A Computational Implementation for Creating Electric Vehicles Profiles

Cindy P. Guzman[1], Eduardo Gomes[1,2], Lucas Pereira[2], and Hugo Morais[1]

[1]INESC-ID—Instituto de Engenharia de Sistemas e Computadores-Investigação e Desenvolvimento, Department of Electrical and Computer Engineering, Instituto Superior Técnico—IST, Universidade de Lisboa, 1049-001 Lisboa, Portugal

[2]Interactive Technologies Institute, LARSyS, Universidade de Lisboa, 1049-001 Lisboa, Portugal

Email: {cindy.lascano, eduardo.c.gomes, lucas.pereira, hugo.morais}@tecnico.ulisboa.pt

***Abstract*—The need to achieve carbon neutrality has boosted the mass adoption of electric vehicles (EVs). However, the electric mobility demand uncertainty can create several technical issues in the power system management and operation. This paper presents a computational implementation based on different probability distributions for creating EVs charging profiles. Initially, aspects related to trips, EVs characteristics, and user profiles are considered as inputs to be used to define the EVs profiles. Then, in the second step, the processing of the inputs aiming to obtain information such as trips during the day, types of EVs, user profiles, trips by users, trip duration, and energy needs are considered. The proposed case studies demonstrate the effectiveness of the computational implementation since the EV profiles created taking into account different numbers of EVs show reliable information related to the EV charging profiles and charging station usage for different days of simulation (weekdays and a weekend).**

***Index Terms*—Charging station usage, computational tool, Electric Vehicles profiles, power system impact.**

I. Introduction

The increase in greenhouse gas emissions, particularly carbon dioxide ((CO_2)), is a major contributor to climate change. Power and transport sectors are two of the most important contributors to (CO_2) emissions. At a global level, in 2022, (CO_2) from the power and transport sector increased by 261 Mt and 254 Mt, respectively, when compared with 2021 [1]. Electric vehicles (EVs) are a sustainable alternative to substitute internal combustion engine vehicles and consequently contribute to achieving carbon neutrality targets. Therefore, EV adoption continued to gain momentum in 2022, with over 10 million cars sold, exceeding 14% of global car sales and with an expectation of an EV massive adoption for the next 10 years [1], [2].

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Despite their advantages, EVs mass adoption represents an important challenge for the power system, mainly due to the uncertain nature created by user behavior. Several issues, such as the creation of new peaks of consumption, overloading, voltage instability, and degradation of the local equipment, among others, can be introduced in the electric distribution system due to a lot of EVs charging without control [3], [4].

In response to these concerns, the best solution is to develop effective EV management strategies [4]. A bidding strategy to coordinate the EV charging using blockchain smart contract was developed by the authors in [5]. The strategy considered different driving characteristics to optimize an energy transaction based on the EV charging/discharging through a demand response program. The management of EVs in a parking lot considering fairness rules is proposed in [6]. Nevertheless, the information related to the EVs profiles that considered real aspects of trips across the day, trip duration, energy needs, and level is disregarded in both works. A smart aggregation strategy for a pool of EVs participating in the secondary reserve market has been proposed in [7]. Although the EVs are managed to their optimal participation in the reserve market, the information related to the periods for EV connection and EV trips is based on assumptions without previous analysis of the EV typical patterns.

To implement EV management strategies is necessary to process data related to the EV trip requirement, hours of the trips, type of charging usage, and type of EV, among others [3]. The main challenge regarding the data information of EVs is the uncertainty associated with the user pattern [8]. Several research works have focused on developing strategies to create EV charging profiles [9], [10]. In [11], the Electric Vehicle Scenario Simulator (EVeSSi) tool is proposed, which enables the definition of EVs scenarios using a built-in movement engine. The analysis is centered on their impact on distribution networks. A stochastic simulation methodology to generate daily travel patterns and EV charging profiles was proposed by the authors in [12]. The methodology considers information related to the travel pattern model and a database with data pertaining to 18,300 journeys undertaken on weekdays. Even with the novelty, data such as several EV types and their technical characteristics (battery capacity, charging/discharging efficiency, kWh/km, among others) are disregarded.

