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Article

Probabilistic Agent-Based Model of Electric Vehicle Charging Demand to Analyse the Impact on Distribution Networks

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Abstract: Electric Vehicles (EVs) have seen significant growth in sales recently and it is not clear how power systems will support the charging of a great number of vehicles. This paper proposes a methodology which allows the aggregated EV charging demand to be determined. The methodology applied to obtain the model is based on an agent-based approach to calculate the EV charging demand in a certain area. This model simulates each EV driver to consider its EV model characteristics, mobility needs, and charging processes required to reach its destination. This methodology also permits to consider social and economic variables. Furthermore, the model is stochastic, in order to consider the random pattern of some variables. The model is applied to Barcelona's (Spain) mobility pattern and uses the 37-node IEEE test feeder adapted to common distribution grid characteristics from Barcelona. The corresponding grid impact is analyzed in terms of voltage drop and four charging strategies are compared. The case study indicates that the variability in scenarios without control is relevant, but not in scenarios with control. Moreover, the voltages do not reach the minimum voltage allowed, but the MV/LV substations could exceed their capacities. Finally, it is determined that all EVs can charge during the valley without any negative effect on the distribution grid. In conclusion, it is determined that the methodology presented allows the EV charging demand to be calculated, considering different variables, to obtain better accuracy in the results.

Keywords: electric vehicles charging; agent-based modelling and simulation; distribution network; coordinated charging; load flow analysis; stochastic modelling

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1. Introduction

Electric vehicles (EVs) are presented as an alternative to current internal combustion vehicles powered by fossil fuels. Increasing oil prices, greenhouse gas emissions and environmental concerns of citizens boost interest in this technology. Energy supply from power networks is required and the impact on the distribution grids in a massive EV integration scenario has to be analyzed in detail [1]. Thus, studies about EV impact on power networks are needed to ensure the viability of the systems [2–4].

The EV charging demand model should allow the analysis of possible effects of this new demand supplied in present-day power networks.

In order to do so, an EV charging model should include specific characteristics for each case, such as mobility, and it should allow one to compare different cases. Moreover, it should consider probability distribution functions (PDF) to analyze the uncertainties of possible EV charges. In addition, this model should be designed to analyze the application of control strategies and enable their comparison.

Literature proposes models to calculate the demand with respect to vehicle, charging infrastructure, mobility, and social parameters. [5–9] use different parameters such as EV model, distance, and charging process among others to determine the EV charging demand.

1.1. EV Type

From the point of view of EV charging demand, EVs main characteristics are the vehicle type: Plug-in Hybrid Electric Vehicle (PHEV) or Battery Electric Vehicle (BEV), battery capacity, battery technology, EV range and energy consumption. Amjad *et al.* [10] expose an analysis about EV design considerations. Different authors only consider PHEV [2,3,5,11–15]. Others only BEV [16–20] or a combination of both [9,21–23]. Another option is to suppose average EV models, BEV and PHEV, with average characteristics like different authors do [5,6,18]. Pang *et al.* [24] simulate only two representative EV models: Chevy Volt (PHEV) and Nissan Leaf (BEV) and Valsera *et al.* [17] simulate Mitsubishi i-MiEV (BEV) only.

Soares *et al.* [9] proposed a stochastic model with mobility variables, but the vehicle characteristics are determined by a Gaussian distribution with standard values for the capacity, energy consumption and charging power of EVs.

The majority of papers simplify the EV model selection, but the capacity and the energy consumption are significant variables to be considered. The model presented proposes using real EV models and their technical data to define the battery capacity and energy consumption of each EV model. Moreover, the probability of each EV model is based on sales forecasting [25] to decide which EV model is more probable.

1.2. Battery and Charging Process

Regarding EV batteries, there are three variables linked: capacity (kWh), range (km) and energy consumption (kWh/km). [19,26] consider the battery characteristics of real models and [15,20,27,28] consider average battery characteristics. Moreover, it is important to take into account the relation between the power consumed and the State-of-Charge (SoC). Valsera *et al.* [17] determine a relation between EV model, battery characteristics (Li-ion, 50 Ah, 16 kWh and 330 V) and its charging process.

The charging process standards of IEC 61851 [29] from Europe and SAE J1772 [30] from the USA could also change the impact in the power system. Maitra *et al.* [22] compare the impact of each SAE standard. The voltage level in Europe for slow charges is 230 V and a maximum current of 16 or 20 A. In Belgium, houses have a protection up to 20 A [31] and in Spain, the common protection is up to 16 A [17]. Valsera *et al.* use the power ratio of Mitsubishi i-MiEV when the initial SoC is 20% and the EV needs 4 h to reach 100%. Zhang *et al.* [32] use level 1 (120 V–15 or 20 A) in the studio located in the United States. To compare, Grenier *et al.* [33] use 230 V and 15 A and the study is located in New Zealand. The efficiency used in the studies is around 90%, as Collins *et al.* proposed [34] in 1983 and this assumption was recently confirmed by Shuang *et al.* [12] and Clement *et al.* [2,35].

Different authors, such as Clement *et al.* [2] and Guo *et al.* [36], use constant power profiles. On the other hand, Maitra *et al.* [22] consider variable power during the charging profiles. Qian *et al.* [37] propose a charging process model which links the power of the charger and SoC. Gao *et al.* [38] link the SoC and the charging time. Different authors use the specific EV charging profile of a real EV. For example, Qian *et al.* [37] and Lojowska *et al.* [39] use the charging profile of the Nissan Altra EV with a battery of 29 kWh, while Multin *et al.* [40] use a three-phase charging profile of Opel Meriva, which has a battery of 16 kWh.

1.3. Charging Infrastructure

Charging infrastructure parameters include the EV charging point's socket and availability to charge. The majority of works do not consider the EV infrastructure when calculating the EV charging demand. Inherent to this hypothesis is to neglect the effect of the queues at charging points by supposing there are enough charging stations, and the assumption of full compatibility between charging stations and EV connectors. Both could be reasonable in future scenarios with massive presence of EV, but could be a problem for fast chargers. García-Valle *et al.* [41] introduce the queue theory with exponential distribution function to simulate EV charging time and relate it to the maximum charging power of the EV.

1.4. Mobility

Mobility is the third key point of EV charging demand. There is a strong link between energy consumption of EV and urban mobility. For example, Keirstead *et al.* [42] reviewed the energy consumption in urban areas, including electric mobility.

Some authors employ the NHTS (National Household Travel Survey) to analyse the United States, such as [21,32,36,43–45]. In the United Kingdom, studies use NTS (National Travel Survey) and UKTUS (United Kingdom Time Use Survey), for instance [3,46,47]. In Germany, there is the MID (*Mobilität in Deutschland*) which Schroeder *et al.* [48] and Loise [20] apply. The MON (*Mobiliteitsonderzoek Nederland*) is utilised by Dutch studies, as Lojowska *et al.* [39]. The DTU *Transport, DTU. Transportvaneundersøgelsen* is used by Jull *et al.* [49] for a case study of Denmark. In the case of Spain, there are different databases, for example *Dades Bàsiques de Mobilitat 2008* for Barcelona city [17] and *MOVILIA* for the whole Spain [50].

Metz [27] makes use of the Deutsches Mobilitätspanel to simulate 1000 mobility of household profiles and this includes day and time of departure and arrival, travel distance, vehicle used, and destination. Loise [20] makes projections of EV hourly charging profiles based on MID 2008.

The present work proposes that the reason of displacement be included to determine the destination and the instant of the day to displace. Due to that, it is possible to distinguish between professional and personal mobility.

1.5. Social

There are social variables related to the EV driver profile that could influence EV charging demand as GDP. Kelly *et al.* [43] analyze the EV charging demand considering the income, age and gender of drivers as well as the location (urban or rural). Sikai *et al.* [46] use the number of members of each household and the corresponding number of vehicles based on the UKTUS database. Valsera *et al.* [8] define the number of displacements, the number of houses, and the number of vehicles per house. The proposal of the present work is to combine these three approaches of the previous work to consider social aspects to calculate the EV charging demand.

1.6. Simulation Techniques

To define the characteristics of simulations, there are different details set out by each author. The first one is the data processing, after that the emulation of parameters and lastly, the driver behavior emulation.

Considering data processing, there are different types of simulation models to emulate the EV charging demand and the most used is agent-based. This type of model considers each EV driver autonomously defining the internal (e.g., energy consumption) and external (e.g., power demand to supply EV battery) variables. The bottom-up approach simulates the system coupling all the agents of the system. Different examples of agent-based and bottom-up approach studies are [44,51,52]. On the other hand, the bottom-down approach simulates the EV driver behavior with the average parameters [17,22].

As concerns the emulation of parameters, some models use deterministic variables and others stochastic ones. The deterministic approach considers just average values of parameters and stochastic models use probability distribution functions. The Monte Carlo technique is used to simulate stochastic variables in many applications and it is also used in modeling load, EV charging demand and distributed generation to determine their variability. The majority of studies set out a deterministic approach, but some of them include stochastic variables such as [3,17,20,36,39,46,47]. Some of them use Monte Carlo techniques to simulate the total demand.

