by year. The RES and ESS will decrease GHG emissions and create a clean, sustainable and green environment. However, due to discontinuous and unpredictable RES power prediction, an ESS is most essential to storing generated power.

In this paper, we consider that decentralized ESSs (D-ESSs) are installed in D-EVSEs. Each D-EVSE is powered by the Photovoltaic (PV) energy system. We propose a solution to resolve the problem of the EV charging or discharging process when EVs need to know the best available plug-in time for both EV and D-EVSE before the plug-in phase.

Our contributions are as follows:

1) We introduce a D-GT model to optimize the EV charging and discharging service demand.
2) We propose a D-GT algorithm to guide EVs for charging and discharging service.
3) Also, we consider a realistic scenario in the city of Ottawa, ON, Canada to test our D-GT algorithm.
4) Finally, our D-GT model takes into account the EVs' satisfaction as well as the D-EVSEs' stability.

The structure of this paper is organized as follows. Section II peruses some related works. Section III addresses the proposed system model and the problem formulation. In Section IV, performance evaluations are presented. The conclusions are provided in Section V.

II. RELATED WORKS

Game Theory (GT) operations for EV charging and discharging services in a supply station have attracted the attention of researches. In general, GT is classified into three groups, namely cooperative game theory, noncooperative game theory (competitive), and evolutionary game theory.

Many researchers have studied EVs' charging and discharging services [4]–[10] based on cooperative GT [11] and [12]. The authors of [13] and [14] addressed different mechanisms based on cooperative game theory for EVs' charging and discharging services. In addition, the authors of [13] proposed a day-ahead and real-time cooperative energy management system. The proposed system considered the power provider to be both a power provider and a power buyer. EVs were also considered in their system. The goal of this system was to maximize the revenue for participants. Likewise, the authors of [14] studied EVs' charging behaviour with the smart grid from an economical perspective. The study aimed to increase the revenue for both EV owners as well as the power provider. The authors of [15] presented two models for EV charging services based on GT approach. These two models are a Stochastic Dynamic Programming (SDP) model and a greedy algorithm model. The power providers have used a renewable energy production with an ESS. For all these works the power management was a centralized approach. Other recent studies have explored and examined EVs' charging and discharging services based on noncooperative game theory [16]–[21]. After investigating the problem of energy management in the decentralized control, the author of [22] proposed a game theory-based decentralized control strategy for coordinating multiple hybrid energy systems aiming to maximize the preference of each player. However, RESs were not introduced in the study. Furthermore, the proposed system implemented a Nash equilibrium in each controller stage with a learning algorithm. Also, the paper [23] presented a decentralized charging scheme model based noncooperative game theory. The presented model coordinated the competitive of electric vehicles (EVs) with aggregator via a population coordinator to manage the interaction. The authors of [24] introduced a mean filed (MF) game theory scheduling model to manage and schedule the plug-in hybrid electric vehicles PHEVs (Gas/Electric) charging. The goal of this model was to minimize the trip time as well as trip distance. The authors of [25] proposed an EV charging model based on two stages of noncooperative game theories. The proposed model has considered ideal and non-ideal actions of many aggregators in the same area. The authors of [26] introduced a decentralized hierarchical EV charging mechanism based on the GT model. The GT model is formulated to be combined between MF-GT and Stackelberg-GT. The MF-GT was used to minimize the computational cost and communication overhead between power sellers. The Stackelberg-GT was used to define the optimal linear price for the consumer. The model considered the aggregator as power buyer with power grid and as power seller to the EVs. Also, the aggregator was considered to control EV charging processes as well as the charging power prices.

The authors of [27] and [28] studied the implementation of both competitive and cooperative game theories in the same model of EV charging mechanism in centralized way. The authors of [29] proposed a Bi-level optimization model based on AC/DC hybrid multi-microgrids (HMM). The structure of HMM used distributed power and management mechanisms with two model systems. A Bi-level optimization model has been considered to coordinate between the utility and the supply level, aiming to minimize the operation cost for each level. The difference between the Bi-level optimization model and the proposed D-GT optimization model is that the Bi-level optimization was based on the distributed power source and management system. In contrast, the D-GT optimization model is based on a decentralized power production and management system. Moreover, the Bi-level optimization model has used the Diesel engine generator as the primary power source. Still, our proposed model used the Renewable Energy Source (PV) as the primary power source and used the power grid source as a backup source.

