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Modeling of Electric Vehicles as A Load of the Distribution Grid

Nurullah Aslan[1*], Erdal Kılıç[2] and Mustafa Şekkeli[2]

0000-0003-4056-2094, 0000-0002-1572-6109, 0000-0002-1641-3243

[1] *Electronics and Automatıon Department Aksaray Technical Sciences Vocational School, Aksaray University, Aksaray, 68100, Türkiye*
[2] *Eletrical and Elecronics Engineering, Kahramanmaraş Sutcu Imam University, Kahramanmaraş, 46100, Türkiye*

Abstract

Electric vehicles (EVs) are expected to reduce carbon emissions from transportation. For this reason, many vehicle manufacturers, countries and international organizations develop their energy and transportation policies in this direction and also support them with practices. As a result of the policies implemented and developments in battery technologies, serious increases are expected in the sales of the EV sector. However, there should be sufficient charging stations for EV charging. The increase in charging stations is expected to cause some positive and negative effects on the grid. In order for electric vehicles to be more acceptable in terms of power systems, it is necessary to understand what kind of electrical character they show. In this article, EV electrical modeling is performed over a charging period by Monte Carlo Simulation using the actual charging data of some EV models charged in a single phase 7,2 kW-240 V charger. The generated probabilistic model was validated by comparing it with real data. Thus, a reliable modeling has been presented for EV, which is a new load in power systems.

Keywords: Electric vehicles, Monte Carlo simulation, Probabilistic modeling, Charging stations, Electrification

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* Corresponding author
Nurullah Aslan
nurullahaslan@aksaray.edu.tr
Address: Electronics and Automatıon Department *Aksaray Technical Sciences Vocational School*, Aksaray University, Aksaray, Türkiye
Tel: +903822882013

1. Introduction

In general, global warming, climate change and greenhouse gas (GHGs) emissions caused by fossil fuel use are seen as a major hazard. For this reason, it is frequently on the world agenda [1]. Countries that are more sensitive about the use of fossil fuels, which is the root cause of these problems, aim to reduce this use with alternative solutions. Fossil fuel consumption occurs mostly in the electrical power generation and transportation sectors [2]. The transportation sector accounts for approximately 35% of energy consumption in 2014 [3].

The electricity generation and transportation sector can reduce the use of fossil fuels by switching to renewable energy sources (RES) instead of traditional production methods, and electric transportation instead of traditional internal combustion engine transportation. With this transformation in the transportation sector, greenhouse gas emissions can be reduced [4,5].

Technological advances in EV components (especially the battery) will reduce dependence on fossil fuels, reduce emissions [5], and increase interest in EVs. It is expected that EVs will be charged from an electricity grid with a high generation of renewable energy sources, that is, it will contribute to a cleaner future in a hybrid grid [6].

EV technologies have been used in many different parts of the world such as electric cars, trains, buses, trams and show a rapid increase. However, the reasons why these technologies are not fully accepted today are the expensiveness of the components that make up the vehicle, the range due to the battery capacity, the charging time and the problems of accessing a sufficient number of chargers. However, as the technological developments in the components that make up the vehicles begin to affect the EV prices, it is recommended as an important competitor to the vehicles working with traditional fuels (gasoline, diesel, LPG) [7].

In addition, the electric motor has advantages such as higher efficiency compared to the internal combustion engine, EVs not causing air pollution, and less noisy operation. In parallel with these developments, the policies implemented to encourage the use of EVs on a country basis indicate that there will be an increase in the number of EVs in the future.

EVs can be charged at different times from charging stations with different power levels (slow-medium-fast) to be supplied from the distribution network, medium fast chargers such as street and workplace, and slow chargers used individually at homes [8].

While the integration of EVs into distribution networks increases the use of electric vehicles as an alternative vehicle, it may cause some negativities on the grid side. In particular, studies have found that EVs cause high power demand due to battery capacities and high peak demands due to the power electronics structure of the chargers, voltage drops, harmonic distortions and voltage imbalances due to single-phase installed chargers [9].

This new load [10], which draws a large amount of electrical energy from the power system in a short time and causes different power quality problems with non-linear contents from the chargers of EVs, needs to be modeled accurately. While doing this modeling, many uncertainties such as the charging start time, the power of the charger, the position of the charger, the battery capacity of the EVs, the battery state of charge (SoC) of the EVs at the start of charging [11] should be considered.

Models aimed at providing EV electrical representation can be derived from simplified mathematical notation [12], circuit-based approaches [13], measured data modeling, and big data measurements [14]. Models that allow the electrical representation of the EV to handle both the power demand and its nonlinear properties simultaneously are generally circuit-based [15]. However, this approach has a high computational load, making it a disadvantage for its applicability in large network evaluations.

