Electric Vehicles Load Profile Generator Based on the Probability Density Functions

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Abstract— **This paper provides a prototype of an Electric Vehicles Load Profile Generator based on the probability density function of several parameters such as arrival time, total connection time, energy demand, and the information about the vehicle's battery size of charge and the power level of the charger. This tool of simulation, realised with Python, allows the generation of random EV load profiles and, in the next step, simulates the integration of these patterns in a defined grid through open-source and commercial software's. The Quasi-dynamic simulation approach is used since load profiles are time depending. The electric vehicles load profile generator is tested by simulating scenarios of different load profiles at points of common coupling with proposed simplification to allows maximising the precision of the results and at the same time to minimise the needed simulation time.**

Keywords—distribution system impacts, electric vehicles, power distribution, power system modelling, quasi-dynamic time-series analysis

I. INTRODUCTION

The actual climate conditions, which result in many phenomena such as global warming, require effective and sometimes significant actions to limit these negatives outcomes [1]. According to the Swiss Federal Office for Environment [2], the main action is the reduction of greenhouse gas emissions, particularly in the sectors with the highest reduction potential, such as transports, electrical production/consumption, and heating systems. Developing and improving new or existing eco-friendly technologies, such as power generators based on renewable energies (RES) and Electric Vehicles (EVs), is constantly growing. Countries are showing great interest and effort in regards to this problem, by applying support and investment subsidies for the construction of new power generators based on RES as well as by promoting electromobility [3], or by planning a phase-out of the sales of Internal Combustion Engine (ICE) cars within the next twenty years [4]. In Switzerland, the Swiss Federal Government (SFG) is active at various stages to improve the framework conditions for alternative propulsion systems by applying legal measures such as the introduction in 2012 of the Swiss CO_2 law [5], and to develop pilot projects in cooperation with municipalities [2].

Moreover, the market for electromobility has been pushed forward by developing more efficient batteries and engines. These enhancements allow achieving performances comparable to an ICE car, notably in terms of distance range. Therefore, this increase in the attractiveness of electromobility and the policy strategies adopted to reduce gas emission could lead to an important growth of EVs in the following years.

The growth of the share of EVs and the integration of alternative power generators are a part of the solution against global warming [6]. However, their improvement is not without consequences. With the increase of EVs, electric energy demand will also increase, leading to a possible increase in daily energy consumption. Moreover, an increase in power peak can appear. These incrementations can harm the functionality of power systems by affecting the quality and safety of the grid. Thus, also considering the integration of decentralised power generators, the low-voltage distribution grids (LVDG) will be pushed to their limits [7],[8],[9]. Nowadays, electrical grid engineers are faced with this problem and are trying to figure out solutions for the future [10],[11]. The possible impacts on LVDG must be modelled using simulation software in a simplified and transparent manner, considering limited information from the investigated grid: topology of the grid, customers and their profile type, available and perspective PV and EV charging pole connections. Existing approaches and open-source tools available in the literature: emobpy [12], VencoPy [13] and RAMP-mobility [14], provides comprehensive sources of country-wise information and requires specific information, which is not always available on a local level. Therefore, the main goal of this paper is to present a prototype of an Electric Vehicles Load Profile Generator (EVLPG) based on the probability density function (PDFs) of several parameters derived from previous tools or regional real charging events, such as arrival time during weekdays and weekends, connection time during weekdays and weekends and energy demand with information about battery size of the vehicle in charge and the power level of the charger for further integration of generated patterns in a defined LVDG by means of the open-source and commercial software's.

The work structure is the following. The second chapter presents the EVLPG structure and considerations to achieve realistic results. The third chapter highlights EV load profile calculations with the proposed algorithm. The fourth chapter highlights the modelling of charging fleets (CF). The fifth chapter focuses on the results of the EV load profiles generator and the results of the simulations of the impact of EV in a

The published version of this author accepted manuscript can be found via DOI: 10.1109/RTUCON53541.2021.9711591

complex grid. The final chapter includes an interpretation of the results and a discussion about the possible future impact.

II. Electric Vehicle Load Profiles Generator

This section provides basic knowledge regarding the EVLPG and includes the approach used to calculate load profiles and the simplifications adopted to maximise the precision of results by minimising the time of the simulation. The EVLPG is a Python-based tool and allows defining – based on several input parameters – quasi-realistic EV load profiles of charge over one day.