Other studies have investigated the EVs' charging and discharging services based on evolutionary game theory. The authors of [30] presented an energy management system based on an escort evolutionary game theory. The system's goal was to study the EVs charging behaviour with aggregators as a power provider. The multi-population approach was considered. In addition, a battery storage system based on renewable energy was used to reduce the EVs' charging during the peak demand. The investigation concluded that the peak of EV charging demand and generated power from renewable sources were changed simultaneously. The paper [31] presented a competitive and an evolutionary game theory systems for EV charging mechanisms at the EV charging station. The first model was based on the competitive game theory to manage the charging price contest between charging stations. The second system was based the evolutionary game theory and it was implemented to improve the charging decision maker for all EVs. Also, this model was taken into account both power and transportation systems. The goal was to decrease the charging demand at the peak time and, also to increase the EV charging stations' revenue.

Our work in [32] established an EV interacting with a decentralized energy storage system (DESS) model based on renewable energy. The goal of this study was how to organize the EV demand for charging and discharging services as a way to lower the power stress level as well as to increase the EV owner's satisfaction. Similarly, decentralization of power generation and management in the electric vehicle supply station (D-EVSS) is proposed in [33]. The proposed model introduced two schemes to organize the interaction between EV and the D-EVSS as a public supply station. The first scheme was applied to planned EV charging or discharging requested service, while the second scheme was applied to unplanned EV charging or discharging requested service. The goal of the model was to minimize the power stress level on D-EVSSs and maximize the EV owner's satisfaction by taking into account the reduction in waiting time for service. Furthermore, a realistic case study in the city of Ottawa (Canada) was presented to study the interaction behaviour of EV and D-EVSS. Public supply stations (D-EVSSs) were placed based on the chosen gas station in the city of Ottawa. The last two works, however, did not consider GT.

III. SYSTEM MODEL AND PROBLEM FORMULATION

In this section, we suppose that each D-EVSE operates a set of charging and discharging sockets in a city. We also assume that all D-EVSEs are equipped with a Decentralized Energy storage system (D-ESS) and powered by renewable energy (Photovoltaic [PV]) as the main power source. The generated power from PV is stored in a very large battery (D-ESS) as shown in Figure. 1. Moreover, in our model, we assume that all EVs' batteries have at least 20% of their maximum battery capacity at all times.

We present two investigation systems: random and realistic system. In both models, we consider that each D-EVSE$_j$ broadcasts periodically its updated availability schedule as well as the battery storage capacity D-ESS$(t)_j$ every five minutes. Each EV that willing to participate in charging or discharging service will calculate and choose the best available D-EVSE$_j$ and send a reservation request. As well as, the D-EVSE will send back a conformation response to the EV. Whereas, the D-EVSE will use a reservation system based on first come first served. In the realistic scenario, we have chosen 6 gas stations close to the highways in the city of Ottawa, Ontario and relocate them with our proposed D-EVSEs based on D-GT model as shown in Figures.2,3, 4 and 5.

We propose the following four models, each with two scenarios: (1) charging model, (2) discharging model, (3) D-ESS capacity variation model, and (4) optimization model based on D-GT. The scenarios are mono D-EVSE and multi D-EVSEs.

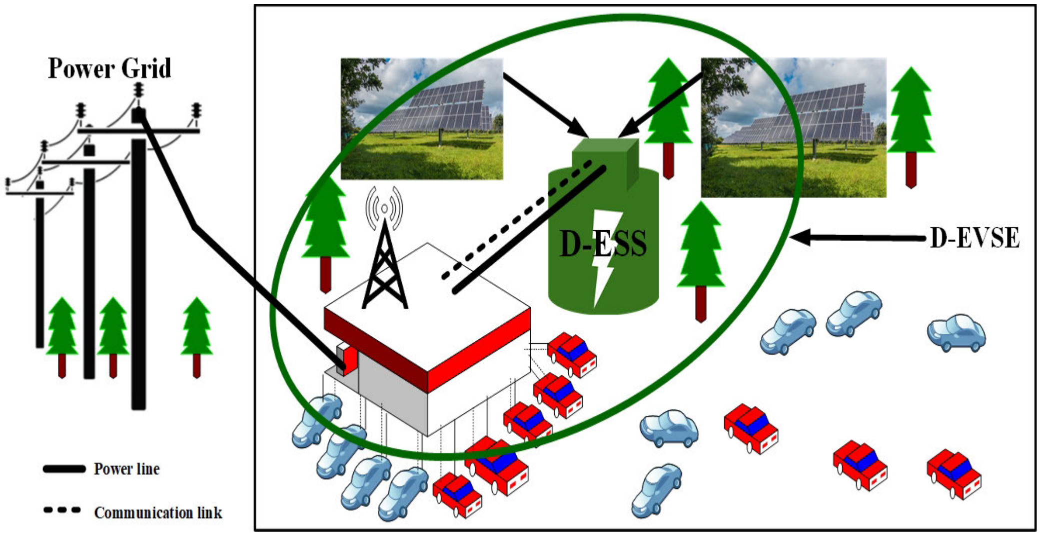

FIGURE 1. System model and problem formulation.

