Queuing Model for EVs Charging at Public Supply Stations

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Abstract— **As electric vehicles become more popular, public charging stations for such vehicles will become common. Since the load introduced by such stations on the grid is high, the smart grid will need to balance the load among charging stations in an area while minimizing the waiting time for users to have their vehicles charged. In this paper, we present an approach for balancing the load among charging stations in an area while minimizing the charging time of electric vehicles. We propose a model where vehicles communicate beforehand with the grid to convey information about their charging status, and develop a mathematical model of handling requests for charging vehicles at public charging station based on queuing theory. Finally, we propose an algorithm for directing vehicles to charging stations in a way to minimize their waiting time to charge completion. The simulation results show the effectiveness of the proposed approach when considering both real electric vehicle and charging station characteristics and constraints.**

Keywords- V2G, EV, charging time, waiting time, smart grid.

I. INTRODUCTION

Electric Vehicles (EVs) are increasingly becoming popular as a result of many factors among which the concern of many road users with greenhouse emissions, and the recent advances in EVs engineering that made them more performing. The popularity of EVs is expected to grow even more in the next years as we see municipalities adopting the technology for their public transportation fleets and with charging stations made available at many public parking areas. A large adoption of EVSs poses, however, many challenges from the point of view of electricity demand management. In fact, EVs charging operations will be one of the most challenging issues for demand response systems in the smart grid [1]. This is because the load introduced by the charging of one vehicle in a neighbourhood may be equivalent to the one of an entire new household in the area [2].

The vehicle-to-grid (V2G) interface within the smart grid has to offer the capability to manage the charging load of EVs wisely both according to demand and to provide smart functionalities to improve the EV charging process experience for users [3,4]. One of the most challenging issues in the EVs charging management is how to satisfy EVs demand adequately, to meet users expectations, in all grid situations while ensuring grid stability. The EV charging process has to be managed in a way to ensure grid operation efficiency, especially at peak load times, while lowering charging times for EVs to maintain users' satisfaction.

Charging time is an important factor to consider from the users' point of view, because charging an EV takes considerably longer than a regular vehicle, i.e. tens of minutes at least [1]. The charging time is composed of two parameters: the waiting time and the service time, which in turn depends on the EV state of charge (SoC) needed. Given a SoC, the service time will only depend on the type of electric vehicle supply equipment (EVSE) (charging stations) used. The waiting time is thus a factor that has to be reduced in each EV public supply station (EVPSS), and therefore, scheduling the charging of EVs at available stations in a way to minimize their waiting time is a key to achieve users' satisfaction.

In this work, we consider the problem of EVs charging time optimization in EVPSS using queuing model techniques. In particular, we propose an optimal charging process for electrical vehicles at EVPSS when the load demand is expected to be high. For this, we consider a model where EVs communicate to the smart grid their individual EV charging demand information before the plug-in phase, i.e. while the EVs are on the road side, to allow the grid to manage adequately their charging process.

Our contributions in this paper are**:** 1) we present an analytical formulation of the EV charging problem based on a multiservice queuing model. This model takes into account a number of constraints including the number of EVPSS with their charging capacity, the arrival process of vehicles with their initial EVs SoC, and the vehicles required maximum loading level at the end of the process; 2) we propose an algorithm called Best Available EVPSS (BA-EVPSS) for assigning vehicles to EVPSS based on the defined constraints which supposes prior EV/smart grid communication when EVs are on road side; 3) we demonstrate that this algorithm can effectively satisfy EVs charging demand within the defined constraints while considering realistic EV charging characteristics.

The remainder of the paper is organized as follows. In Section 2, we present the related work. We formulate EV charging process with multi-servers queuing model in Section3. The EV charging time and EV waiting time are

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analysed in Sections 4 considering a queuing network model for multi-EVPSS. The performance evaluation of our EV charging at EVPSS in terms of EV charging time optimization are presented in Section 5. Finally, Section 6 concludes the paper.