EV driver behavior also influences the EV charging demand. This parameter is linked to time of day and location for EV charging, such as public stations between trips, at charging points at work or just home charging.

Venkatesan *et al.* [53] define user profiles related to estimated behavior in the function of mobility, current electricity price and price forecasting. Waraich *et al.* [51] use microsimulation techniques to emulate the driver behavior. Galus and Waraich [54,55] use MATSim (Multi-Agent Transport Simulation) and this tool allows the creation of more than a million connections between agents in transport issues. Balmer [56] uses evolutionary algorithms; Hedegaard *et al.* [57] propose using the Balmorel program to include distribution network, district heating, optimization, taxes and geographical data.

[58] proposes including the game theory to simulate the interaction between agents and including sale of electricity with V2G service. Smith *et al.* [59] use GPS data and EV metering to calculate the energy consumption and later to optimize the battery sizing of future PHEV.

The present work proposes combining some characteristics presented in literature. The methodology presented is a bottom-up approach to process the data with stochastic variables following the Monte Carlo formulation to emulate the parameters. And the driver behavior is defined in function of the range anxiety, the mobility needs and the energy price.

1.7. Power System Impact

Possible effects on power networks caused by EVs are related to power quality or grid saturation. The majority of studies analyze the voltage drop or transformer load, like Valsera *et al.* [8,17]. Clement *et al.* [2] include Joule losses and Maitra *et al.* [22] include overloading and unbalances. Kleiwegt *et al.* [60] propose a methodology to detect overloads in the course of a year. Moreover, vehicle-to-grid possibility is analyzed in many studies such as [26,61,62]. Another possible impact on the power system is economic and this is reviewed by Dallinger *et al.* [63]. The present work analyses the distribution network in terms of the HV/MV and MV/LV transformer capacities and the voltage of each node.

1.8. Contribution

The state-of-the-art analysis defined seven subjects to be determined in the EV charging demand problem formulation:

- EV type and model: the majority of current models simplifies this aspect with one model or an averaged model to represent a group of models.
- Battery and the corresponding charging process: according to the literature review, the main difference found in literature is the charging process. The most common simplification is to

consider a constant power but the appropriate way is to consider the relation between the SoC and the power consumed.

- Power infrastructure: the majority of articles consider the AC slow charging and the current limit depends in function on the country analyzed.
- Mobility: the papers which consider it try to use the public data according to the country analysed.
- Social: the majority of the papers do not consider any economic or social variables.
- Simulation technique: the majority of papers take a bottom-down deterministic approach.analyzed
- How to analyze the impact on the power system: the majority of EV charging models avoid this issue and some of them try to optimize the EV charges to reduce some negative consequences.

The objective of this paper is to define a methodology based on agents to determine EV charging demand. The main contribution of this paper is to propose a methodology based on open data and combining social, technical and economic variables to calculate the EV charging demand and then determine the effects on the distribution networks. To do so, the parameters in literature were used separately; however, this paper proposes that all of them be combined in a single model in order to obtain more precise and realistic results. Figure 1 shows the relation among the variables that are implemented in the present model. For example, EV agents have a set of constant parameters as EV model (technical), place of residence (social), GDP (economic) and others, as well as variable parameters of mobility such as distance, day of the week and others.

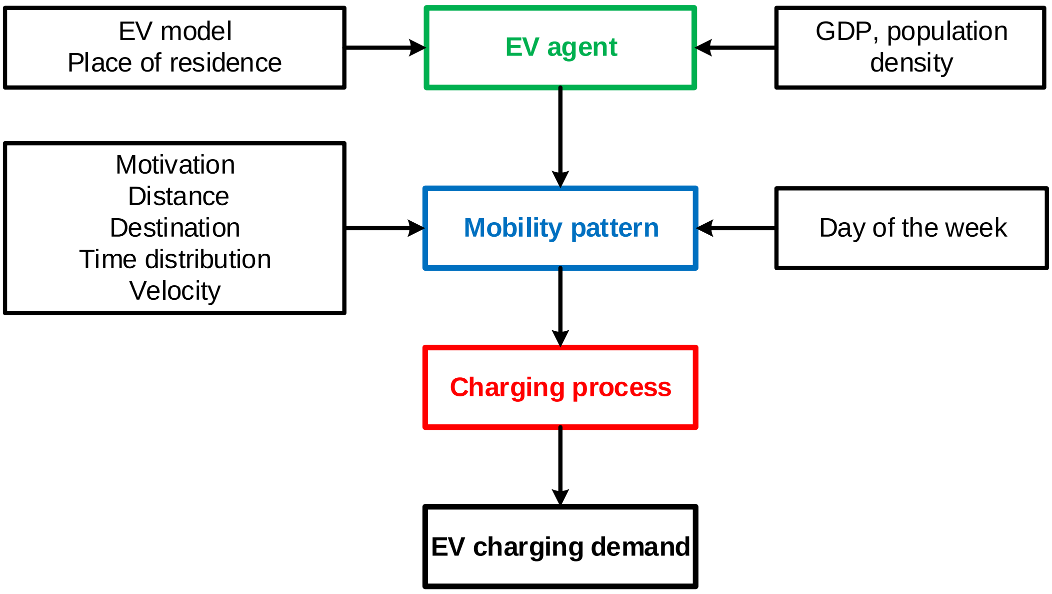


Figure 1. Basic scheme of EV charging demand parameters.

Finally, the result of this methodology leads to the charging process model for each EV agent, the total EV charging demand and consequently, it allows the impact on power networks to be analyzed. The methodology proposed uses all sources from public data and it is applied using statistics from the city of Barcelona.

The EV charging demand model is defined as the electric demand from EVs during a certain time period, such as a day or week, to supply their batteries. EV charging demand depends on EV user driving needs and it is linked to EV characteristics and mobility of users.

The methodology proposed in this paper is the Agent-Based Modeling and Simulation (ABMS). The main strengths and applications of ABMS are listed as follows:

- Heterogeneous individual components: EV model and mobility pattern of each EV owner.
- Flexible systems: to manage the charging demand of each EV.
- Influence of location: to consider the effects of the charging point location in the power network.
- Representation of social interactions: different types of EV owners could have different influences on the total system.

For these reasons, this methodology has been used for obtaining EV mobility patterns with an heuristic approach [64]. Furthermore, this methodology enables to simulate complex systems; for instance, load demand in power systems [7] or virtual power plants to include different types of agents [65]. Thus, agent-based modeling has been selected for this research.

In this work, the EVs are a set of agents that has been defined as autonomous entities with their attributes and their processes are dynamic and time-dependent [66,67]. It allows defining each EV driver as an agent considering the usage of each vehicle. Each agent is simulated individually including possible interactions through the relationships between agents. Section 2 describes the characteristics of the agent-based model to obtain the charging demand from EVs and their impact on the distribution network.

2. EV Charging Demand Model

According to the Figure 1, the parameters needed to model the EV charging demand can be clustered in three groups: the EV agent (Section 2.1), mobility pattern (Section 2.2) and the charging process (Section 2.3). All these parameters permit the determination of all charging processes needed to reach each destination.

2.1. EV Agent

In the model developed, every EV agent represents an EV driver and its vehicle. The EV agent attributes are the EV model, the mobility needs, and the charging preferences. The EV agent behaviors are the trips taken (mobility), their corresponding energy consumption from their battery, the energy consumed from the electricity network to charge the battery, and the charging decision. For instance, when EV agents reach their destination, their charging process begin depending on the EV agent preferences and the energy price. The EV agent states with their corresponding variables are: waiting, driving, and charging.

Moreover, there are two other agents that influence on EV agents behavior: the Electricity Retailer Agent, who determines the electricity price for each instant, and the EV Aggregator Agent, who control the EV charges to reduce the electricity price. In the scenarios A, B and C, explained in the Section 3, there is no EV aggregator and the price is determined by the Electricity Retailer Agent. In contrast, in the scenario D, also explained in Section 3, the price is determined by the EV Aggregator Agent and the Electricity Retailer Agent does not influence on EV agents.

The main rule is that each EV agent, after each trip, takes the decision of charging in function of the battery state-of-charge, the electricity price and, in scenario D, the signal from the EV aggregator.

Moreover, before changing the state of an EV agent from waiting to driving state, it is necessary that the battery has enough energy to reach the destination. The EV agents structure, their relationships with other agents and their environment are shown in Figure 2. Note that there are two environments related to the EV agents: spatial distribution and electricity network. Furthermore, the electricity market is the environment of Electricity Retailer Agent and EV Aggregator Agent.

When the simulation begins, the system computes the EV agent mobility needs and the battery state-of-charge variation.

