Electric Vehicles Charging Management in Communication Controlled Fast Charging Stations

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Abstract—We present and analyze an Electric Vehicle (EV) charging management model for a fast charging station network in a smart grid environment. The proposed model considers a charging station network that provides service to multiple EV charging-classes. The basic feature of the proposed model is when EVs are blocked by their preferred station due to the unavailability of charging outlets, they are prompted via a communication system to select their next station, which either provides fixed or elastic charging services. We derive an analytical framework for the determination of the arrival procedure to the additional stations, which is then used for the derivation of the distribution of occupied charging outlets in both stations. Simulation results verify the high accuracy of the proposed analysis. The proposed analysis can be used for the determination of the number of stations that should be installed in a specific geographical area, so that EVs do not suffer charging delays.

Keywords—Electric vehicles, charging stations, charging failure probability, performance evaluation.

I. INTRODUCTION

Electric Vehicles (EVs) have been considered as an effective solution to deal with concerns over the shortage of fossil fuel and the negative environmental impact of conventional vehicles. The expansion of the EV deployment is expected to introduce a significant pressure on the existing power grid infrastructure. A resourceful solution to this subsequent increased power demand is the emerging smart grid, which will enhance the efficiency and reliability of the power grid, while it will contribute to the reduction of CO₂ emissions, through the incorporation of renewable energy resources [1].

EV charging is an important issue and there is a significant research effort on this subject that introduce either uncoordinated or scheduling charging scenarios, e.g. [2], [3]. The majority of these studies assume that EVs are stationary in the users’ premises or parking lots and target either on the utilization maximization of the grid’s resources or the delay-optimal charging scheduling. However, little attention has been given on the design of charging stations. The models in [4] and [5] target the waiting-time minimization in a charging station by considering queuing models with Poisson arrivals. On the other hand, the model of [6] does not consider waiting spaces and targets on the calculation of blocking probabilities. The main disadvantage of these studies is the consideration of a single chargers’ type; this assumption averts the applicability of these models to EVs with different charging classes.

In this paper, we present and analyze an EV charging management model in a communication controlled, fast charging station network. The basic assumption of our model is that EVs are classified into multiple charging-classes, with different demands and charging times. The consideration of differentiated charging-classes is applied in order to allow the accommodation of EVs with different technological constraints. We consider that a number of charging stations are located in a specific geographical region. Customers request service from their preferred station, which responds for the availability of the station and the recommended charging outlet. If the station is fully occupied, it informs the customer about the availability of two additional stations, located into the specific geographical region. The first station provides fixed-demand service, while the second station provides elastic-demand service, depending on the occupancy of the station. Price incentives are offered to customers to select the elastic supply station, since additional charging delays may occur.

The main target of this paper is the derivation of an analytical model that provides a computational efficient method (compared to simulations), which can be used for the determination of charging failure probabilities in all charging stations (the main stations and the two additional stations). Charging failure occurs when an EV cannot find an available charging outlet at the time of arrival at the station. To this end, we initially develop an analytical framework for the determination of the EV arrival procedure to the additional stations. The arrival distributions are then used for the derivation of the occupancy distribution of the additional charging stations. The main advantage of the proposed analysis is the utilization of low computational-complexity recursive formulas for the calculation of the charging failure probabilities, which provide near-real time results, in contrast to time-consuming simulations. The accuracy of the proposed analysis is verified through simulation and found to be completely satisfactory. Moreover, results indicate that the incorporation of the two additional stations significantly reduces, or even eliminates the charging failure probabilities. Hence, the proposed analysis can be used either in EV charging networks that suffer of high charging failure probabilities, or for the efficient dimensioning of a EV charging network (e.g., to determine the optimal number of stations that are connected with the two additional stations in a large geographical area), so that no charging failure occurs, which increases the waiting time of customers at the station.

This paper is organized as follows. In Section II we present the general features of the charging network model. In Section III the EV management model is presented and analyzed. Section IV is the evaluation section, where analytical and simulation results are presented. We conclude in Section V.

II. EV CHARGING NETWORK MODEL

We consider a set of $S$ stations that support a specific geographical region. Each station is equipped with a power storage device that receives power from a power generating plant through a distribution system and is used for the EVs direct charge. Furthermore, each station $s$ ($s = 1, \ldots, S$) is

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capable of charging a specific number of EVs through a number of $N_s$ charging outlets. All charging outlets support $C$ classes of charging service, depending on the charging time and the requested power; an EV that requests the $c$-th class ($c=1,\ldots,C$) of service, requires $m_c$ power units (kW) with a charging rate of $\mu_c$ sec$^{-1}$ (generally distributed). We consider that the $1^{\text{st}}$ charging-class requires the smallest amount of power, while the $C$-th class requires the maximum power $m_C$; i.e. $m_1<m_2<\ldots<m_C$. Besides, class $c$ EVs arrive at station $s$ by following a Poisson process, with mean $\lambda_{s,c}$.