A. Statistical Approach

In a real case, the charge of an electric vehicle depends on several parameters. Thus, it is not possible to define exactly what would be the load profile, therefore, it is necessary to pass through a statistical approach to define these load profiles. The EVLPG module is based on a probabilistic selection of variables. Load profiles of charging stations are calculated based on random variables such as the connection time of the car to the charging station, the starting time of charge, the energy demand which can be interpreted as the state of charge (SoC) of the battery, and the model of the car that defines the maximal capacity of the battery and the maximal power of charge. Arrival time, connection time, and energy demand PDFs were derived from 10.000 real charging events provided by the company ELaadNL [15],[16] from the Netherlands and are divided into three categories:

- Private customer (charging at home)
- Public customer (public place such as parking)
- Work customer (charging at the workplace)

Univariate distributions of charging events does not resemble common probability distributions. Data has two peaks (bimodal distribution) or many peaks (multimodal distribution). It is possible to distinguish – as shown in Fig. 1 – a PDF during the weekdays (from Monday to Friday) where the arrival time for public (orange line) and workplace (yellow line) charging points is concentrated in the morning, while for private charging (blue line) is condensed mostly in the evening. While during the weekend, the arrival time is distributed over all day for all three categories of charging infrastructures. Fig. 2 and Fig. 3 depict EV's energy demand and connection time distributions. Used PDFs have similarities with the statistical mobility data of Switzerland [17], and were used in this work without adjustments.

According to power levels in Europe, they are defined by the standard IEC 61851 [18] and [19], only the level 2 mode has been considered, with a maximal power of 22kW. Four power levels based on possible limitations of current are used and presented in TABLE I. , where the current limitation of 16 Amps is for households and workplaces, while in a public place, the maximal current could achieve 32 Amps.

TABLE I. Considered values of possible power of charge

Current [A]	10	13	16	32
Power of charge [kW]	7	9	11	22

These power values can be easily changed according to the user's requirements and can easily delete, modify, or add new power values in the software by changing variables.

Different models of cars are provided to the EVLPG, and in this work, the list of cars refers to the top-selling models in Switzerland [20]. Some of them are listed in TABLE II. with the parameters defined for each car.

TABLE II. EV models in CH with their main characteristics. Values according to the Electric Vehicle Database [21].

Model	Battery capacity [kWh]	Power of charge [kW] (Level 2)	Probability [%]
Tesla Model S	100	≤22	20
Tesla Model 3	75	≤22	7
Renault ZOE	52	≤22	10
VW e-Up	36	≤7.2	3
Nissan Leaf	62	≤7	10
BMW i3	38	≤11	8

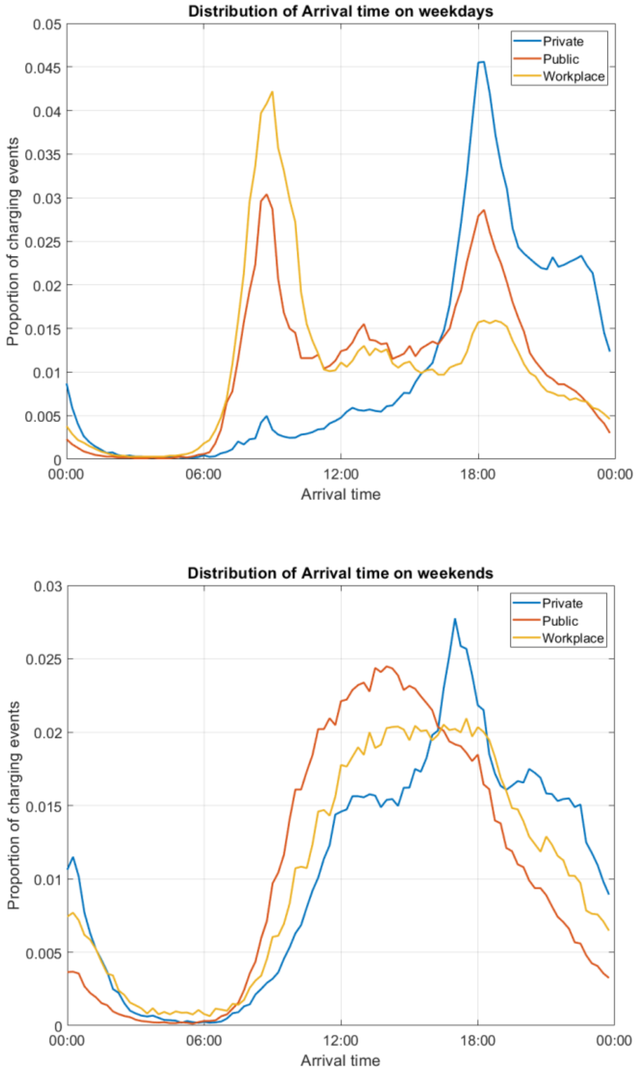

Fig. 1. Distribution of arrival time over one day. During weekdays on the top and during weekends on the bottom.

