Intelligent route guidance for Electric Vehicles in the Smart Grid

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Abstract—
In recent years, the number of electric vehicles (EVs) on the road has been steadily increasing. At the same time, availability of the charging infrastructure on the road is still limited. In this paper, we propose a new scheme to guide EVs toward charging stations so as to minimize their waiting time and power energy consumption to get a charging service. The scheme uses wireless communication between EVs and the smart aggregator. It takes into account the state-of-charge (SoC) of EVs, their position, and available charging stations on the road. It also considers traffic, and occupancy of charging stations. Simulations were performed to assess the performance of our proposed scheme. Results show that the scheme effectively minimizes energy consumption and waiting times for EVs.

Keywords— EV, energy consumption, waiting time, charging station.

I. INTRODUCTION

Electric vehicles (EVs) development has progressed tremendously during the last few years. Incentives to buyers, lower energy consumption and lower environmental costs compared to their fossil fuel-dependent counterparts, led to a steady increase in EVs adoption by the public. Today, there are over 500 000 registered EVs around the world, and in the next year, 2.7 million more EVs are expected to join the road [1]. However, the increase in the numbers of EVs brings about new challenges. Indeed, the limited number of charging stations, together with the lengthy process of charging, can make for very long waiting times in public charging stations if vehicles randomly target stations for charging. The so called range-anxiety of drivers, who fear that EV battery will run out of power before the destination or a suitable charging point is reached, is also common [2].

In this paper, we propose an architecture where EVs wirelessly exchange information with the smart aggregator (SA), in order to guide them to suitable charging stations (CS). To this end, a guidance scheme is proposed, so as to allow EVs to reach a charging station while minimizing their waiting time and energy consumption. The optimal stations and corresponding routes are computed by the SA based on the state of occupancy of CSs, the traffic state, and also based on information collected from EVs such as their current SoC and position. The scheme also takes into account the waiting times of CS on the road, road speeds and traffic density.

Our contributions in this paper are summarized as follows: 1) we propose an architecture where SA is responsible for managing and planning EVs guidance to public stations for charging. The SA uses wireless communications to exchange information with EVs on the road; 2) we propose an optimization scheme which takes into account constraints related to the capacity of CSs and their state of occupancy, constraints related to road layout, speed limits, and traffic, and also constraints regarding the position and SoC of vehicles, in order to optimally plan their charging process at CS. The main goal of the optimization scheme is to reduce the waiting time and energy consumption for EVs to attain a CS.

The remainder of this paper is organized as follows: Section II presents related works. Section III presents the system architecture and the optimization scheme. Section IV evaluates the proposed scheme through simulations. Finally, Section V concludes the paper.

II. RELATED WORK

In the last few years, several approaches have been proposed to address the problem of charging of EVs in public CSs. For example, an optimization of the charging process by minimizing the waiting time of the EVs in charging stations was proposed using queuing theory [3]. Another work presented a scheme for finding a suitable charging station by selecting the CS that has the minimum distance and occupancy time [4]. However, in these works, issues of the traffic density or speed limits along the road were not considered. In [5] and [6], the authors proposed two approaches for EVs eco-routing (i.e. selecting suitable routes in terms of energy-savings) by considering traffic conditions. However, the SoC of EVs was not taken into account. In [7], a communication protocol to support the booking process between EVs and EVSEs was presented. The work also aims to minimize the latency time of EVs in CSs. However, selecting suitable CSs based on energy-savings was not considered. In [8], the shortest-path problem was addressed using a mathematical optimization model which assumes a battery exchange at public stations as an alternative to EV charging. The authors did not consider in their mathematical model the time needed to exchange the battery nor any waiting time at charging stations. In [9], an architecture for EVs itinerary planning was proposed which computes the shortest