II. RELATED WORK

Existing related work can be classified into two classes: 1) Stochastic modeling for EV charging processes, and 2) V2G on-wire protocols and standardization for EV and electric vehicle supply equipment (EVSE) (charging stations) communication.

In the first class, paper [5] describes a tool based on a stochastic model for distribution grid planning, providing a characterization of possible grid operation conditions, regarding voltage profiles, branch loading, grid peak power and energy losses. In [6], the authors present a Monte Carlo simulation approach for the derivation of the system load due to EVs based on a model representing real commuting patterns. In these two works, the EVs charging time optimization problem according to the specific constraints associated with such EV, is not evocated. In [7], an electric car charging station is modeled using mathematical models to have an idea about the parameters needed for charging stations planning. However, the EV charging process managed by the smart grid and EV users' satisfaction such as the charging time and priority is not taken into account in the scheduling process.

For the second class, the works [8] and [2] have made a good summary of current standard protocols and related architectures for EV and grid interaction. In [9], the basic principles of standard V2G communication interfaces currently under specification in the ISO/IEC are presented, with a focus on control communication but without a regard to administrative data, especially for V2G integration when EVs are on road side. In [10], the authors present a generic V2G information model allowing mutual charge scheduling negotiations between EVs and grid operators. The work discusses a system model with theoretical considerations without treating a specific existing charging mode (slow, rapid or fast) as in realistic situations. Moreover, it does not study the case where an EV needs to communicate with the grid to know the best EVPSS in terms of waiting time and cost.

In our proposal, we present an optimization of EVs charging process in terms of charging time minimisation while taking into account constraints including a random arrival and position of vehicles with a random initial value of EVs SoC and each one requiring a maximum threshold for charging. Furthermore, realistic EV supply equipment characteristics were used.

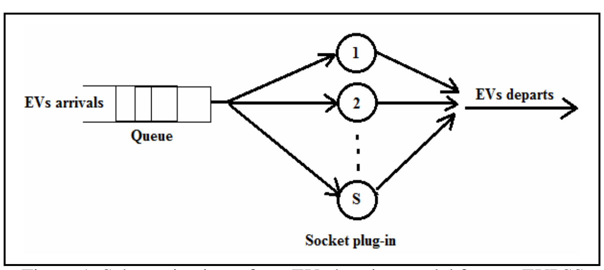

Figure 1: Schematic view of our EV charging model for one EVPSS.

III. M/M/S MODEL OF ONE EV PUBLIC SUPPLY STATION

In this section, we present a basic queuing theory which will be used to illustrate our EV charging model with some defined constraints related to a realistic EV charging situation.

Let us first state the assumptions made;

- All EVPSS have plug-in sockets with identical chracteristics. In current available EVPSS, for example, plug-in sockets are level 3 type [1].
- We consider fairness for EV charging to be based on a first-come-first-serve (FCFS) policy.
- The time EVs need to physically travel to an assigned EVPSS is out of the scope if this work. Therefore we consider the charging time to be solelly composed of the waiting time and the service time.

Figure1 shows the system considered in this paper which is the EV charging process in an EVPSS.

The input data are the EVs needing electrical power loading and the output data are the EVs with full charge. We consider a multi-server queue with *s* identical servers, each operating with an exponential service rate μ . In our case, a server *s* is a charging socket at the EVPSS.

The EV arrival process is assumed to be Poisson with an arrival rate λ.

In general, every EV that arrives can immediately enter service if there is an available plug-in socket in the EVPSS; if all servers are occupied, then the EV has to wait. The scheduling FCFS until a plug-in socket becomes available.

In principle, any practical queuing process tends to derive its major results with Markov chains [11, 12, 13, 16] by incorporating information in the state description. In this work, each state of the chain corresponds to the number of EVs in the queue, and state transitions occur when a new EV arrives or an EV reaches its full charge and depart.