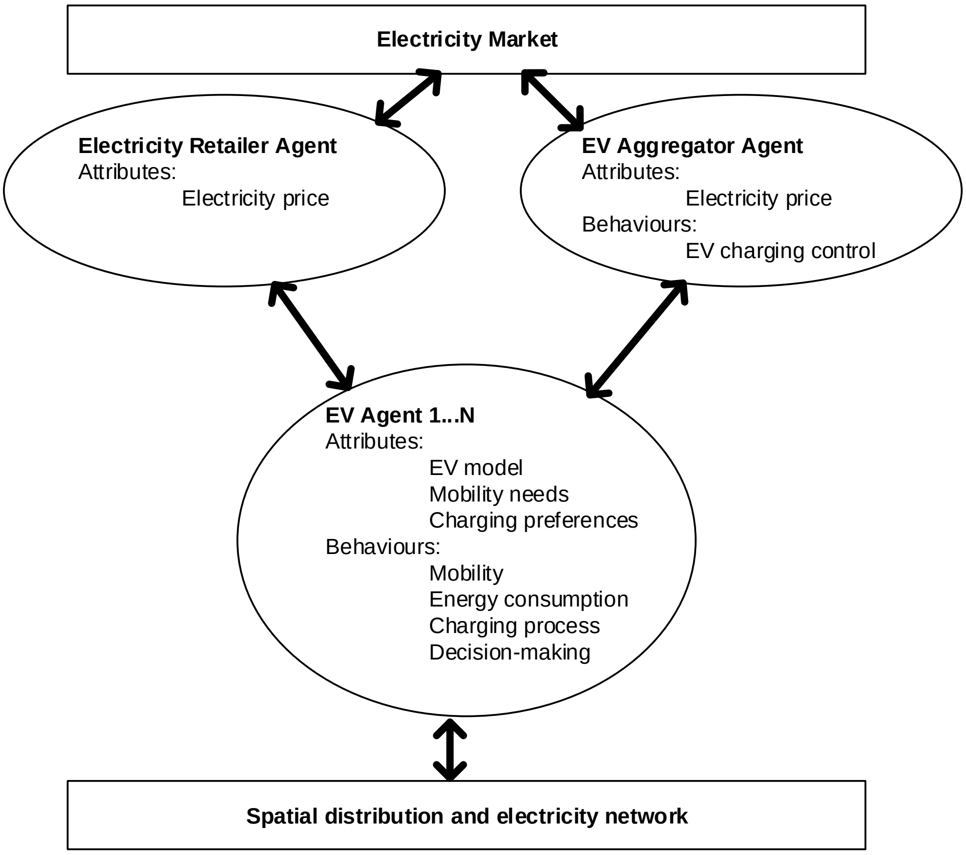


Figure 2. EV agent structure

The first step to define the EV agents is the definition of EV agent groups (C_i) and their variables. For each group, it is necessary to define the number of agents (N), spatial distribution of influence and charging preferences. And the EV model of each agent is defined with variables EC_i, Aut_i, Cap_i, Ps_i and $Type_i$. The place of residence, defined in R_i, is considered for each agent, and this depends on the power network scenario and is modeled as a constant probability, based on public data such as [68]. R_i is linked with the charging point in home usage.

The PDF of each EV model is based on [25] data and it just considers passenger vehicles and $Type_i$. This data was filtered for the case study in relation to EV model characteristics and technical data available from automakers. It is shown in Figure 3.

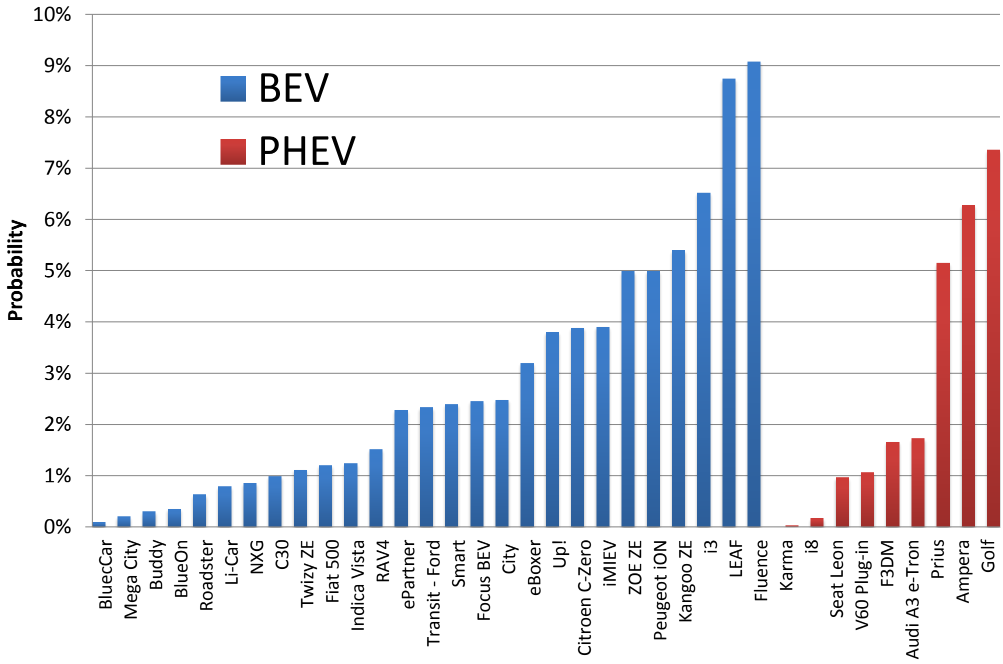


Figure 3. EV model probability distribution function EV_i. Based on [25] and adapted to Barcelona-Spain and automakers data.

In this model it is assumed that the PHEV drive is fully electric until the end of the energy stored in the battery, when they consume gasoline as hybrid electric vehicles. Other assumptions are exhibited in Section 2.4.

2.2. Mobility Pattern

Mobility variables are assigned to each EV agent in order to model its mobility behaviour. Different mobility patterns are based on open data sources. The variables considered to define a mobility pattern are defined as follows:

- **Trips per day** (S_i). The total trips are determined using a probabilistic variable which is generated through a Poisson distribution function, which is defined as [69] proposes with Poisson parameter (λ) of Equation (1).

$$P(k, \lambda) = (e^{-\lambda}\lambda^k)/k! \tag{1}$$

  This parameter is based on the average statistic value. It should ensure at least two trips per day and is defined by Equation (2).

$$S_i = 2 + \lambda \tag{2}$$

  In the present study analyzed, $\bar{S}_i = 3.53$ trips/day are based on [70].
- **Distance** (L_i) and **Distance per trip** (l_{ij}). They are calculated using the exponential distribution function from public reports. Figure 4 shows cumulative exponential distribution functions of distance traveled per day from different countries and the relation between L_i and l_{ij} is shown the following equation:

$$L_i = \sum_{j=1}^{S_i} l_{ij} \tag{3}$$

In the case study analyzed, $\bar{L}_i = 83$ km/day is based on [71]. If $l_{ij} > 10$ km, the trip j is considered as metropolitan considering Barcelona characteristics.

- **Destination** (D_{ij}). The model considers the reason of displacement to determine the destination. The reasons considered for the case study are based on the destination of each trip: for personal issues and for commuting. It is strongly linked to grid node, where the EV is connected in relation to social data and mobility pattern. The destination is modeled with a constant PDF according to the power network topology.
- **Day of the week** (d_i) and **Time distribution** (m_{ij}). These parameters allow knowing when an EV consumes energy as a function of the EV user's motivation to travel on a specific day. It is implemented in a PDF, as shown in Figure 5 and Table 1 as an example applied in the case study.
- **Velocity** (v_{ij}). According to mobility data, velocity is modelled as a constant value, depending if the trip is urban or metropolitan. The average velocity from [70] and $v^{urban} = 22.2$ km/h and $v^{metrop} = 59.3$ km/h are applied.
- **Initial/Final time** (t_0, t_1). The relation between them is the average velocity (v_{ij}) and distance (l_{ij}). Each pair of time variables is grouped in the matrix Y_i, which stores the mobility data of an EV agent.

$$Y_i = \begin{bmatrix} t_0^1 & t_1^1 \\ \vdots & \vdots \\ t_0^{S_i} & t_1^{S_i} \end{bmatrix}$$

- **Social variables**. Regarding the case study, it is necessary to take into account different variables such as Gross Domestic Product (GDP) and population density to determine the total number of agents (N) that could charge the EV at the same connection point. C_i definition was described in Section 2.1 and applied in Section 3.1.

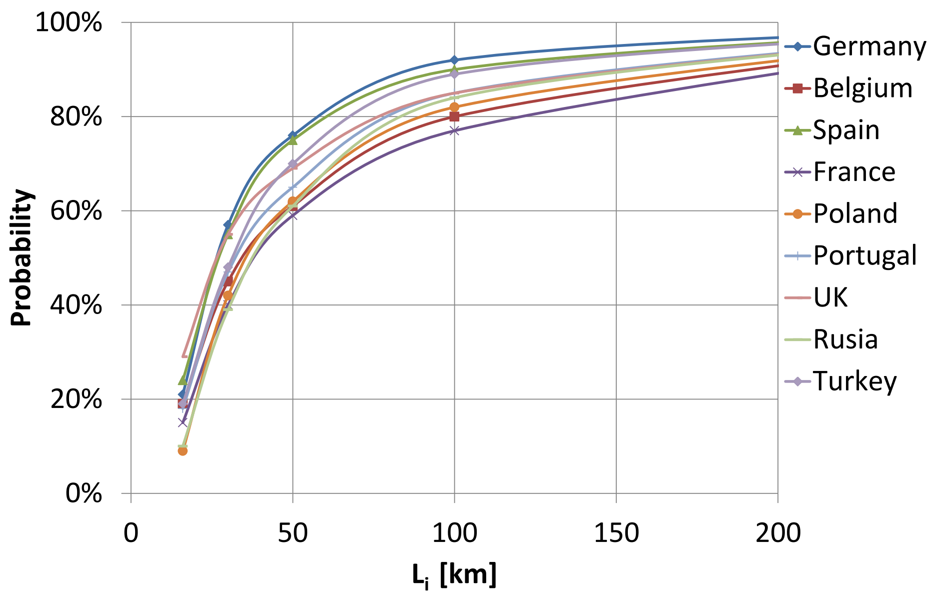


Figure 4. Probability distribution function of Distance L_i [71].