FIGURE 2. Overview of D-EVSE locations.

A. CHARGING MODEL

The only EV services considered in this model are the charging services. The purpose of this model is to find a charging service for EVs without taking into account our defined constraints. We also aim to investigate the interaction behaviour between EVs' charging requests and D-EVSEs as power provider. In the proposed model, the state of charge (SoC) of i^{th} EV is given by Eq. 1:

$$SoC_{\min} \leq SoC_{ch}^{EV_i} \leq SoC_{\max} \tag{1}$$

where the i is the EV number, $i = 1..\, N_{ch}$.

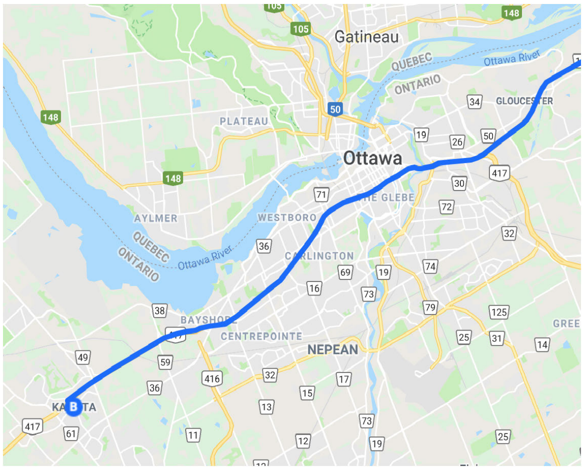

FIGURE 3. 417 and 174 highways in the city of Ottawa, Ontario, Canada.

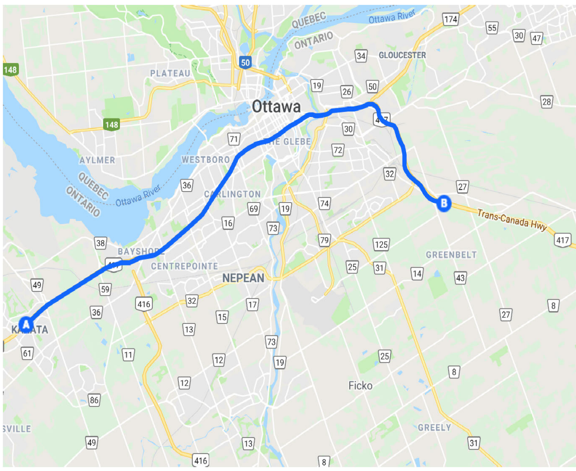

FIGURE 4. 417 highway in the city of Ottawa, Ontario, Canada.

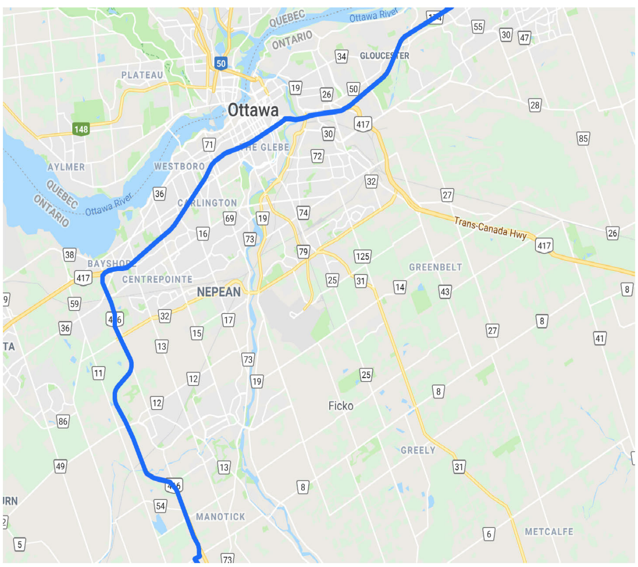

FIGURE 5. 417, 174, and 416 highways in the city of Ottawa, Ontario, Canada.

The SoC requirement to reach the final destination for the i^{th} EV is given by Eq. 2:

$$SoC^{i}_{Trip} = Trip^{i} \times D_{rate} \tag{2}$$

where the $Trip^{i}$ is the distance between EV^{i} and the final destination.

