A queuing theory decision support model and discrete event simulations for the smart charging of electric vehicles

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Abstract: Electric Vehicles (EVs) seem to represent a promising solution for the replacement of traditional internal combustion engines due to the growing concerns on the pollution in urban environments. However, their wide diffusion is expected to cause relevant issues for the operation of existing power grids. The proper management of EVs charging stations is considered as one of the most challenging questions, due to the high temporal and spatial stochasticity of power demands. The aim of the present work is to propose decision support models for the design of EV charging processes able to adequately satisfy EVs power demand, by assuring the quality of service level required by end-users, expressed in terms of queuing and service times. This study introduces two analytical models based on the queuing theory for the optimization of EVs charging process, by balancing the power demand at available charging stations, and by improving the quality of service perceived by the users. Two simulation models are then proposed to evaluate the service level offered to users in the current uncoordinated charging process, as well as in future smart charging processes. A real case concerning the charging process at the University of Brescia North Campus is presented.

Keywords: Electric vehicles; queuing theory; simulation; electrical demand management.

1. Introduction

The transportation sector is one of the main responsible for the consumption of fossil fuels and for the emission of Greenhouse Gases (GHGs). A recent report of the International Energy Agency (IEA) showed that transportation systems currently account for the 23% of global energy-related GHG emissions (IEA, 2017a), and also remarked that major restrictions are required to reach the stringent targets imposed by the Paris Agreement. In addition, recent studies reported that the worldwide diffusion of road vehicles is expected to grow in the next few years, by following the increase of urbanization and the effects of macroeconomics (McKinsey & Company, 2016). As a consequence, local governments and the research community are looking at alternative technologies for the replacement of fossil fuels as the primary energy source in transportation systems. The electrification of the transport sector and the transition to high efficiency technologies play a relevant role towards the decarbonization of the energy sector (IEA, 2017b). Electric Vehicles (EVs) are considered one of the best solutions for the replacement of road vehicles powered by conventional internal combustion engines, thanks to their independence from primary energy sources, and to the total absence of direct GHG and pollutant emissions. Specifically, recent studies demonstrated that battery EVs are the less carbon-intensive option if compared to other solutions, such as hybrid EVs (Onat, Kucukvar and Tatari, 2015). Moreover, it is expected that a large penetration of EVs can help to significantly reduce even indirect GHG emissions and air pollution in urban areas (Buekers *et al.*, 2014). In 2016, registrations of electric cars hit a new record, with over 750 thousand sales worldwide. Even though the sales of EVs showed a slowdown in the market growth rate compared with previous years (IEA, 2017a), these are expected to continuously increase of about 35% every year from 2017 to 2025 (IEA, 2017c). Nevertheless, existing power networks, charging infrastructure, and management systems are not yet ready for a large penetration of EVs (IEA, 2017a; Shareef et al., 2016). Several studies recently addressed this concern, by concurring that the large and uncontrolled penetration of EVs would cause relevant issues to the management and operation of distribution networks (Habib, Kamran and Rashid, 2015). The main expected adverse impacts include: voltage instability, increase of peak demand, power quality issues, increase of power losses, and degradation of grid equipment (Shareef, Islam and Mohamed, 2016). In addition, the high temporal and spatial stochasticity of the power demand of EVs strongly collides with the intermittency and uncertainty of Renewable Energy Sources (RESs), thus introducing additional limitations related to the optimal management of such resources. Recent works in the literature suggested that the proper use of stationary Energy Storage Systems (ESSs) supported by advanced demand-side management strategies could help to solve this issue (Pasetti, Rinaldi and Manerba, 2018). However, whilst a noteworthy focus has been recently given to the implementation of stationary EESs, their economic feasibility is still rather uncertain. Examples can be found in (Marchi, Zanoni and Pasetti, 2016), which addressed the economic feasibility of the application of li-ion batteries in support of distributed photovoltaic power systems, in (Marchi *et al.