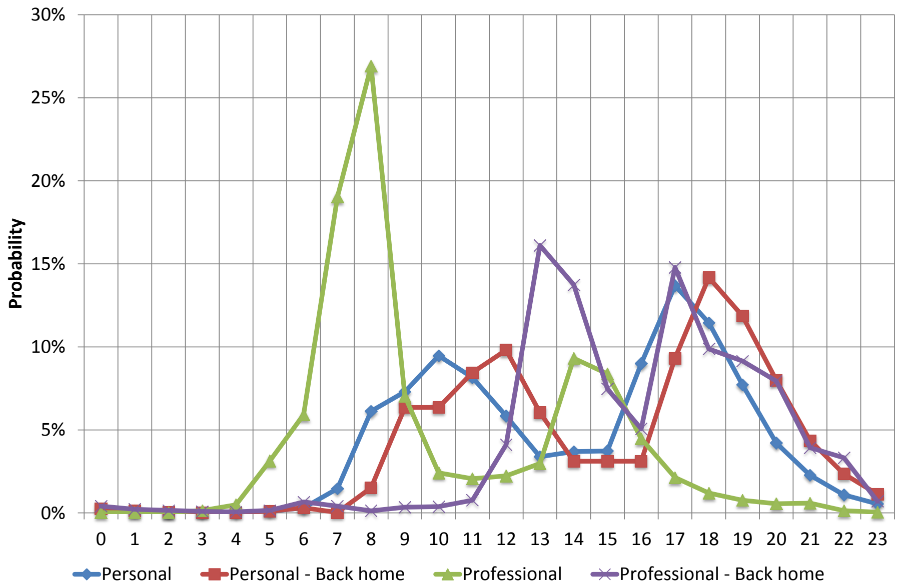


Figure 5. Probability distribution function of Time distribution m_{ij} [71].

Table 1. Time distribution considered in case study.

m_{ij}	**Description**
1	Personal
2	Personal—Back home
3	Professional
4	Professional—Back home

2.3. Charging Process

The charging process considered is slow charging—AC single-phase, depending on EV model, battery capacity, SoC, Energy required to arrive to next destination and time between displacements.

All the EV models are supposed to have Li-ion batteries and the slow charging process corresponds to a typical charging curve with two periods: constant period I and descendant period II [72]. The power rate Ps_i considered for charging is 3.7 kW (230 V, 16 A) because it is commonly available in residential and commercial areas in Europe [73] and it is also used by Marra *et al.* [72]. The charging process depends on initial SoC and energy required (E_{req}) in the process. Figure 6 shows the charging process of a battery with Cap_i and E_{req} of 16.5 kWh.

In this model, it is assumed that period I requires 50% of time for a full charge and period II finishes when the power output reaches 8% of Ps_i.

- Total energy (Battery capacity) is: $Cap = E_I + E_{II}$.
- μ and k are the exponential function parameters used in Equation (6).
- Total process efficiency considered is 90% [2].

The equations of EV charging process described before are:

- Period I is described by the following equations:

$$P_I(t) = Ps_i \tag{4}$$

$$E_I(t) = \int_0^a Ps_i dt \quad (5)$$

- Period II is described by the following equations:

$$P_{II}(t) = ke^{-\mu t} \quad (6)$$

$$E_{II}(t) = \int_a^b ke^{-\mu t} dt \quad (7)$$

where:

$$\mu = \frac{-ln(0.08)}{a} \quad (8)$$

$$k = \frac{Ps_i}{0.08} \quad (9)$$

$$c = 0.08 Ps_i \quad (10)$$

The initial SoC depends on the EV agent consumption. In the first simulation, the battery starts fully charged.

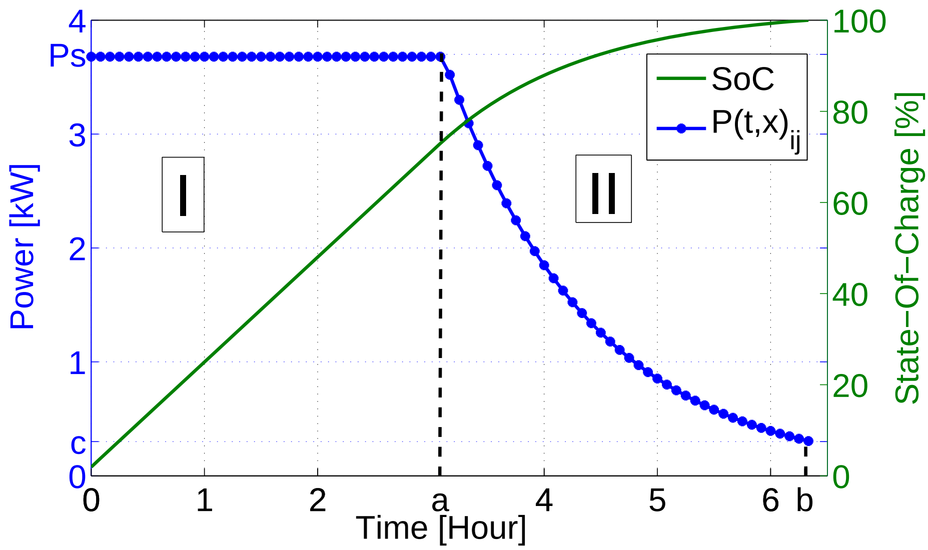


Figure 6. Slow charging profile—General scheme in relation to battery capacity. Based on [72].

2.4. Monte Carlo Simulation

Based on Figure 2, this paper proposes using the algorithm shown in Figure 7 to calculate the EV charging demand in a certain power network. This algorithm is based on Monte Carlo Methodology to include stochastic variables per agent and they are: R_i, S_i, L_i, l_{ij}, D_i, t_0, t_1 and EV_i. For this reason, it is necessary to define the number of iterations (T). Furthermore, to start the algorithm, it is necessary to define the number of agents (N) that charge the EV in the network analyzed. The time step used is 5 min.

The algorithm is used to define the EV agent group, the mobility variables and then the charging process for each EV agent.

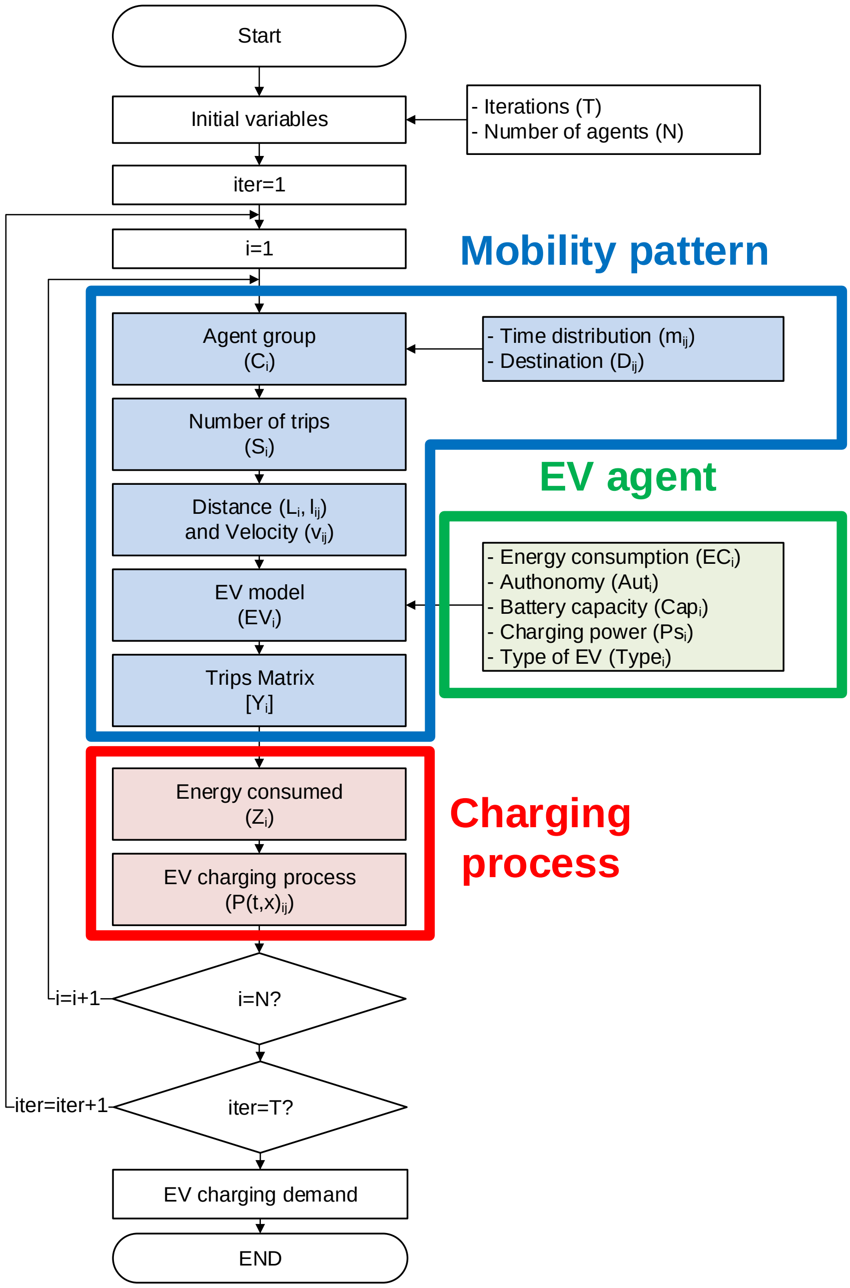


Figure 7. EV charging demand algorithm based on Monte Carlo.