The SoC requirement to reach the D-EVSE$_j$ [34] for the i^{th} EV is given by Eq. 3:

$$SoC^{i}_{j} = Trip(i,j) \times D_{rate} \tag{3}$$

The amount of charging energy for the i^{th} EV is given by Eq. 4:

$$SoC^{i}_{need} = SoC_{\max} - SoC^{EV_i}_{ch} + SoC^{i}_{Trip} \tag{4}$$

where the SoC^{i}_{need} is the power needed by EV and If $SoC^{i}_{need} \geq SoC_{\max}$ then $SoC^{i}_{need} = SoC_{\max}$.

The charging time [32] for the i^{th} EV is given by Eq. 5:

$$t^{EV_i}_{ch} = \frac{SoC^{i}_{need}}{R_{ch}} \tag{5}$$

The arrival time for the i^{th} EV is given by Eq. 6:

$$t^{EV_i}_{1} = \frac{Trip(i,j)}{Sp^{EV_i}} + \beta \tag{6}$$

where the β is the weather and driver behaviour.

The arrival and departure time for the i^{th} EV is given by Eq. 8:

$$t^{EV_i}_{2} = t^{EV_i}_{1} + t^{EV_i}_{ch} \tag{7}$$

$$t^{EV_i}_{1} \leq t^{EV_i}_{ch} \leq t^{EV_i}_{2} \tag{8}$$

The total amount of energy requested by N^{j}_{ch} EVs is given by Eq. 9:

$$SoC^{j}_{ch} = \sum_{i=1}^{N^{j}_{ch}} SoC^{i}_{need} \tag{9}$$

1) FOR MONO D-EVSE

The dynamic variation of the j^{th} D-ESS battery SoC which depends on the its previous status is given by Eq. 10:

$$\text{D-ESS}(t)_j = \text{D-ESS}_j(t-1) - P^{j}_{ch}(t) + P^{j}_{PV}(t) \tag{10}$$

where:

$$P^{j}_{ch}(t) = SoC^{j}_{ch}(t) \times b^{EV}_{Max} \tag{11}$$

2) FOR MULTI D-EVSEs

The dynamic variation of the total energy storage in the D-EVSEs is given by Eq. 12:

$$\sum_{j=1}^{M} \text{D-ESS}(t)_j = \sum_{j=1}^{M} \text{D-ESS}_j(t-1) - \sum_{j=1}^{M} P^{j}_{ch}(t) + \sum_{j=1}^{M} P^{j}_{PV}(t) \tag{12}$$

B. DISCHARGING MODEL

The only EV services considered in this model are the discharging services. The aim of this model is to find a discharging service demand for EV. We also aim to investigate the EVs' discharging interaction behaviour with D-EVSEs. In this model, d_0 which is Deep of Discharge (DoD) for each EV, must meet Eq.13:

$$d_0 \leq SoC_{\min} \leq SoC_{dis}^{EV_h} \tag{13}$$

The SoC requirement to reach the final destination for the h^{th} EV is given by Eq. 14:

$$SoC_{Trip}^{h} = Trip^{h} \times D_{rate} \tag{14}$$

The SoC requirement to reach the D-EVSE$_j$ for the h^{th} EV is given by Eq. 15:

$$SoC_{j}^{h} = Trip(h,j) \times D_{rate} \tag{15}$$

The amount of discharging energy for the h^{th} EV is given by Eq. 16:

$$SoC_{Av}^{h} = SoC_{dis}^{EV_h} - [d_0 + SoC_{Trip}^{h}] \tag{16}$$

The arrival time for the h^{th} EV is given by Eq. 17:

$$t_1^{EV_h} = \frac{Trip(h,j)}{Sp^{EV_h}} + \beta \tag{17}$$

The discharging time [33] for the h^{th} EV is given by Eq. 18:

$$t_{dis}^{EV_h} = \frac{SoC_{Av}^{h}}{R_{dis}} \tag{18}$$

The arrival and departure time for the h^{th} EV is given by Eq. 20:

$$t_2^{EV_h} = t_1^{EV_h} + t_{dis}^{EV_h} \tag{19}$$

$$t_1^{EV_h} \leq t_{dis}^{EV_h} \leq t_2^{EV_h} \tag{20}$$

The total amount of energy that is offered by N_{dis}^{j} EVs is given by Eq. 21:

$$SoC_{dis}^{j} = \sum_{h=1}^{N_{dis}^{j}} SoC_{Av}^{h} \tag{21}$$

where the SoC_{dis}^{j} is the total EVs discharging power offered.

