Modeling Spare Capacity Reuse in EV Charging Stations based on the Li-ion Battery Profile

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***Abstract*—Lithium-ion batteries, widely used in electric vehicles (EVs), have a specific charging profile where the power consumed varies over time and defines the amount of power the charging station needs to deliver. Achieving a proper tradeoff between charging levels, number of vehicles, and electric capacity of the plant is challenging. In order to give a solid basis for the deployment of efficient charging systems, we propose a bi-dimensional Markov chain model that considers the practical characteristics of Li-ion charging profiles. To this end, we build two scenarios that differ in their capacity to handle idle slots. We show through extensive numerical analysis that the use of spare sockets in different sizes of charging stations contributes to better energy utilization. Moreover, we apply the proposed model to the case of the city of Rio de Janeiro and show that, in a foreseeable future, if all ICE (Internal Combustion Engine) vehicles were replaced by EVs, the adoption of charging station with spare sockets will produce significantly better results in terms of availability of the station, number of admitted vehicles, and energy utilization.**

I. Introduction

Due to the well known problem of "range anxiety", electric vehicles (EVs) must be able to charge their batteries at charging stations that adopt fast algorithms to refuel the battery in 30 minutes or so to continue the journey [1]. A major problem is that fast charging stations consume significant power from the grid [2]. For this reason, the number of vehicles charging at the same time must be *strictly controlled*, especially during peak hours, in order to avoid local blackouts at substations.

Achieving fine-grained control over the charging process depends on the expected distribution of charging requests throughout the system. EVs generate a mobile load that substantially changes the grid requirements in terms of energy provisioning. As a consequence, *modeling the power demand generated by EVs is of utmost importance*. The problem is that the charging curve of batteries is in general non-linear. We propose in this paper to consider the charging profiles of Li-ion batteries to model the system in a much more realistic fashion than previous studies. The reason for the choice of Li-ion batteries is that they are widely adopted in EVs [3].

Li-ion batteries have a particular charging profile that consists of 3 phases (Fig.1). The first phase occurs when the battery is totally depleted. During this "pre-charge level" phase, the current is $I_{PRE} = 0.1$C.[1] The second phase is

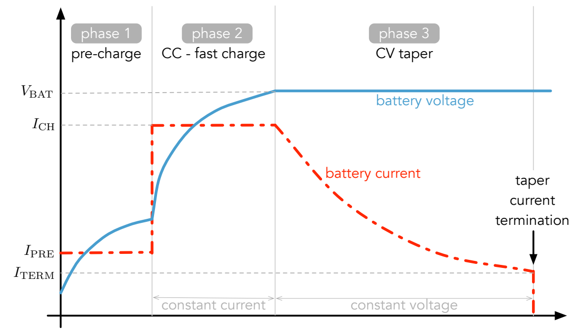

Fig. 1: Li-ion battery charging profile.

the constant-current (CC) phase (I_{CH}). During fast charging, the charging current is kept constant until the voltage of the lithium cell reaches V_{BAT} (typically 4.2 V). Then, the third phase starts. The voltage is constant as the current decays exponentially and tapers, typically, to one-tenth of the fast-charge current (I_{TERM}). Approximately 70% of total charge is delivered during the CC phase. The remaining 30% are obtained during the constant-voltage (CV) phase [4].

In this paper, we show that considering the charging profile of Li-ion batteries allows deriving a charging model for EV charging stations that is more precise than other models of the literature. Moreover, by reusing the spare capacity produced by the Li-ion charging profile, we can better provision the smart grid. To demonstrate that, we build two Markov chain models to describe the behavior of a charging station in two scenarios, whether reusing or not the spare capacity. In the first scenario (no reuse), there is a predetermined number of charging points, which is defined by the total energy that the station can provide divided by the maximum energy (CC-mode) that a electric car drains to fast refuel its battery. When all charging sockets are busy, the system blocks, even if some of the vehicles are in the phase of lower consumption (CV-mode). To circunvent this situation, we consider a second scenario in which spare sockets are available. With these extra slots, more vehicles can be admitted in the system as long as the total energy consumed is lower than the capacity of the charging station.

Through extensive numerical analysis, we show that we manage to use ∼70% of total available power in the first scenario, while this value increases to ∼90.65% in the second scenario. In a nutshell, we observe that more customers are served with spare sockets in the system, and this with better Quality of Service (QoS).

[1]The amount of charge of a battery is generally expressed in ampere- or mili-ampere-hours. It is a figure of metric of battery life between charges. It is denoted in "C"-ampere-hours. As for charging procedures, the current is described in C-rate units. As an example, for a 2500 mA-h battery, the current corresponding to 1 C is 2500 mA.

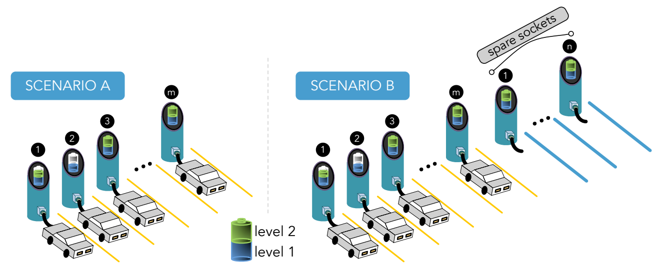

Fig. 2: Charging stations scenarios, traditional (A) and with spare capacity reuse (B).