Of the models mentioned above, circuit-based models can provide an accurate representation of the electrical behavior of the charger that characterizes the charger through power electronics components. A new bidirectional charger for EVs is proposed in [16]; this circuit model describes the electrical representation of the charger through an average model technique that reduces the computational load relative to other circuit-based models. In [15], the electrical behavior of the charger is represented by the AC-DC rectifier-converter and the battery as a Thevenin equivalent. Built using a pulse width modulation controller, this model can represent the change in current power demand as a function of SoC level. In [17], a high-frequency charger is proposed for fast chargers, which we call DC chargers, and an analysis of the response of harmonic currents to the SoC connection is performed. A new power electronics topology is proposed for single-phase chargers in [18]. However, for circuit-based models, the accuracy of the results depends on the modeling of the charger electronics. For this reason, it causes the need for the data of the circuit manufacturers [19]. But one advantage of these models is that they can represent the electrical behavior of the charger depending on the SoC level. That is, they can offer a correct approach by modeling the constant current mode covering a large part of a full charge mode (up to an 80-95% SoC) and the remaining constant voltage modes [20].

When looking at mathematical modeling approaches, the electrical behavior of the vehicle is handled through probabilistic models [14,21]. Specifically, the authors in [21] measured power consumption data from the EV fleet to detail stochastically on the aggregated EV power demand profile.

In [14], a stochastic method is adopted to consider charging power variations based on real characteristics such as EV battery capacity, SoC, driving habits and their effects on grid voltage imbalance.

This article will consider a probabilistic approach to EA modeling using real measured data. It is advantageous to approach modeling from this perspective, due to the probabilistic nature of many of the above-mentioned parameters for EA modeling to be possible. In addition, considering the measurement periods of the real data used (5 sec), it will increase the accuracy of the modeling. Thus, positive or negative situations that may occur in the network as a result of partial or full integration of EV, which is a new load in the distribution network, can be handled.

Three levels of charging are available under its standards, where the Society of Automobile Engineers (SAE) defines the primary types of charging available for EVs in the SAE J 1772 standard. These are Level 1,2,3 charges [22]. EV charging can be carried out in a home garage where it can be plugged into a suitable outlet for Level 1 (slow) charging. Level 2 (medium) charging, on the other hand, is typically described as the first to come to mind for an EV battery charger for both private and public locations, requiring a single phase 240 V socket. As future developments focus on Level 2, this article uses charging data for four vehicles charged from a 7.2 kW 240 V single phase Level 2 charger. This moderately fast charge provides plenty of power and is applicable in most environments [23-26]. Single-phase solutions are usually used for level 1 and 2 charging. Level 3 (fast) and DC fast charging are designed for commercial and public applications and work like a charging station. Three-phase solutions are applied to Level 3 chargers and high power. It uses Level 2 or 3 chargers placed in public places such as parking lots, shopping malls, hotels, recreational facilities, theaters, restaurants [26-30].

2. Material and Method

The proposed modeling methodology, as mentioned in the first section, is probabilistic modeling obtained by processing big data. Due to its probabilistic nature, the electrical characterization of EV is handled randomly. In particular, the core of our proposed modeling approach is to characterize the data of the electrical components of the charger through probabilistic models based on real measured data. For this, the raw data obtained as a result of the tests carried out by the Argonne National Laboratory for on-board chargers of EVs were processed and applied [31]. The current, voltage and power components drawn by the charger built on the LV network side are measured in five-second periods. Selecting this modeling variable data allows us to fully consider all electrical variables of the charger without requiring additional measurements to charger circuit characterizations or electrical measurements. Probabilistic electric models developed using real data are used to calculate the change of state of charge (SoC) from the battery along with the power demand from the charger. The proposed probabilistic model will also provide an accurate estimation of the charging time by relating the electrical variables to the equations given later.

Probability Distribution Functions (PDFs) based on real data were chosen as the modeling technique to characterize the electrical data of the charger. These PDFs use Monte Carlo Simulation to create time series that fully describe the electrical data of the EV charger during the full charge period and calculate the power demand of the charger at each stage of charging. But an important point for this purpose is that the natural process of battery charging and sequential processes should be studied. These are the constant current phase (CCP) and the constant voltage phase (CVP). Since the electrical variables from the charger show different trends during charging, CCP and CVP measurements need to be separated in the data collection process [21].

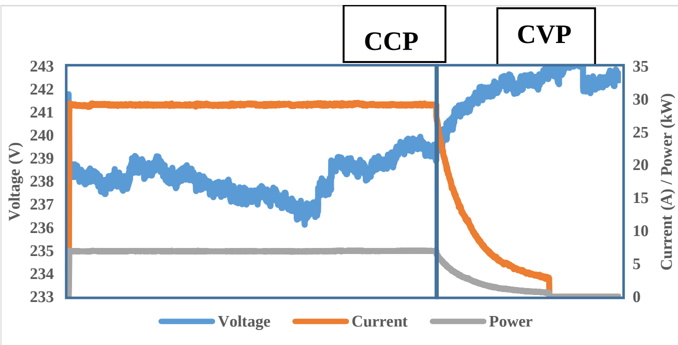

Fig. 1. Full charge mode- CCP-CVP- mode for BMW İ3

The data we have received is Level 2 7.2 kW 240 V onboard charger data. 2014 BMW İ3, 2013 Ford Focus, 2013 Nissan Leaf and 2015 Volkswagen Egolf vehicle data with these features were taken and included in the evaluation. The technical specifications of these vehicles are shown in Table 1. The battery capacity of these vehicles is approximately 24 kWh. Due to the above-mentioned feature of the charging profile, the data has been evaluated within this scope and separated, as an example, the full charge period, CCP and CVP modes of the 2014 BMW I3 are shown in figure 1, respectively.