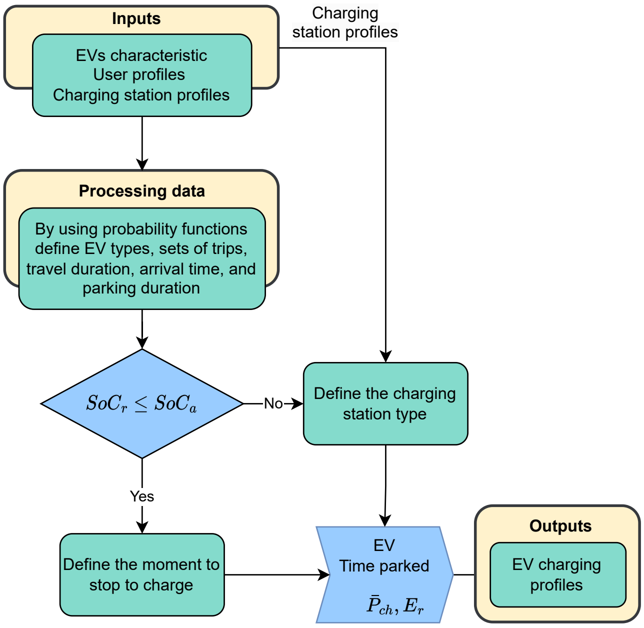

Fig. 1: Methodological framework proposed

Against this background, this paper presents a computational tool for creating EVs charging profiles. Real characteristics related to the EV user behavior, such as EV trips, EVs characteristics, and user profiles, are considered to obtain the EV charging profiles with suitable information such as trips during the day, types of EVs, user profiles, trips by users, trip duration, and energy needs. Moreover, the computational tool allows generating the EV charging profiles for a very large number of EVs with satisfactory scalability.

After this introductory section. the methodology behind the EVs profiles generation tool is presented in Section II. Section III presents the results obtained in a case study, and the main conclusions are presented in Section IV.

II. Electric Vehicles Profiles Generation

According to [13], society and mainly the utilities must be prepared for an expected worldwide mass adoption of EVs. Hence, it is necessary to create tools and solutions to estimate and determine the EV power demand. This estimation is important to define the charging station deployment requirements and assess their impact on the power systems. [14]. For the power system, typical user patterns such as driving time, type of charging station used, driving time, and power level of the charging stations make the EV power demand an uncertain variable that can represent several issues, such as high voltage variations during the day or congestion in some points of the network [4]. A computational Tool enabling the EV creation profiles was developed, as shown in Fig. 1. For this purpose, the methodology starts with the inputs read, then executes the processing data, and finally, the outputs are obtained (EV charging profiles).

A. Inputs

In this step, several data such as EVs characteristics, user patterns, and charging station information are received for the tool, more details are described below.

- EVs characteristics: information related to the EVs characteristics, such as the number of EVs, the most popular EVs and their probability of usage, EVs model, EVs battery type, i.e., if the EV is a battery electric vehicle (BEV), or a plug-in hybrid electric vehicle (PHEV), energy consumed per kilometer of each EV model, EV battery charging efficiency, EV battery discharging efficiency, minimum state of charge (SoC), and maximum SoC.
- User's patterns: the user's patterns are important information since EV usage depends on users. Hence, the tool also receives information such as typical profiles of trips executed by the users, i.e., typical hours to start and finish the trip, type of trip (medium, short, long), and the average speed of the users for the trip.
- Charging station information: information related to the charging stations (CSs) profiles, such as CSs type (public ultrafast, public fast, public semi-fast, public slow, private ultrafast, private fast, and private slow), location of the CSs, i.e., residential CS or private CS, CS power, CS efficiency, charging station probability of usage, CS and cost are also important to be considered as inputs for the tool. At this point, it is important to highlight that this information is used from real data sources. For instance, to define the probability of usage of the most EVs used, real data from a population of EVs is analyzed, and based on this, this probability in % is defined.

B. Processing data

In this step, the computational tool processes all the information detailed in the previous step, more details are described below.