The total power that is supported in station $s$ is $E_s$ (kW). We consider that the charging stations are designed so that they are able to simultaneously service $N_s$ EVs of the lowest charging-class; therefore, $E_s = N_s \cdot m_1$. Consequently, if a number of EVs request higher charging-classes, there is a probability that the total requested power from higher charging-classes EVs will exceed $E_s$, although a number of outlets will be vacant. We denote this probability as charging failure probability, which is different for each charging-class, since each class requires different power and charging times.

We firstly define the baseline case, where no EV charging management occurs, in order to determine the upper bound of the charging failure probability in each station. EVs choose and inform their preferred station for their charging-class via a communication system, such as 3G/4G system. The charging station responds for its availability and the recommended charging outlet. If the total charging power that the station provides exceeds $E_s$ upon the arrival of the EV, charging failure occurs. In such a case, the station sends a charging failure message to the customer, who is then able to either retry after a specific time period (equal to the inter-arrival time of EVs to this station) or search for another proximal station. The charging failure probability calculation is based on the knowledge of the occupied charging outlets distribution, which is a function of the total power $E_s$, the number $S$ of charging-classes, and EVs’ arrival and charging rates. We define the occupied charging outlets distribution $q_s(j)$ of station $s$ as:

$$j \cdot q_s(j) = \sum_{c=1}^{C} (\lambda_{s,c} \cdot \mu_c^{-1}) \cdot m_c q_s(j-m_c) \quad (1)$$

for $j = 1,\ldots,N_s$. A similar recursive formula is used for the distribution of the occupied bandwidth in multi-rate communication networks [7]; for the derivation of (1), we adopt the same procedure as the one used in [7], since in the latter case, similar assumptions are utilized (Poisson call arrivals and generally distributed service times). Since (1) is a recursive formula, it can be solved by using an iterative method, where the initial value is $q_s(0) = 1$ and the remaining values of $q_s(j)$ are calculated through (1). These un-normalized probabilities are normalized over the summation $Q_s = \sum_{j=0}^{N_s} q_s(j)$ to derive the final values of $q_s(j)$. Equation (1) can be used in order to calculate the charging failure probability $B_{s,c}$ of charging-class $c$ EVs in charging station $s$, as a function of $m_c$:

$$B_{s,c} = \sum_{j=N_s-m_c+1}^{N_s} q_s(j) \quad (2)$$

Equation (2) is derived based on the fact that a class $c$ EV cannot be serviced when the number of occupied outlets is above $N_s - m_c + 1$ (charging failure probabilities are obtained by summing up the probabilities $q_s(j)$ of blocking states), although each EV uses a single charging outlet. However, since the charging station is able to simultaneously service $N_s$ EVs of the lowest charging-class, if the charging-class $c$ EV is accepted for service, the total requested power will exceed the maximum value $E_s$, even if an idle charging slot is available.

III. EV MANAGEMENT MODEL

The proposed EV management model considers the same assumptions as the baseline case, regarding the numbers of charging stations and charging outlets per station. However, the proposed model considers that in the geographical region under consideration there exists two additional charging stations, where customers are forwarded when they are blocked by their preferred station. The first additional station provides service in the same way as the initial $S$ charging stations, while in the second additional station an EV is not blocked; instead, it is charged with reduced power, and at the same time the power that is used for the charging of all in-service EVs is also reduced. Furthermore, when an EV departs from this station, then the power allocated to the in-service EVs is increased, in order to reduce the charging time. Based on their functionality, we label the two stations as Fixed Power Charging Station (FPCS) and Elastic Power Charging Station (EPICS) (Fig. 2).

Customers that receive a charging failure message are informed that they can retry to access the same station after a time period equal to the EVs’ inter-arrival time to this station or navigate to two additional charging stations. The customer decides the preferred additional charging station and responds with a new message to the original station. We consider that
a class \( c \) EV, which is blocked by the \( s \)-th station, selects the FPCS with probability \( p_{s,c} \), while the EV selects the EPCS with probability \( 1-p_{s,c} \) (Fig. 2). Since the EPCS offers elastic charging services that may result in delays, incentives are offered to the customers to select the EPCS, in terms of lower charging prices. The charging prices that are offered by both the FPCS and EPCS are included in the message that the customers receive for their preferred station unavailability.