1) FOR MONO D-EVSE

The dynamic variation of the j^{th} D-ESS battery SoC is given by Eq. 23:

$$P_{Dis} = SoC_{dis}^{j} \times b_{Max}^{EV} \tag{22}$$

$$\text{D-ESS}(t)_j = \text{D-ESS}_j(t-1) + P_{PV}^{j}(t) + P_{Dis}^{j}(t) \tag{23}$$

2) FOR MULTI D-EVSEs

The dynamic variation of the total energy storage in the D-EVSEs is given by Eq. 24:

$$\sum_{j=1}^{M} \text{D-ESS}(t)_j = \sum_{j=1}^{M} \text{D-ESS}_j(t-1) + \sum_{j=1}^{M} P_{PV}^{j}(t) + \sum_{j=1}^{M} P_{Dis}^{j}(t) \tag{24}$$

C. D-ESS CAPACITY VARIATION MODEL

Both EV charging and discharging services are considered in this model. The purpose of this model is to update and monitor the D-ESS battery status regarding the charging and discharging service demands that are requested or ordered by EVs. In addition to this model, we considered the use of the charging model's Eqs. 1 to 9 and the discharging model's Eqs. 13 to 21.

1) FOR MONO D-EVSE

The variation of the charging and discharging D-EVSE batteries is given by Eq.25

$$\text{D-ESS}(t)_j = \text{D-ESS}_j(t-1) - P_{ch}^{j}(t) + P_{PV}^{j}(t) + P_{Dis}^{j}(t) \tag{25}$$

2) FOR MULTI D-EVSEs

The total variation of the charging and discharging D-EVSE batteries is given by Eq.26

$$\sum_{j=1}^{M} \text{D-ESS}(t)_j = \sum_{j=1}^{M} \text{D-ESS}_j(t-1) - \sum_{j=1}^{M} P_{ch}^{j}(t) + \sum_{j=1}^{M} P_{PV}^{j}(t) + \sum_{j=1}^{M} P_{Dis}^{j}(t) \tag{26}$$

D. OPTIMIZATION MODEL FOR CHARGING AND DISCHARGING SERVICES BASED ON GAME THEORY FOR MULTI D-EVSEs

Each EV aims to increase each D-ESEV's stability and maximize its own satisfaction by using a Decentralized GT (D-GT) approach. The purpose of this model is to find an optimal charging or discharging service for each EV while taking into account our defined constraints. As well, we aim to investigate the EVs' charging and discharging interaction behaviour with D-EVSEs. First, we optimize the EV charging model, and still, we considered the use of Eqs. 1 to 12 in this optimization model. Second, we optimize the EV discharging model; also, we considered the use of Eqs. 13 to 24 in this optimization model. Finally, we optimize both the charging and discharging model, and likewise, we considered the use of Eqs. 1 to 9, 13 to 21 and 25 to 26 in this optimization model.

$$Max \left(\sum_{i=1}^{N_{ch}^{j}} SoC_{ch}^{i}(t), \sum_{h=1}^{N_{dis}^{j}} SoC_{dis}^{h}(t) \right) \tag{27}$$

$$st. \left\{ \begin{array}{c} SoC_{\min} \leq SoC_{ch}^{EV_i}(t) \leq SoC_{\max} \\ SoC_{\min} \leq SoC_{dis}^{EV_h}(t) \\ t_1^{EV_i} \leq t_{ch}^{EV_i} \leq t_2^{EV_i} \\ t_1^{EV_h} \leq t_{dis}^{EV_h} \leq t_2^{EV_h} \\ \text{D-ESS}_{\min}^{j} \leq \text{D-ESS}^{j}(t) \leq \text{D-ESS}_{\max}^{j} \\ 0 \leq \frac{\text{D-ESS}_{\min}^{j}}{\text{D-ESS}_{\max}^{j}} \leq \frac{\text{D-ESS}^{j}(t)}{\text{D-ESS}_{\max}^{j}} \leq 1 \end{array} \right\} \quad j = 1..M$$

$$\text{D-ESS}_0 = \min(\text{D-ESS}_j(t)) \tag{28}$$

$$0 \leq \text{D-ESS}_0 \leq \text{D-ESS}_{\min}^{j} \tag{29}$$

Both EV charging and discharging services are considered in this optimization model. The purpose of this model is to determine and select the optimal solution for the EV charging or discharging request that fulfills our constraints. Eq. 27 represents the optimal solution considering both EV charging and discharging services. The defined constraints are applied to help the EV choose the optimal solution. We assume that each EV in the optimization model will interplay with all D-EVSEs for its charging or discharging service request while aiming to maximize the D-EVSEs' stability and the EVs' satisfaction level. Once the EV selects the proper D-EVSE, then the EV needs to find the best available charging or discharging spot.