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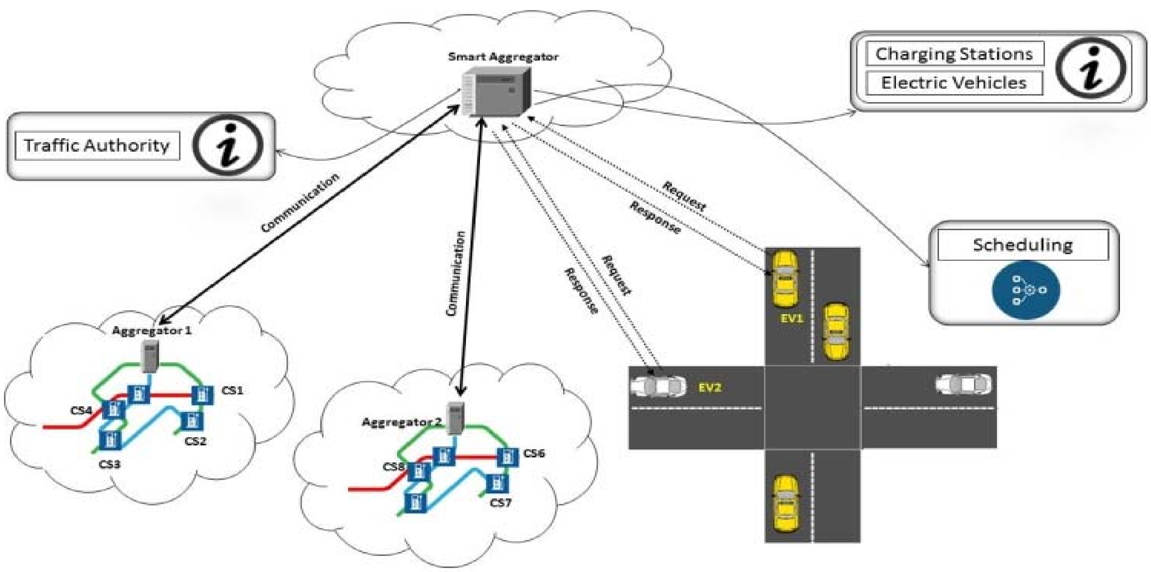

Fig.1. Proposed architecture

economic path in terms of energy-savings, based on some information (e.g., Status of CSs, EVs position, SoC, traffic conditions etc.). However, the work does not consider the waiting time in charging stations.

In this work, we propose a new approach for the EVs itinerary planning towards CSs, which minimizes EVs energy consumption and waiting times to reach a charging station. The approach takes into account the occupancy of CSs, the SoC of EVs and their positions, road traffic and speed limits in the road.

III. INTELLIGENT ROUTE GUIDANCE

A. System Description

In the proposed architecture, EVs can communicate their profile to the SA using wireless communications technology (e.g. WiFi, DSRC, LTE, etc.). This profile comprises an identification (ID), SoC and current position. We assume that EVs are always within the communication range of SA either directly or through some intermediary equipment (e.g. road-side-unit). We also consider that SA can exchange information with different aggregators (Ag) which are, each, connected directly to several CSs in their area through wireless (mesh networks, LTE, etc.) or wired network technologies. The Ag have a global view on the status of occupancy of CS in their area. We suppose that a Traffic Authority can provide information about traffic to the SA when needed. The SA uses the information collected from EVs, Ag, and the Traffic Authority to computes the best CS, and best routes for EVs in terms of minimizing their waiting time for charging and their total energy consumption. Subsequently, the SA notifies EVs about the CS where they need to stop for charging.