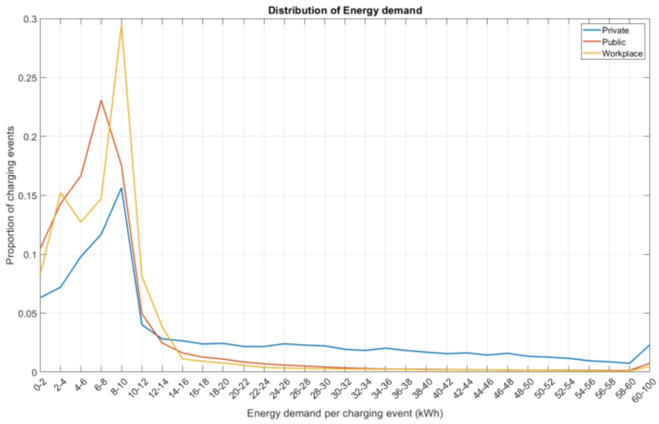

Fig. 2. Distribution of energy demand.

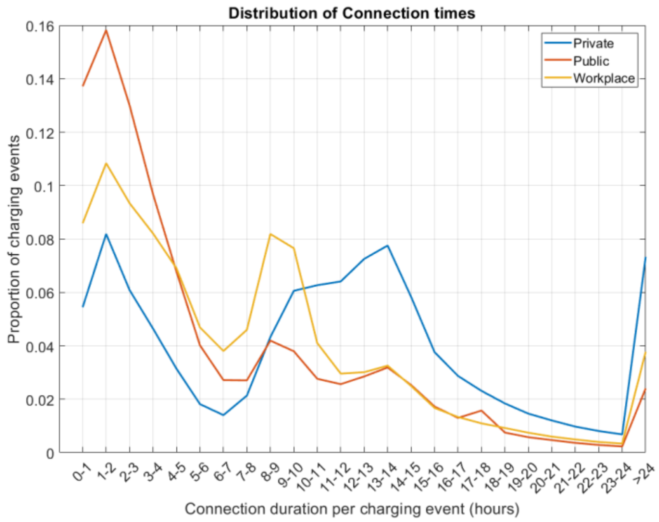

Fig. 3. Distribution of connection time.

The battery capacity allows defining the car's state of charge before starting to charge, while the power of charge acts as a limitation in case the power of charge chosen by the EVLPG is higher than the maximal value. All these steps are fundamental for the algorithm that calculates the load profile.

Results regarding the impact on the LVDG are extracted by applying the method of Monte Carlo [22], [23] Simulation, which is a powerful approach for statistical calculation. EVLPG approach is based on a multitude of simulations that allow exploring the behaviour of the system and converge to a realistic result. Monte Carlo Simulation is composed of four steps:

- PDFs definition: all distributions explained above are integrated into the EVLPG.
- Creation of scenarios based on PDFs: for each charging station, a scenario is defined, and this scenario is characterised by the arrival time, connection time, charging power level, the model of the car, and the energy demand.
- Calculation of intermediate and output values: by applying the algorithm of calculation and based on the scenario, the load profiles is calculated and used to perform quasi-dynamic simulations to study the impact on the grid.
- Aggregation and definition.

Fig. 4 shows an example of three possible scenarios defined by the EVLPG. Load profiles are then calculated starting from this information.

Arrival Time WD	Charge time	End charge time	Power [W]	Model of car	Energy demand [kWh]
14:30	5:50	20:20	11000	BMW i3	31
17:30	4:00	21:30	3700	Tesla Model S	9
19:30	4:12	23:42	7000	BMW i3	9

Fig. 4. Example of three scenarios created by the EVLPG.

Fig. 5 shows a flowchart of the Monte Carlo Simulation approach applied to the EVLPG.