We use Algorithm 1 to test our optimization model. The D-GT select Algorithm is started once the EV receives the updated information from the D-EVSEs and selects the best D-EVSE that satisfies the predefined constraints. We consider the off-grid mode if the D-ESS is not empty (eg. For a sunny day). If D-ESS is empty, we switch to the power grid to provide continuity of EV charging services.

Algorithm 1 D-GT Select Algorithm

Input EV [N_{ch}, N_{dis}, N_{ch}^{j}, N_{dis}^{j}, D-ESS$_j$(t), P_{PV}^{j}, $SoC_{\min}$, $SoC_{\max}$, $SoC_{ch}^{EV_i}$, $SoC_{dis}^{EV_h}$, SoC_{Av}^{h}, D-ESS$_j$, d_0, D-ESS$_0$].
Output D-EVSE [j].

for i = 1.. N_{ch} **do**
  if $SoC_{ch}^{EV_i} \leq SoC_{\min} + SoC_{Trip}^{i}$ **then**
    Charging services is not available
  end if
  Calculate SoC_{need}^{i} according Eq. (4)
  select " j " according Eq. (27 to 29)
  $N_{ch}^{j} = N_{ch}^{j} + 1$ **% update D-EVSE state %**
end for
for h = 1.. N_{dis} **do**
  if $SoC_{Av}^{EV_h} \leq SoC_{dis}^{EV_h} - SoC_{Trip}^{h}$ **then**
    Discharging services can not be done
  end if
  Calculate SoC_{Av}^{h} according Eq. (16)
  select " j " according Eq. (27 to 29)
  $N_{dis}^{j} = N_{dis}^{j} + 1$ **% update D-EVSE state %**
end for

IV. PERFORMANCE EVALUATION

In this section, we discuss the performance of the proposed model. Also, we consider two scenarios on our simulation discussion: Random and Realistic scenarios.

A. RANDOM SCENARIO

Table 1 shows the random simulation parameters. We suppose that all D-EVSEs are equipped by level 3 DC. We assume that there are six distributed D-EVSEs, each with a storage capacity of 30 MW. The number of EVs is 3000, 4000, 5000, and 8000. Also, we assume that each EV will make its decision using our proposed model. Moreover, the D-EVSE will send the reservation confirmation based on first come, first served as mentioned previously. Each D-EVSE will broadcast its availability schedule once every five minutes. In addition, all D-EVDEs will operate from 6 a.m. until 6 p.m.

The discussion of performance is divided into two parts. The first part discusses the average satisfaction of EVs, and the second part discusses the average of D-ESS SoC during the daytime (6 a.m. to 6 p.m.). The Monte Carlo technique is used to calculate the average values for both parts.

TABLE 1. Simulation parameters for random scenario.

Number of EVs N	3000 - 8000
$SoC_{\min}$ %	20 %
$SoC_{ch}^{EV_i}$ %	20 - 90 %
$SoC_{\max}$%	100%
$SoC_{dic}^{EV_h}$ %	20 - 90 %
D-ESS$_0$ %	20 %
D-ESS$_{\max}$ %	100 %
d_0 %	20 %
EV's Trip $Trip^i$	Random from 40 - 60 km
EVs' speed (Sp^{EV_i})	20 - 60 km/h
Number of D-EVSEs M	6
PV Power $_{everyday}$	25 MW
max D-ESS Capacity	30 MW
T	72
Duration of a time slot	10 min
R_{ch}	60 kW DC [35]
R_{dis}	60 kW DC [35]
b_{Max}^{EV}	24 kW
D_{rate}	1%/km(0.187 kWh/km) [36]
$Trip(i, j)$	Random from 10 - 20 km

Figure. 6 shows the results of using the proposed model with different numbers of EVs. We can see that the average EV satisfaction is usually higher than 78% when the number of EVs is 3000 or 4000. However, when the number of EVs is 8000, the average EV satisfaction decreases after four hours due to the massive number of EVs and their power demand. According to Table 2, we can see that the EV satisfaction level at the beginning and the end of operation is not the same as the EV satisfaction level during the day due to the renewable energy production.

Figure. 7 shows the average of D-ESS SoC during the operation time (6 a.m. to 6 p.m.) between the proposed model based on D-GT and the EV charging and discharging

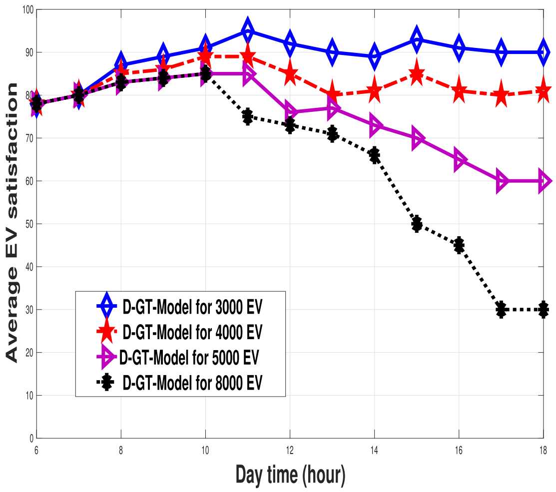

FIGURE 6. Average EV satisfaction level during the operation time for Random Scenario.