*, 2017), which investigated how the reform of the electricity tariffs could affect the diffusion of ESSs, and (Marchi, Pasetti and Zanoni, 2017), which presented a life cycle cost model taking into account all the most relevant cost components during the entire operation of the system. To overcome these drawbacks, the adoption of proper EV charging management strategies (usually referred to "smart charging") should be investigated. Rinaldi *et al.* (2018) defines the objective of unidirectional and bidirectional smart charging consisting of the determination and implementation of the temporal and spatial operational schedules for, respectively, the power supply of EVs, and the management of power flows among EVs and the power grid. In the unidirectional smart charging mode, a supervisor (who may be the distribution system operator or an independent operator) controls the time of activation of the charging process, and the maximum power supply deciding, thus, the overall duration of the charging process. Similarly, in the bidirectional smart charging mode the process is controlled by a supervisor, who is also allowed to decide whenever the EV batteries must be charged or discharged. They also discussed the communication requirements for the demand-side management of EVs in urban environments, by focusing on the mobile communication among EVs and smart grids. The management and optimization of EVs charging times is considered one of the most interesting area of research for the overcoming of queueing issues in public supply stations. In this context, the application of the queuing theory already proved to be an effective instrument for the solution of this kind of problems. Queues occur if there is an imbalance between the demand and the availability of resources. The queuing theory is the branch of operational research that explores the relationships between the demand for a service system and the delays suffered by users of that system. It provides mathematical models for the analysis of waiting lines, and allows the formulation of decision support systems for the minimization of service imbalances (Winston and Goldberg, 2004). Several works in the current literature investigated the use of queuing theory models for the optimization of EVs charging processes. Baek et al. (2011), proposed a queuing model with an infinite population with random interruptions for the charging system during on-peak periods. Bae and Kwasinski (2012) presented a spatial and temporal model of electric vehicle charging demand for a rapid charging station located near a highway exit still considering an infinite population. Gusrialdi et al. (2017) addressed both the system-level scheduling problem and the individual EVs decisions about their choice of charging locations, while requiring only distributed information about EVs and their charging at service stations along a highway. Zhang *et al.* (2016) introduced a variation in the queuing model for EV charging process considering a finite population. Also Said et al. (2013) proposed a queuing model with a finite population introducing the assumption that vehicles can communicate in advance with the grid to convey information about their charging status. Li and Zhang (2012) developed a similar model for multiple plug-in hybrid EVs at an EV charging station and in a local residential community. Aveklouris et al. (2017) considered a stylized equilibrium queueing model that takes into account both congestion in the distribution grid, as well as congestion in the number of available spaces in a parking lot with charging stations. The EVs have a random parking time and a random energy demand. Finally, Tan, Sun and Tsang (2014) developed a mixed queueing network model with an open queue of EVs and a closed queue of batteries.