- Type of EVs and their kWh/km associated: aiming to obtain this information, the numbers of EVs, the most popular EVs used and their probability of usage, EVs model, battery size, type of charging/discharging efficiency, energy per km and EVs battery type is processed through a probability density function [15].
- Trips during the day: aiming to define the trips during the day, the tool processes information on the number of EVs and average trip distance through a gamma distribution function [16].
- Technical information from EVs user profiles: each of the user´s profiles and their respective percentage is associated. So, with this input data, the tool can generate random values based on a normal distribution [17] and the percentage of users in each profile. With this, it is possible to obtain technical information from the behavior of the EV users' profiles, such as charger power $\bar{P}_{ch}$, the energy capacity of the EV $\bar{E}$, and the energy required for the trip E_r. Ultimately, with this process, the computational tool associates the trips with the EVs, considering that the EVs with higher battery capacity will be associated with longer trips. Consequently, the trips for each EV user can be obtained.

TABLE I: Charging station profiles.

CS type	Location	Charging time	Power [kW]	Units	% of CS	Public	Private
Ultrafast	Highway	t>1h	P≥150kW	120	2.33	✓	
Fast	Shopping area	1h≤t<1h30min	22kW≤P≤150kW	2235	43.40	✓	
Semi-Fast	Comercial area	t<4h	7.4kW≤P≤22kW	2263	43.90	✓	
Normal	Public area	t>4h	P≤7.4kW	532	10.33	✓	
Fast	Private housing zone	1h≤t≤1h30min	22kW≤P≤150kW	3	4.05		✓
Semi-Fast	Private housing zone	t≤4h	7.4kW≤P≤22kW	71	95.95		✓

- Duration of the trips: the process also executes an association of the trips with the EVs and the average speed. Therefore, it is possible to determine the duration of the trip, the energy spent on the trip, and the SoC of each EV.
- CSs usage: Concerning the CS data input, the computational tool compares the actual SoC (SoC_a) and the required SoC (SoC_r) to define if the EV user can perform a normal charge or, otherwise, whether the EV user needs a faster charge. In case of a faster charge, the tool defines the specified period to stop to charge the EV battery, the CS that can be used by the EV user, sets the charging duration, and makes an update of the travel duration and (SoC_a). If the EV user requires a normal charge, the strategy defines the CS type and defines the EV parking time, the power level of the CS used, and the EV energy consumption required.

C. Outputs

In this final step, the EV charging profiles are obtained. Hence, information such as EVs type population, arrival hour in the charging station, type of charging station usage, hour EV trips, and number of EVs charging their batteries in a specific hour can be visualized through figures and tables.

III. Case Study and Results

A. Case Study Specification

Based on real information from Portugal, the following case study is proposed to analyze the computational tool's performance. First, aiming to validate the scalability of the computational tool, two EV populations were considered, 1) a small EV population, with 100 EVs; 2) a big EV population, with 16146. For the small EV population, were created weekday charging profiles, considering three days of simulation. On the other hand, for the large EV population, both weekday and weekend charging profiles were tested, considering a weekend (two days). Concerning the average distance traveled per day, the information was set to $46km/day$ as per the work in [18], The percentage of usage of CSs was obtained from [18], stating that the most used was 22 KW for public areas, at 43.9% and 7.4 KW at 95.95% for private areas, as shown in Table I. The information on the most popular EVs in Portugal was obtained from [19], in which 44% of the total EV registered (16146) are BEV and 56% are PHEV, as illustrated in Table II. The average speed of cars in Portugal was defined as $50km/h$ [20].

Based on [21], in Europe, nowadays 64% of the EVs charge at home while 36% of the EVs charge at the workplace. In both cases, relying on private charging stations.The daily profiles of EV usage have been defined following the profiles presented in [22]. Moreover, several driver profiles were defined considering EV users' behavior for a normal workday and a weekend, as shown in Tables III and IV. For that, different types of trips were considered (short, medium, and long), in which a short trip is related to users that travel a short distance, for instance, a worker that lives close to the workplace. Medium and long trip types refer to users that live far away. During the weekdays, five user profiles can charge their EVs only at home, i.e., these EV users have their own CSs at home and prefer to charge their batteries at night. Three user profiles can charge their EVs at home or the workplace. This kind of EV user can charge their batteries during the day. On the other hand, during the weekend, all EV users can charge their EVs only at home. More details about the results obtained are discussed in the following subsection.