TABLE 2. Average EV satisfaction for random scenario.

Number of EVs	6 a.m.-10 a.m.	10 a.m.-2 p.m.	2 p.m.-6 p.m.
3000	85%	90.5%	89.5%
4000	83.5%	85%	81%
5000	81%	78.5%	66.5%
8000	80.5%	76%	51.5%

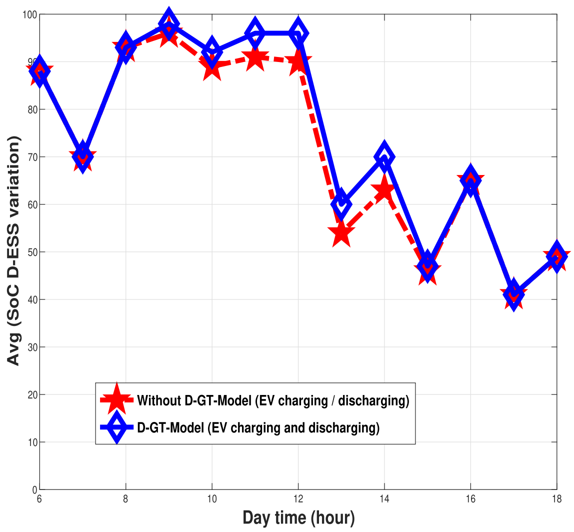

FIGURE 7. Average of the D-ESSs' SoC level during the operation time for Random Scenario.

without using D-GT model. We can observe that the proposed model shows better performance than the other model during the operation time, more specifically from 8 a.m. to 3 p.m. Table 3 presents a clear comparison of the savings rate between both models. As we can see, the savings rate for the proposed model is good from 6 a.m. to 10 a.m.; however, between 10 a.m. to 2 p.m. there is a significant savings rate of almost 26.6%.

As demonstrated in both figures and tables, the D-GT model in the random scenario can manage the interplay between EVs and D-EVS effectively while taking into account the defined constraints.

TABLE 3. D-ESSs' Soc average level for random scenario.

Number of EVs	6 a.m.-10 a.m.	10 a.m.-2 p.m.	2 p.m.-6 p.m.
D-GT model	88.8%	83%	54.2%
Regular model (without D-GT)	87%	77.4%	52%
Saving rate	13.85%	26.6%	4.6%

TABLE 4. Simulation parameters for the realistic scenario.

EV's Trip $Trip^i$	Random from 50 - 70 km
EVs' speed (Sp^{EV_i}) on highway	60 - 120 km/h
Number of D-EVSEs M	6 (see Figure. 2)
Ottawa's PV Power (Jul 2019) each D-ESS	40 [37]
$Trip(i, j)$	Random from 10 - 30 km
EV's battery size (b^{EV}_{Max})	$\sim$ 60 kW (Nissan Leaf) $\sim$ 60 kW (Chevrolet Bolt)
D_{rate}	1%/km (0.499 kWh/km) Nissan Leaf [38] 1%/km(0.45 kWh/km) Chevrolet Bolt [38]

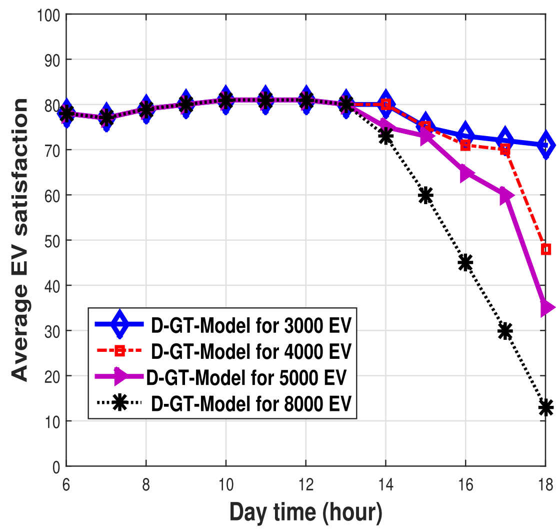

FIGURE 8. Average EV satisfaction level during the operation time for realistic scenario.