Table 1. EVs Technical Properties

EV Model	Battery Capability (kWh)	Electric Range (km)
2014 BMW İ3	24	144
2013 Ford Focus	23	122
2013 Nissan Leaf	24	120
2015 VW e-Golf	24,2	133

PDFs for electrical parameter estimation for vehicles were generated at 10-minute intervals. While creating the PDFs, the maximum and minimum values of the electrical parameters that each electric vehicle has seen were determined and the range for the PDFs was determined. Accordingly, 233.2-245 V and 0.2 V increments were determined for voltage, and 28-30 A and 0.2 A increments were determined for current. For these intervals, PDFs were produced by dividing a full charge period into 10-minute periods. Using the random number generation technique with these PDFs, the average voltage and current that the vehicle will draw from the network in a full charge period have been determined. Similarly, the estimation accuracy for a full charging period of the vehicles was checked by calculating the average value of the voltage and current in 10-minute periods within the real measured data and comparing the generated PDFs. The 10-minute average of the measured data and the full charge graphs obtained at the end of the generated 10-minute PDFs are given in figure 2-9 for the vehicles, respectively.

When the full charge cycle, that is, figure 1, is examined; While there is a certain decrease in voltage at the start of charging, current and active power remain constant and operation continues in CCP mode. When the SoC level reaches 95%, the charging process switches to CVP mode, while the voltage makes small oscillations at a constant value, while the current and active power tend to decrease, indicating that the charge has started to be completed. This time is approximately 4 hours on a Level 2 charger for a full charge cycle and an EV with a 24 kWh battery.