TABLE II: Most used EV models.

Model	Battery Type	# of EVs	Evs in percent
Tesla	BEV	2195	14%
Peugeot	BEV	1378	9%
BMW + BMW I	BEV	1362	8%
Mercedes-Benz + BMW I	BEV	1284	5%
Hyundai	BEV	826	20%
Mercedes-Benz	PHEV	3279	16%
BMW + BMW I	PHEV	2505	16%
Volvo	PHEV	1764	11%
Peugeot	PHEV	980	6%
Wolkswagen	PHEV	573	4%

TABLE III: EV users profiles for Weekdays.

Profile	Trip hours	User type	Trip type
Home 1	8h, 18h	Charge at home	Short
Home 2	5h, 19h	Charge at home	medium
Home 3	9h, 19h	Charge at home	short
Home 4	8h, 10h, 12h, 15h, 17h	Charge at home	long
Home 5	8h, 10h, 19h	Charge at home	short
Work 1	8h, 10h, 14h, 16h, 18h	Charge at home/work	long
Work 2	9h, 19h	Charge at home/work	medium
Work 3	10h, 20h	Charge at home/work	medium

B. Results and Discussion

The main results for the small EV population considering three workdays of simulation are shown in Fig. 2. Fig. 2 (left) shows the EV charging profiles created by the tool. It is possible to observe that since 64% of the EV users charge their batteries at home and considering the EV user's profiles shown by Table III, the computational tool generates profiles with the most EVs, around 60%, charging between 17:00–23:00. Moreover, taking into account that 36% of the EV users have the possibility to charge their batteries at the workplace (Table III), it can be noted that around 26 EVs charge their batteries in the workplace. Fig. 2 (right) illustrates the CSs

TABLE IV: EV users profiles for a Weekend.

Profile	Trip hours	User type	Trip type
Home 1	10h, 20h	Charge at home	Short
Home 2	11h, 15h	Charge at home	medium
Home 3	8h, 21h	Charge at home	short
Home 4	12h, 13h, 20h	Charge at home	long
Home 5	8h, 10h, 19h	Charge at home	short
Home 6	9h, 14h	Charge at home	long
Home 7	11h, 19h	Charge at home	medium
Home 8	12h, 21h	Charge at home	medium

usage by the 100 EVs that the tool can generate. It is possible to note that during the EV charging events at the workplace, hours 8:00–10:00, 14:00, and 16:00, the most used CSs are private semi-fast (22kW). On the other hand, when charging at home (17h–23h), the most used CSs are residential slow of 3.6kW and 7.2kW, which verifies the tool's effectiveness in generating reliable EV charging profiles using the input data.

The main results for the large EV population considering the three workdays of simulation are shown in Fig. 3. It is possible to observe that for this EV population, the results are similar to the previous EV population tested. Nevertheless, the number of EVs considered by the tool is a notable difference in Fig. 3, since around 4000 EVs are charging at 9:00, around 2000 at 10:00/14:00, representing 25% and 12% of the EV users are charging at workplace. On the other hand, around 8000 EVs are charging at 18:00, showing that 49% of the users are charging at home. Moreover, the CCs usage for this EV population created by the computational tool verifies its performance since, during the day, only private CSs are used, and only residential CSs are used between 18:00–23:00.

During a weekend test, all the EV users only can charge their batteries at home, as illustrated by Table IV. The main results for this simulation are shown in Fig. 4. Based on the inputs related to the EV user's profiles, the computational tool can define the possibility that the EV users have to charge in a specific location. This fact can be observed in Fig. 4 (left), in which the most EV charging profiles are at night, with around 8000 EVs charging at 20:00 and 4000 EVs charging at 21:00, representing 31% and 25% of the users, respectively. An important fact to highlight is that most CSs used are residential, see Fig. 4 (right), and no private charging stations are used. Furthermore, at several hours, for instance, 15:00–17:00, some EV users choose to charge at public charging stations. In summary, for both EV populations analyzed, the computational tool can create reliable EV charging profiles following the inputs received. Likewise, it was also possible to assess the tool's scalability by generating a population of EVs that is 161 times larger than the other. Finally, the results illustrated in Fig. 2, Fig. 3, and Fig. 4 can be exported in comma-separated values files, allowing their use in EV management strategy tools, which can be very useful to implement more realistic EV coordination, mainly due to the fact that electric mobility is seen as an interesting alternative to achieve the carbon neutrality.