3. Case Study

The proposed EV charging demand model is applied in a case study with a 37-node IEEE test feeder adapted to a typical distribution network and mobility data of Barcelona (Spain) [70]. The modeling of the case study was implemented in MATLAB and the power flow is solved by means of the Newton-Raphson method.

Four charging scenarios (A-D) were defined to model EV agent behavior, which are described in the following sections. The results are the energy (Z_i) and charging demand from EVs ($P(t, x)$) and the voltage profile in the distribution network.

3.1. Distribution Network

This case study is an adapted MV network 37-node IEEE test feeder, which is seen in Figure 8, and it applies Barcelona's mobility data. This network is adapted to a typical 25 kV MV network of Barcelona and the number of houses connected at the same MV/LV transformer [8]. In order to do that, it is necessary to consider social variables such as population density and technical regulation [74]. The maximum voltage drop permitted by the distribution system operator is 10% according to the EN 50160.

The total number of agents of group C_i is defined in relation to network topology and population density of different neighborhoods. According to social data from Barcelona and network branches, there are three zones: high, medium and low inhabitants per house and vehicles per inhabitant density. The farthest branch is linked with the high density zone. In this way, D_{ij} of group C_1 at the end of the day is the corresponding network node. In Barcelona, 38% of vehicles are driven each day and this percentage is used to determine active vehicles [70].

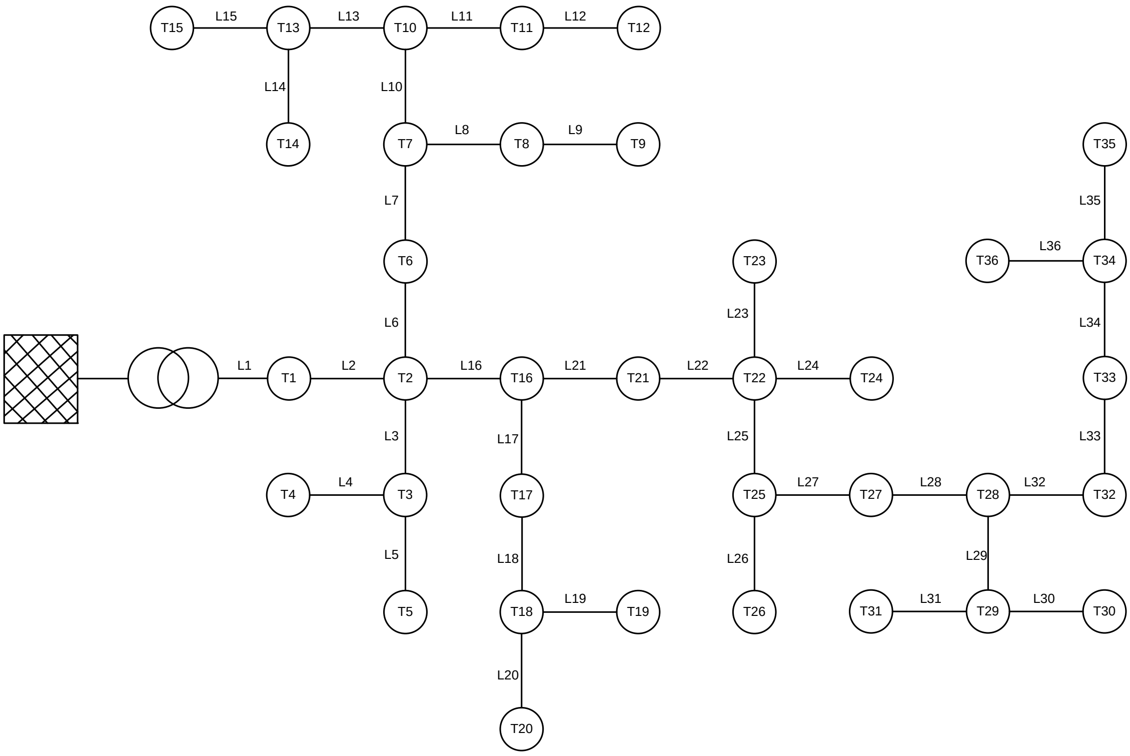


Figure 8. MV network - IEEE Test-feeder 37 node.

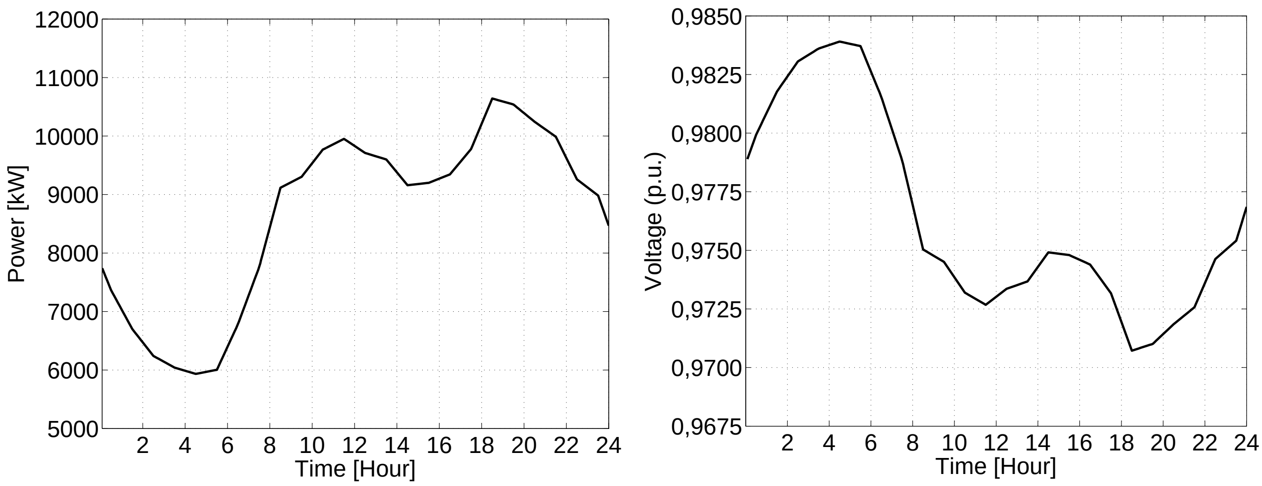
Table 2 shows calculations to get N of group C1.

Table 2. Number of agents C_1.

Zone	Nodes	Inhab./Hou.	Veh./Inhab.	Inhab.	Active Veh.
High	22–36	2.61	0.50	5016	950
Medium	3–5, 6–15	2.52	0.47	2541	448
Low	1, 2, 16–21	2.34	0.38	3288	471
				Total C1	**1870**

Load demand: Base load demand in this distribution network is based on system operator data [75] from national demand and it is adapted to network power capacity as 80% of HV/MV transformer power. Analyzing the consumption in Spain between 2007 and 2011, load demand used in the case study is from 17 December 2007, when the maximum energy demand reached 45,911 MWh between 18:00 and 19:00. This allows analyzing EV charging increase relative to this base load.

The load presented in Figure 9a is the base case, without EVs, of the distribution system analyzed. The peak demand is 10,640 kW and it occurs at 18:30. The load demand of the distribution system increases during the morning (8–10 o'clock), decreases during lunch time (13–16 o'clock) and increases during the evening (19–21 o'clock), when people come back home. The peak period is 79% higher than the valley period and the energy consumed during the course of a single day is 207.36 MWh. The voltage in the worst node is shown in Figure 9b; the minimum voltage is 0.9707 p.u. at 18:30 and the maximum is 0.9839 p.u. at 4:45. The voltage follows a similar behavior to the load demand. The lower limit of the voltage magnitude permitted by EN 50160 is 0.90 p.u.



(a) (b)

Figure 9. Residential and commercial demand without EVs. (**a**) Load demand; (**b**) Voltage drop.

3.2. Agent Profile

Six agent groups (C1–C6) were defined to consider mobility and residence. Mobility is divided between personal and professional reasons. According to the usual place where the EV is connected at the end of the day, three different areas of residence were defined: local, urban and metropolitan. Local area refers to the distribution network analyzed, urban refers to the city, and metropolitan is outside the city. Urban and metropolitan agents can plug in between displacements. On the other hand, local agents can charge at any time. Table 3 shows the main characteristics of each group. N is the number of EVs of each agent that charge their batteries in the case study network.