II. Service model

We model the fast charging station using Continuous Time Markov Chains. The pre-charge phase must be considered only if the battery charge is completely depleted. From a practical point of view, it rarely occurs: typically, when the driver of an ICE vehicle sees a "low fuel" indication in the vehicle panel, he/she heads to the closest gas station for refueling. We assume the EV drivers have the same behavior. Thus, we approximate the charging process by two phases to build our Markov chain. The first phase adopted is constant current mode (CC-mode). Most of the power is delivered during this phase. The battery charge level at this phase is low. By the end of CC-mode, the charger switches to constant voltage mode. It remains on CV-mode until the remaining voltage drop in the internal resistance disappears. The CV-mode corresponds to a period of less power, but it is necessary to battery conditioning.

We investigate two scenarios. Scenario A of Fig. 2 represents a charging station with m fast chargers. The arrival rate of EVs follows a Poisson distribution with a rate of λ, the service has an exponential distribution with a rate of μ, and the system presents m servers or chargers. When the physical space at a charging station is large enough to install m chargers, if the local substation delivers to the station G kW, and the power spent in level-1 is p kW, the system supports $m = G/p$ chargers.

There is another perspective, called scenario B, that deals with idle sockets in spare mode. If the chargers are all busy, in CC-mode, the charging system is in $(m, 0)$ blocking state. The charging station is at its maximum capacity and the local substation delivers G kW. Therefore, when some of the cars reach the second phase, there is a waste of capacity. The reduced power consumption allows more vehicles to charge in the system, if spare charging sockets are installed. When some vehicles reach the second phase, new arrivals can be served, as long as the full capacity is not reached.

A. Modeling Scenario A

We use a continuous-time Markov chain to model Scenario A, considering the 2 charging phases. Scenario A can be modeled as a birth-death model based on finite 2-dimensional state-space (2D-Markov chain). We assume that the CC-mode (phase-1) and CV-mode (phase-2) are two well-defined intervals of time and consumed power, with service rates μ_1 for phase-1 and μ_2 for phase-2. In Scenario A, the number of chargers is limited by the maximum power the substation can provide divided by the power consumed in CC-mode. It also defines the number of vehicles that the station can serve in parallel. The states at Markov chain model used at this scenario has 2 variables (i, j). The variable i represents the number of vehicles that are charging in CC-mode, whereas j is the number of vehicles in CV-mode. The Markov chain of Fig. 3 describes the behavior of the charging station in Scenario A of Fig. 2. When a vehicle arrives at the system, the state of the Markov chain jumps to $(i+1, j)$. When phase-1 finishes, the CV-mode starts and the new state becomes $(i, j+1)$. When the light red states occur, the system can not accept more vehicles under the risk of substation blackouts. These states are blocking states since all sockets are busy. The $(m, 0)$ state is consuming practically all of the available power of the charging station. Any other blocking state in this model consumes less than the total power, because some vehicles already entered phase-2 charging. Thus, at these states, there is enough power to supply more vehicles. Nevertheless, the idle power available in the charging station is not used because there is no remaining charging socket.

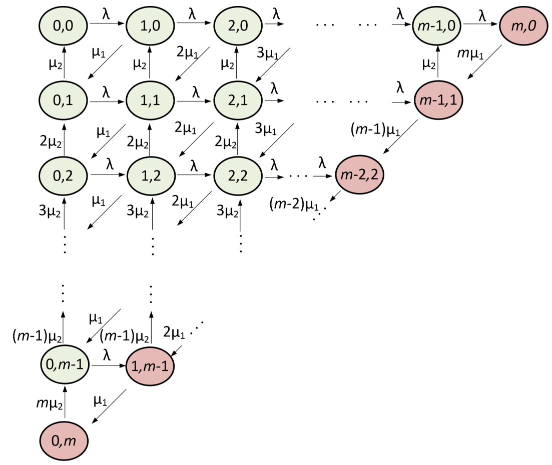

Fig. 3: Markov Chain Model - Scenario A.

At any instant $t \geq 0$ the system must be in some state of Fig. 3. The system is time-continuous and the chain is irreducible. In steady state, the probability vector $\pi = [\pi_{00}, \pi_{01}, \pi_{10}, \pi_{02} ... \pi_{m0}]$ will be represented in a vector-matrix form $\pi \mathbf{Q} = 0$, where $\mathbf{Q}$ is the infinitesimal generator matrix [5]. Thus, it is known that $\sum \sum_{i,j \in I} \pi_{ij}(t) = 1$, where I is the number of states that the system can assume. To find a unique solution different from zero, it is necessary to adopt the condition $\sum \sum_{i,j} \pi_{ij} = 1$. When the solution of the linear system $\pi \mathbf{Q} = 0$ and $\sum \sum_{i,j \in I} \pi_{ij} = 1$ yields positive limit-probabilities results π_{ij}, the Markov Chain is known as positive-recurrent [5]. These results are called steady-state probabilities, which have an asymptotic behavior when $t \to \infty$. The charging station model is a special case of a birth-death process, has a 2-dimensional finite state space, and the number of states is $(m^2 + m)/2$, where m is the number of chargers. The probability that the system remains in a given state decreases at a rate that is equal to the sum of the transition rates to neighbor states [6]. We place the states in the columns and rows of the generator matrix, $\mathbf{Q}$, by traversing the states diagonally in Fig. 3. The transition-rate matrix $\mathbf{Q}$ for Scenario A is given by Eq. 1. Then, if we solve the system formed by $\pi\mathbf{Q} = 0$ and $\sum\sum_{i,j \in I} \pi_{ij}(t) = 1$, we obtain the following metrics which are of interest both to the client and the station.