IV. Conclusions

A computational tool for the creation of electric vehicles (EVs) charging profiles has been proposed in this paper. Real data related to Portugal, such as the most EVs used by the population, average trip distance, average speed, and the most charging station (CSs) installed, among others, are used for the tool aiming to create reliable EV charging profiles. Two types of EV populations are simulated, a small EV population and a big EV population, considering different user profiles and three days of operation for weekdays and two for a weekend. Simulation results demonstrated that the computational tool proposed is able to create several reliable EV charging profiles that follow the distributions of the input data. Moreover, the scalability of the computational tool is verified since for the big EV population (1614 EVs), the results indicate the same performance as in the case of the small EV population.

In future work, the authors contemplate implementing the computational tool for more days of simulations (one year) and considering the outputs of the tool as inputs to be analyzed to execute smart EV charging coordination in different tools and applications, such as for buildings management (residential and business), to access the impact on the distribution system or even in the global energy system.

References

[1] IEA, "Co2 emissions in 2022," in *International Energy Agency: Paris, France*, 2022, pp. 1–19.

[2] N. Hooftman, M. Messagie, J. Van Mierlo, and T. Coosemans, "The paris agreement and zero-emission vehicles in europe: Scenarios for the road towards a decarbonised passenger car fleet," *Towards User-Centric Transport in Europe 2: Enablers of Inclusive, Seamless and Sustainable Mobility*, pp. 151–168, 2020.

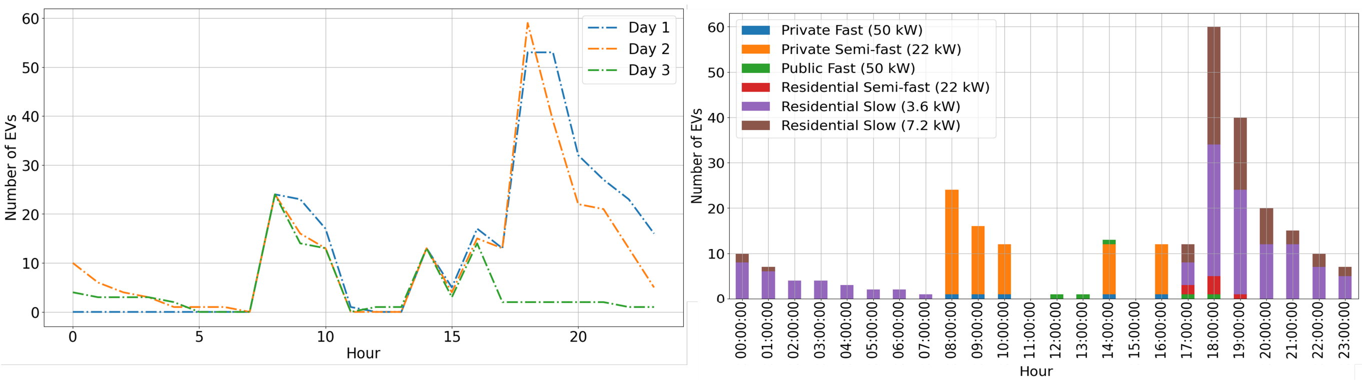

Fig. 2: EV charging profiles (left side) and Charging stations usage (right side). For a population of 100EVs during weekdays