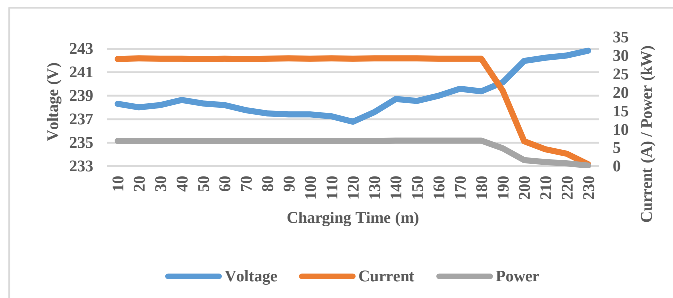

Fig. 2. Real data full charge mode for BMW İ3

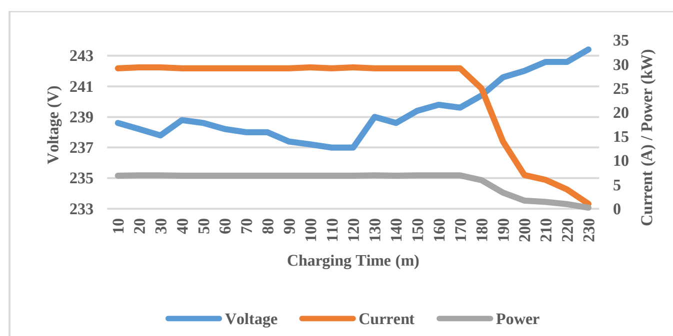

Fig. 3. PDFs data full charge mode for BMW İ3

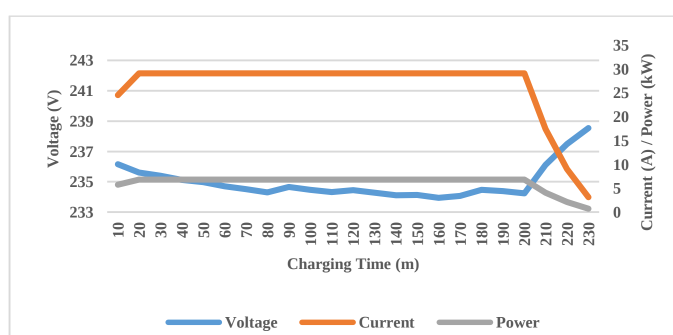

Fig. 4. Real data full charge mode for Ford Focus

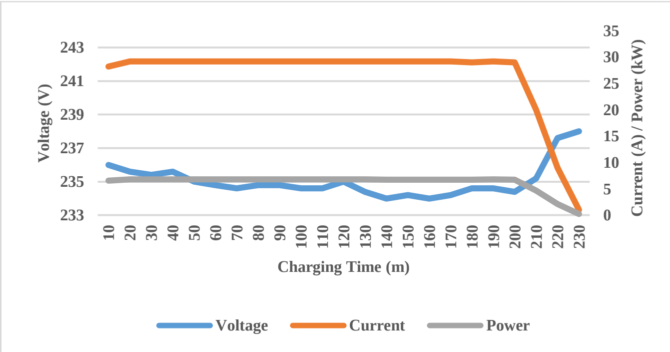

Fig. 5. PDFs data full charge mode for Ford Focus

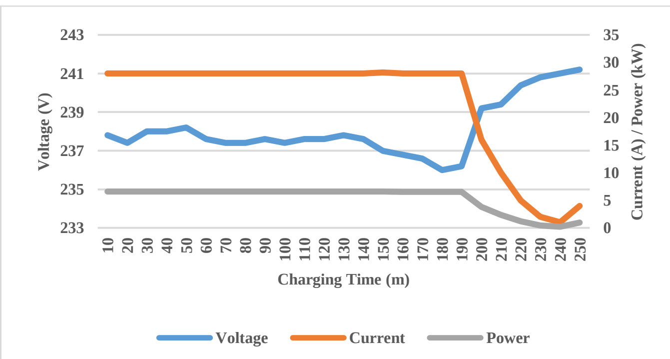

Fig. 6. Real data full charge mode for Nissan Leaf

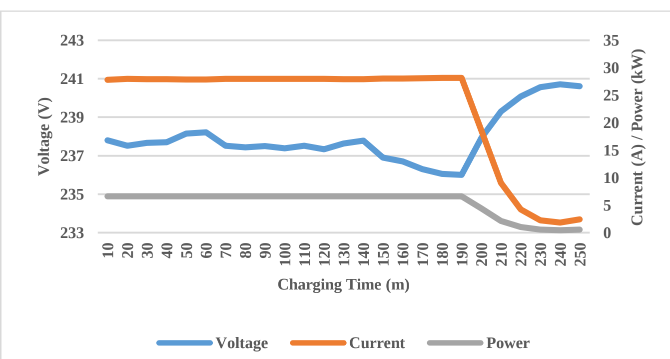

Fig. 7. PDFs data full charge mode for Nissan Leaf

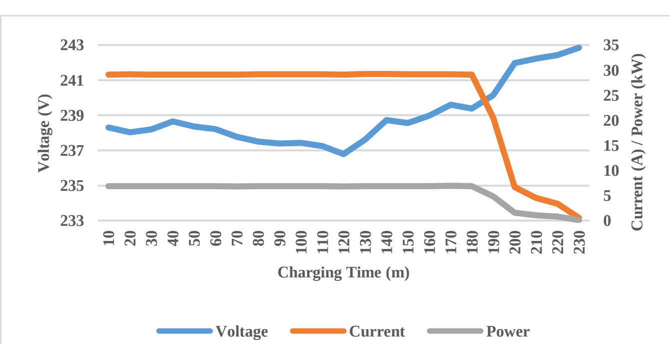

Fig. 8. Real data full charge mode for VW e-Golf

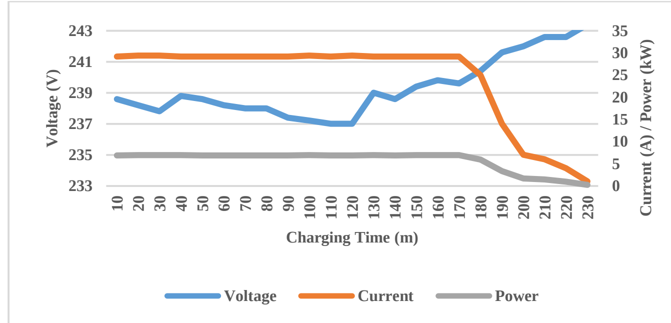

Fig. 9. PDFs data full charge mode for VW e-Golf

2.1 An Average EV Electrical Model

To build the electrical model for electric vehicles, we have evaluated each vehicle individually in the previous sections. In this section, instead of representing each one separately, a single model has been created by creating an average electric vehicle model by using both real data and PDFs that we have created. Considering the 10-minute periods, voltage and current values were calculated for real data show figure 10, and data derived from PDFs were used for probabilistic data and show figure 11. Using these data, the electrical model of an average EV was obtained by calculating the power, energy and SoC values, and its accuracy was proven by comparing it with the average electrical model obtained with real data.

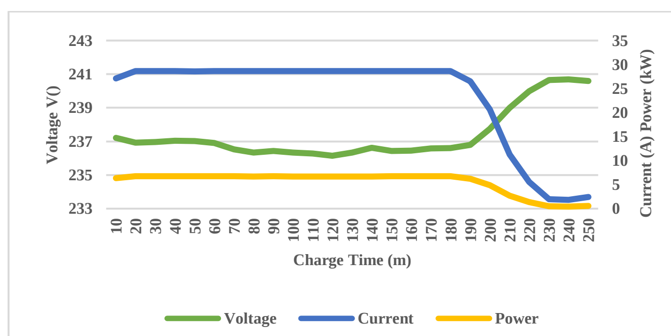

Fig. 10. Average EV electrical model with real data

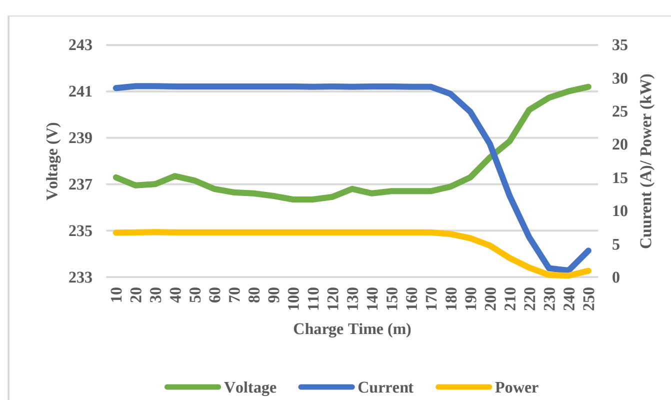

Fig. 11. Average EV electrical model with PDFs data

2.2 Power Demand and SoC Variation

The active and reactive power demand of the electric vehicle are important variables to evaluate the effect on power quality factors. However, in the proposed modeling, no measurements are needed to evaluate these features. Instead, they can be related to the charger's current and voltage as follows:

$$P(t) = \sum_{i=1}^{t} (V_i(t) I_i(t) \cos \theta_i (t)) \quad (1)$$

$$Q(t) = \sum_{i=1}^{t} (V_i(t) I_i(t) \sin \theta_i (t)) \quad (2)$$

Here $P(t)$ and $Q(t)$ represent the active and reactive power demand at time t. The magnitude of the ith voltage and current component $V_i(t)$ and $I_i(t)$ represent, $\theta_i(t)$ represents the phase angle and t is the charging time. These calculations for EVs are shown in table 2 and 3.

The reason why the cosφ value is taken as 0.99 here is the average value resulting from the calculation made with the actual measured data. Calculated values of active and reactive power can be used to create time series describing the power demand characteristic of the charger, thereby modeling the EV as a grid load. By correlating the nonlinear and power demand characteristic as mentioned earlier, a simultaneous assessment of the affecting harmonic distortion, voltage unbalance and voltage level of the distribution network can be obtained. However, an important feature to model is the variation in the battery's SoC level. This parameter not only affects the charging time, but also defines the charging phase at which PDFs of electrical data should be retrieved.

To model this parameter, the time series of active power demand can be used to calculate the corresponding SoC variation over defined time intervals as follows.

$$SoC(t+1) = SoC(t) + \frac{100xP(t)}{3600Cb} \quad (3)$$

Here $SoC(t)$ stands for SoC level at time t and CB corresponds to battery capacity of EV. Different electrical behavior from CCP and CVP will be reflected in both the power time series and the SoC variation calculation. This ultimately leads to a realistic charge time modeling to the formulas given above and the features specified, the SoC data of the vehicles and the average graphics created by using these vehicle data are given in figures 12-17, respectively.

Table 2. Active power demand for BMW İ3 and Ford Focus with PDFs data

	BMW PDFs Data			Focus PDFs Data		
Time (m)	**Voltage (V)**	**Current (A)**	**Power (kW)**	**Voltage (V)**	**Current (A)**	**Power (kW)**
10	238,6	29,2	6,90	236	28,2	6,59
20	238,2	29,4	6,93	235,6	29,2	6,81
30	237,8	29,4	6,92	235,4	29,2	6,80
40	238,8	29,2	6,90	235,6	29,2	6,81
50	238,6	29,2	6,90	235	29,2	6,79
60	238,2	29,2	6,89	234,8	29,2	6,79
70	238	29,2	6,88	234,6	29,2	6,78
80	238	29,2	6,88	234,8	29,2	6,79
90	237,4	29,2	6,86	234,8	29,2	6,79
100	237,2	29,4	6,90	234,6	29,2	6,78
110	237	29,2	6,85	234,6	29,2	6,78
120	237	29,4	6,90	235	29,2	6,79
130	239	29,2	6,91	234,4	29,2	6,78
140	238,6	29,2	6,90	234	29,2	6,76
150	239,4	29,2	6,92	234,2	29,2	6,77
160	239,8	29,2	6,93	234	29,2	6,76
170	239,6	29,2	6,93	234,2	29,2	6,77
180	240,4	25	5,95	234,6	29	6,74
190	241,6	14	3,35	234,6	29,2	6,78
200	242	7	1,68	234,4	29	6,73
210	242,6	6	1,44	235,2	20	4,66
220	242,6	4	0,96	237,6	9	2,12
230	243,4	1	0,24	238	1	0,24

Table 3. Active power demand for Nissan Leaf and VW e-Golf with PDFs data

Nissan Leaf PDFs				VW Egolf PDFs		
Time (m)	**Voltage (V)**	**Current (A)**	**Power (kW)**	**Voltage (V)**	**Current (A)**	**Power (kW)**
10	237,8	28	6,59	236,8	28,6	6,70
20	237,4	28	6,58	236,6	28,6	6,70
30	238	28	6,60	236,8	28,6	6,70
40	238	28	6,60	237	28,6	6,71
50	238,2	28	6,60	236,8	28,6	6,70
60	237,6	28	6,59	236,6	28,6	6,70
70	237,4	28	6,58	236,6	28,6	6,70
80	237,4	28	6,58	236,2	28,6	6,69
90	237,6	28	6,59	236,2	28,6	6,69
100	237,4	28	6,58	236,2	28,4	6,64
110	237,6	28	6,59	236,2	28,4	6,64
120	237,6	28	6,59	236,2	28,4	6,64
130	237,8	28	6,59	236	28,4	6,64
140	237,6	28	6,59	236,2	28,6	6,69
150	237	28,2	6,62	236,2	28,4	6,64
160	236,8	28	6,56	236,2	28,4	6,64
170	236,6	28	6,56	236,4	28,4	6,65
180	236	28	6,54	236,6	28,4	6,65
190	236,2	28	6,55	236,8	28,4	6,66
200	239,2	16	3,79	237	28,4	6,66
210	239,4	10	2,37	238,2	13	3,07
220	240,4	5	1,19			
230	240,8	2	0,48			
240	241	1	0,24			
250	241,2	4	0,96			