The first step for the charging failure probability calculation is the determination of the arrival procedure of the blocked EVs to the two additional stations, which cannot be considered as Poisson. Instead, this arrival procedure follows a general distribution that is characterized by a mean, a variance and a peakedness factor. The calculation of these metrics is realized by using a method that was initially proposed for the determination of overflow traffic in multi-rate networks [8]. The application of this procedure to the EV management model is feasible due to the same assumptions of the two systems; both systems assume differentiated classes with Poisson arrivals and general service times. Based on this procedure we define the mean \( R_{s,c} \), the variance \( \sigma_{s,c}^2 \), and the peakedness factor \( Z_{s,c} = \sigma_{s,c}/R_{s,c} \) of the demand intensity of charging-class \( c \) EVs that depart from charging station \( s \). The mean \( R_{s,c} \) equals the percentage of blocked class-\( c \) EVs in station \( s \):

\[
R_{s,c} = \frac{\lambda_{s,c}}{\mu_c} B_{s,c} \quad (3)
\]

For the determination of the variance \( \sigma_{s,c}^2 \) we apply [8]:

\[
\sigma_{s,c}^2 = R_{s,c} \left( \frac{(\lambda_{s,c}/\mu_c)}{N_s/m_c + 1 - (\lambda_{s,c}/\mu_c) + R_{s,c} + 1 - R_{s,c}} \right) \quad (4)
\]

where \( N_{s,c} \) is the number of charging outlets in a fictitious charging station that is derived by the decomposition of the real charging station \( s \) into \( C \) fictitious groups. The value of \( N_{s,c} \) can be calculated as a function of the real number of charging outlets of charging station \( s \):

\[
N_{s,c} = N_s - \sum_{i=1}^{C} \left( \frac{\lambda_{s,i}}{\mu_i} (1 - B_{s,i}) m_i \right) \quad (5)
\]

where the summation of the right hand side of (5) indicates the number of charging outlets that are occupied by EVs of classes other than class \( c \). By considering that \( p_{s,c} \)\% of blocked EVs choose the FPCS and the other \((1-p_{s,c})\)% choose the EPCS, the mean and the variance of the demand intensity for charging-class \( c \) EVs that arrive at FPCS and EPCS are calculated by:

\[
R_{F,c} = \sum_{s=1}^{S} p_{s,c} R_{s,c}, \quad \sigma_{F,c}^2 = \sum_{s=1}^{S} p_{s,c} \sigma_{s,c}^2 \quad (6)
\]

\[
R_{E,c} = \sum_{s=1}^{S} (1-p_{s,c}) R_{s,c}, \quad \sigma_{E,c}^2 = \sum_{s=1}^{S} (1-p_{s,c}) \sigma_{s,c}^2 \quad (7)
\]

Based on (6) and (7) we can calculate the peakedness factors \( Z_{F,c} \) and \( Z_{E,c} \) of all charging-classes, as the ratio of variance to mean value; these values are used for the charging failure probabilities calculation in both FPCS and EPCS, by using the analysis presented in the following subsections.

A. Charging failure probability in the FPCS

The demand intensity from EVs that request service by the FPCS is considered as “bursty”, since the peakedness factor is greater than 1 (not Poisson). This arrival procedure to \( N_F \) charging outlets is called batch Poisson process [9], where the burst size for each charging-class is a function of demand intensity’s mean and peakedness factor. More precisely, the mean arrival rate of class \( c \) EVs to the FPCS equals the product of the mean demand intensity by the mean charging rate:

\[
\lambda_{F,c} = R_{F,c} \mu_c \quad (8)
\]

while the batch size of charging-class \( c \) has a mean value \( \gamma_{F,c} \) and a second moment \( \gamma_{F,c}^2 \) that are functions of the peakedness factor of the corresponding traffic intensity [10]:

\[
Z_{FPCS,c} = \frac{\gamma_{F,c}^2 + \gamma_{F,c}}{2 \gamma_{F,c}} \quad (9)
\]

Consequently, we have the freedom to select a batch size distribution \( \Gamma_{F,c}(\gamma) \), i.e. the probability that there are \( r \) EVs in a batch, with a mean and variance that satisfy (9), e.g. a geometric or a negative Binomial distribution. By using the batch size distribution \( \Gamma_{F,c}(\gamma) \), we can calculate the distribution \( q_F(j) \) of the occupied charging outlets, by using the following recursive formula [9]:

\[
q_F(j) = \sum_{i=1}^{j} \left[ \frac{\lambda_{F,c} m_c}{\mu_c} \sum_{m_i=1}^{\lfloor j/m_i \rfloor} \Gamma_{F,c}(i-1)q_F(j-m_i) \right] \quad (10)
\]

where \( j = 1, \ldots, N_F \) and \( \lfloor j/m_i \rfloor \) is the largest integer less than or equal to \( j/m_i \). In order to solve (10) we use the successive iterations method that is used for solving (1).