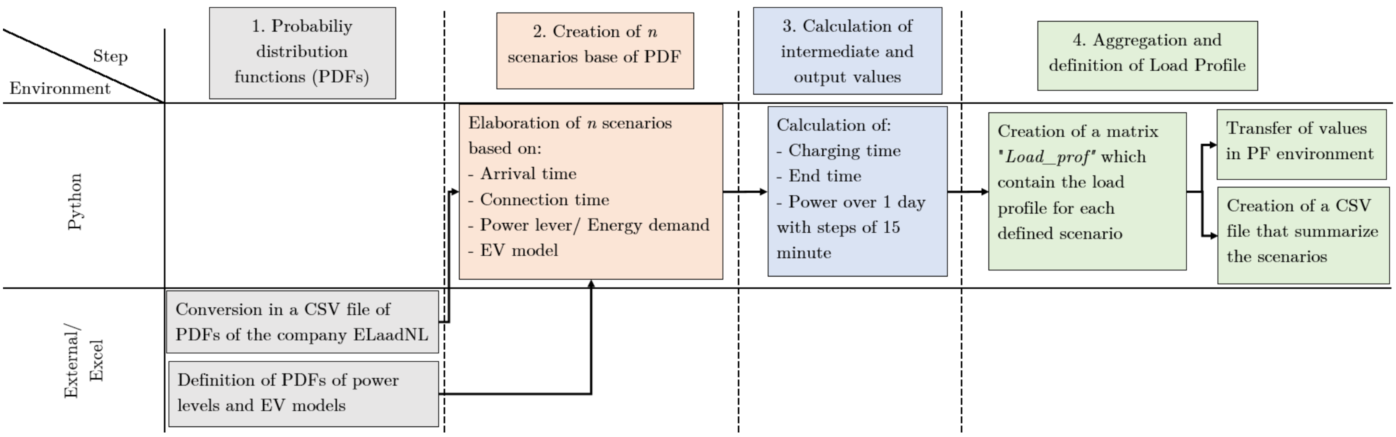

Fig. 5. Flowchart of Monte Carlo Simulation applied to the EVLPG.

III. EV LOAD PROFILE CALCULATION

EV charge trend corresponds to a typical Lithium-ion battery's behaviour (Li-ion). This battery's technology is mostly used in the domain of EVs because of its property to achieve high energy density. This characteristic of a battery plays an important role since the space available for the battery pack is limited, and the purpose is to maximise the distance range. A typical charge of a Li-ion battery is composed of three steps [24]:

1. Pre-charge: the current has a low value so that the cell voltage achieves a minimum value of the charge. This phenomenon appears if the state of charge of the battery is lower than 10%.
2. Constant Current charge (CC mode): this step represents the constant part of the charge at nominal power. The battery starts charging at a nominal current until the moment in which the state of charge achieves approximately 50-70%.
3. Constant Voltage charge (CV mode): the cell voltage achieves its nominal value, and the value of current decreases exponentially until the moment in which the battery is fully charged.

A. EV Charging Profile behaviour

Different algorithms, with the aim of calculating a profile of charge similar to the one of a Li-ion battery, have been developed and tested:

- *Real measure-based behaviour* fits the reality (Fig. 6) since knowing the full charge behaviour of a car is sufficient to adjust this behaviour based on the power chosen and apply it at a given time of day, and the new behaviour is ready for the simulation. The disadvantage of this approach is that to simulate different cars, it is necessary to know for each car its charge behaviour, which is not always available.

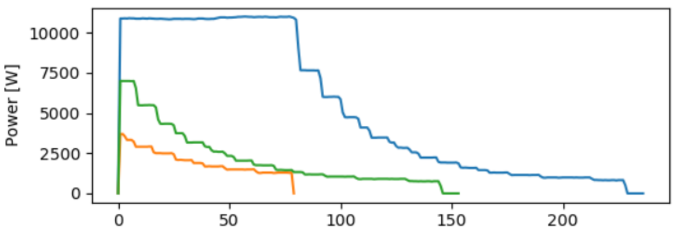

Fig. 6. EVs charging profiles in minutes, using a real measure base approach. Blue line: BMW i3, Orange line: Tesla model S, Green line: second BMW i3

- *Exponential Ideal Power behaviour* consists two-part*:* Constant current (approximately 70% of total charge) and exponential behaviour charge (30% of total charge), as shown in Fig. 7. Suppose the percentage of energy demand is higher than 30%. In that case, there will be a percentage of charge equal to the difference between the total percentage of energy needed and 30%, which follows the constant current behaviour ($P(t) = P_0$).

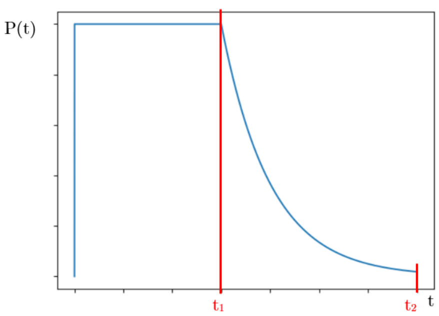

Fig. 7. Example of an Exponential Ideal power behaviour

The last 30% of charge, the pattern of the power can be estimated as:

$$P(t) = P_0 \cdot e^{-\frac{t}{\tau}} \tag{1}$$

where: τ is the constant of time and is considered τ=20[min] based on the whole charge behaviour of a car; P_0 is charging power at CC mode.

The energy of a complete charge is estimated according to the following equation:

$$E = \int_{0}^{t_{CC}} P_0 dt + \int_{t_{CC}}^{t_{CV}} P_0 \cdot e^{-\frac{(t-t_{cc})}{\tau}} dt \tag{2}$$

where: t_{CC} is CC mode time, t_{CV} is the difference from the end of charge time (SoC=100%) and t_{CC}

Transforming (2), with respect to the total charge time t_{CV} becomes:

$$t_{CV} = t_{CC} - \ln\left(1 - \frac{1}{\tau} \cdot \left(\frac{E}{P_0} - t_{CC}\right)\right) \cdot \tau \tag{3}$$

Since the energy E, the level of power P_0 and the time constant are known, t_{CV} can be calculated. In the case where the percentage of energy needed is less than 30%, the time of charge can be calculated by subtracting the t_{CC} time to the total time t_{CV}.