Fig.2 explains the sequence of exchanges between EVs, SA and Ags. The sequence diagram also shows the data exchanged. In the figure, we consider a geographical area having a number n of EVs which communicate with SA. The SA can communicate with a number m of Ag that have a

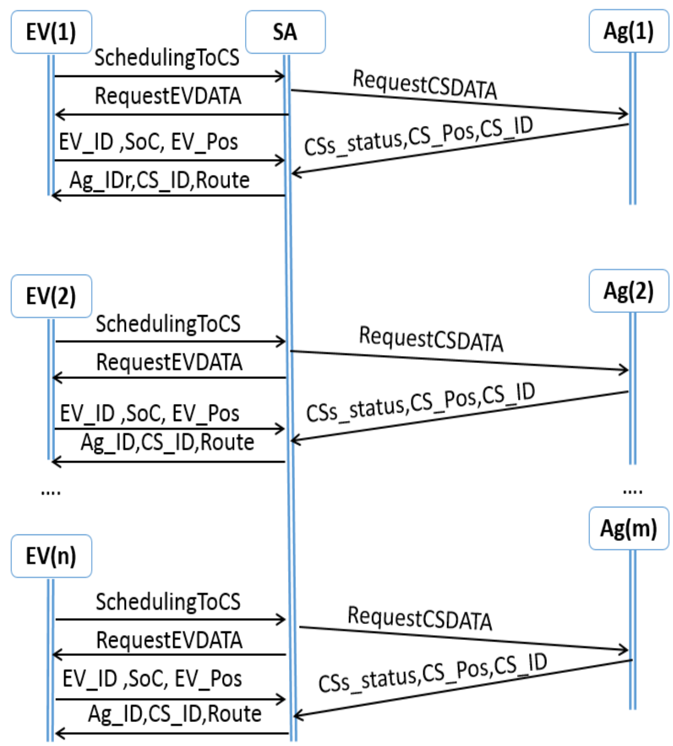

Fig.2. Sequence diagram

global view over the status of occupancy of CSs in their area. EV sends a request (SchedulingToCS) to SA. The latter responds by asking the EV (RequestEVProfile) about its profile. This profile comprises EV information such as ID, SoC and EV position. Once the EV replies, SA send a request (RequestCSProfiles) to Ag in order to get some information of CSs such as IDs, occupancy statuses and positions. These data is used to determine the best suitable CSs for the EV. Subsequently, SA responds to EV by delivering (Ag_ID, CS_ID, Route).

B. Waiting time

We study the waiting time at each station. The queuing model at each CS is illustrated in Fig. 3. In order to calculate the waiting time at a charging station, we assume that a set of EVs can be assigned to the same charging station, with each EV having a different charging target value in eq. (3).
To calculate the probability variation, we use a method which is similar to the one proposed in [4]. Random EV arrivals can be modeled by a poison distribution. The probability that a certain number of EVs are assigned to the same charging station can be computed as:

$$P_n = \frac{1}{N_{CS}} p(x < n) \quad (1)$$

$$P_n = \frac{1}{N_{CS}} \left[\sum_{k=1}^{n} \frac{\lambda^k}{k!} e^{-\lambda} \right] \quad (2)$$

Where: n is number of EVs, which are assigned to the same, CS N_{CS} is number of CS x is random variable. k is number of arrivals of EVs, and λ is average arrival rate of EVs.

We can calculate the waiting time of each station as in eq. (3).

$$W_{EV_n}^{CS} = \sum_{i=1}^{n-1} [EV^{target}(i) - EV^{current}(i)] \frac{1}{R_{charging}.N_{EVSE}} \quad (3)$$

Where $EV^{target}(i)$ State of charge after charging, $EV^{current}(i)$ is State of charge before charging, $R_{charging}$ Charging power at CS and N_{EVSE} is number of charging points at CS.