The charging failure probability in the case of batch EV arrivals is defined as the probability that at least one EV is blocked, due to the unavailability of charging outlets. By following the rationale for the definition of the charging failure probability in the baseline case (2), we define the batch charging failure probability of class \( c \) EVs as follows:

\[
B_{FPCS,c} = \sum_{j=N_F-m_c+1}^{N_F} q_F(j) \quad (11)
\]

B. Charging failure probability in the EPCS

When a customer selects the EPCS for charging his EV, the station checks the availability of its \( N_E \) charging outlets. If an available charging outlet does not exist, or it exists but the total power that is provided to the in-service EVs will exceed the station’s capacity by accepting the incoming EV for service, this EV is not blocked (as in the case of the baseline and the FPCS cases). Instead, the EV is accepted for charging with a reduced power, and at the same time the power that is used for the charging of all in-service EVs is also reduced, so that the total provided power is lower than the station’s capacity. Hence, the power that is supplied to each EV can be considered as elastic that fluctuates between a minimum and a maximum value. For a class \( c \) EV the maximum value is equal to the initial demand \( m_{\text{max}} = m_c \), while the minimum value is a percentage of the initial demand, so that \( m_{\text{min}} = w_{\text{min}} m_c \). After this reduction, the charging times are also adjusted, so that the product (power demand) by (charging time) remains constant. Therefore, there is a probability that charging times
will be increased, when a large number of EVs are charged. However, when a compressed-demand EV departs from the EPCS, the remaining EVs expand their demands and reduce their charging times.

The derivation of a recursive formula for the distribution of occupied charging outlets is based on the assumption that the total number $N_E$ of charging outlets is increased by a factor $w_{\text{min}}$, so that the new number is $N_{E}^{\text{max}} = N_E / w_{\text{min}}$. The assumption of the fictitious number $N_{E}^{\text{max}}$ of charging outlets is applied in order to model the maximum demand compression (higher compression rates result in higher values of $N_{E}^{\text{max}}$). Furthermore, for the EVs arrival procedure, the same assumptions that are used in the FPCS case are considered. Therefore, the mean arrival rate $\lambda_{E,c}$ and the mean $\gamma_{E,c}$ and variance $\gamma_{E,c}^{2}$ of the $c$ charging-class batch size are calculated by (8), (9), with the substitution of $R_{E,c}$ with $R_{E,c}^{c}$.

As in the case of the FPCS, the mean and variance values of the batch size are used in order to define the batch size distribution $\Gamma_{E,c}(r)$ of class $c$ EVs, i.e. the probability that there are $r$ EVs in a batch. The batch size distribution is used in order to derive the distribution $q_{E}(j)$ of charging outlets:

$$\min(j, N_{E}) - q_{E}(j) = \sum_{c=1}^{C} \left[ \frac{\lambda_{E,c}}{\mu_{E,c}} \cdot \left( \sum_{i=1}^{j/m_{E,c}} \Gamma_{E,c}(i-1) q_{E}(j-i m_{E,c}) \right) \right]$$

for $j = 1, \ldots, N_{E}^{\text{max}}$. Equation (12) is an extension of (10) for the case of elastic services, while it is derived by following the procedure that was initially used for the case of multi-rate networks [11]. The recursive formula of (12) is applied to the extended number $N_{E}^{\text{max}}$ of charging outlets, and not to the real capacity $N_E$, that is applied in the fixed-service case of the FPCS. Finally, the charging failure probability of class $c$ EVs is given by (11), where $N_E$ is replaced by $N_{E}^{\text{max}}$.