- *Linear Ideal Power behaviour* considers a linear behaviour in CV charging mode. It appears quite different from the curves presented before, but it still fits reasonably well the reality by comparing it to the real charge patterns.

The first example shows how the load profile is calculated considering an energy demand higher than 30% of the battery capacity. This means that the charge will be composed of both modes of charge, as illustrated in Fig. 8. In this example, the energy demand corresponds to 80% of the battery capacity.

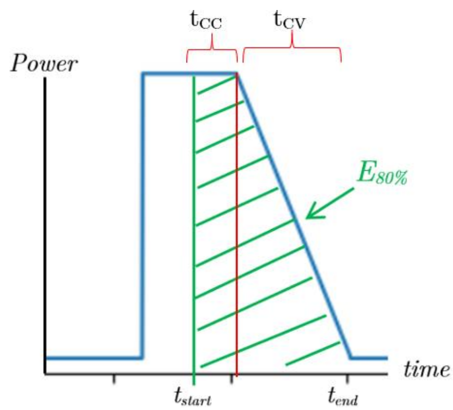

Fig. 8. The behaviour of EV charge profile is estimated for energy demand higher than 30%.

The second example represents the case of an energy demand lower than 30% of the battery capacity. In this case, the charge will exclusively include the CV mode. Fig. 9 shows the case where the energy demand corresponds to 20% of the battery capacity.

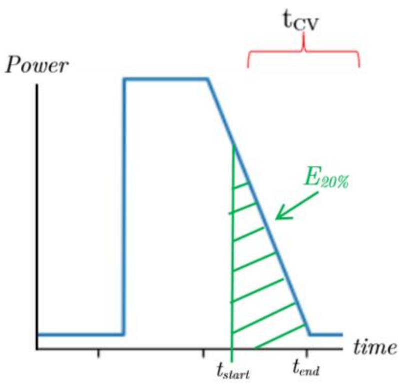

Fig. 9. The behaviour of EV charge profile is estimated for energy demand lower than 20%.

After comparisons and tests, it has been chosen to pursue the EVLPG by considering the simplified algorithm for a linear power behaviour since it fits reality and is the easiest method to implement. Comparison with real data [25] shows an error of ~4% in a complete charge and ~30% in the case of a partial charge.

B. Load profile algorithm

The algorithm used to define possible load profiles is generally composed of four steps, as described in Fig. 10.

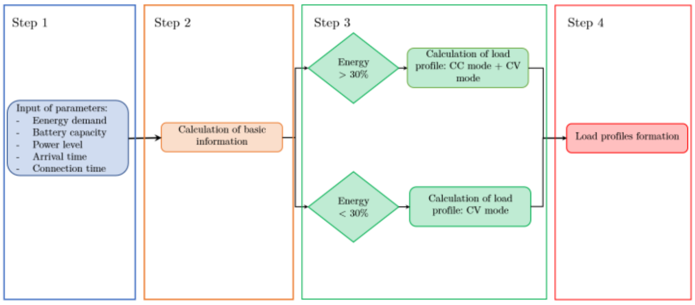

Fig. 10. Flowchart of the EV load profiles calculation algorithm.

- In step one, several fundamental parameters are defined and used as input values for the calculations.
- The times needed to charge the battery, considering a SoC equal to 0%, are calculated in step two. The time of charge in CC mode (t_{cc}), the time of charge in CV mode (t_{cv}), and the total time t_{tot} are obtained in the following way:

Since the amount of energy covered by the CC mode is known and it is equal to 70% of the battery capacity (E_{Tot}), the time in CC mode (t_{cc}) is calculated:

$$t_{cc} = \frac{E_{Tot} \cdot 0.7}{P_0} \tag{4}$$

While, for the case of t_{cv}, this last part of the charge is considered as a triangle, where the area corresponds to the last 30% of battery capacity. Based on the equation of the area of a triangle, it is possible to extract the value of t_{cv}:

$$t_{cv} = \frac{E_{Tot} \cdot 0.3 \cdot 2}{P_0} \tag{5}$$

Total time of charge becomes:

$$t_{tot} = t_{cc} + t_{cv} \tag{6}$$

- In step three, load profiles are calculated based on the input parameters.
- Step four forms the vector of the load profiles over one day and summarises them in the matrix (Fig. 11), which contains the values of each time step and is saved as a text file.