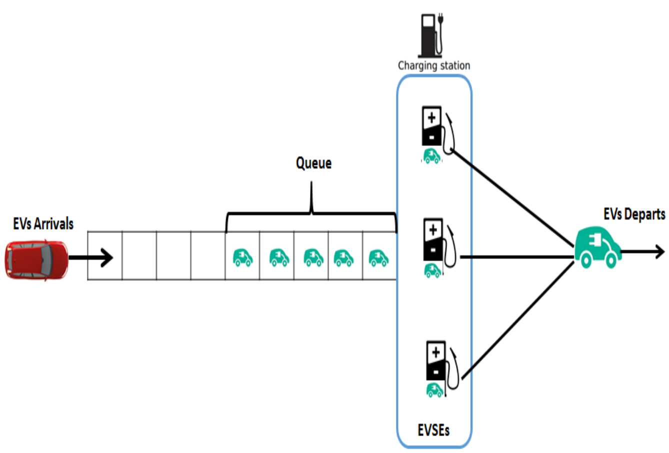

Fig.3. Schematic view of CS model

C. Energy Consumption

We now will consider the principals of vehicles dynamics to calculate the required power of EVs to reach a suitable charging station in terms of energy consumption. First, we calculate the traction force needed by the electric vehicle to move at a given speed. We use graph theory for modeling EV charging process.

$$Ft = \sum F = F_{roll} + F_{grade} + F_{air} + F_{acc} \quad (4)$$

Where,

F_{roll} : is the rolling resistance force between pneumatic tires and the road F_{roll} can be calculated by the following equation.

$$F_{roll} = K_{roll}.M.g.cos(\alpha) \quad (5)$$

Where α is the road grade.

F_{grade} : represents the force of gravity and can be calculated by the flowing equation

$$F_{grade} = M.g.\sin(\alpha) \quad (6)$$

F_{air} : is the aerodynamics force of the EV against the air. It depends on the speed of the EV.
Table I summarizes the symbols used.
We consider that we do not have a constant speed along an edge which is made up of some successive sub-edges, each sub-edge have a different speed limit. For the sake of computing the energy consumption of EV, we use the speed limit in each sub-edge, which is determined by the Traffic Authority. However, each edge will be made up of some successive sub-edges. We consider that each sub-edge is represented by $[des_{ij}, V_{ij}]$ where des_{ij} is the distance and V_{ij} is the speed limit of the sub-edge, and i and j are the points of the road defining the sub-edge. Then the aerodynamics force is given by:

$$F_{air_{ij}} = \frac{1}{2}.\rho_a.C_D.A_C.V_{ij}^{\ 2} \quad (7)$$

$F_{acc_{ij}}$: The inertia of the vehicle is given by:

$$F_{acc_{ij}} = M.a_{ij} \quad (8)$$

From eq. 4, the power needed to move EV at the speed limit through the traffic can be calculated by the following equation:

$$P_{ij} = v_{ij}.Ft_{ij} \quad (9)$$

v_{ij} : The velocity through the traffic can be calculated by the following equation:

$$v_{ij} = V_{ij}\,(1 - Tr_{ij}) \quad (10)$$

Let consider that the traffic density factor of each sub-edge is denoted by Tr_{ij} using eq 3.11 which is varied from 0 (no traffic) to 1 (blocking of the sub-edge), however we can deduce that the speed of the sub-edge trip is effected by Tr_{ij}.

$$Tr_{ij} = \frac{K_{ij}{}^{d}}{k_{ij}^{jam}} \quad (11)$$

Where $K_{ij}{}^{d}$ represent the EV density which is expressed by EVs/km on the sub-edge.
k_{ij}^{jam}: Traffic density on the road.
Let consider η_x be the efficiency of the electric engine motor. Then the energy consumption:

$$Cons_{ij} = des_{ij}.Ft_{ij}.\eta_x \quad (12)$$

Where $Cons_{ij}$ represent the energy consumption of the sub-edge. We use $Cons_{ij}$ for calculating the edge consumption by gathering the energy consumptions over all the sub-edge as shown in eq.13.

$$Cons_e = \sum_{i,j} Cons_{ij} \tag{13}$$

The successive sub-edges of edge E_e are defined by the pints j and I. The energy consumption between EV Current position and CS is given by:

$$Cons_{EVtoCS} = \sum_e Cons_e \tag{14}$$

TABLE I
SYMBOLS

Symbol	Definition
A_C	Vehicle front area
C_D	Aerodynamic drag coefficient
ρ_a	Air density
M	Vehicle mass
g	Gravity acceleration
a	Acceleration
V	limit Velocity
K_{roll}	Rolling coefficient
W_t	Waiting time
NEVSE	Number of charging point
Cons	Energy consumption
K	Parameter chosen by EV
η_x	efficiency of the electric motor
$R_{Charging}$	Charging power at charging station
EV^{target}	SoC target: after charging
$EV^{current}$	State of charge before charging