The aim of the present study is to present a decision support model for the design of the EV charging process satisfying the power demand of EVs, the users' requirements and the perceived quality of service in terms of the queuing and service times. Two analytical models based on the queuing theory (i.e., considering an infinite and a finite population) and two discrete event simulations for the optimization of the charging process of EVs are presented. Both the analytical models and the simulations take a variable arrival rate into consideration, which, to the best knowledge of the authors, has not yet been considered in literature. In addition, the service level offered to users in the current uncoordinated charging process, as well as in future scenarios based on smart charging processes is evaluated by considering the number of charging stations as the main decision parameter. Specifically, the models proposed are defined in Table 1.

Table 1: Models proposed in the study.

Model	Approach	Arrivals	Population
M/M/s//∞	Analytical	f(timing)	∞
M/M/s//N	Analytical	f(frequency)	N
Uncoordinated	Simulation	f(timing)	∞
Smart	Simulation	f(timing)	∞

The remainder of the article is organized as follows: Section 2 defines the analytical models based on the queuing theory; while Section 3 proposes the discrete event simulations. In Section 4, a case study of the engineering campus of the University of Brescia is presented. Finally, Section 5 summarizes the main findings of the study, and provides suggestions for future research.

2. Analytical queuing models

In this section, two M/M/s//Z analytic models based on the queuing theory are presented. The first letter defines the arrivals rate (i.e., M specifies exponential arrivals), the second the service rate (i.e., M specifies exponential services), the third the number of servers (i.e., s stands for a multi-server queue), and the last the size of the population. The first model proposed in subsection 2.1 is a queuing model with an infinite population, while the second, formulated in subsection 2.2, considers a finite population of N EVs. The main assumption made for both the models are:

- The EVs waiting at the first free station are in the same queue, and the policy that regulates the queue is a first-in-first-out (FIFO) policy;
- The EVs arrival times and the service times are assumed to be independent;
- The EV arrival process is assumed to be defined through a Poisson distribution with an arrival rate λ;
- A multi-servers queue is considered with *s* identical servers (i.e. the charging stations), operating at an exponential service rate μ;
- The overall charging time is given by the waiting time and the service time, since we assume that all the stations are in the same area and so the time to reach them is not differential;
- The service time is assumed to be constant and so independent of the State of Charge (SoC) of the EV battery and of the timing at which the EV arrives;
- Once the EVs are in the system, they do not leave until they are served.

The system can be defined by a state which identifies the number of EVs currently in the system. When an EV arrives, or is sufficiently charged and departs leaving the system, a state transition occurs. Figure 1 shows the schematic view of the system considered in this work for the EV charging process characterized by *s* servers.

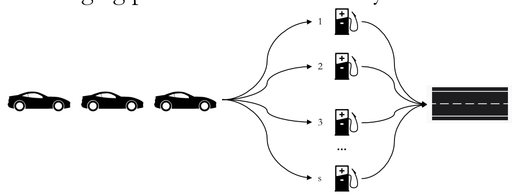

Figure 1: Schematic view of the EV charging process for *s* charging stations.

2.1. Queuing model with an infinite population (M/M/s//∞)

The frequency of the arrivals and of the services depend on the system's state, *i*, which represents the number of EVs present in the system. Theses frequencies are defined in Eq.s (1) and (2) respectively. Since the population (i.e., the number of EVs that might access the system) in this model is infinite, the arrival frequency is equal to the arrival rate, λ, at every state. While the service frequency is given by the lower value between the number of EVs in the system, *i*, and the number of the servers, *s*, multiplied to the service rate, μ.

$$\lambda_i = \lambda \; \forall i \tag{1}$$

$$\mu_i = \begin{cases} 0 & i = 0 \\ i\mu & 1 \le i \le s \\ s\mu & i \ge s \end{cases} \tag{2}$$

Based on the arrivals and services frequency formulations, it is possible to obtain the state transition diagram (Figure 2), which shows the transitions probabilities to switch from a state to another one. Winston and Goldberg (2004) demonstrated how the transition probabilities defined in Eq. (3) are obtained.

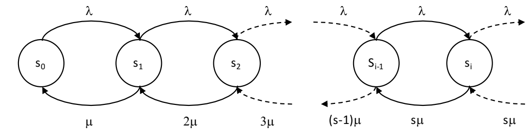

Figure 2: State transition diagram for the queuing model with an infinite population (M/M/s//∞).

$$p_i = \begin{cases} \dfrac{\lambda^i}{s!\, s^{i-s} \mu^i} p_0 & i > s \\ \dfrac{\lambda^i}{i!\, \mu^i} p_0 & 0 \le i \le s \end{cases} \tag{3}$$

Since the sum of the system probabilities to be in the different states should be equal to 1, it is possible to obtain the value of p_0, Eq. (4), which is required to obtain the individual probabilities.

$$p_0 = \left[\sum_{i=0}^{s-1} \frac{1}{i!} \left(\frac{\lambda}{\mu}\right)^i + \frac{1}{s!} \left(\frac{\lambda}{\mu}\right)^s \frac{s\mu}{s\mu - \lambda} \right]^{-1} \tag{4}$$

To evaluate the system's performance, several indices exist and two of the most relevant are the average number of EVs in queue defined in Eq. (5), L_q, and the average waiting time in the system defined in Eq. (6), W_q.

$$L_q = \frac{\left(\frac{\lambda}{\mu}\right)^s \lambda\mu}{(s-1)!\,(s\mu - \lambda)^2} p_0 \tag{5}$$

$$W_q = \frac{L_q}{\lambda} = \frac{\left(\frac{\lambda}{\mu}\right)^s \mu}{(s-1)!\,(s\mu - \lambda)^2} p_0 \tag{6}$$

2.2. Queuing model with a finite population (M/M/s//N)

Even in this model, the frequencies of the arrivals and of the services depend on the state, *i*, at which the system is and are defined in Eq.s (7) and (8) respectively. In this case, the arrival frequency is not equal to the arrival rate at every state since it is function of the number of EVs already in the system. While the service frequency is the same of the previous model.

$$\lambda_i = \begin{cases} (N - i)\lambda & 0 \le i < N \\ 0 & i \ge N \end{cases} \tag{7}$$

$$\mu_i = \begin{cases} 0 & i = 0 \\ i\mu & 1 \le i \le s \\ s\mu & i \ge s \end{cases} \tag{8}$$

The state transition diagram for the model with a finite population is depicted in Figure 3.