Out[70]:

	Load46	Load40	Load48	Load41	...	Load51	Load31	Load43	Load19
0	0.0	0.000000	0.0	0.000000	...	0.000	0.0	0.000000	0.0
1	0.0	0.000000	0.0	0.000000	...	0.000	0.0	0.000000	0.0
2	0.0	0.000000	0.0	0.000000	...	0.000	0.0	0.000000	0.0
3	0.0	0.000000	0.0	0.000000	...	0.000	0.0	0.000000	0.0
4	0.0	0.000000	0.0	0.000000	...	0.000	0.0	0.000000	0.0
...	...	...	...	...	...	...	...	...	...
3307	0.0	3.180558	0.0	12.875118	...	6.525	0.0	4.277778	9.0
3308	0.0	2.567516	0.0	11.902255	...	6.300	0.0	4.141667	9.0
3309	0.0	2.014167	0.0	10.929392	...	6.075	0.0	4.005556	9.0

Fig. 11. Part of the matrix created by the module, which contains the information regarding each load profile.

Fig. 12 shows the graphical results of the algorithm's application. In this case, five load profiles have been calculated. One can notice the influence of the initial conditions of charge (arrival time, energy demand, etc.) on the calculation of load profiles. Load profiles represented by the orange and purple lines clearly show a charge defined exclusively by the CV mode, while the first part of the charge characterises the red shape in CC mode and the second one in CV mode. However, some of the load profiles are stopped before achieving a full charge. This phenomenon occurs when the connection time to a charging station defined by the module is shorter than the required time to charge the battery completely.

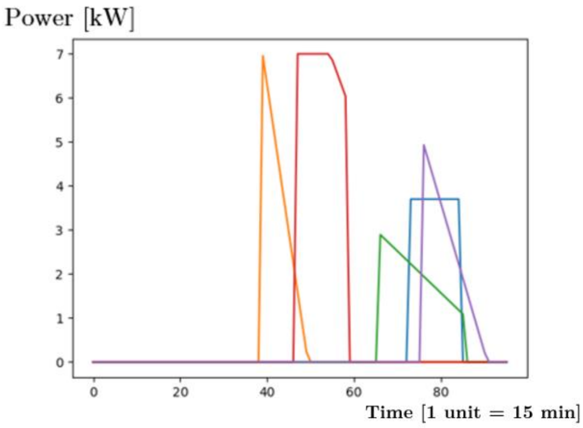

Fig. 12. Generation of five load profiles over one day.

IV. Modelling of Charging Fleets in Power Analysis Tools

Points of common coupling (PCC) are connected exclusively to two load elements in the PowerFactory (PF) environment (Fig. 13). One load element represents the fixed load (house, block of flats, etc.), and it is characterised by standard load profiles (SLP). While the second load element represents the charging fleet (CF). The term "charging fleet" is introduced. A charging fleet could be composed of one or more charging stations according to the number of customers of the fixed load. For instance, if the fixed load represents a block of ten flats, the number of charging stations could also be ten (one charging station per flat). Therefore, the load profile assigned to the charging fleet should be the sum of load profiles of all charging stations connected to the PCC.

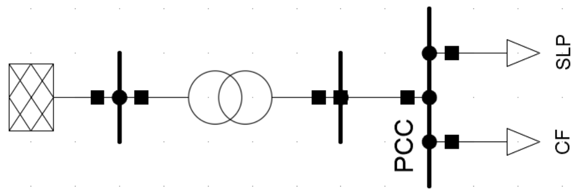

Fig. 13. Representation of a PCC with a load and a charging fleet.

In a real grid, there a different kind of loads and each topology is represented by only one load. It means that a house is one load as well as a building that contains several apartments is another load. In the EVLPG, the information concerning the number of customers of each load is considered. It allows simulating different scenarios, e.g., in a house with one family, there is one charger, and in a building with five apartments, there is a charger for each apartment.

Once selected the CF for the simulation, the EVLPG read the value of the number of customers of each CF and chooses a random number from one to the number of customers. TABLE III. below shows the specifications of a scenario.

TABLE III. DEMONSTRATION OF A SCENARIO THAT CONSIDERS A RANDOM NUMBER OF CUSTOMERS ON THE SAME LOAD

Name of charger	Type of load	No. of customers chosen by the EVLPG	Maximal No. of customers
MixPP6	Block of flats	30	33
MixWPub6	Gas station	2	10
MixPP7	Block of flats	15	25
Work3	Block of flats	1	6
MixPP8	Block of flats	11	33