We use the birth-death process as a stochastic model to describe the evolution of our system. The state transition diagram is presented in figure 2. The model has two cases. The first one is where the number of EVs plug-in $k \leq s$, the overall completion rate is $k\mu$. The second is where the number of EVs plug-in $k \geq s$ and the entire plug-in sockets are occupied and the completion rate is $s\mu$.

Definition: a stochastic process with state space $\xi = \{1, 2, 3, ...\}$ is said to be a Markov chain [12,14,15] if

$$P(X_{n+1} = j | X_n = i, X_{n-1} = x_{n-1}, ..., X_0 = x_0) = P(X_{n+1} = j | X_n = i) \quad (1)$$

Where, X_n is a random variable that represents the value of the chain at step *n*.

The transition probabilities function with homogenous time is defined as:

$$p(m, m+n) = p_{ij}(0, n) \equiv p_{ij}^{(n)}, \quad \forall \; m \tag{2}$$

and the transition matrix is defined as:

$$P = \lfloor p_{ij} \rfloor \tag{3}$$

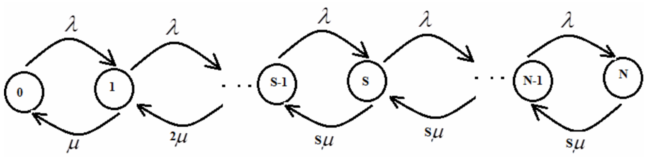

Figure 2: The state transition diagram.

Considering the equations and the state transition diagram given above, the correspondent transition matrix is

$$P = \begin{bmatrix} -\lambda & \lambda & 0 & 0 & & & & & \\ \mu & -(\lambda+\mu) & \lambda & 0 & 0 & & & & \\ 0 & 2\mu & -(\lambda+2\mu) & \lambda & 0 & 0 & & & \\ 0 & 0 & 3\mu & -(\lambda+3\mu) & \lambda & 0 & 0 & & \\ . & & & & & & & & \\ . & . & . & . & . & .... & . & .... & . \\ . & & & & & & & & \\ . & . & . & . & s\mu & -(\lambda+s\mu) & \lambda & & \\ . & . & . & . & . & .... & . & .... & . \end{bmatrix} \tag{4}$$

The stationary condition related to our Markov chain model is given by:

$$\bar{\pi} * P = \bar{0} \tag{5}$$

where $\bar{\pi} = [\pi_0, \pi_1, ..., \pi_N]$ is the vector of stationary distribution. N is the state number.

To solve this Markov chain model, we have to solve balance equations in each state and we use the total probability to solve the initial condition π_0 .

Stat 0 : the leaving rate due to arrivals is $\pi_0 \lambda$. The entering rate to state 0 due to departures from state 1 is $\pi_1 \lambda$.

$$\pi_1 = \frac{\lambda}{\mu} \pi_0 \tag{6}$$

Stat 1 : the leaving rate of state 1 is $(\lambda + \mu)\pi_1$. The entering rate to state 1 due to arrivals from state 0 is $\pi_0 \lambda$ and the entering rate due to departures from state 2 is $2\mu\pi_2$ where the number two (2) is the result of having two EVs in EVPSS simultaneously.

$$(\lambda + \mu)\pi_1 = \lambda\pi_0 + 2\mu\pi_2 \tag{7}$$

With Eq. (6) and (7), we obtain;

$$\pi_2 = \frac{1}{2}\left(\frac{\lambda}{\mu}\right)^2 \pi_0 \tag{8}$$

The balance equation for state 2 is:

$$(\lambda + 2\mu)\pi_2 = \lambda\pi_1 + 3\mu\pi_3 \tag{9}$$

With Eq. (5) and (6), we have

$$\pi_3 = \frac{1}{3*2}\left(\frac{\lambda}{\mu}\right)^3 \pi_0 \tag{10}$$

The general recursive form of the stationary distribution (state *k*) is:

$$\pi_k = \begin{cases} \frac{1}{k!}\left(\frac{\lambda}{\mu}\right)^k \pi_0 \;,\; if \;\; k \le s \\ \left(\frac{1}{s}\right)^{k-s} \frac{1}{s!}\left(\frac{\lambda}{\mu}\right)^k \pi_0 \;,\; if \;\; k \ge s \end{cases} \tag{11}$$