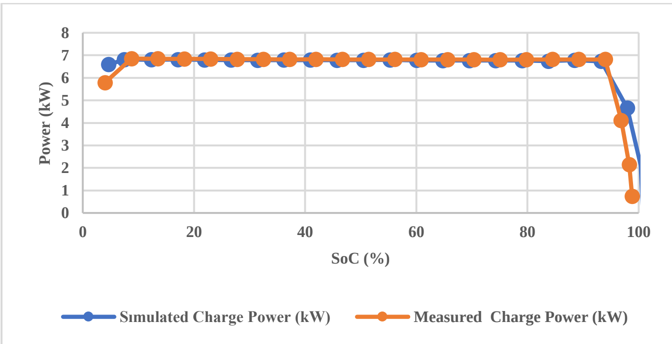

Fig. 12. Ford Focus

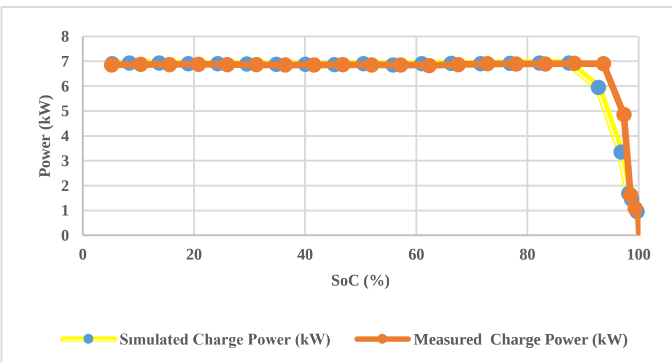

Fig. 13. BMW İ3

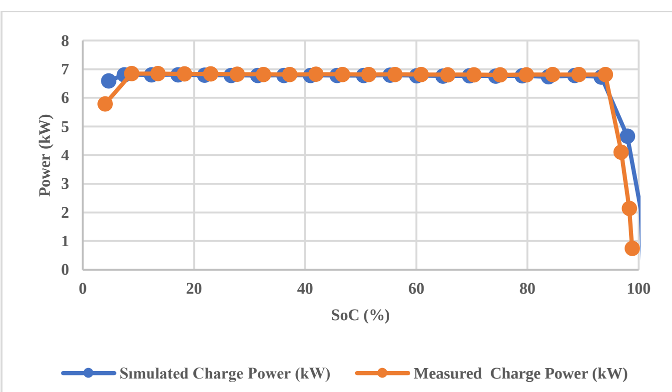

Fig. 14. Nissan Leaf

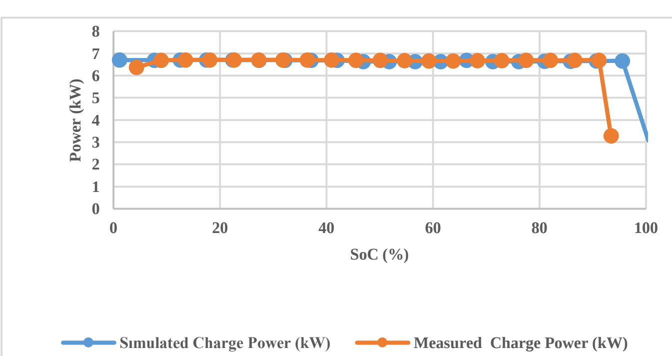

Fig. 15. VW e-Golf

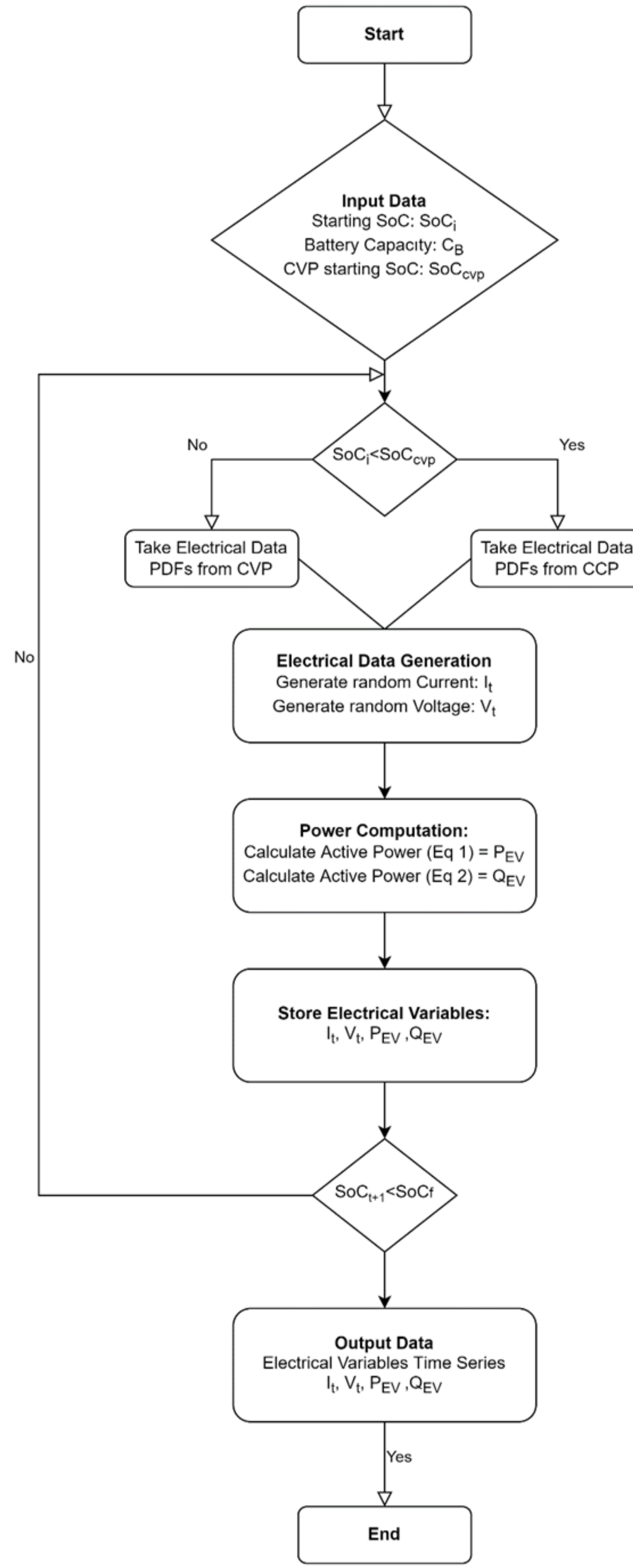

Fig. 16. Flow diagram for Monte Carlo Simulation [32]

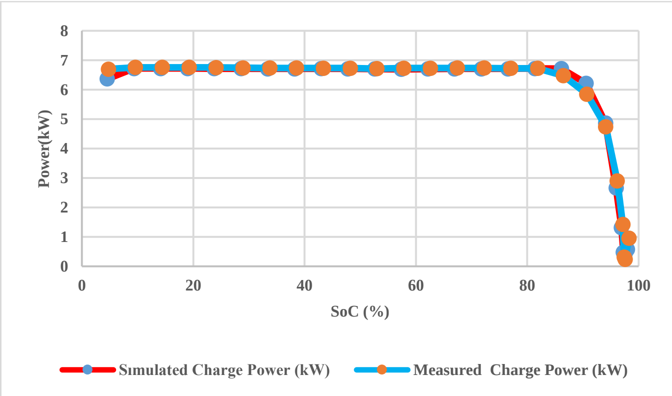

Fig. 17. Average power demand for EVs

3. Monte Carlo Simulation for EVs

Monte Carlo Simulations is a computerized stochastic simulation approach that works with statistical probability theory and can.
Based on the electrical model presented in section 2.1 and the power and SoC calculation model in section 2.2, it outputs the full EV electrical model as in figure 16. Thus, a model is obtained that provides a complete description of the electrical behavior of the charger.

As shown in the flowchart in figure 16, four initial inputs are required for the model, which are used to model the charge time and determine the operating charge stage. These are a CVP SoC (SoC_{CVP}), where the EV terminates its CCP and runs on the CVP, a connect SoC (SoC_i), battery capacity (CB), a disconnect SoC (SoC_f) [32].
Using the above inputs, the first step of the methodology consists of determining the electrical behavior at the start of charging. In this regard, we need to determine the charging stage in which the charger operates by comparing SoC_t with SoC_{CVP}. For this article, this value was calculated when examining the actual data, while the charging mode switched to CVP mode at % 95 SoC. Therefore SoC_{CVP}= %95 in the modeling. In addition, the model created by randomly assigning the initial SoC SoC_i was run. If SoC_t is higher than SoC_{CVP}, the vehicle is running in CVP, otherwise it continues to receive data via CCP. We then proceed to model the nonlinear characteristic of the charge via electrical time series. This is accomplished using electrical PDFs from the ongoing charging phase to generate random values whose components represent both magnitude and phase angle if voltage and current are electrical. At this point, the magnitude and phase angle time series are used to find the instantaneous power demand of the vehicle using equations (1) and (2). Then, the SoC change caused by the active power demand is calculated by equation (3).
Finally, the previous process is repeated until the SoC level reaches the target value SoC_f [32].
As outputs of the model, we obtain simulated time series of both the value of the electrical components and the power demand of the charger, which reflect different behavior from the CCP and CVP.

In the final modeling created according to the flow diagram, the temporal SoC levels, SoC level change tables and graphs according to the charging power were obtained, along with the charging times for the EVs according to the different initial SoC levels. These are given in figures 18-21, respectively.
it will shed light on the new study subjects mentioned above.

