Electronics and Electrical Engineering

https://www.aimspress.com/journal/ElectrEng

AIMS Electronics and Electrical Engineering, 8(1): 53–70.
DOI: 10.3934/electreng.2024003
Received: 01 December 2023
Revised: 04 February 2024
Accepted: 19 February 2024
Published: 26 February 2024

*Research article*

# Simulation-based probabilistic-harmonic load flow for the study of DERs integration in a low-voltage distribution network

**Cristian Cadena-Zarate**[1,*], **Juan Caballero-Peña**[2] **and German Osma-Pinto**[2]

[1] Groupe de recherche industrielle en technologies de l'énergie et en efficacité énergétique (Groupe t3e), Département de génie électrique, École de technologie supérieure (ÉTS), Montréal, Québec, Canada

[2] Grupo de Investigación en Sistemas de Energía Eléctrica (GISEL), Escuela de Ingenierías Eléctrica, Electrónica y de Telecomunicaciones, Universidad Industrial de Santander, Bucaramanga, Santander, Colombia

* **Correspondence:** Email: cristian-david.cadena-zarate.1@ens.etsmtl.ca.

**Abstract:** The integration of distributed energy resources (DERs) and, therefore, power electronic devices into distribution networks leads to harmonic distortion injection. However, studying harmonic distortion solely through deterministic approaches presents challenges due to the inherent random behavior of DERs. This study introduced a strategy that leverages PowerFactory's harmonic load flow tool. By combining it with Python co-simulation, probabilistic load flows can be developed. These load flows utilize current sources to represent harmonic distortion emitters with predefined harmonic spectra. The proposed strategy was implemented on a real network, where two different capacities of DERs were integrated at various locations within the network. The distributions for the total harmonic distortion of voltage ($THD_v$) and the total harmonic distortion of current ($THD_i$) were obtained 24 hours a day in nodes and lines of the network. The procedure allowed considering the uncertainty associated to the DERs integration in distribution networks in the study of harmonic distortion, which, speaking from a simulation approach, is scarce in the literature.

**Keywords:** harmonic; probabilistic; DERs; PowerFactory; Python

## 1. Introduction

Distributed energy resources (DERs) are fundamental actors in the energy transition [1] because they can contribute to reducing carbon emissions by up to 90% [2]. Therefore, the integration of these technologies in electrical networks is increasing, especially at the distribution level [3].

The more DERs are integrated into the networks, the higher the number of power electronic devices such as DC/AC (direct current/alternating current) inverters (for photovoltaic systems, PVS) and AC/DC rectifiers (for electric vehicles, EVs) [4]. The harmonic injection and propagation through the network can lead to increased losses, reduction in electrical components' useful life [5], harmonic over-standard [6], resonance [7], and errors in control signals [8].

Deterministic harmonic load flows, both in the frequency and time domain, have traditionally been utilized to assess harmonic impacts in distribution networks. The deterministic approach assumes fixed power values for loads and generation, accommodating linear or nonlinear loads. Furthermore, this analysis can employ various solution methods based on hourly [9], seasonal [10], or scenario-based [11] considerations. Solution techniques for load flows in this approach include sweep [12], impedance [13], and Newton-Raphson [13]. Nevertheless, these methods may be limited to specific scenarios and may lack the required accuracy for making informed decisions in system planning and operation [14].

In any case, electrical systems inherently possess a probabilistic nature due to factors such as the stochastic output of renewable generations, the random occurrence and magnitude of harmonic sources, and the presence of conventional uncertainty sources [14]. These random variations can further contribute to increased harmonic distortion [15]. Consequently, harmonic probabilistic analysis becomes essential for evaluating such effects [8]. Traditionally, the natural probabilistic approach enables the analysis of steady-state operating characteristics in electric systems with associated uncertainties arising from prediction errors, measurement data, fluctuations in input variables, or component operation interruptions [16]. There exist three main types of methods for solving probabilistic load flow: numerical methods (e.g., Monte Carlo), approximate methods (e.g., point estimation), and analytic methods (e.g., cumulant method) [5].

Harmonic probabilistic load flow has been the subject of research aimed at addressing its challenges. A pioneering study by M. Lehtonen [17] in 1996 employed a probabilistic approach to the harmonic power flow. The network was modeled using an impedance matrix for each harmonic order, and the load flow was solved using the current injection method. Statistical estimation was utilized to determine the expected levels of harmonics.