The total probability condition is

$$\sum_{k=0}^{s-1} \frac{1}{k!}\left(\frac{\lambda}{\mu}\right)^k \pi_0 + \sum_{k=s}^{N} \left(\frac{1}{s!}\right)^{k-s} \frac{1}{s!}\left(\frac{\lambda}{\mu}\right)^k \pi_0 = 1 \tag{12}$$

N is the number of states and S is the number of plug-in slots in EVPSS.

By simplifying this equation, the π_0 expression can be easily derived as:

$$\pi_0 = \left(\sum_{k=0}^{s-1} \frac{1}{k!}\left(\frac{\lambda}{\mu}\right)^k + \sum_{k=s}^{N} \left(\frac{1}{s!}\right)^{k-s} \frac{1}{s!}\left(\frac{\lambda}{\mu}\right)^k \right)^{-1} \tag{13}$$

Therefore, the behavior of the Markov chain is completely characterized once its transition matrix *P*, the transition diagram, and the initial condition π_0 are given.

The mean queue length is given in [12] by:

$$E(L_q) = \sum_{k=S}^{N} (k - S).\pi_k \tag{14}$$

and the mean waiting time in queue is given by [10,11] :

$$E(W_q) = \frac{E(L_k)}{\lambda(1 - \pi_N)}. \tag{15}$$

IV. QUEUING NETWORKS MODEL FOR MULTI- EVS CHARGING STATIONS

In this section, we suppose that our EV charging system is composed by a number m of EVPSS where each one is formed by a number S_i ($i = 1 ... m$) of plug-in sockets. Figure 3 illustrates our multi EVPSS model as parallel M/M/S queues. Our model is then completely characterized by giving the transition matrix. We use a form of block matrix notation to highlight the transition matrix of our multi-EVPSS model

P_{EVPSS} and to allow a good saving of computation effort. Each $P_{i=1...m}$ represents the transition matrix of M/M/S$_i$ illustrated in Figure 3.

$$P_{EVPSS} = \begin{bmatrix} P_1 & 0 & 0 & 0... \\ 0 & P_2 & 0 & 0... \\ 0 & 0 & P_3 & 0 & 0.. \\ . \\ . \\ . \\ 0 & 0 & 0 & 0 & 0.. & 0 & 0 & 0 & P_m \end{bmatrix} \quad (16)$$

Similarly to equation (5), we have:

$$\overline{\pi_{EVPSS}} * P_{EVPSS} = \bar{0}$$

where $\overline{\pi_{EVPSS}} = \left[\pi^1{}_{EVPSS}, \pi^2{}_{EVPSS}, ..., \pi^m{}_{EVPSS}\right]$ is the vector of stationary distributions of the multi-queue model, and $\pi^{k=1...m}{}_{EVPSS}$ is the single stationary distribution vector of each queue model.

In our model, we suppose that an EV which needs to charge its battery can communicates its position and current SoC to the smart grid to know the best EVPSSs to serve this EV at its area. The smart grid finds out the available EVPSSs in terms of the smallest waiting time in each EVPSS by running our proposed BEST EVPSS algorithm. This algorithm takes into account the initial SoC and the initial position of each EV and updates EVPSSs state after each EV satisfaction.

Algorithm . ***BA- EVPSS algorithm***

Input: current EV position, EV SoC, P_{EVPSS} π_0 ,

Output: @ EVPSS /*station selected */

1. EV coordinates and SoC received /* EV profile received by the smart grid */

2. Calculate for each EVPSS in area, the average queue length and the average waiting time using the matrix P_{EVPSS} and

$$E(L_q)_{k=1..m} \ , \ E(W_q)_{k=1..m}$$

3. Assign $BA - EVPSS = EVPSS\{min\{E(W_q)\}\}$

4. Send @ of EVPSS to EV

5. Update the EVPSS state./*Smart grid updates EVPSS state*/

From the description above, we can see that the complexity of the BA-EVPSS algorithm is in the order of $O(n)$.