Number of vehicles in charge ($N(A)$). This value is of great interest for the owner of the charging station. When more vehicles are in charge, it means that the station is more profitable. From the point of view of the service user, when the station is busy, it can not receive vehicles, thus another station must be found. Assuming that n_{ij} is the number of vehicles at state (i, j), the number of vehicles in charge is:

$$N(A) = \sum_i \sum_j n_{ij}\pi_{ij}, \tag{2}$$

where $(i, j) \in I(A)$.

Blocking probability ($P_{bl}(A)$). This value measures the unavailability of the system which results in the rightmost states of Fig. 3. Any vehicle that arrives at the charging station when the system is in a blocking state ($I_{bl}(A) = \{(m, 0), (m-1, 1), (m-2, 2), ..., (0, m)\}$) has to drive to an alternative charging station. The blocking probability is:

$$P_{bl}(A) = \sum_i \sum_j \pi_{ij}, \tag{3}$$

where $(i, j) \in I_{bl}(A)$ and $I_{bl}(A) = \{(m, 0), (m-1, 1), (m-2, 2), ..., (0, m)\}$.

B. Modeling Scenario B

Scenario B in Fig. 2 is the case where some spare charging sockets are available to admit some vehicles when the total power of the charging station is not used. According to this assumption, the number of spare sockets is $(m - 1)$. The state $(m, 0)$ is the only state of the chain where the charging grid is under stress and no spare charging sockets can be used (because all vehicles are in CC-mode). There are other states where the station is using total power, but they combine CC and CV charging modes. The rightmost states represent the maximum power that a station can deliver. These are also the blocking states. The charging station can not admit more vehicles. Fig. 4 shows the behavior of the chain. We can see that the ideal number of spare chargers is equal to $(m - 1)$ to utilize the total power that a charging station can deliver. It assures the maximum use of power if all vehicles are in the CV-mode. Note that some states are almost in the limit, but do not reach total power. This is the case of the light-red $(m - k, 2k - 1)$ states for $k = 1, 2, 3, ..., m$. In Scenario B, the number of states of the Markov chain model increases as compared to Scenario A. It can be defined as $[(m^2 + m)/2] + \sum_{q=0}^{m-2}(m - q)$. We build the matrix of transitions following the same concept of the Markov chain of the first scenario. Nevertheless, the number of states increases due to the spare sockets. The Q matrix is presented in Eq. 4.

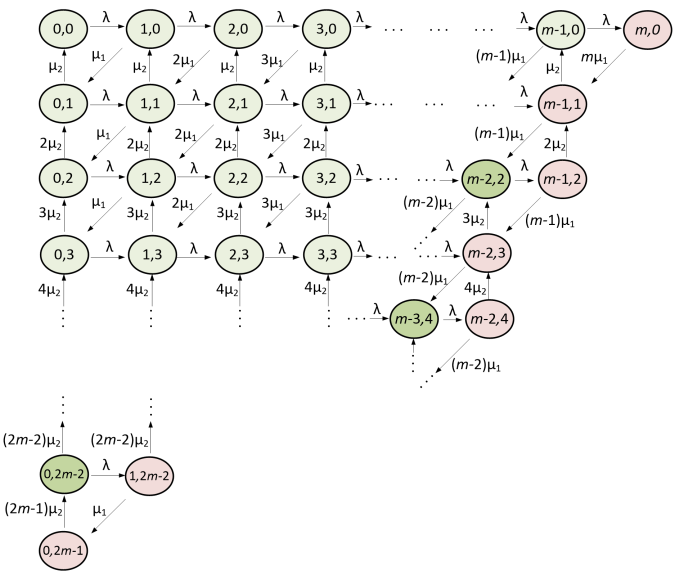

Fig. 4: Markov Chain Model - Scenario B.

Number of vehicles in charge ($N(B)$). In Scenario B, spare sockets will enable more efficient utilization of the station capacity, admitting more vehicles. Nevertheless, again, from the point of view of the user, if the station is busy another station must be found. The number of vehicles in charge is:

$$N(B) = \sum_i \sum_j n_{ij}\pi_{ij}, \tag{5}$$

where $(i, j) \in I(B)$.