Each group has specific energy requirements for charging (E_{req}). Preferences are related to when to charge and they are described above relative to agent group definition. Regarding the E_{req} for each feasible charge between displacements, it is defined as the energy required to reach the next destination (D_{ij}) and distance (l_{ij}).

Mobility variables from Barcelona data [70] are implemented in the case study. S_i depends on agent group, d_i is the average weekday and L_i is according to [71].

Table 3. EV charging social characteristics in function of group.

C_i	m_{ij}	**Active Veh.**	**N**	**Area**	**Preferences**
C1	1 & 2	1870	561	Local	At-the-end
C2	1 & 2	449	135	Urban	Between disp.
C3	1 & 2	273	82	Metropolitan	Between disp.
C4	3 & 4	41	12	Local	At-the-end
C5	3 & 4	41	12	Urban	Between disp.
C6	3 & 4	10	3	Metropolitan	Between disp.
Total		2684	805		

3.3. Charging Scenarios

According to agent preferences, E_{req} and electricity market assumptions, four scenarios of EV charging demand are described, shown in Table 4.

Table 4. Table of charging scenarios.

Charging Scenario	**Description**	**Range Anxiety**
A—Intensive charge	As soon as possible	High
B—Plug-and-Play	Just at home	Medium
C—Tariff controlled	Off-peak tariff	Medium
D—Smart charging	With Aggregator	Low

Scenarios A and B consider constant electricity price for the whole day. In scenario A, EVs charge at the end of each trip due to the high range anxiety of EV agents. In scenario B, the EV agents have lower range anxiety and they charge the vehicle at home, when SoC is lower than 20% or lower than E_{req}. In scenario C it is considered that the EV agents have a Time-of-Use (TOU) tariff, special for EVs [76]. The cheapest period of this tariff begins at 1:00 am, based on the Spanish regulation [77], and then the EVs initiate the charge. The TOU tariff is an indirect control strategy to manage the EV charges. Scenario D considers one aggregator who manages all EV charges to consume the minimum power at the HV/MV transformer. This is based on an aggregator dedicated to reducing the impact in the transmission system, according to the Spanish regulation [77]. This scenario shows a direct control strategy to manage the EV charges and the aggregator offers lower electricity prices for EV agents.

3.4. Results

The following discussion presents the results of the four scenarios simulated. The analysis is focused on the EV demand, total demand and the voltage drop in the worst node. Due to the probabilistic design of the model, the results are variable and the plots show the variation between the maximum and minimum energy consumption. Furthermore, the plots also show the average consumption as the most probable value.

All scenarios are simulated considering that 30% of active vehicles are electric (N), based on maximum scenarios in [2,22,78]. EV_i PDF is based on [25]. What is also considered is that the EV agents with the value L_i greater than 100 km are only PHEV ($Type_i$).

The impact on power system is analyzed through voltage drop located in the farthest node, which is the 35. Figure 10 shows the minimum voltage per node during the whole day and the maximum voltage drop is located in node 35.

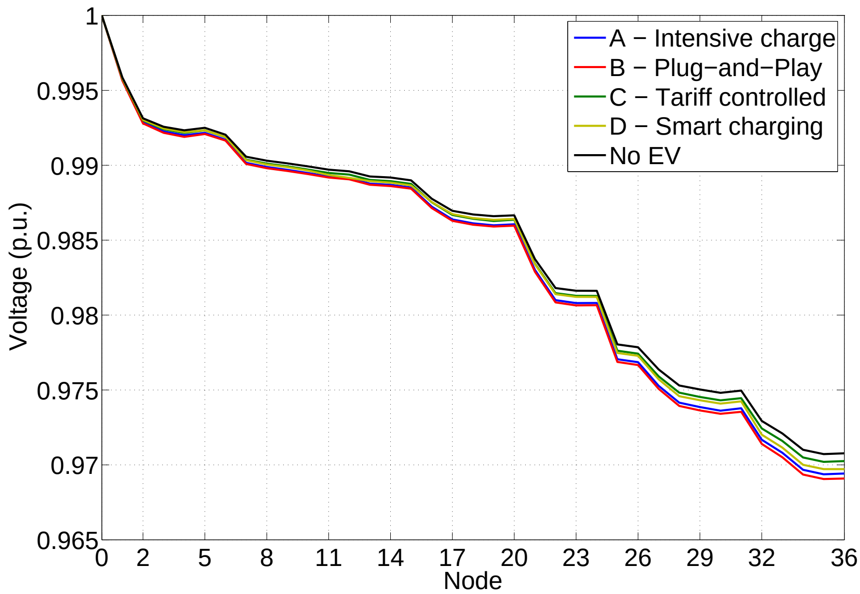


Figure 10. Voltage per node.

Iterations ($iter$)**.** The standard deviations (std. dev.) of power demand are evaluated to determine the number of iterations (T) to obtain valid results. To do that, a simulation with 1200 iterations in scenario A for C1 group and with 30% of EVs was carried out.

Figure 11 shows the std. dev. around hour 21 and it varies during the first 100 iterations significantly; it is nearly stable from iteration 200 and is constant from iteration 600. The ideal should be to do 600 iterations for all the cases, but the computing time to do it is very high and the volume of results to be stored requires a huge amount of memory. For these reasons, it is not possible to simulate 600 iterations for all the scenarios and the number of iterations has to be lower. The std. dev. varies around 10 kW from iteration 100 and from iteration 200, the results are more stable than previously. According to this, the number of iterations applied in the case study is 200. Other instances and scenarios are also checked and they comply with the std. dev. analysis. The consumption variation is also checked and it behaves similarly to the std. dev.

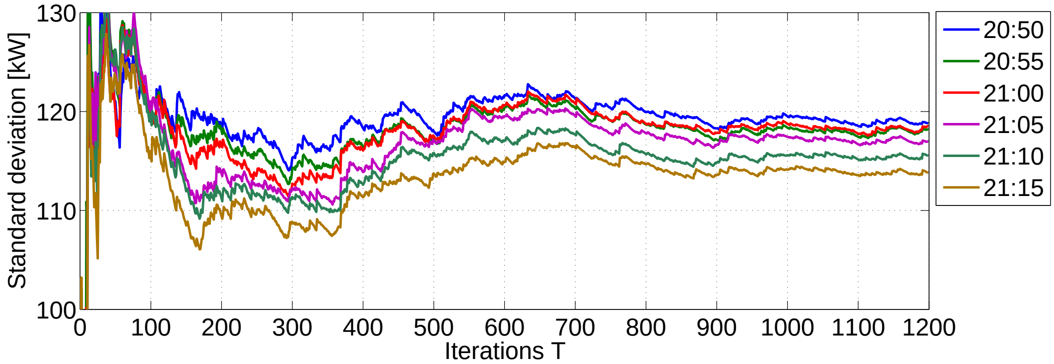


Figure 11. Standard deviation variation in function of iterations T.

3.4.1. A—Intensive Charge

EV charging demand: As is shown in Figure 12a, the EV charging demand presents two peaks with more consumption around 10:00 and 19:00. Both peaks are related to Barcelona's mobility pattern illustrated in Figure 5, which shows the same peaks: the peak during the morning is caused by professional mobility and the peak during the evening is caused by professional and personal back home reasons. The EV charging demand variability, the difference between the minimum and the maximum case, is significant in this scenario, and it can reach the 50% of the EV consumption as it occurs at 20:00.

The EV peak demand is near to 500 kW and the total peak demand is 11.04 MW, 3.75% higher than in the base case without EVs, as Figure 12b demonstrates. Furthermore, the peak during the morning is coupled with the residential and commercial demand. This is reflected in Figure 12b, where the active power increase is steeper from 6 to 12 hours due to the EV charging demand.

Impact on power system: Figure 12c shows that the minimum voltage in node 35 is 0.9694 p.u. and it is 0.13% lower than in the No EV case, which is higher than the lower limit of the standard of 0.9 p.u.