In more recent studies, new approaches have been developed to enhance accuracy and computational efficiency. Russo et al. [18] applied the *2m+1* point estimate method (PEM) to solve the probabilistic harmonic power flow. Their aim was to achieve improved accuracy and reduced computational effort compared to Monte Carlo-based methods. In their study, the loads themselves served as the harmonic sources.

Yu and Lin [19] also employed the *2m+1* PEM approach to solve the harmonic power flow. However, they addressed the issue of grid-tied distributed generators, including synchronous generators, induction generators, and power electronic inverters.

Mohammadi [8], once again utilizing the PEM, introduced the fast point estimation method (FPEM) in an actual network where loads caused harmonic distortion. The objective was to minimize computational burden in the calculations.

Nasrfard-Jahromi and Mohammadi [7] proposed an enhanced kernel density estimator for harmonic probabilistic load flow analysis. Their method obtains probabilistic density functions (PDFs) of output variables for each harmonic of interest. The procedure involves executing multiple Monte Carlo simulations using a randomly generated input matrix for a specified sample size and harmonic order. Subsequently, a Gaussian density estimator is applied. The IEEE (Institute of Electrical and Electronics

Engineers) 14 bus test feeder is commonly used in previous studies.

In a different approach, Xie and Sun [6] utilize a piecewise probabilistic harmonic load flow method specifically designed for unbalanced distribution networks with harmonic distortion originating from loads. They employ a probabilistic harmonic coupled model and calculate the harmonic load flow using graph theory and the current injection method.

Another study by Xie et al. [15] also employs a piecewise probabilistic harmonic load flow approach but adopts a data-driven perspective. In this approach, both loads and PVS are considered as harmonic-emitting devices.

Galvani et al. [14] introduced a novel approach utilizing the clustering method for probabilistic evaluation in harmonic load flow analysis of unbalanced distribution systems. The study includes assessing uncertainties associated with harmonic sources and the randomness associated with their location and magnitude (nonlinear load magnitudes).

Sherif et al. [20] utilized a Monte Carlo analysis simulation in their study, albeit without explicit formulation of a probabilistic load flow methodology. This approach generated numerous probabilities for uncertain parameters, and the 95th percentile of each parameter was calculated to perform a probabilistic analysis, incorporating harmonic load flow, for the system's hosting capacity. The investigation specifically addresses PVS penetration within a balanced industrial distribution system. In contrast, Gandoman et al. [21] evaluated total harmonic distortion at main and point of common coupling buses, both with and without a proposed green plug-switched filter capacitor (GP-SFC), and compared it with a conventional distribution static synchronous compensator (D-STATCOM). Their study showcased the harmonic mitigation capabilities of the GP-SFC, effectively reducing total harmonic distortion (THD) percentages for voltage and current. The analysis focuses on a microgrid network featuring a wind turbine as the AC source and a hybrid AC load with nonlinear, linear, and motor components. However, no probabilistic component was incorporated into this assessment.

Despite the substantial advancements made in equation-based or model-based methodologies for harmonic probabilistic load flow analysis, aiming to reduce computational efforts, enhance accuracy, and address various uncertainties, there remains a noticeable gap in the literature, particularly concerning the integration of DERs in low distribution networks. There is a lack of a probabilistic harmonic approach that leverages simulation software, and no existing analysis in the literature addresses the problem using a simulation approach that is both useful and reproducible.

This paper proposes an alternative solution that capitalizes on the capabilities of a powerful tool, PowerFactory, for harmonic analysis. By combining PowerFactory with Python in a co-simulation framework, a probabilistic harmonic analysis is achieved. The proposed method offers several advantages, including considering system unbalance, integrating multiple harmonic sources with defined harmonic spectra, and accommodating various network types, multiple sources, and multiple scenarios. This approach provides flexibility and robustness in conducting harmonic probabilistic load flow analysis.

For this purpose, a low-voltage electrical network and corresponding DERs, including PVS and EVs, are modeled in PowerFactory. The intention is to integrate DERs into the network under proposed penetration scenarios. Once the modeling process is completed, the utilization of Python facilitates the extension of PowerFactory's harmonic load flow simulation capabilities with a probabilistic approach. Through an iterative procedure, input probability distribution functions are sampled, considering the associated uncertainty of DERs and load variations in terms of irradiance and temperature. Output sample groups are then obtained for a predefined number of samples. Ultimately, this approach enables the examination of harmonic distortion data populations under different DER penetration scenarios.