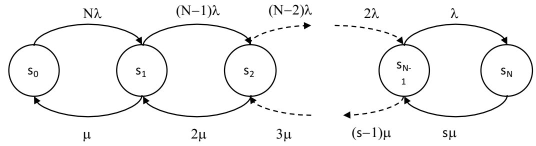

Figure 3: State transition diagram for the queuing model with a finite population (M/M/s//N).

Eq. (9) proposes the transitions probabilities; while, Eq. (10) defines the probability to be in the state in which no EVs are present in the system Winston and Goldberg (2004).

$$p_{i+1} = \begin{cases} \frac{(N-i)\lambda}{(i+1)\mu} p_i & 0 \le i < s \\ \frac{(N-i)\lambda}{s\mu} p_i & s \le i \le N \end{cases} \tag{9}$$

$$p_0 = \left[\sum_{i=0}^{s} \frac{N!}{i!\,(N-i)!} \left(\frac{\lambda}{\mu}\right)^i + \sum_{i=s+1}^{N} \frac{i!}{s!\,s^{i-s}} \frac{N!}{i!\,(N-i)!} \left(\frac{\lambda}{\mu}\right)^i \right]^{-1} \tag{10}$$

The main performance indices for the model with a finite population, i.e. the average number of EVs in queue, L_q, and the average waiting time in the system, W_q, are defined in Eq.s (11) and (12) respectively.

$$L_q = L - s + \sum_{i=0}^{s-1} (s-i) p_i \tag{11}$$

$$W_q = \frac{L_q}{\lambda(N-L)} \tag{12}$$

where

$$L = \sum_{i=0}^{N} i p_i. \tag{13}$$

3. Discrete event simulations model

Analytical models based on the queuing theory present huge limits due to the strict assumptions required. Two discrete event simulations are then proposed to simulate more realistic scenarios since they can relax the assumptions and allow to overcome the limitation of the models proposed in Section 2. Specifically, the main improvements introduced are that the arrival rate can be different accordingly to the hour of the day, the service time is not the same for every EVs since the necessities of charge can differs in accordance to the battery SoC when the EV enter the system and to the different required level of charge, and the vehicles can leave the system if they are not served after a certain time. In the first simulation, it is considered an uncoordinated charging which characterizes the currently used process, i.e. when the EV is connected to a charging station, the grid immediately provides the maximum allowed power depending on the requirements and on the physical constraints of the EV battery charger. In the second simulation, a smart charging process is considered in which the communication among the users and the grid is bidirectional. In this case, the process is controlled by a supervisor, and the EVs can interact with the supervisor communicating their actual level of SoC, the time at which the users want to leave, and the desired final amount of charge. The grid supervisor can let the users know which is the best charging station and plug-in present in the area. At the same time, once the battery reach the required amount of charge, the supervisor communicates to the user when he should remove the EV from the system in order to accelerate the charging process of other EVs. The simulations have been performed with the software AnyLogic 8.2.3.