Blocking probability ($P_{bl}(B)$). Here, the unavailability of the system is represented by the rightmost states of Fig. 4. In this model the blocking states are $I_{bl}(B) = \{(m, 0), (m - 1, 1), (m - 2, 2), ..., (1, 2m - 1), (0, 2m - 2)\}$. Thus, the blocking probability is:

$$P_{bl}(B) = \sum_i \sum_j \pi_{ij}, \tag{6}$$

where $(i, j) \in I_{bl}(B)$ and $I_{bl}(B) = \{(m, 0), (m-1, 1), (m-2, 2), ..., (1, 2m-2), (0, 2m-1)\}$.

Power demand ($P_d(A)$ **and** $P_d(B)$). This metric accounts for the power consumed by vehicles, or delivered by the station, considering the number of chargers. It is limited by the total power available in the station, which is enough to support all of the m chargers in CC-mode. States in the Markov chain also define the amount of consumed power, computed as P_{ij} times the probability of that state π_{ij}. It means the power needed when the system has i vehicles in CC-mode and j vehicles in CV-mode. The computation is carried out for each arrival rate and for each number of chargers. It is similar for Scenarios A and B. The power demand is computed as:

$$P_d = \sum_i \sum_j P_{ij}\pi_{ij}, \tag{7}$$

$$
\begin{array}{cc}
 & \begin{array}{ccccccccccccc} (0,0) & (0,1) & (1,0) & (0,2) & (1,1) & (2,0) & (0,3) & (1,2) & (2,1) & (3,0)\ \cdots & (m-1,1) & (m,0) \end{array} \\
\begin{array}{c} (0,0) \\ (0,1) \\ (1,0) \\ (0,2) \\ (1,1) \\ (2,0) \\ (0,3) \\ (1,2) \\ (2,1) \\ \vdots \\ (m,0) \end{array} &
\left[\begin{array}{cccccccccccc}
-\lambda & 0 & \lambda & 0 & 0 & 0 & 0 & 0 & 0 & 0\ \cdots & 0 & 0 \\
\mu_2 & -(\lambda+\mu_2) & 0 & 0 & \lambda & 0 & 0 & 0 & 0 & 0\ \cdots & 0 & 0 \\
0 & \mu_1 & -(\lambda+\mu_1) & 0 & 0 & \lambda & 0 & 0 & 0 & 0\ \cdots & 0 & 0 \\
0 & 2\mu_2 & 0 & -(\lambda+2\mu_2) & 0 & 0 & 0 & \lambda & 0 & 0\ \cdots & 0 & 0 \\
0 & 0 & \mu_2 & \mu_1 & -(\lambda+\mu_1+\mu_2) & 0 & 0 & 0 & \lambda & 0\ \cdots & 0 & 0 \\
0 & 0 & 0 & 0 & 2\mu_1 & -(\lambda+2\mu_1) & 0 & 0 & 0 & \lambda\ \cdots & 0 & 0 \\
0 & 0 & 0 & 3\mu_2 & 0 & 0 & -(\lambda+3\mu_2) & 0 & 0 & 0\ \cdots & 0 & 0 \\
0 & 0 & 0 & 0 & 2\mu_2 & 0 & \mu_1 & -(\lambda+\mu_1+2\mu_2) & 0 & 0\ \cdots & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & \mu_2 & 0 & 2\mu_1 & -(\lambda+2\mu_1+\mu_2) & 0\ \cdots & 0 & 0 \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\ \cdots & m\mu_1 & -m\mu_1
\end{array}\right]
\end{array}
\tag{1}
$$

$$
\begin{array}{cc}
 & \begin{array}{ccccccccccccc} (0,0) & (0,1) & (1,0) & (0,2) & (1,1) & (2,0) & (0,3) & (1,2) & (2,1) & (3,0)\ \cdots & (0,2m-1) & (1,2m-2) \end{array} \\
\begin{array}{c} (0,0) \\ (0,1) \\ (1,0) \\ (0,2) \\ (1,1) \\ (2,0) \\ (0,3) \\ (1,2) \\ (2,1) \\ \vdots \\ (0,2m-1) \\ (1,2m-2) \end{array} &
\left[\begin{array}{cccccccccccc}
-\lambda & 0 & \lambda & 0 & 0 & 0 & 0 & 0 & 0 & 0\ \cdots & 0 & 0 \\
\mu_2 & -(\lambda+\mu_2) & 0 & 0 & \lambda & 0 & 0 & 0 & 0 & 0\ \cdots & 0 & 0 \\
0 & \mu_1 & -(\lambda+\mu_1) & 0 & 0 & \lambda & 0 & 0 & 0 & 0\ \cdots & 0 & 0 \\
0 & 2\mu_2 & 0 & -(\lambda+2\mu_2) & 0 & 0 & 0 & \lambda & 0 & 0\ \cdots & 0 & 0 \\
0 & 0 & \mu_2 & \mu_1 & -(\lambda+\mu_1+\mu_2) & 0 & 0 & 0 & \lambda & 0\ \cdots & 0 & 0 \\
0 & 0 & 0 & 0 & 2\mu_1 & -(\lambda+2\mu_1) & 0 & 0 & 0 & \lambda\ \cdots & 0 & 0 \\
0 & 0 & 0 & 3\mu_2 & 0 & 0 & -(\lambda+3\mu_2) & 0 & 0 & 0\ \cdots & 0 & 0 \\
0 & 0 & 0 & 0 & 2\mu_2 & 0 & \mu_1 & -(\lambda+\mu_1+2\mu_2) & 0 & 0\ \cdots & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & \mu_2 & 0 & 2\mu_1 & -(\lambda+2\mu_1+\mu_2) & 0\ \cdots & 0 & 0 \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\ \cdots & -(2m-1)\mu_2 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\ \cdots & \mu_1 & -(\mu_1+(2m-2)\mu_2)
\end{array}\right]
\end{array}
\tag{4}
$$