D. Optimization Scheme

In order to calculate the optimal station for charging, the SA proceeds in two stages. First the EVReachability(ER) algorithm is run. EVReachability(ER) algorithm aims to verify the reachability of CSs by an EV based on its own SoC. Second, the SmartRouteGuidance algorithm is used to calculate the best route to a next charging station in order to minimize the waiting time and energy power consumption.

We consider that An EV profile includes information about the ID of EV, SoC and current location. The EV profile is represented as follows:

$$EV_{profile}[EV_{ID}, SoC, EV_{position}]$$

The CS profile is represented as follows:

$$CS_{profile}[CS_{ID}, Number_{EVSE}, CS_{position}]$$

We assume that all aggregators can have a global view of the CSs in their area in real time including the waiting time of each charging station.

Algorithm1 EVReachability(ER) which aims at finding the range of each EV based on its own SoC is presented hereafter. This algorithm takes the EVs profile and CSs profile as input parameters. The algorithm calculates the energy consumption between each EV and all charging CSs in the area. Once the calculation is done, the algorithm verifies the reachability of EVs: Reachability =1 represents that EV can reach CS given its SoC and current road conditions, and Reachability =0 represents that EV cannot reach CS with given its SoC and current road conditions.

The SmartRouteGuidance Algorithm (SRG) is illustrated bellow. Each EV sends its profile to the SA. EVs information is taken into account based on a first-come-first-serve (FCFS) policy. The assignment of EVs to charging stations is executed according to the factor K, the K-shortest [10] energy consumption, and the minimum waiting time. The algorithm calculates the waiting time at each CS, which is reachable from an EV. Then, the assignment and updating CS takes place. For each EV. The SA selects the best CS which is suitable to EV.

Algorithm 1:EVReachability(ER)

Input: EVs_Profile, CSs_Profile.
Output : ReachabilityMatrixEV_CS

```
For(each EV ) do
  For(each CS in area) do
    Compute energy Consumption between EVs&CSs:
    Add to the Cons matrix all Consumption 'EV&CS'
  Endfor
Endfor
For(each EV) do
  If(SoC<= Cons ) then
    Add to the ReachabilityMatrixEV_CS all CSs
  Endif
Endfor
Update ReachabilityMatrixEV_CS.
```

Algorithm 2:SmartRouteGuidance(SRG)

Input : EVs_Profile{EV_ID, SoC_EV , Position, k},CSs_Profile{CS_ID, NEVSE , Position }, Waiting time, Algorithm.1. /*Wt=waiting time*/
Output : @ of the best CS, update waiting time /* selected charging stations*/

```
Each EV sends to SA its profile asking for charging.
EV_ priority=FIFO(EV)
For(each EV in EV_priorty) do
  Select ReachabilityMatrixEV_CS according to K for each EV
  Select CSs from ReachabilityMatrixEV_CS according to
   minimum Wt
  Assign EV to selected CS
  Send @CS to each EV
Endfor
Update CSs
```

IV. SIMULATION RESULTS

We present the simulation results of the proposed route guidance model. To simplify the simulation, we assume that the speed limit of EVs is constant at each edge. We consider a geographical area where a hundred EVs and twenty charging stations are randomly deployed. The locations of EVs are randomly chosen. The parameters of the simulation are illustrated in Table II and were taken from the EV prototypes which where build by Université de Sherbrooke on the basis of eVUE vehicles [11]. These values allow estimating the energy consumption of EVs based on Eq.14.