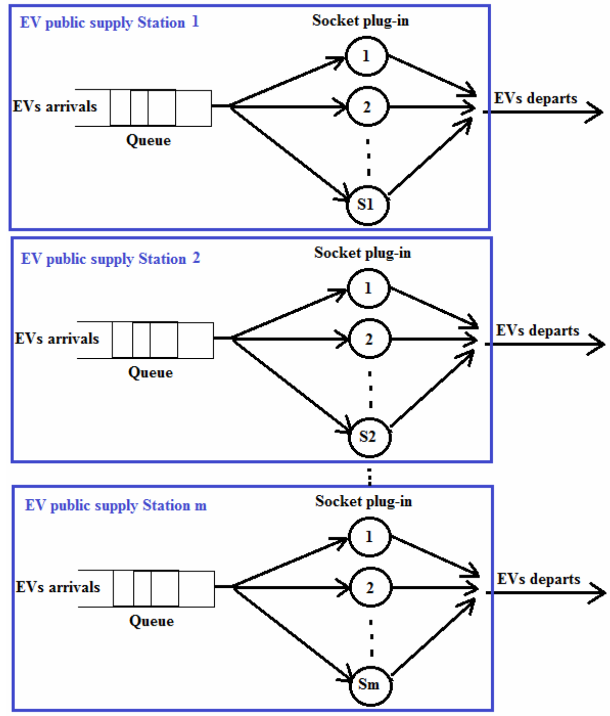

Figure 3: The multi M/M/S queue model.

Figure 4 illustrates the exchange of information between the grid and each EV. First, an EV starts by sending its position and SoC to the smart grid. The smarts grid uses the BA-EVPSS algorithm to send back to the EV, the information about the best available EVPSS.

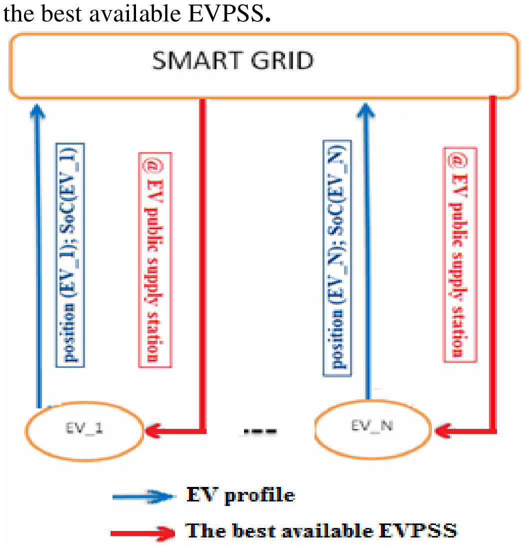

Figure 4: Schematic view of information flow between the Smart Grid and EVs by considering the BA-EVPSS algorithm.

V. Simulation Results

In this section, the simulation results and discussions about the performance of the proposed EV charging algorithm at public supply stations are presented. We present a comparative simulation performance of BA-EVPSS algorithm and an algorithm that we call R-EVPSS algorithm. In R-EVPSS, an

EVPSS is selected according only to its queue length. Therefore, with R-EVPSS, an arriving EV is directed to the EPVSS which has the smallest EV number in its queue without taking into account the cumulative EV charging time needed by all EVs in each queue.