TABLE I: Parameters used in the evaluation.

Notation	Description	Values
λ	Vehicle Arrival Rate ($vehicles/hour$)	5 to 50
μ	Total Service Rate ($vehicles/hour$)	2
μ_1	CC-phase Service Rate ($vehicles/hour$)	4
μ_2	CV-phase Service Rate ($vehicles/hour$)	4
m	Number of chargers	3 to 8
n	Number of spare chargers	0 to 7

where $(i, j) \in I(A), I(B)$.

III. EVALUATION OF CHARGING SCENARIOS

This section introduces the parameters and approximations used in the Markov chains shown in the previous section. The total time spent in the charging process, considering CC and CV modes, is 30 minutes (the pre-charge phase is neglected). The energy delivered at CC-mode is twice as large as in CV-mode. Therefore, the service rate of our model is split in 2 service rates, $\mu_1 = 4\ vehicles/hour$, the service rate in CC-mode, and $\mu_2 = 4\ vehicles/hour$, the service rate in CV-mode. The vehicle arrival rate λ is the number of vehicles per hour arriving in the charging station. We vary the arrival rate in the range $\lambda = 5$ to $50\ vehicles/hour$, in steps of $5\ vehicles/hour$. Table I summarizes the parameters used in our evaluation. We make some simplifications in the definition of the size of the charging station, as follows. First, we take the Nissan Leaf as example [7]. Its battery capacity is 24 kWh. When the battery is charged using the on-board charger (level-1 at 3.3 kW), the battery reaches full capacity after 8 hours of charge. On the other hand, using the fast charging procedure, the battery reaches 80% of its capacity in approximately 30 minutes. The total energy stored in this case is 19.2 kWh. Thus, for the first CC-mode phase, 51.2 kW will be needed to reach 12.8 kWh in 15 minutes, and 25.6 kW to complete 6.4 kWh in the remaining 15 minutes (CV-mode). As discussed before, we considered 2 different Scenarios, A and B. Both are implemented based on the simplified calculation of the number of main chargers (m) as a result of the division of the total available power at the charging station by the power consumed by a vehicle at the first phase (CC-mode). For example, if the charging station has a capacity of 420 kW ($m =$ 420 kW/51.2 kW = 8.2 chargers), then it can accommodate up to 8 chargers. In Scenario A, the station will only have 8 chargers. The worst case happens when all the chargers are supplying vehicles at CC-mode, delivering 409.6 kW, less than 420 kW. The other extreme case is when all the vehicles are in CV-mode and the total energy demand is 204.8 kW. Despite of all chargers being occupied, there is a waste of half the station's capacity. In Scenario B, some spare sockets are available that allow using some of this idle power. In Fig. 4, all the dark green and light red states (except the state $(m, 0)$) use spare sockets. More vehicles can be admitted in the system when the vehicle rate increases, and only a small fraction of energy is not used.

A. Results

The results presented here were produced using the proposed models and Matlab. We compare Scenarios A and B with different arrival rates (λ) and number of chargers (m).

Number of vehicles in charge (N) – Observing Scenario A in Fig. 5, we see that for $m = 3$ chargers the number of vehicles asymptotically tends to 3 as the arrival rate increases. This behavior repeats for all numbers of chargers (m = 4, 5,..., 8). The vehicles do not occupy all of the available chargers, even if the arrival rate is maximum (50 $vehicles/hour$). We can observe that the number of vehicles, in increasing order, is N =2.8758, 3.8279, 4.7761, 5.7200, 6.6590, 7.5927, in the last bar group of Fig. 5 (50 $vehicles/hour$). For Scenario B and the same arrival rates, the number of vehicles in charge for m = 3, 4, 5,..., 8 is N = 3.4636, 4.7234, 5.9751, 7.2579, 8.9691, 9.6697, respectively. N increases with the reuse of available energy, thanks to the spare sockets. The increase in the number of served vehicles is as large as 20.43%, 23.39%, 25.10%, 26.89%, 34.69%, and 27.36%, for m = 3 to 8