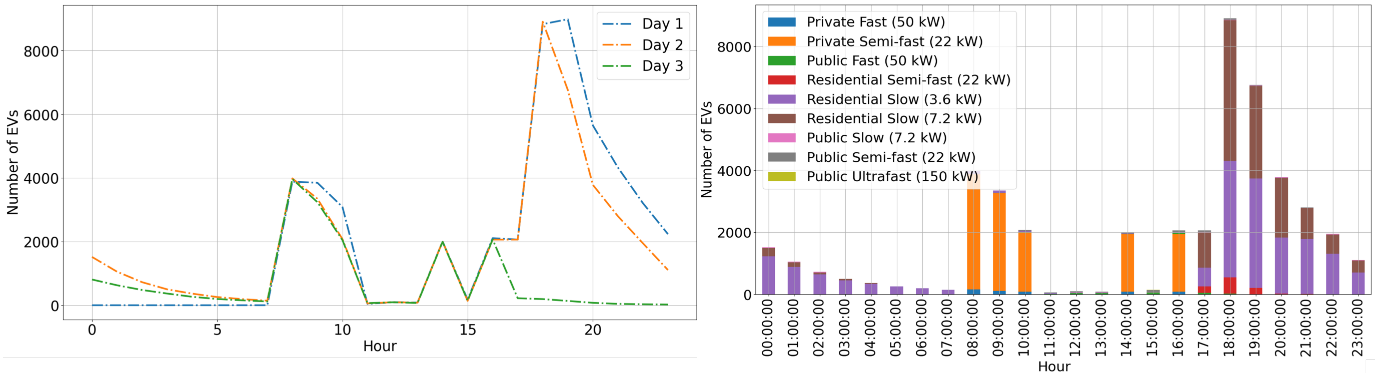

Fig. 3: EV charging profiles (left side) and Charging stations usage (right side). For a population of 16140 EVs during weekdays

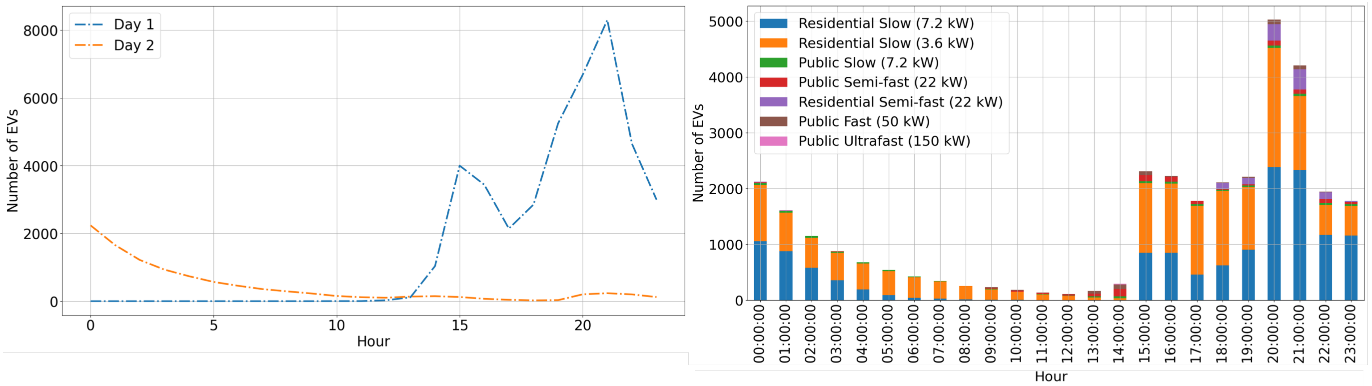

Fig. 4: EV charging profiles (left side) and Charging stations usage (right side). For a population of 16140 EVs during a weekend

[3] C. P. Guzman, N. B. Arias, J. F. Franco, J. Soares, Z. Vale, and R. Romero, "Boosting the usage of green energy for ev charging in smart buildings managed by an aggregator through a novel renewable usage index," *IEEE Access*, vol. 9, pp. 105 357–105 368, 2021.

[4] Y. Wu, Z. Wang, Y. Huangfu, A. Ravey, D. Chrenko, and F. Gao, "Hierarchical operation of electric vehicle charging station in smart grid integration applications—an overview," *International Journal of Electrical Power & Energy Systems*, vol. 139, p. 108005, 2022.

[5] B. Wang, W. Liu, M. Wang, and W. Shen, "Research on bidding mechanism for power grid with electric vehicles based on smart contract technology," *Energies*, vol. 13, no. 2, p. 390, 2020.