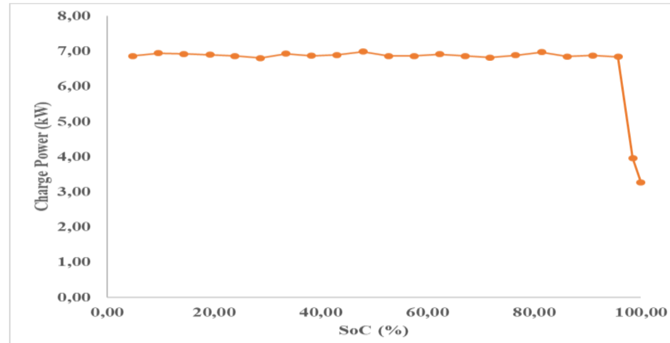

Fig. 18. % 0 SoC entry-level EV charging profile

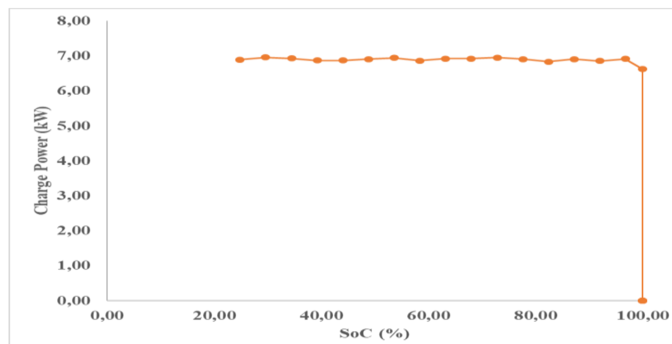

Fig. 19. % 20 SoC entry-level EV charging profile

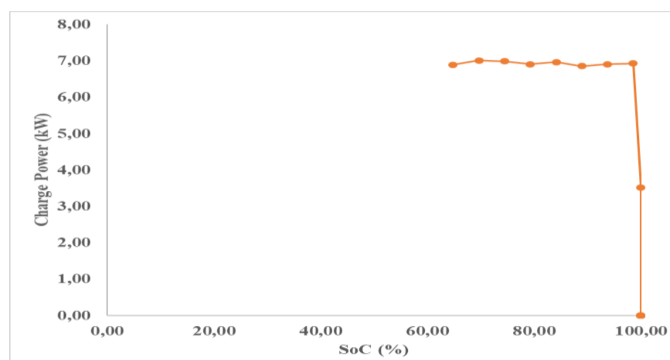

Fig. 20. % 60 SoC entry-level EV charging profile

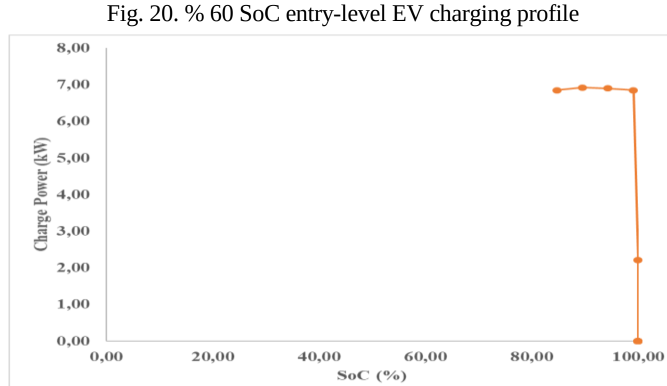

Fig. 21. % 80 SoC entry-level charging profile

4. Conclusions

Electric vehicles have emerged as the most important of the new loads included in the electricity distribution network in recent years. However, the effect of the current network against this new load, which is rapidly spreading, continues to be the subject of research.

In this article, in order to be useful to this point, real measurement data were evaluated as probabilistic and EAs were modeled thanks to Monte Carlo Simulation. The accuracy of the PDFs created for this has been proven by comparing them with real data graphics. In addition, estimation of charging time can be made for vehicles arriving at any SoC level. SoC level and charge time estimates are shown in table 4. It is possible to determine whether the network infrastructure is sufficient in the new condition, and what its effect will be on the network in terms of network quality, by using the modeling made in further studies, by analyzing it in various real-time power system analysis programs. In addition, by using modeling, coordinated or smart charging methods can be developed for EVs in terms of grid continuity, and it can be worked on to manage the situation with the usual grid. Similarly, in vehicle-to-grid (V2G) technologies, where EVs are used as an energy storage unit, they can be transferred to the grid as an additional resource.

Table 4. Charging Time Estimation for EVs

Level 2 (7,2 kW-240 V) Charger		
SoCinitial (%)	Charging Time (m)	SoCfinally (%)
22	170	100
46	120	100
64	80	100
78	50	100
85	40	100
93	30	100

In addition, by using modeling, coordinated or smart charging methods can be developed for EVs in terms of network continuity, and it can be worked on to manage the situation with the usual network. Similarly, in V2G technologies, where EVs are used as an energy storage unit, they can be transferred to the grid as an additional resource. As a result; The developed probabilistic EV modeling gives ideas in terms of electrical components about how EVs, which are a new load of the network, will present a load profile in the network. It is also thought that it will shed light on the new study subjects mentioned above.

Conflict of Interest Statement

The authors declare that there is no conflict of interest in the study.

CRediT Author Statement

N. Aslan: Conceptualization, Investigation, Resources, Visualization, Writing-original draft, Writing-review and editing, Supervision,

E. Kilic: Formal analysis, Validation, Writing-original draft, review and editing.

M. Sekkeli: Formal analysis, Validation, Writing-original draft

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