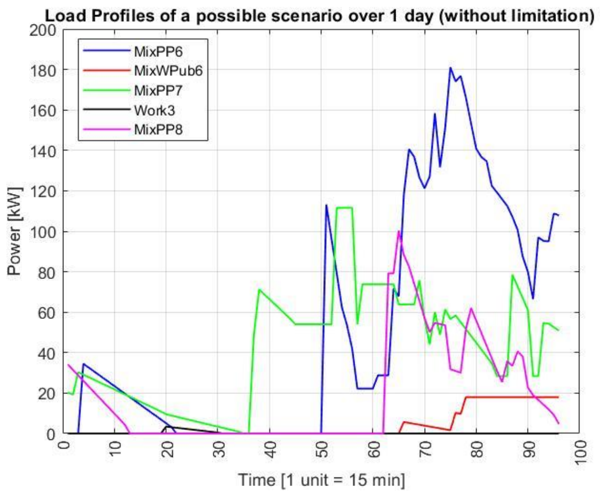

Fig. 14. Load profiles of possible scenarios over one day by considering a random number of customers per load.

Fig. 14 illustrates how EV load profiles look like during one day for different load types. It is possible to observe that the MixPP6 load profile has the highest impact. It also has a higher number of customers, while, Work3 has practically no effect on the grid compared to the other profiles since there is only one customer.

V. Application of EVLPG on a Complex Grid

The following section presents the results and comparisons of the quasi-dynamic time-series analysis based on a complex grid [8]. The goal is to simulate the integration of EVs in an LVDG for one year and repeat simulations thousands of times with the scope to converge to a realistic result regarding the possible impact.

A. Simplifications

Different simulation methods have been implemented and compared to each other to achieve the best configuration, which allows maximising the precision of the results and minimising the time needed to simulate.

- The initial method (Complex Grid Year Daily based (CGYD)) was based on a time frame of one day, and the simulation was repeated 365 times to simulate every day for one year. It means that the load profiles were calculated over one day and quasi-dynamic simulations were performed considering a timeframe of one day.
- The second method (Complex Grid Year based (CGY)) was based on a time frame of one year. Therefore, load profiles were calculated over one year instead of one day. Afterwards, quasi-dynamic simulation over one year was performed.
- A third method (Complex Grid (CG)) analogous to the initial one was implemented. This third method is based on a time frame of one day, but the simulation is repeated 24 days and not 365 like the first case. The choice of 24 days is made by considering two days per month which is a good compromise that allows reducing the number of repetitions, which at the same time, keeps the seasonality of SLPs over one year. Another important parameter is that by considering two days per month, it is still possible to simulate a weekday as well as a weekend day.

B. Results

For each method, four cases have been performed and each case is characterised by a different CF distribution. In their turn, each case has been simulated (or repeated) five times. The results presented are an average of all results obtained by using the relative method. TABLE IV. presents results in terms of the time of simulation according to the method and for different percentages of integration. Meanwhile, Fig. 15 and Fig. 16 show through boxplots the distribution of line-loading according to the method of simulation and the percentage of integration, which are 30% and 70%, respectively.

TABLE IV. SUMMARY OF TIME OF SIMULATION ACCORDING TO THE METHOD OF SIMULATION AND THE PERCENTAGE OF INTEGRATION.

	Percentage of integration		
Method	30 [%]	50 [%]	70 [%]
C.G.Y.D.	21.4 min	30 min	37.6 min
C.G.Y.	18.6 min	29.2 min	45.8 min
C.G..	6.8 min	9.15 min	26.7 min

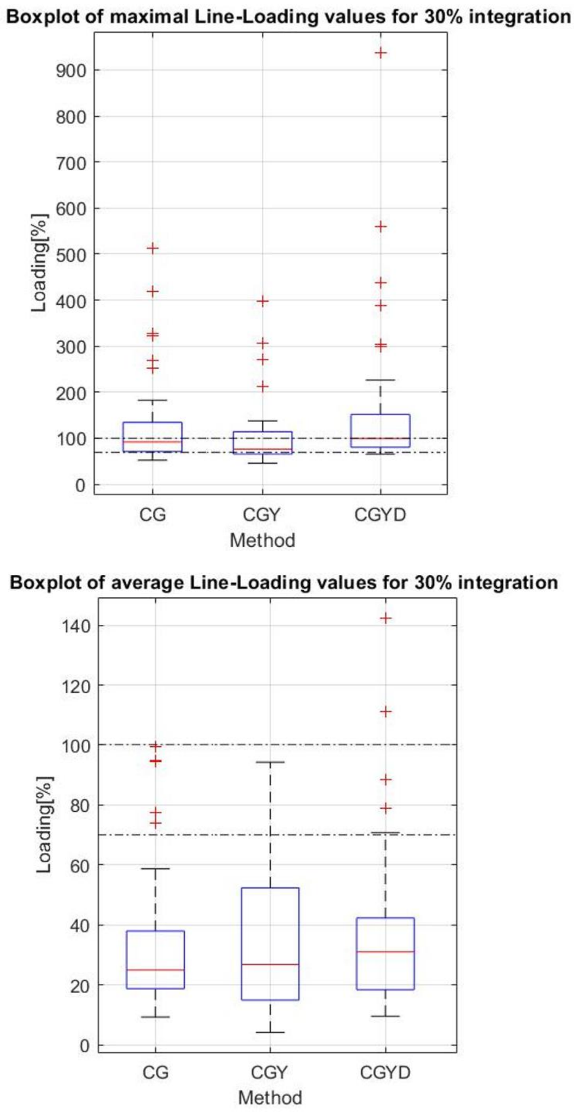

Fig. 15. Line-Loading comparison between methods for 30% integration.