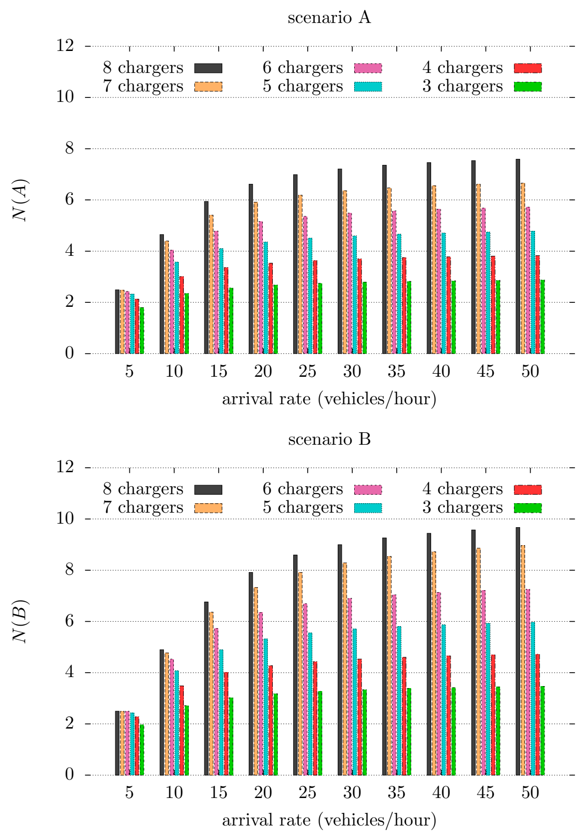

Fig. 5: Vehicles in charge (N) in Scenarios A and B.

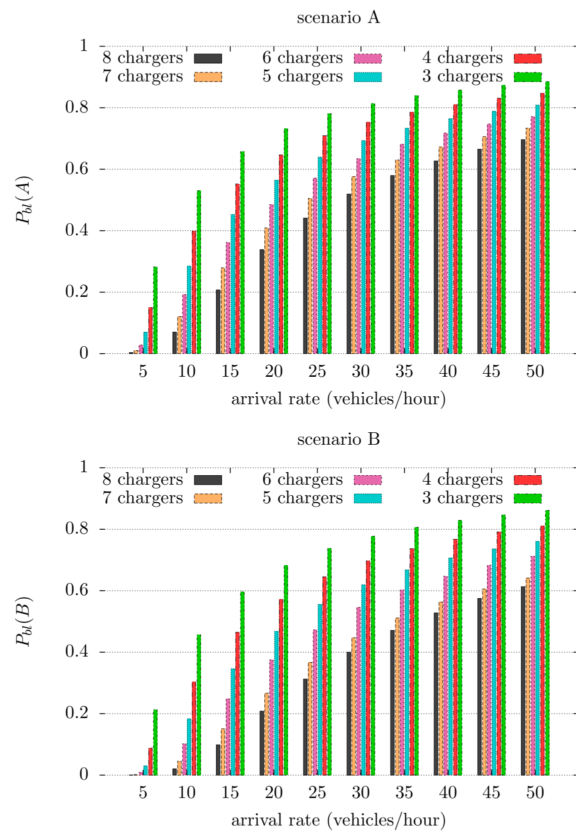

Fig. 6: Blocking probability (P_{bl}) in Scenarios A and B.

chargers, respectively. The results show that the use of spare chargers allows a significantly better use of available power and the benefits are larger for higher arrival rates. On the other hand, the Markov chain model shows that the adoption of 2 more spare sockets is enough to accommodate all the vehicles.

Blocking probability (P_{bl}) – Fig. 6 shows a noticeable difference in the blocking probability between the two scenarios. For example, taking m=3 chargers and $\lambda = 5\ vehicles/hour$, $P_{bl}(A) = 0.2822$ and $P_{bl}(B) = 0.2123$. The difference decreases for the maximum arrival rate. We can show that $P_{bl}(A) = 0.8850$ and $P_{bl}(B) = 0.8615$ for $\lambda = 50\ vehicles/hour$. Thus, again we conclude that the adoption of spare chargers contributes to reducing the blocking probability in Scenario B, which better uses the capacity of the station.

Power demand (P_d **(kW))** – This metric is of utmost importance in the design of the charging station. Such value will be matched with the number of available charging sockets, and it is mandatory to plan the physical space of the charging station. As discussed before, we assume a typical BEV (Battery Electric Vehicle). The number of charging sockets is simplified as the total power delivered to the EV charging station divided by the amount of power consumed in CC-mode. The use of spare sockets in Scenario B allows a more efficient utilization of power as compared to Scenario A, shown by the larger power consumption in Fig. 7. The difference is more apparent in the power delivered at $\lambda = 50\ vehicles/hour$ and $m =$ 8 chargers. The consumed powers are $P_d(A) = 291.56$ kW versus $P_d(B) = 371.21$ kW, for a difference of 79.75 kW.