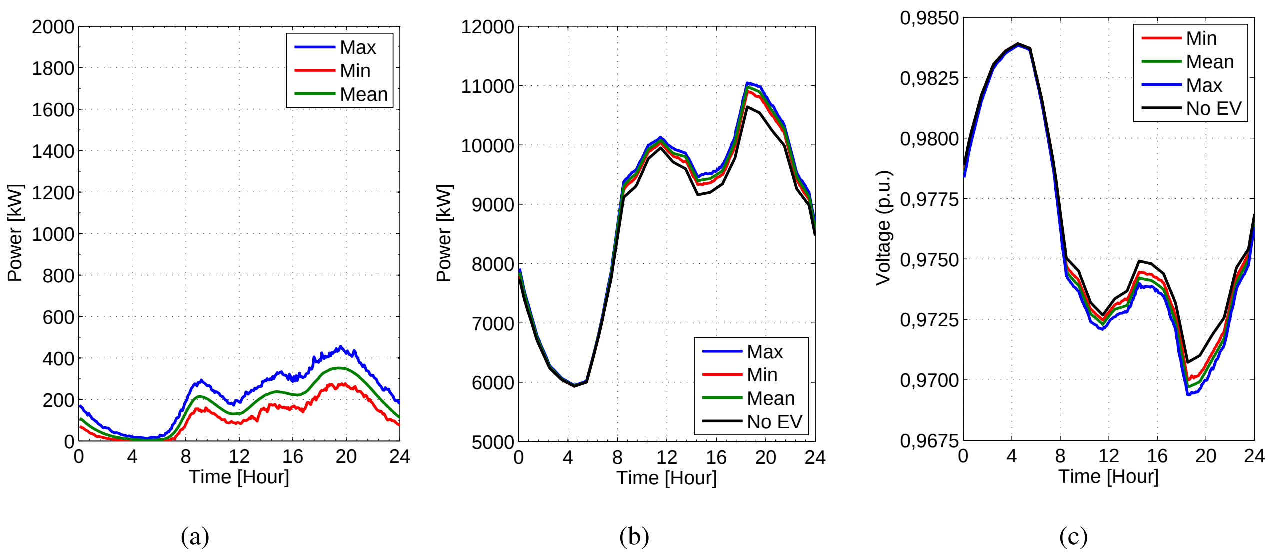


Figure 12. A—Intensive charge. (**a**) EV charging demand; (**b**) Total demand; (**c**) Voltage drop.

3.4.2. B—Plug-and-Play

EV charging demand: In this scenario, the EV agents prefer to charge at home, according to the back home time distributions (m_{ij}). As shown in Figure 13a, the first peak demand is lower than in scenario A because the agents do not charge at work. Moreover, the second peak demand is higher than before because the agents have not charged at work and the energy required by them is higher than in scenario A. In this scenario, the EV charging demand variability is also significant and it can reach the 33% of the EV consumption, as it occurs at 20:00.

As Figure 13b shows, this effect causes that the peak during the morning in the total demand is lower than the previous case. And the peak during the evening is higher due to the energy required and the maximum power consumed is 11,12 MW at 18:35 and the relative increase from the case without EV is 4.51%. Moreover, the power consumption during the night is higher than in case A, because the SoC of EV agents when they arrive at home is lower than previously.

Impact on power system: Figure 13c shows that the combination of the peak from the residential demand with the EV demand causes a higher voltage drop than scenario A, due to the different behaviors of the EV agents. The minimum voltage reached during the peak demand is 0.9691 p.u., 0.16% lower than the case without EV, and higher than the lower limit of 0.90 p.u.

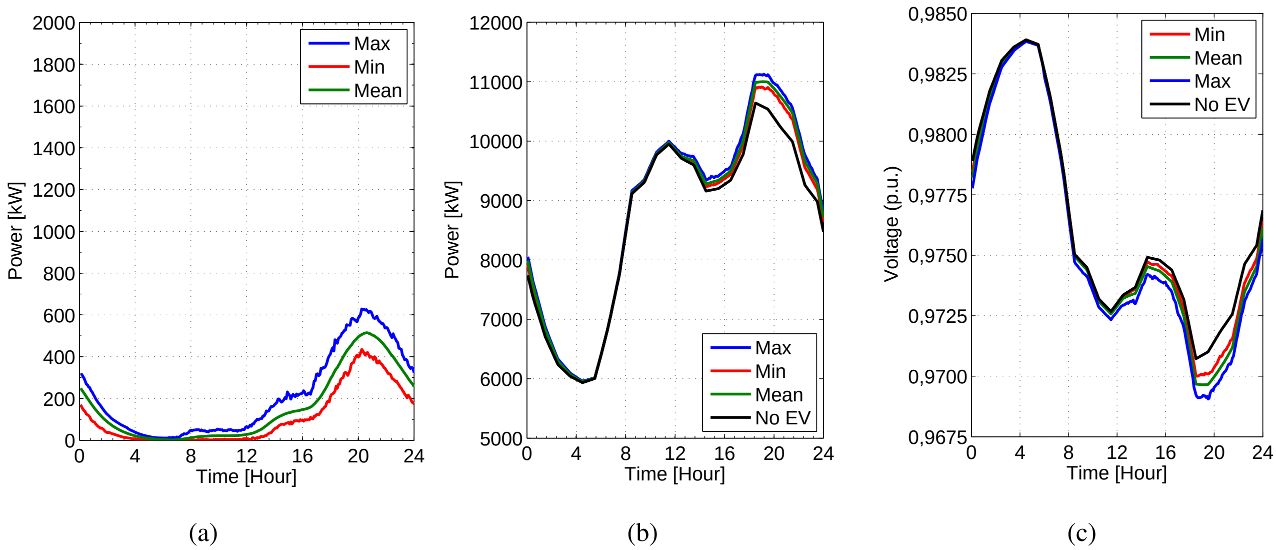


Figure 13. B—Plug-and-Play. (**a**) EV charging demand; (**b**) Total demand; (**c**) Voltage drop.

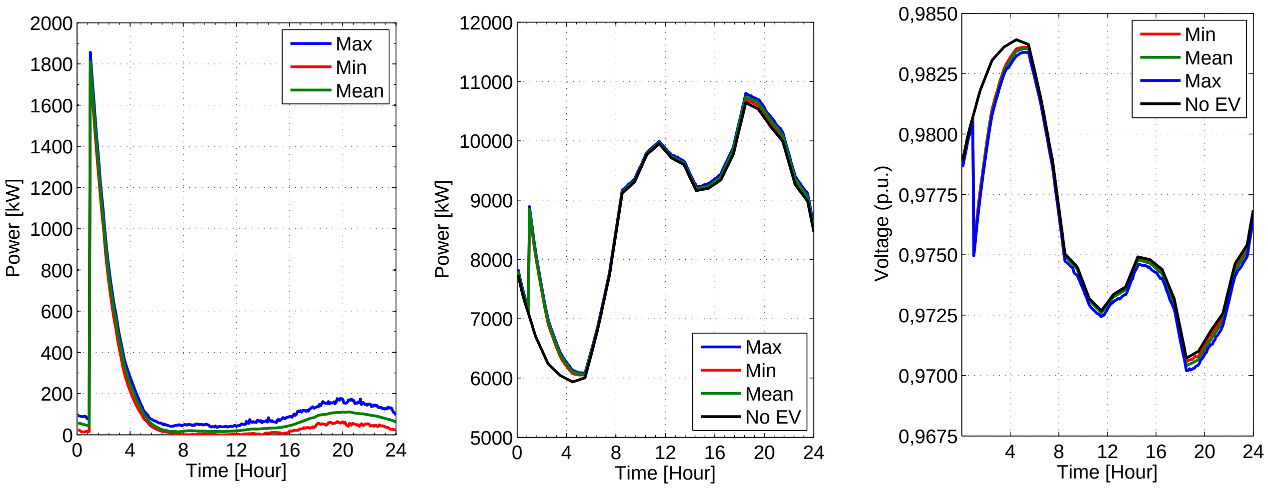
3.4.3. C—Tariff Controlled

EV charging demand: In this case, the TOU tariff causes that the EV agents begin to charge at 1:00, when the energy is cheaper. Therefore, the EV charging demand presents a peak of 1.86 MW at this moment due to the simultaneous EV charges, as seen in Figure 14a. What is more, the control reduces the EV charging demand variability.

The consumption during the rest of the day is related to the energy required (E_{req}) to reach the next destination (D_{ij}) and the low SoC of each EV agent. The maximum power consumed is 10.8 MW at 18:30, which means an increase of 1.5% from the original case.

Figure 14b shows that this EV peak happens during the off-peak period and the total demand increase is not significant. Despite this, the power generation gradient could be a problem, which should be analysed from the point of view of the power generation and from the system stability point of view.

Impact on power system: The minimum voltage, shown in Figure 14c, is similar to the original case without EVs. The minimum voltage reached is 0.9702 p.u., 0.05% lower than without EVs, and higher than 0.90 p.u. The voltage variation at 1:00 could be a problem, which could be analyzed in a transient analysis.