We used MATLAB to perform the simulations. The EVs arrival flow variation is modeled by Poisson distribution in all our study. We assume that all EVPSS are equipped with a level 3 plug-in [2,3] which is the most rapid kind of EV charger. This kind of charger is the one expected to be available in most EVPSSs. The time spent by smart grid to respond for each EV is neglected. After the end of the overall charging time duration, all vehicles need to be satisfied. The parameters for our EV charging process study are generated as follows:

- The total EV number is 1000;
- EVs communicates with smart grid when they are on road side prior to heading towards an EVPSS;
- The initial EV SoC is an uniform distribution between1% and 90%;
- The 1% of EV SoC is a sufficient value to arrive to nearest EVPSS;
- The number of available EVPSS is 20;
- The maximal EV SoC is 7 kW;
- The charging rate in each EVPSS is 20 kW/h and the maximal time for EV to be fully charged is 20 min;
- $\lambda = 1/3$; arrival intensity;
- $\mu = 1/50$ service intensity;

The simulations were run 50 times and we took the average values for each EV.

It is worth noting that the number of EVs, the number of available EVPSS with their maximum available charging slots, and the arrival and the service intensity values, were all chosen so as to illustrate cases of frequent EVs arrival at EVPSS, and cases where EVs frequently need to wait in EVPSS queues to be served. Also the maximal EV SoC, the charging rate at EVPSSs and the maximal time for EVs to be fully charged correspond to realistic values for level 3 EVPSSs [2, 10].

We show in figure 5, the simulated initial EV SoC which is random between 1% and 90%. Based on the initial SoC value and the EV position, the smart grid will choose the available EVPSS.

We assume that an EV always consumes energy with its maximum power limit until its performance threshold is satisfied. Figure 6 shows the queue length variation during the whole charging process operations for 1000 vehicles. The maximum average EV number in the queue is under 60 EVs. It is clear that BA- EVPSS can also be seen as another form of scheduling algorithm used by the smart grid to manage grid power consumption by EVPSSs.

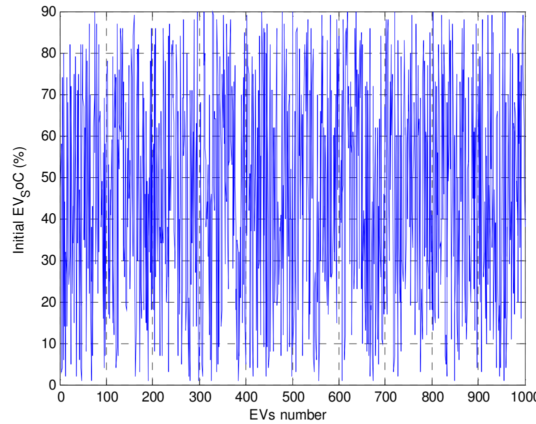

Figure 5.Initial EV State of Charge (simulation for 1000 EV)

Indeed a load balancing strategy, according to the queue filling level in each EVPSS is done when the smart grid directs each arriving EV to the EVPSS which have a reduced number of EV in its queue.

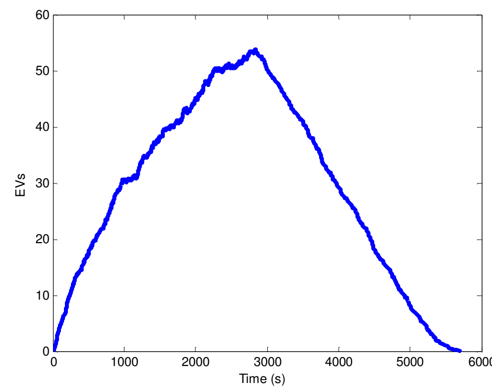

Figure 6: Average queuing length

Figure 7 shows the arrival time per number of EVs (blue continuous curve) compared to their departure time (highlighted by the red dash color). We observe that the departure time is sensitive to the number of arriving EVs as the red curve evolves away from the blue one. For each EV, the departure time depends on the charging time of all EVs which priory joined the same EVPSS and did not leave yet, which explains the increase in departure time with the number of EVs.