Percentage of used power ($P_u(\%)$) – This metric indicates the fraction of the total available power actually used. We assume that the total available power in the station is equal to the number of chargers multiplied by the power consumed in CC-mode (Table II). We observe, in both scenarios, that the use of energy is more efficient in stations with less chargers, when the arrival rate is low. That behavior is explained by the Markov chain models. Low arrival rates cause the occupation of the first states of the Markov chain. For example, the total available power at a station with $m = 3$ chargers is lower than that of a station with $m = 4$, 5,..., 8 chargers. Yet, when $\lambda =$ 5 $vehicles/hour$, the probability that the 3 chargers station is serving 2 or 3 vehicles is higher than other states. In contrast, if the station has m =8 chargers and λ =5 $vehicles/hour$ (low arrival rate), the probability of low number of charging vehicles is greater than high number of vehicles. This results in less power consumed if compared with the total available power. Thus, the energy utilization is more efficient for smaller stations and low arrival rates. As the arrival rate increases ($\lambda \geq 30$), the use of power is approximately equalized for all sizes of charging stations. We can see that, in Scenario B, the use of energy is still improved by the use of spare sockets. In Scenario B, at most $P_u(B) = 90.65\%$ of the total available

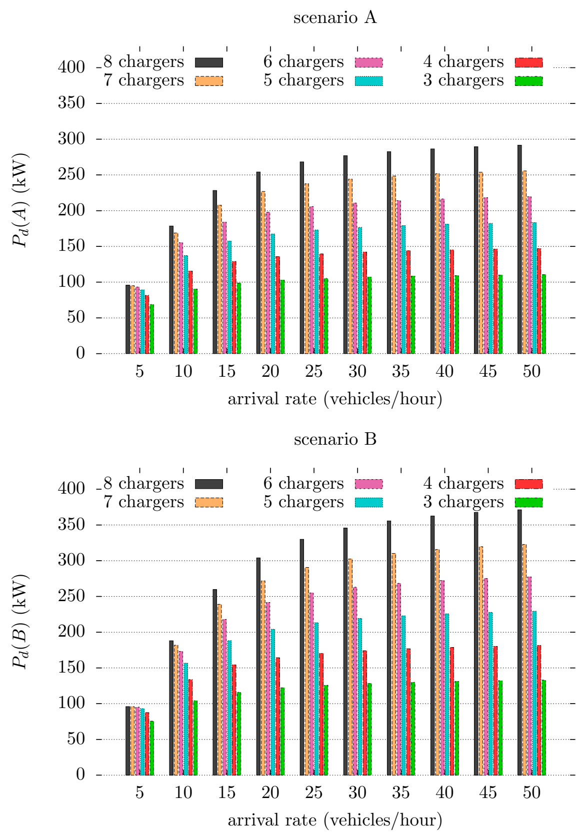

Fig. 7: Power demand (P_d) in Scenarios A and B.

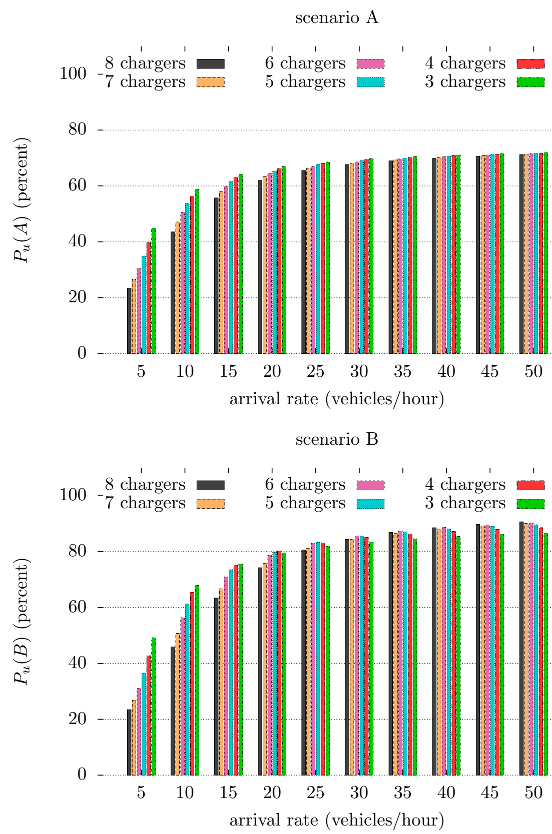

Fig. 8: Power utilization (P_u) in Scenarios A and B.

TABLE II: Total Available Power in the Charging Station.

Chargers (m)	**Power in CC-phase (kW)**	**Total Power (kW)**
3	51.2	153.6
4	51.2	204.8
5	51.2	256.0
6	51.2	307.2
7	51.2	364.7
8	51.2	409.6

TABLE III: Comparison between Scenarios A and B.

m	$N(A)$	$N(B)$	$P_d(A)$ (kW)	$P_d(B)$ (kW)	$P_{bl}(A)$	$P_{bl}(B)$	$P_u(A)$ %	$P_u(B)$ %
3	2.79	3.34	107.11	128.23	0.81	0.77	69.73	83.49
4	3.70	4.53	142.13	174.08	0.75	0.69	69.39	85.00
5	4.60	5.70	176.70	219.01	0.69	0.62	69.02	85.55
6	5.48	6.91	210.75	262.99	0.63	0.55	68.60	85.61
7	6.36	8.29	244.19	302.39	0.57	0.45	68.13	84.37
8	7.21	9.00	276.91	345.62	0.52	0.40	67.60	84.38

power is used versus $P_u(A) = 71.18\%$ in Scenario A (Fig. 8).