(a) (b) (c)

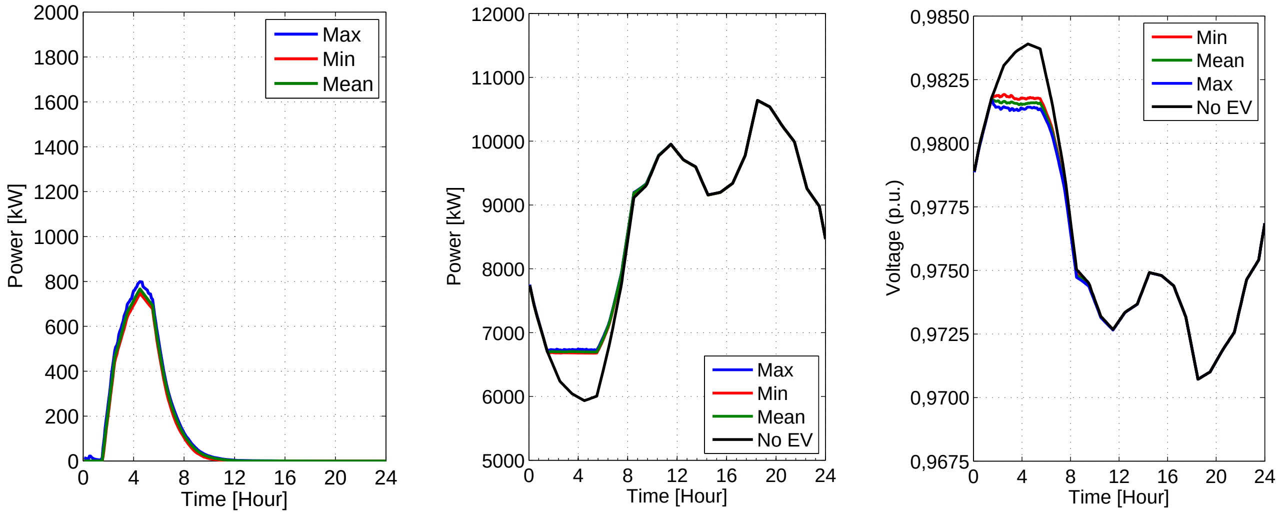
Figure 14. C—Tariff controlled. (**a**) EV charging demand; (**b**) Total demand; (**c**) Voltage drop.

3.4.4. D—Smart Charging

EV charging demand: Figure 15a shows the EV charging demand controlled by the aggregator which controls domestic EV charges. The EV charging demand is shifted to the valley period to reduce the consumption through the HV/MV transformer and to minimize the impact on the transmission system. According to this, the EV charges occur between 2 and 8 o'clock and the variability, the difference between the minimum and the maximum case, is very small.

Figure 15b shows that the total demand increases during the valley periods and the power consumption is constant at 6.6 MW. During the rest of the day, sporadic charges could occur, but the mean curve is near to the case without EVs.

Impact on power system: The minimum voltage is not increased by the EV charges, as is exhibited in Figure 15c. The voltage during the valley period is lower than in the original case according to the total demand, but this voltage is higher than during the peak hours, and the difference between the minimum voltages is 0.02%, and the minimum value of 0.90 p.u. is not reached.



(a) (b) (c)

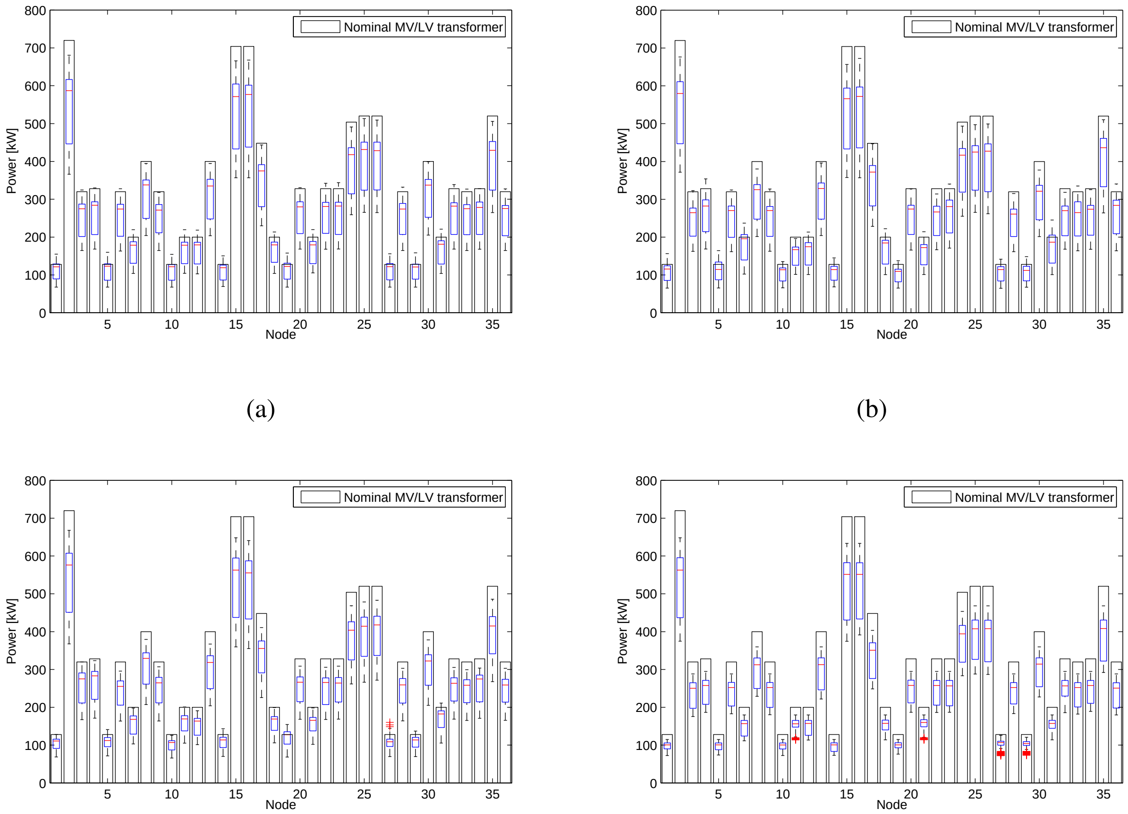
Figure 15. D—Smart charging. (**a**) EV charging demand; (**b**) Total demand; (**c**) Voltage drop.

The summary of all the scenarios is presented in Table 5. Voltage value is the minimum and it means the maximum voltage drop.

Table 5. Maximum results.

Scenario	EV Demand (Max) [kW]	Peak Time	Total Demand (Max) [kW]	Variation	Peak Time	Voltage (Min) [p.u.]	Variation
No EV		18:30	10640		18:30	0.9707	
A—Intensive charge	457	18:30	11040	3.76%	18:30	0.9694	-0.13%
B—Plug-and-Play	628	18:35	11120	4.51%	18:35	0.9691	-0.16%
C—Tariff controlled	1857	01:00	10800	1.50%	18.30	0.9702	-0.05%
D—Smart charging	799	04:30	10720	0.75%	18:35	0.9705	-0.02%

Box plots Figure 16a–d show total consumption in each node and this is compared to MV/LV transformer capacity. The results show that the nodes with less capacity could reach the nominal value in some cases, but the average value is under nominal power. In the case of scenario D, total demand never exceeds the nominal capacity of transformers, which means that there is enough capacity to supply the EVs.



(a) (b)

(c) (d)

Figure 16. Total demand in each MV/LV transformer. (**a**) A—Intensive charge; (**b**) B—Plug-and-Play; (**c**) C—Tariff controlled; (**d**) D—Smart charging.

4. Conclusions

The probabilistic agent-based model (ABM) obtained in this paper allows the EV charging demand to be determined, taking into account different variables of EV characteristics such as battery capacity and energy consumption of each trip, economic and social attributes, mobility needs, and charging strategies of each agent. The model developed takes into account the interaction of these variables, allowing the obtainment of better accuracy in the results.

The probabilistic approach is useful to include the uncertainties related to the real behavior of EV users, like the time distribution and energy consumed on each trip. Therefore, the model permits the determination of the impact provoked on the grid by these uncertainties.

Moreover, the model proposed is a benchmark to compare case studies, such as different cities or areas in the same city. With this model, the weak regions of the grid or the areas with high EV density can be detected.

The case study presented shows that the uncertainties cause variability in the EV charging demand in scenarios without control on the EVs, as it is shown in scenarios A and B. In contrast, the consumption variability in scenarios with indirect and direct control on the EV charges, like scenarios C and D, respectively, is small.

The distribution feeder analyzed in the presented case study does not have a significant impact on the smart charging strategy (D) during the off-peak period and all EV agents can charge their EV. In contrast, some MV/LV transformers could exceed their nominal power in the scenarios without control. The voltage in all the scenarios is higher than the limit of 0.90 p.u. according to the EN 50160.

In further work, it could be very interesting to analyze the dynamic behavior of the system in case C during the connection of all EV at 1:00. Furthermore, the model permits analyzing the impact on distribution networks, but it can be applied for transmission and low voltage grids, too. Finally, this model could be applied and compared with a real distribution network with EVs to verify the accuracy of the model.

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Author Contributions

Pol Olivella-Rosell, Roberto Villafafila-Robles and Andreas Sumper conceived the model; Pol Olivella-Rosell performed the simulations; Pol Olivella-Rosell, Roberto Villafafila-Robles, Andreas Sumper and Joan Bergas-Jané analysed the data; Pol Olivella-Rosell wrote the paper.

Nomenclature

Aut_i	Autonomy	C_i	Agent group
Cap_i	Battery capacity	d_i	Day of the week
D_{ij}	Destination	EC_i	Energy consumption
EV_i	EV model	i	Agent
$iter$	Iteration	j	Trip
L_i	Distance	l_{ij}	Distance per trip
m_{ij}	Time distribution	$P(t,x)_{ij}$	Charging process
Ps_i	Power supply	R_i	Place of residence
S_i	Number of trips	t_0, t_1	Initial/Final time
$Type_i$	Type of EV (BEV or PHEV)	v_{ij}	EV velocity
Y_i	Trips matrix	Z_i	Energy consumed

Conflicts of Interest

The authors declare no conflict of interest.

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