[6] H. Morais, "New approach for electric vehicles charging management in parking lots considering fairness rules," *Electric Power Systems Research*, vol. 217, p. 109107, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0378779622011567

[7] C. P. Guzman, R. Romero, N. B. Arias, M. J. Rider, and J. F. Franco, "Secondary reserve provision through a smart aggregation strategy of electric vehicles," in *2021 IEEE Madrid PowerTech*. Ieee, 2021, pp. 1–6.

[8] B. Wang, R. Huang, Y. Wang, H. Nazaripouya, C. Qiu, C.-C. Chu, and R. Gadh, "Predictive scheduling for electric vehicles considering uncertainty of load and user behaviors," in *2016 IEEE/PES Transmission and Distribution Conference and Exposition (T&D)*. IEEE, 2016, pp. 1–5.

[9] R. Maia, M. Silva, R. Araújo, and U. Nunes, "Electric vehicle simulator for energy consumption studies in electric mobility systems," in *2011 IEEE Forum on Integrated and Sustainable Transportation Systems*. IEEE, 2011, pp. 227–232.

[10] H. W. Won, "Development of a hybrid electric vehicle simulation tool with a rule-based topology," *Applied Sciences*, vol. 11, no. 23, p. 11319, 2021.

[11] J. Soares, B. Canizes, C. Lobo, Z. Vale, and H. Morais, "Electric vehicle scenario simulator tool for smart grid operators," *Energies*, vol. 5, no. 6, pp. 1881–1899, 2012. [Online]. Available: https://www.mdpi.com/1996-1073/5/6/1881

[12] J. Brady and M. O'Mahony, "Modelling charging profiles of electric vehicles based on real-world electric vehicle charging data," *Sustainable Cities and Society*, vol. 26, pp. 203–216, 2016.

[13] IEA, "Global ev outlook 2022: Securing supplies for an electric future," in *International Energy Agency: Paris, France*, 2022, pp. 1–221.

[14] G. Doluweera, F. Hahn, J. Bergerson, and M. Pruckner, "A scenario-based study on the impacts of electric vehicles on energy consumption and sustainability in alberta," *Applied energy*, vol. 268, p. 114961, 2020.

[15] M. Ren, Q. Zhang, and J. Zhang, "An introductory survey of probability density function control," *Systems Science & Control Engineering*, vol. 7, no. 1, pp. 158–170, 2019.

[16] A. Fischer, R. E. Gaunt, and A. Sarantsev, "The variance-gamma distribution: A review," *arXiv preprint arXiv:2303.05615*, 2023.

[17] Z.-x. Jiang and H. Chen, "A new early warning method for dam displacement behavior based on non-normal distribution function," *Water Science and Engineering*, vol. 15, no. 2, pp. 170–178, 2022.

[18] "Mobi.e Electric Mobility Bringing future to life," Jan. 2023. [Online]. Available: https://www.mobie.pt/en/redemobie

[19] "Uve, Vendas de Veículos Elétricos em Portugal," Jan. 2023. [Online]. Available: https://www.mobie.pt/en/redemobie

[20] "Portugal driving laws, Speed limits in Portugal (in km/h)," Jan. 2023. [Online]. Available: https://portugaldrivinglaws.com/speedlimits.php

[21] "Chargeup, Charging up Europe through binding capacity targets for publicly accessible charging infrastructure and Member State action plans," Jan. 2023. [Online]. Available: https://static1.squarespace.com/static/5e4f9d80c0af800afd6a8048/t/60d426dda0462c583a9d0353/1624516320310/Charging+up+Europe+through+binding+capacity+targets+for+publicly+accessible+charging+infrastructure+and+Member+State+action+plans+.pdf

[22] "Mobi.e, Modelo e Sistema de Carregamento para Veículos Elétricos em Portugal," Jan. 2023. [Online]. Available: https://www.imt-ip.pt/sites/IMTT/Portugues/Noticias/Documents/Semin%C3%A1rio%2008%20Mar%C3%A7o%202010%20-%20PDFs/Luis_Reis.pdf