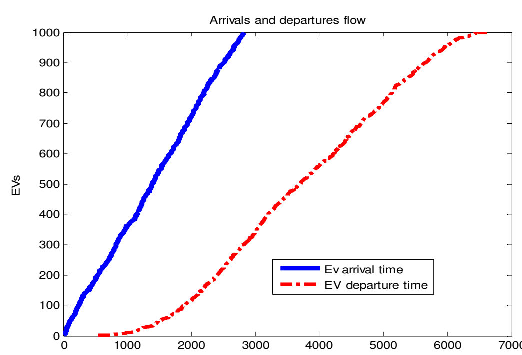

Figure 7: Arrivals /departures flow (simulation for 1000 EV)

In figure 8, we show the waiting time of EVs that is calculated by BA- EVPSS depending on the number of available plug-in socket in EVPSSs. We observe that the average waiting time is sensitive to the number of plug-in sockets in each EVPSS. BA-EVPSS uses waiting time of EVs in order to minimize the individual waiting time for each EV. The algorithm identifies the EVPSS which has the smallest average waiting time for the next EV that needs charging. In figure 8, the smart grid chooses, for example, the third EVPSS which has 10 plug-in sockets available, but most importantly the lowest waiting time, to satisfy an EV demand for an available EVPSS.

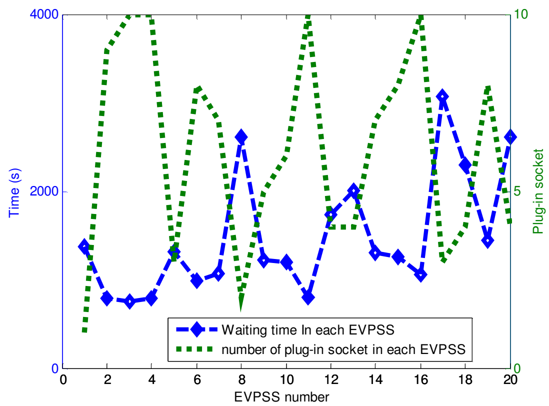

Figure 8: Waiting time in each EVPSS versus plug-in socket number.

Hereafter, we study the wiating time of the BA-EVPSS algorithm compared with the R-EVPSS one. In R-EVPSS algorithm, an EVPSS is selected according to its queue length; in fact, the arriving EV is directed to the EPVSS which has the smallest EV number in its queue without taking into account the cumulative EV charging time needed by all EVs in all the queues.

Figure 9 compares the waiting time for our algorithm (represented by the blue dash curve) and the R-EVPSS algorithm (highlighted by red curve). We observe that the waiting time given by R-EVPSS algorithm is higher than the corresponding waiting time given by BA-EVPSS.

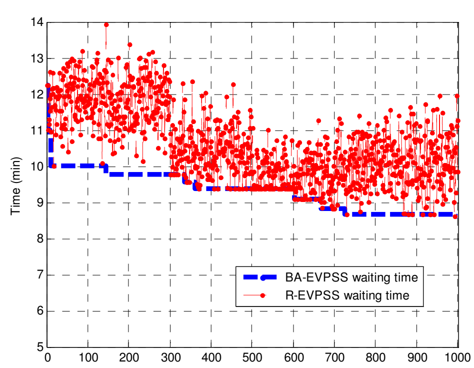

Figure 9: Waiting time comparison between our BA-EVPSS algorithm and R-EVPSS .

VI. CONCLUSIONS

In this paper, a dynamic charging algorithm for EVs at public station based on a multi-queuing model is formulated, developed and examined through simulations considering realistic EVs and EVPSS constraints. Two principal factors have been considered: 1) satisfying single EV charging demands, and 2) minimizing the waiting time, and therefore the charging time for each EV. Simulations that considered realistic EV characteristics and public stations charging models (socket level 3) show that the proposed charging algorithm manages the EVs demand in an efficient way. Moreover, simulation results show that the algorithm can be seen as a scheduling form of EVs access to the grid at EVPSSs, and can reduce the waiting time for EVs even when the number of EVs increases. Additionally, as the algorithm balances EVs usage of EVPSS, BA-EVPSS can contribute to grid EV load stabilization (i.e., regulation service).

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