4. Case study

4.1 System definition and input data

In this section, the models previously defined are applied to a real case concerning the charging process of the stations installed at the University of Brescia North Campus. Currently, six identical charging stations are installed, i.e. the number of server, s, is 6. For the analytical models, the service time is assumed to be exponentially distributed with a service rate of one hour (μ = 1 EV/hour). The equal service time for the different charging stations and EVs is due to the assumption required by the queuing theory for which the server should be identical. This assumption is relaxed in the simulations in which the service rate μ is modelled with a triangular distribution of parameters (1; 3.5; 8 hour). In particular, 1 hour refers to the user that stay at the university only for a short period or to the ones that disconnect the EV from the station as soon as the battery is completely charged; 8 hours refers to that users disconnecting the EV only at the end of the day; while 3.5 hours is the average duration of a university lecture and thus refers to the users that disconnect the EV as the lecture ends. Three arrival rates, λ, were assumed in the models depending on the frequency of the arrivals (i.e., high, medium, and low). In the model with an infinite population, the day is divided into three time slots to which correspond a different inflow of EVs. The first slot refers to the time-period from the beginning to the end of the morning lecturers (i.e., from 8 am to 12 am) hence a high arrival rate is considered: i.e., 5 EVs per hour. The second slot refers to the early afternoon (i.e., from 12 am to 3 pm) with a lower arrival rate, since a part of the users are already at the University from the morning: i.e., 4 EVs per hour. The last slot is in the late afternoon (from 3 pm to 7 pm) in which a small number of user enter the system: i.e., 1 EV per hour. In the model with a finite population, the scenario with a high frequency considers that the N electric vehicles require a charge every day; the scenario with a medium frequency a charge every two days, and finally the one with a low frequency a charge every three days. The simulations were iterated over a time interval of one year, beginning in February 2018 and ending in February 2019. This choice is mainly due to two reasons: to reach a stationary condition of incoming EVs, which only takes place a few days after the start of the simulation, and to define a common interval for all the tested models for the comparison of the obtained results.

4.2 Results of the analytical queuing models

The analytical models defined in Section 2.1 and 2.2 were applied to the three time slots in order to assess the performance of the charging process. The results of the model with an infinite population (M/M/s//∞) are shown in Table 2. The average number of EVs in queue, the average time they should wait, and the service level (*SL*) presents noteworthy differences between the time slots. The service level was defined as the ratio of the service time over the overall time spent in the system (i.e., service time plus waiting time).

Table 2: Results of the M/M/s//∞ model for different time slots.

M/M/s//∞		Slot 1 (high freq.)	Slot 2 (medium freq.)	Slot 3 (low freq.)
L_q	EV/h	2.94	0.57	0.0001
W_q	min	35.25	8.54	0.007
SL	-	62.99 %	87.54 %	99.99 %

Figure 4 shows the probabilities of occurrence of state *i* for each time slot considered, where *i* represents the number of EVs in the system for that specific time slot. For instance, in the morning (time slot 1), there is a probability of about the 12% to have exactly 5 EVs in the system. The graph shows also that the time slot of the morning is the one in which a higher number of EVs is more probable. Moreover, the probability to have a queue generated when the number of EVs in the system is higher than the number of the charging stations, is of about the 50 %, 30 % and < 1% in time slot 1, 2, and 3 respectively.

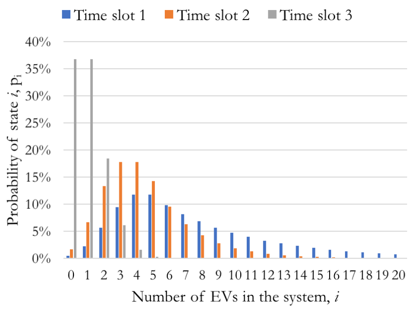

Figure 4: Transition probabilities for each time slot considered.

Increasing the number of charging stations (servers) it is possible to reduce the waiting time and thus to improve the performance of the charging process. In Table 3, the optimal number of station that maximize *SL* is reported for every time slot.

Table 3: Service level values (*SL*) obtainable with increased number of charging stations for the different time slots.

s	Slot 1	Slot 2	Slot 3
6	62.99 %	87.54 %	99.99 %
7	86.05%	95.69%	**100.00%**
8	94.72%	98.55%	100.00%
9	98.03%	99.53%	100.00%
10	99.28%	99.85%	100.00%
11	99.75%	99.96%	100.00%
12	99.92%	99.99%	100.00%
13	99.97%	**100.00%**	100.00%
14	99.99%	100.00%	100.00%
15	**100.00%**	100.00%	100.00%

In the model with a finite population, we considered twenty EVs, since it represents a good estimation of the current number of EVs regularly in the area. The average number of EVs in the system and in queue (L and L_q respectively), the average waiting time (W_q), and the service level (*SL*) are shown in Table 4. The probabilities of occurrence of the admissible states for the three arrivals frequencies are depicted in Figure 5. The service level of the current charging process is near to 100 % even for the case in which a high arrivals frequency is considered, and the number of charging stations already installed (i.e., six) covers almost all the transition probabilities.