Some parameters values used in our simulation are produced randomly as follows:

TABLE II
VEHICLE SPECIFICATIONS USED IN THE MODEL

Symbol	Value	Unit
A_C	2.4	m^2
C_D	0.35	–
ρ_a	1.223	$kg.m$
M	1000	kg
g	9.81	m/s^2
K_{roll}	0.02	–

- The initial EV SoC is a uniform distribution between 10% and 45%.
- The EV SoC target value to complete EV trip after charging at CS is a uniform distribution between 70% and 100%.
-The distance between EVs and CSs is uniformly distributed over the area.
-The velocity between EVs and CSs is uniformly distributed over area.
-The maximum EV battery capacity equal to 7KWh.

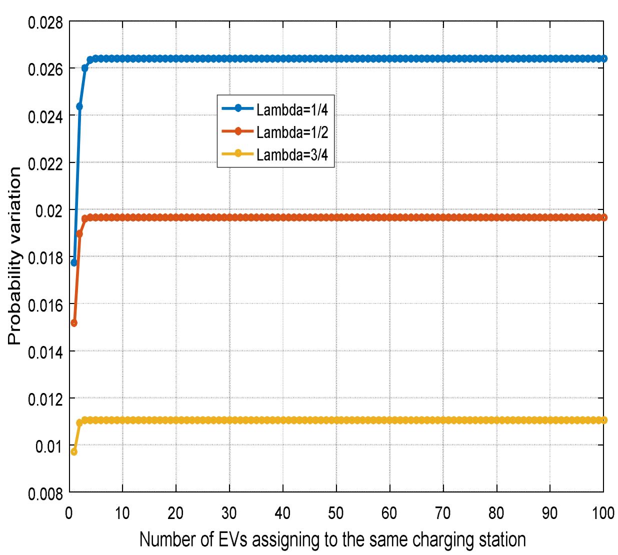

Fig.4. Lambda impact on the probability variation

Fig.4 and Fig.5 illustrate the variation of the probability of EVs assigned to the same CS according to the value of Lambda and the number of charging points EVSE, respectively. It can be deduced that the probability increases when Lambda and the number of charging points decrease. Lambda and number of charging EVSE have a huge impact on the probability variation of having EVs assigned to the same charging station.

Fig.6 represent the average waiting time of EVs allocated to the same CS according to the number of EVSEs at CS. As shown in the figure, the average waiting time is higher if the number of EVSEs is small. This means that the number of EVSEs does impact on the average waiting time.