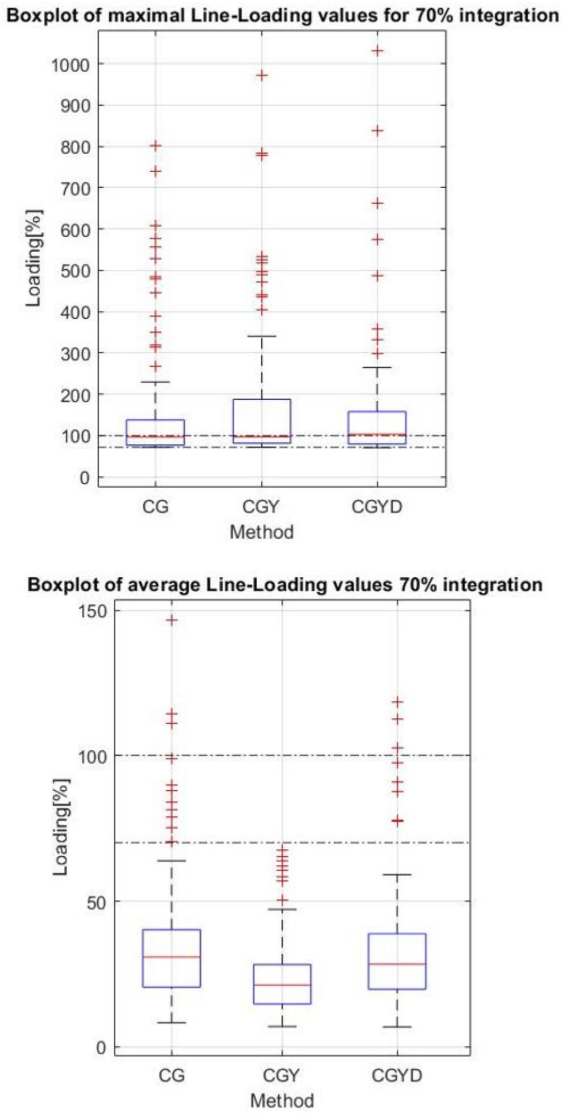

Fig. 16. Line-Loading comparison between methods for 70% integration.

According to these results, the CG method has been chosen since it provides results in the same range as the other methods, requiring a lower simulation time. For these comparisons, it should be considered that the conditions of simulations (input parameters, load profiles, etc.) were not the same. Only the percentages of integration were the same. Therefore, some differences between the methods may be accepted.

VI. Conclusion

The work demonstrates EV Load Profile Generator, which is based on the probability distributions of real data such as the arrival time, total connection time, energy demand, the battery size of charge and the power level of the charger. The generator's algorithm is based on a typical Lithium battery charging profile, thus considering two parts of the charge. The first part of the charge is in constant current (CC) mode until 70% of the total charge, while the second part – from 70% to 100% of charge – is in constant voltage (CV) mode. However, the CV behaviour has been considered linear for practical reasons. Even considering the assumption of linear behaviour in CV mode, results show that the performance of EVLPG is high by providing almost realistic results. A comparison with real data measurements from the field shows an error ~4% in the case of a complete charge and ~30% in a partial charge. The EVLPG prototype's functionality was linked with the PF environment, transferring the load profiles in a CSV file and executing Quasi-dynamic power flows. The EVLPG has been tested in a practical case. The generator's results have been implemented in an extensive model in PF to simulate the integration of EVs. The results obtained show that in the high EV share scenario, the grid starts to be pushed to its operating limits by reaching a maximal line-loading. The main effect that leads to a large overload on the grid is the possibility of considering a high number of EVs on the same charging fleet. It must be said that these results are based on statistics and mimic the real impact close to reality. The results obtained reveal a possible tendency and allow to define already a range of limits of integration, but still not precise enough. In fact, the range is between 30% and 40%, where EV integration violates lines capacity and under voltage limits.

EVLPG in the current version allows specify the topology of the charger (private, public or workplace) and introduces the distinction between weekdays and weekends. EVLPG balanced profiles can be linked with open-source and commercial simulation environments for further EV impact investigation to LVDG and the Power System domain.

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