Table 4: Results of the M/M/s//N model with 20 EVs for different arrivals frequencies.

M/M/s//N		High freq.	Medium freq.	Low freq.
L	EV/h	2.23	1.18	0.80
L_q	EV/h	0.007	0.0001	0.00001
W_q	min	0.20	0.007	0.0008
SL	-	99.67 %	99.99 %	100 %

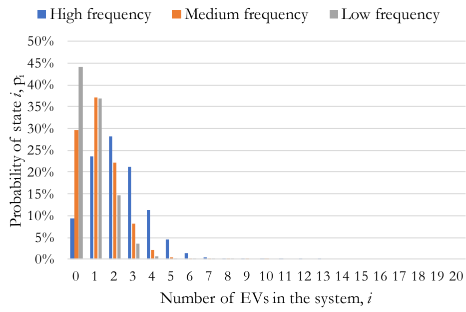

Figure 5: Transition probabilities for each arrivals frequency considered.

The good performance in the M/M/s//20 model is due to the low number of EVs currently in circulation. Figure 6 shows an analysis of the service level (*SL*) as a function of the number of EVs in the area, since this parameter is expected to considerably vary in the near future. In the high arrivals frequency scenario, the service level falls down with a little increase of the number of vehicles. Hence, an improved integration and communication among the EVs and the grid, or additional charging stations are required so as to guarantee the desired service level.

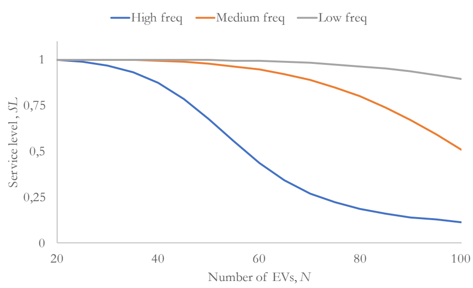

Figure 6: Service level offered by of the charging process for the model M/M/s//N as a function of the number of EVs visiting the area considered (*N*) for each arrivals frequency considered.

4.3 Results of the simulations

In the uncoordinated charging process (first simulation), the number of users effectively served represents only a small share of the total number of the EVs entering the system. This is due to the high percentage of users leaving the system before being served since their waiting time is too high, (i.e., over 10 minutes). For the same reason, the resulting average number of EVs in queue is very low (~ 0.014 hours). Moreover, the average time in the system, W, and in service, W_s, are 4.179, and 4.165 hours respectively. The probability distribution of time in the system is presented in Figure 7. The service time in this simultaion is much higher than the one in the analytical models (i.e., one hour) because of the uncoordinated charging process. Since the stations do not communicate to the user when the service ended, the timing is considerably lengthened and new users can't enter the system, as it is still occupied.

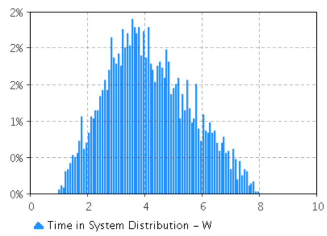

Figure 7: Probability distributions of the time in the system W for the uncoordinated charging process.

In the second simulation, an integrated and bidirectional communication is considered which allows to highly improve the performance. In this case, the possibility for the users to leave the system after a predetermined period is not considered, since the simulation lead anyway to good level of service. Indeed, the average values of L_q, W, W_q, and W_s, are 0.52 vehicles per hour, 0.713 h, 0.229 h, and 0.484 h respectively. The probability distribution of the time spent in the system is presented in Figure 8.

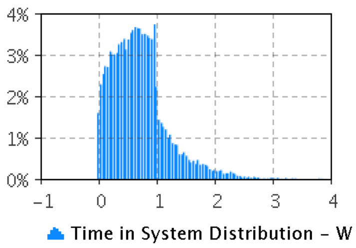

Figure 8: Probability distributions of the time in the system W for the simulation with integrated and bidirectional communication.

In Figure 9, the comparison on the service level (i.e. the number of users satisfied over the overall users entered in the system) reached through the uncoordinated and the smart charging processes is shown as a function of the number or charging stations. Specifically, the number of charging stations currently installed at the campus allows the process to reach a service level of about 63% in the first simulation; while in the second of about the 98%. In order to reach at least a service level of 90% also in the uncoordinated charging process, a huge investment should be made in upgrading the infrastructure, since eleven stations are required.