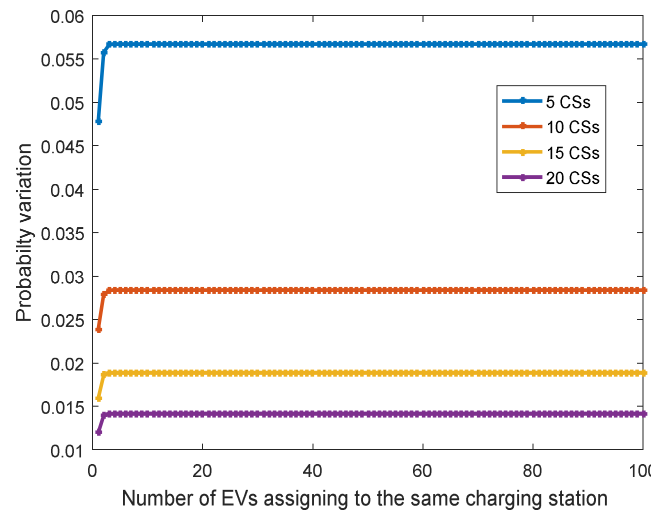

Fig.5.CSs impact on the probability variation

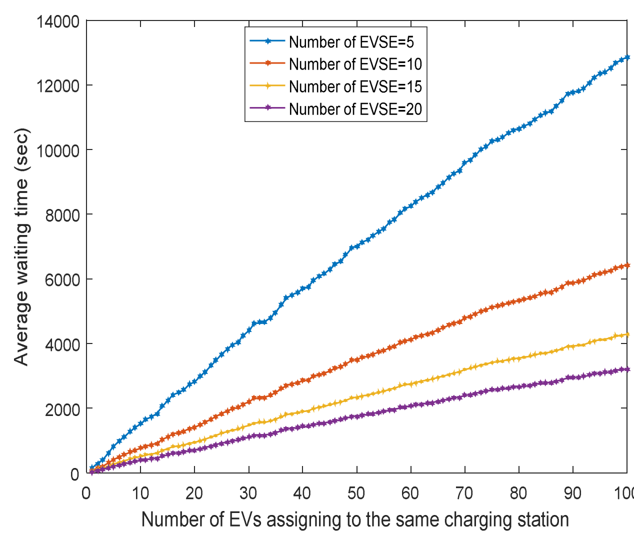

Fig.6. Impact number of EVSEs on average waiting time

Fig.7 shows the energy consumption of electric vehicles for reaching the charging stations. Using eq.4, we deduce the energy consumption of 100 electric vehicles (on the y-axis) and 20 charging stations (on the x-axis) located in a given geographical area, as well as the energy to be consumed by EVs to reach the charging station (on the z axis, represented by different colors). For example, as shown in Fig.7, the EV ID=9 to reach the CS ID=17, it consumes 2372 Wh as energy power consumption. Now we study the reachability of all EVs to reach CSs using the EVReachability algorithm. Fig.8 shows the reachability of EVs as the matrix of 100EV and 20CS ; when EV can reach the CS, the reachability is 1, else 0. For example, EV ID= 60 cannot reach the CS ID=1 because its

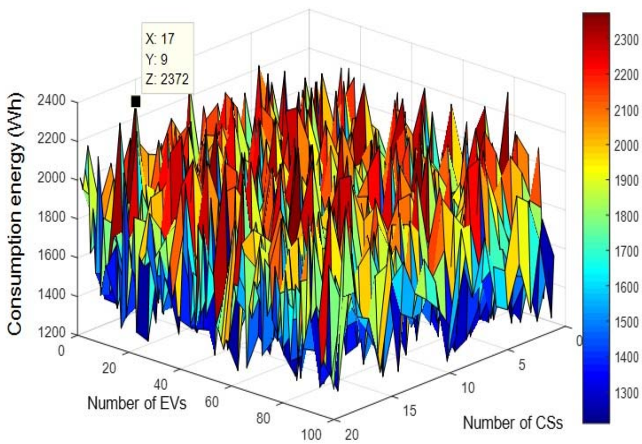

Fig.7. Energy consumption of EVs to reach CSs

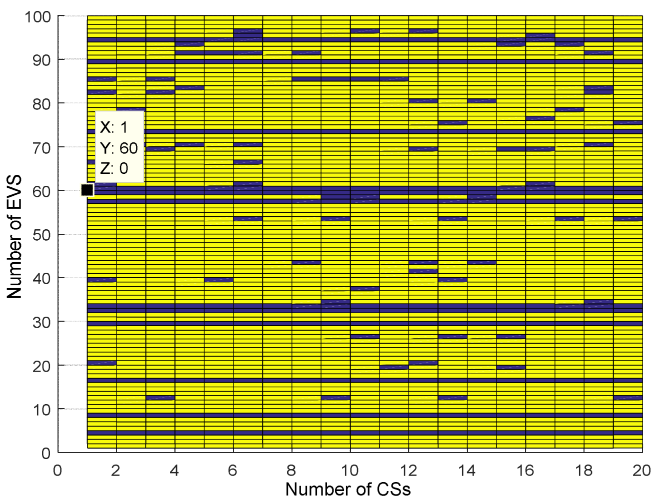

Fig.8. EVs reachability to CSs in terms of energy

state of charge is not enough. The grey color shows that the EV cannot reach the CS, while the yellow color represents the reachability of EVs to CSs. The colors represent the energy consumption; the high values are represented by the red color, while the blue color is devoted to the lowest values.