B. REALISTIC SCENARIO

Table 4 shows our realistic scenario simulation parameters. We suppose that all D-EVSEs are equipped by level 3 DC. We assume that there are six distributed D-EVSEs, each with a storage capacity of 40 MW based on real PV date [37]. The number of EVs is 3000, 4000, 5000, and 8000 same as the random scenario. Also, we assume that each EV will make its decision using our proposed model.

In the realistic scenario, the average EV satisfaction level during the operation time (6 a.m. to 6 p.m.) is shown in Figure. 8. As seen from this figure, the average EV satisfaction level for all cases (3000 to 8000) EVs starting from (6 a.m. to 10 a.m.) are similarly the same with

TABLE 5. Average EV satisfaction for random scenario.

Number of EVs	6 a.m.-10 a.m.	10 a.m.-2 p.m.	2 p.m.-6 p.m.
3000	79.4%	80.6%	74.2%
4000	79.4%	80.4%	68.6%
5000	79.4%	79.4%	61.8%
8000	79.4%	78.8%	43.4%

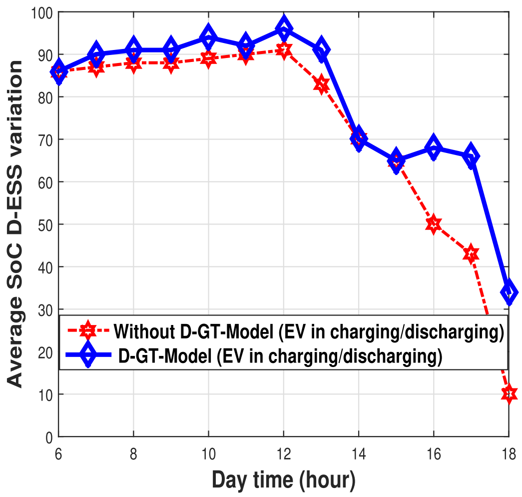

FIGURE 9. Average of the D-ESSs' SoC level during the operation time for realistic scenario.

TABLE 6. D-ESSs' SoC average level for realistic scenario.

Number of EVs	6 a.m.-10 a.m.	10 a.m.-2 p.m.	2 p.m.-6 p.m.
D-GT model	90.8%	89.2 %	60.4%
Regular model (without D-GT)	87. %	84.4 %	47.4%
Saving rate	3.75%	5.4%	21.53 %

small differences. However, the huge differences in the average EV satisfaction level between (3000, 4000, and 5000) EVs and 8000 EVs is growing after 1 p.m. duo to the rush hour in high ways. Table 5 illustrates the average EV satisfaction level for the random scenario for all cases which divided into three zones. The D-GT model for 3000 EVs is the most effective result for the whole entire operation time. Also, the average EV satisfaction level is kept more than 74%.

The average of the D-ESSs' SoC level during the operation time for realistic scenario comparison between the D-GT and the regular model is depicted in Figure. 9 and Table 6. The ability of the D-GT optimization model can be seen by looking to the average saving rate from 6 p.m. to 2 p.m. which is 4.6%. Furthermore, the saving rate is much better from 2 p.m. to 6 p.m., which is more than 20%, as shown in figure and table.

From the previous two figures and tables, it is clear that the performance of the proposed optimization model based on D-GT has proven its robustness of this optimization in terms of managing the interactions among the EVs and D-EVSEs while taking into account our defined constraints.

V. CONCLUSION

In this paper, we discussed a decentralized EVSE in terms of power generation and management model based on a GT for EVs interacting with D-EVSEs. Renewable energy production (Photovoltaic) is chosen to be the main power source for our D-EVSE and we considered the connection to the grid when the solar renewable energy system is failing to respond to the demand. We proposed a D-GT scheme for the optimization of the EVs' interaction with D-EVSE. Our optimization model considered both EV's satisfaction as well as D-EVSEs' stability. The optimal available solution for EV charging or discharging that satisfied the EV's driver and maintained the D-EVSE stability is achieved by using the D-GT algorithm. A realistic scenario in the city of Ottawa is considered as a testbed for our D-GT optimization model. Simulation results showed that the proposed model can manage and control the interactions between EVs and D-EVSEs efficiently.

Two case studies were presented for our D-GT optimization model in terms of managing and facilitating the interaction between D-EVSEs and EVs. Besides, the proposed model is based on decentralized power generation and management. Furthermore, the realistic scenario's results showed that the proposed model can manage EV charging and discharging services more efficiently during the operation time and more specifically after 2 p.m. to 6 p.m.

As future work, we will conduct additional investigations of our D-GT model such as a priority level for EV charging or discharging demand.

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