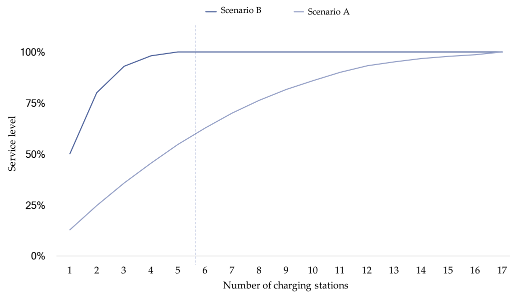

Figure 9: Service level for different number of charging stations installed, based on the current inflow of electric vehicles.

According to the estimations presented in the Global EV Outlook of 2017 by the International Energy Agency (IEA) (IEA, 2017a; IEA, 2017c), it is reasonable to suppose a 35% increase of the number of EVs present in the market, from 2017 to 2025. Figure 10 shows the service levels as a function of the number of charging stations installed based on the future shares of EVs. The trend depicted in Table 5 shows how from 2020 the current number of charging stations will not be sufficient even for the smart charging process.

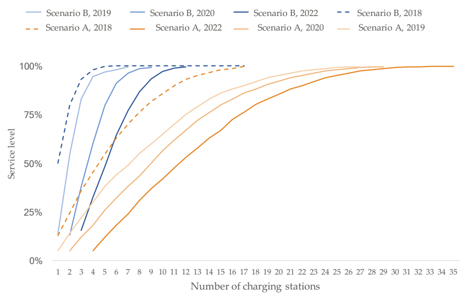

Figure 10: Service level for different number of charging stations installed, based on the future inflow of EVs.

Table 5: Service level for the current number of charging stations based on the future trend in the EV market.

Simulation	2019	2020	2022
1st	44%	32%	18%
2nd	98%	91%	63%

5. Conclusions and future researches

In this study, two analytical models based on the queuing theory (i.e., with an infinite and with a finite population) and two discrete event simulations are presented for evaluating the service level offered to the users by the charging process under analysis. In addition, they allow to assess which improvements are required to increase the users' experience. Results from the models highlight that if the number of EVs in the area will be characterized by a huge growth, as it is expected, additional charging station are needed. However, since the current EVs habitually visiting the campus area are limited, the waiting time are almost zero even if a high arrivals frequency is considered. The main finding from the simulations is that the smart charging process, characterized by a strong coordination among users and grid, and a bidirectional communication, performs better that the uncoordinated charging process and represents a great opportunity since it allows to reach high service level (above the 95%) even with a low number of charging stations. The smart charging process allows the current infrastructures to be sufficient also in the next years: in fact, additional charging stations are required after 2020. Two main research streams can be identified in the possible further development of this study. Specifically, the first aims to improve the analytical models based on the queuing theory considering the opportunity for users to leave the system if the waiting time is too long. However, the queuing model is too limited to detect all the peculiarities of EVs and of the communication and integration among users and the grid. For this, the focus of the second streams should be shifted to the simulative models through which it is possible to better evaluate the performance of the charging process. Other relevant aspects that should be analyzed are the evaluation of the best time interval in which the EV should be charged, and the integration of renewable energy sources and energy storage systems with the charging stations (Yao, Damiran and Lim, 2017), while ensuring grid stability and operation efficiency.

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References

Aveklouris, A., Nakahira, Y., Vlasiou, M. and Zwart, B. (2017) 'Electric vehicle charging: a queueing approach', *ACM SIGMETRICS Performance Evaluation Review*, 45(2), pp. 33–35.

Bae, S. and Kwasinski, A. (2012) 'Spatial and Temporal Model of Electric Vehicle Charging Demand', *IEEE Transactions on Smart Grid*, 3(1), pp. 394–403.

Baek, S. J., Kim, D., Oh, S.-J. and Jun, J.-A. (2011) 'A queuing model with random interruptions for electric vehicle charging systems', *IEEE International Conference on Consumer Electronics ICCE*, pp. 679–680.

Buekers, J., Van Holderbeke, M., Bierkens, J. and Int Panis, L. (2014) 'Health and environmental benefits related to electric vehicle introduction in EU countries', *Transportation Research Part D: Transport and Environment*. Elsevier Ltd, 33, pp. 26–38.