Finally, we study the best assignment of EVs to charging stations using the algorithm SmartRouteGuidance (SRG). The algorithm aims to assign EVs to CSs by minimizing their waiting time and energy power consumption. We compute the K-shortest energy power consumption based on [10]. For the sake of simplicity, we assume that K =2 in our implementation. This gives the two best paths of EVs from their current position to the charging stations in terms of energy power consumption. After we choose the best paths in terms of waiting time which is updated at each iteration of assignment, the SA can advertise this service to the EVs. We consider that the initial waiting time at CSs is uniformly distributed between 5 minutes and 60 minutes. Fig.9 presents the energy power consumption of EVs for random choice over an economic range compared to our SmartRouteGuidence algorithm. From this figure, it can be deduced that our

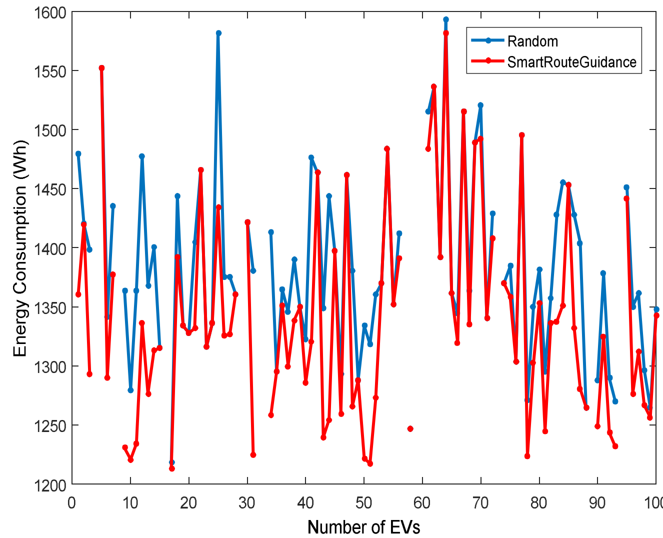

Fig.9. Energy power consumption of EVs

algorithm gives more energy-efficient results in terms of energy consumption.

We observe that there are few discontinuities in the curves due to the insufficient EVs SoC to reach the charging stations.

Fig.10 illustrates the waiting time of EVs in the CSs associated with the energy consumption in Fig. 9. The results show that the waiting time is lower for the proposed SmartRouteGuidence algorithm compared to the random algorithm.

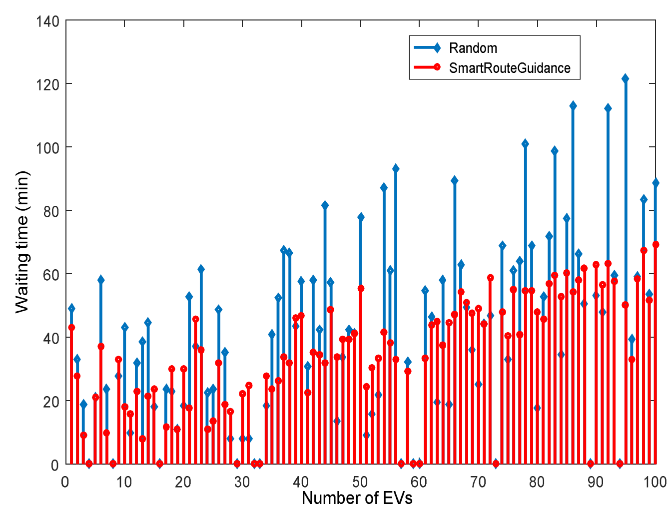

Fig.10. Waiting time of EVs

V. CONCLUSION AND FUTURE WORK

In this paper, we presented an intelligent route guidance for EV in smart grid for facilitating the charging service, by minimizing the waiting time of charging and energy consumption of EVs. We studied the impact of EV SoC target on the waiting time of EVs at charging stations. We used a reachability algorithm to manage the charging stations assignment process. The simulation results show that the proposed SmartRouteGuidance algorithm can effectively determine the best route in terms of energy consumption and waiting time. In our future work, we will take into account pricing constraints in the assignment process for charging stations.

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