### IV. EVALUATION

In this section we evaluate the proposed analytical models through simulation. To this end, we consider that $S=20$ charging stations are located in an urban area, and provide

<table>
<thead>
<tr>
<th>Arrival rate points</th>
<th>Arrival rate (EVs/min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.20</td>
</tr>
<tr>
<td>2</td>
<td>0.25</td>
</tr>
<tr>
<td>3</td>
<td>0.30</td>
</tr>
<tr>
<td>4</td>
<td>0.30</td>
</tr>
<tr>
<td>5</td>
<td>0.30</td>
</tr>
<tr>
<td>6</td>
<td>0.30</td>
</tr>
<tr>
<td>7</td>
<td>0.35</td>
</tr>
<tr>
<td>8</td>
<td>0.40</td>
</tr>
<tr>
<td>9</td>
<td>0.40</td>
</tr>
</tbody>
</table>

### TABLE II. DEMAND INTENSITY PARAMETERS OF EACH EV CLASS OFFERED TO BOTH THE ADDITIONAL STATIONS

<table>
<thead>
<tr>
<th>Arrival rate points</th>
<th>Demand intensity parameters ($R$, $\sigma$, $\zeta$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>(0.03, 0.04, 1.11)</td>
</tr>
<tr>
<td>2</td>
<td>(0.05, 0.06, 1.15)</td>
</tr>
<tr>
<td>3</td>
<td>(0.07, 0.08, 1.18)</td>
</tr>
<tr>
<td>4</td>
<td>(0.11, 0.13, 1.17)</td>
</tr>
<tr>
<td>5</td>
<td>(0.15, 0.21, 1.16)</td>
</tr>
<tr>
<td>6</td>
<td>(0.21, 0.27, 1.16)</td>
</tr>
<tr>
<td>7</td>
<td>(0.33, 0.38, 1.16)</td>
</tr>
<tr>
<td>8</td>
<td>(0.59, 0.47, 1.21)</td>
</tr>
<tr>
<td>9</td>
<td>(0.15, 0.15, 1.21)</td>
</tr>
</tbody>
</table>

For the presented numerical results we consider various cases for the EV arrival rates. In Table I we present 9 arrival rate points that correspond to different values of the arrival rates, which are assumed to be the same for all stations. In Table II we present the values of the mean, variance and peakedness factor of the demand intensity that is offered to the additional stations, which are calculated by applying the arrival-rate values of Table I to the set of equations (3)-(9); these values are used for the definition of the batch size of each charging-class, which is assumed to follow a geometrical distribution, since it is considered as the discrete equivalent of the exponential distribution (EV’s inter-arrival times that arrive at the main stations are exponentially distributed) [12]. The geometric distribution has a mean value of $1/\beta$ and a variance of $(1 - \beta)/\beta^2$. Finally, for the EPCS, we assume that $w_{\text{min}} = 0.1$ (power demands are compressed up to 10%).
In Fig. 3, 4 and 5 we present analytical and simulation results for the charging failure probability of the three charging-classes, respectively, versus the 9 arrival rate points. In each figure, we present analytical results from the baseline case and analytical and simulation results for the FPCS and EPCS cases. The comparison of analytical and simulation results reveals the high accuracy of the proposed models. We notice the significant decrease of the charging failure probability, as a result of the incorporation of FPCS and EPCS in the station network. Notably, there are cases where the charging failure probability is eliminated. Furthermore, we observe that the EPCS charging failure probabilities are lower than of FPCS. This fact proves that the application of elastic services may significantly reduce the charging failure probabilities.

Finally, we use the proposed models in order to find the optimal number $S$ of charging stations that constitute the main charging network, so that the failure charging probabilities are below a maximum threshold. In Fig. 6 and 7 we present analytical results of the charging failure probabilities of all charging-classes in the FPCS and EPCS, respectively, versus the number $S$ of stations. These results are obtained by using the same parameter values that are used for the derivation of the results in Fig. 3, 4 and 5, while the EVs’ arrival rate correspond to point 8 of Table I. By considering a threshold of $10^{-4}$ for the charging failure probabilities, we observe that the minimum number $S$ is 12. Therefore, the proposed model can be used for the determination of the number of charging stations that should be incorporated with FPCS and EPCS, in order to achieve minimal charging failure probabilities.

V. CONCLUSION

We present and analyze a EV management model for the charging failure probabilities calculation in a communication-controlled fast charging station. EVs that are blocked by their preferred charging station are informed that two additional stations exist; a FPCS that provides fixed demand services and an EPCS, with elastic services. We provide the analysis for the calculation of the arrival procedure to both the FPCS and EPCS and the distribution of the occupied charging outlets. The comparison of analytical charging failure probabilities results with corresponding simulation results showed the high accuracy of the proposed model. The results indicate that the incorporation of the FPCS and the EPCS significantly reduces the charging failure probabilities. An appropriate charging mechanism is the subject of our future work that targets on the optimal pricing incentives determination that guarantees maximum FPCS and EPCS utilization.

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