Gusrialdi, A., Qu, Z. and Simaan, M. A. (2017) 'Scheduling and Cooperative Control for Charging of Electric Vehicles' at Highway Service Stations', *IEEE Transactions on Intelligent Transportation Systems*, 18(10), pp. 2713–2727.

Habib, S., Kamran, M. and Rashid, U. (2015) 'Impact analysis of vehicle-to-grid technology and charging strategies of electric vehicles on distribution networks - A review', *Journal of Power Sources*. Elsevier B.V, 277, pp. 205–214.

IEA (2017a) Global EV Outlook 2017: Two million and counting, *IEA Publications*.

IEA (2017b) 'Energy Technology Perspectives 2017: Catalysing Energy Technology Transformations', *IEA Publications*.

IEA (2017c) Tracking Progress: Electric Vehicles. Available at: https://www.iea.org/etp/tracking2017/electricvehicles/ (Accessed: 3 April 2018).

Li, G. and Zhang, X.-P. (2012) 'Modeling of plug-in hybrid electric vehicle charging demand in probabilistic power flow calculations', *IEEE Transactions on Smart Grid*, 3(1), pp. 492–499.

Marchi, B., Pasetti, M. and Zanoni, S. (2017) 'Life cycle cost analysis for BESS optimal sizing', *Energy Procedia*, 113(C), pp. 127–134.

Marchi, B., Pasetti, M., Zanoni, S. and Zavanella, L. E. (2017) 'The Italian reform of electricity tariffs for non household customers: the impact on distributed generation and energy storage', *Proceedings of the Summer School Francesco Turco*, 2017-September, pp. 103-109.

Marchi, B., Zanoni, S. and Pasetti, M. (2016) 'A techno-economic analysis of Li-ion battery energy storage systems in support of PV distributed generation', in *Proceedings of the Summer School Francesco Turco*, 13-15-September-2016, pp. 145-149.

McKinsey & Company (2016) Automotive Revolution - Perspective Towards 2030, Advanced Industries.

Onat, N. C., Kucukvar, M. and Tatari, O. (2015) 'Conventional, hybrid, plug-in hybrid or electric vehicles? State-based comparative carbon and energy footprint analysis in the United States', *Applied Energy*. Elsevier Ltd, 150, pp. 36–49.

Pasetti, M., Rinaldi, S., Manerba, D. (2018) 'A Virtual Power Plant Architecture for the Demand-Side Management of Smart Prosumer', *Applied Sciences*, 8 (3).

Rinaldi, S., Pasetti, M., Sisinni, E., Bonafini, F., Ferrari, P., Rizzi, M. and Flammini, A. (2018) 'On the Mobile Communication Requirements for the Demand-Side Management of Electric Vehicles', *Energies*, 11(5).

Said, D., Cherkaoui, S. and Khoukhi, L. (2013) 'Queuing model for EVs charging at public supply stations', 2013 *9th International Wireless Communications and Mobile Computing Conference*, IWCMC 2013, pp. 65–70.

Shareef, H., Islam, M. M. and Mohamed, A. (2016) 'A review of the stage-of-the-art charging technologies, placement methodologies, and impacts of electric vehicles', *Renewable and Sustainable Energy Reviews*. Elsevier, 64, pp. 403–420.

Tan, X., Sun, B. and Tsang, D. H. K. (2014) 'Queueing network models for electric vehicle charging station with battery swapping', *IEEE International Conference on Smart Grid Communications*, pp. 1–6.

Winston, W. L. and Goldberg, J. B. (2004) *Operations and Research: Applications and Algorithms*. 4th edn. Edited by Thomson/Brooks/Cole. Belmont, CA.

Yao, L., Damiran, Z. and Lim, W. H. (2017) 'Optimal charging and discharging scheduling for electric vehicles in a parking station with photovoltaic system and energy storage system', *Energies*, 10(4).

Zhang, K., Mao, Y., Leng, S., Zhang, Y., Gjessing, S. and Tsang, D. H. K. (2016) 'Platoon-based electric vehicles charging with renewable energy supply: A queuing analytical model', *IEEE International Conference on Communications*, ICC 2016.