IV. Example Scenario: The City of Rio de Janeiro

In order to contextualize the proposed model, we apply it to a realistic future case, the city of Rio de Janeiro, Brazil. Rio de Janeiro is mobilized to achieve the target of 16% reduction of greenhouse gas emissions by 2016. Rio has recently deployed an experimental fleet of 15 Nissan Leaf taxis. To predict some values observed in the real world, we make some assumptions. There are currently around 1,200 gas stations throughout the city [8]. According to the department of motor vehicles of Rio de Janeiro State [9], the city of Rio has 2.75 million vehicles. A typical driver in Rio de Janeiro daily travels about 50 km in average. Given the autonomy of a typical BEV (e.g. the Nissan Leaf) is in the range of 160 km, a typical driver would need to refuel every 3 days in average. Assuming a number of charging stations similar to that of current gas stations and an electric fleet with the size of the current number of registered ICE vehicles, and assuming an uniform distribution of vehicle arrivals, we divide the number of vehicles by the number of supposed charging stations and again divide it by 72 hours. The result is an uniform $\lambda = 31.8$ $vehicles/hour$ arrival rate at the charging stations. Therefore, consider $\lambda = 30$ $vehicles/hour$. Using this arrival rate in the proposed models, the values of Table III can be drawn for the case of Rio de Janeiro. Moreover, a typical gas station in Rio has 8 fuel pumps. In the future, considering that the stations will occupy the physical spaces of the gas stations, the deployment of spare sockets will increase the number of clients from 7.21 to 9.00, decrease the blocking probability from 0.52 to 0.40, and provide a 16.78% better use of energy.

V. Related Work

The deployment of fast-charging stations leads to a high electric power demand. With the increasing number of EVs, if the fast charging process occurs in an uncontrolled manner, the smart grid infrastructure would risk collapsing. Lewandowski *et al.* [10] point out the need for a communications infrastructure and propose a simulation framework to model simultaneous charging processes of a large number of EVs. The exchange of messages between EVs, charging stations, and load coordinators are key points for balancing the load among a set of charging stations. According to Luo *et al.* [11], PEVs are expected to be widely adopted in the public transportation in China in the horizon 2016-2020. The authors report that the challenges to this wide adoption are mainly related to charging procedures. The specific charging characteristics of each class of vehicle influence not only the charging duration time, but also the period of day charging can occur. This issue is relevant to measure the impact on substations of different battery capacities and different charging power levels used on each kind of electric vehicle. The key challenge to predict the charging demand is to sum up the amount of charging load of each vehicle considering the uncertainties and stochastic behavior of each EV. The charging stations could be located on shopping centers, supermarkets, airports, but along the highways and even within the city, they have a structure similar to a gas station. The main difference lies in the fact that an additional electric energy supply must be assigned to the stations. Fast charging stations, specially, will consume a huge amount of electric energy. To infer the new electrical supply capacity, it is mandatory to assess the main operating parameters of these stations such as the number of charging sockets, the levels of charge, the time to achieve full charge, the parking capacity and so on. Farkas and Prikler [12] use a Markov chain to model the behavior of a fast charging station. They show that the variation of parameters such as the number of charging sockets, the parking capacity of the station, and the charging rate affect the queue waiting time. Bayram *et al.* [13] propose a 2D Markov chain to predict the behavior of a fast charging station that uses a local energy storage backup. When all of the charging sockets fed by the grid are busy, the vehicles are redirected to the sockets supplied by the local energy storage. The objective is to use local storage as a buffer, avoiding additional waiting when all sockets are busy.

In the present paper, we go one step further of the above-mentioned related work, by proposing a novel 2D Markov chain model that takes the characteristics of Li-ion batteries into account. We show that, by considering the charging profile of those batteries, and employing spare sockets in the charging station design, we can increase the number of EVs that can be served, using the same power originally available. To the best of our knowledge, no other work in the literature has used the specificities of the battery charging profile to predict the behavior of a charging station and to extract significant values to aid the design of the physical space and energy requirements.

VI. Summary and Outlook

This paper presented a new proposal to deal with the paradigm of new fleet of urban vehicles in big cities like Rio de Janeiro. This new and electrified type of transportation will represent a challenge to the operators of Electric System because it represents a new load, mainly at the peak hours. We shown that a 2-D Markov chain model can split the charging process of the electric vehicles in 2 phases, considering the Li-ion battery charging profile. Assuming that the total available power can be used if some spare sockets are available, we built Markov chain models for the two different scenarios. Using these models we evaluated variables of interest to the design of a charging station, such as the blocking probability and power demand, for different numbers of charging sockets and EV arrival rates. We have shown that the use of spare sockets results in more vehicles being admitted in the station and efficient use of idle power capacity. Finally, we used our model with realistic numbers, taking the city of Rio de Janeiro as example. In our future work, we will consider different classes of vehicles (buses and trucks, for example), with different battery capacities and energy requirements, which will produce heterogeneous service times.

Acknowledgments

This work was partially funded by CAPES, CNPq, FAPERJ, and FINEP/FUNTTEL Brazilian institutions.

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