The rest of this document is organized as follows: The methodology part addresses the issue of modeling the network, loads, and DERs. In addition, the co-simulation procedure is explained, and the integration scenarios are formulated. Finally, the sections on results and conclusions are presented.

## 2. Materials and methods

This section outlines the procedures involved in conducting a simulation-based probabilistic-harmonic analysis. The key stages of the methodology encompass the modeling of the low-voltage network (LV), the modeling of DERs, and the execution of the probabilistic and harmonic simulation processes. These procedures are implemented using the PowerFactory (developed by the company DIgSILENT) simulation software, with the added integration of Python for task automation. Figure 1 provides an overview of the methodology, illustrating its general diagram.

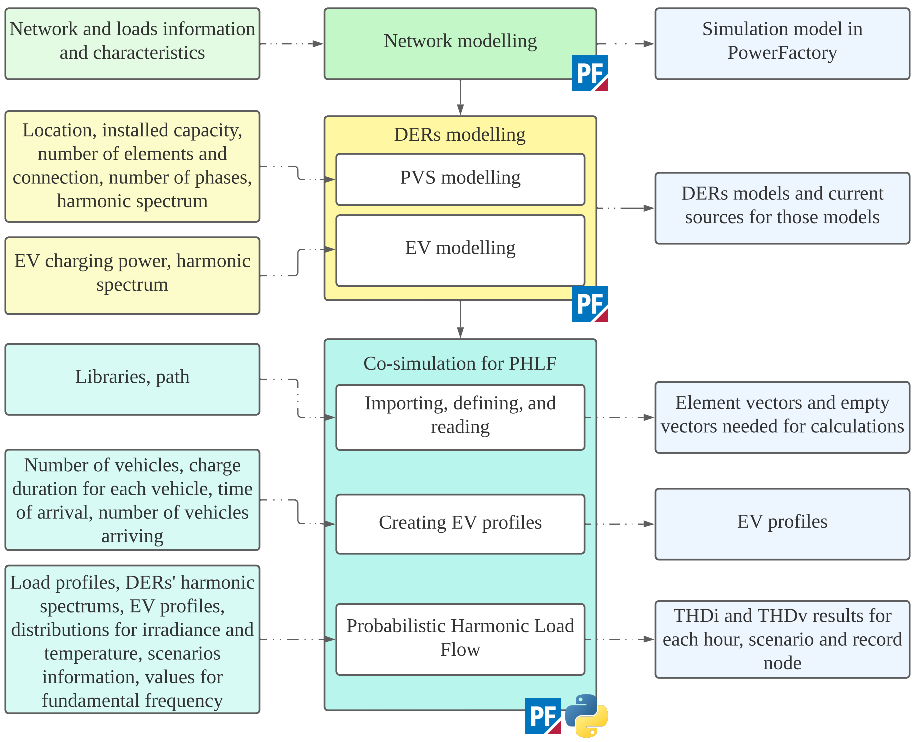


**Figure 1.** General diagram of the methodology.

### 2.1. *Network modeling*

PowerFactory, a powerful multifunctional tool, enables probabilistic and harmonic distortion analysis. However, these analyses are typically performed independently, requiring different inputs and parameters for each case, especially for the modeling of DERs. Additionally, separate network models are necessary to conduct these analyses effectively.

PowerFactory offers the capability to construct high-fidelity models by incorporating detailed information about various elements such as nodes (including voltage level, type, and number of phases), lines (considering parameters like length, configuration, impedance, overhead or grounded status, temperature, and material), transformers (including number of phases, vector group, and power rating), and protection devices, among others. The level of detail provided by the user directly influences the faithfulness and accuracy of the model. Furthermore, specific entries are necessary when modeling DERs, considering their unique characteristics and parameters.

The PowerFactory model developed in this study is based on the data collected from an actual radial topology LV electrical network located in Bucaramanga, Colombia. The model incorporates various elements, including a three-phase transformer with a capacity of 112.5 kVA, operating at a voltage level of 13.2 kV on the primary side and 220/127 V on the secondary side, with a transformer vector group configuration of Dy5. The network consists of 98 users, encompassing residential, commercial, and industrial consumers, with a power factor of 0.9. Additionally, the model considers 42 sodium luminaires with a power rating of 70 W, operating at 220 V with an inductive power factor of 0.98. The conductors between the poles are insulated ASC (aluminum stranded conductor) THW (heat- and water-resistant wire) 1/0, while the conductors for luminaires are insulated copper THW 12. The user connections are made with insulated copper conductors of size THW 8. The model also accounts for the external medium voltage (MV) network operating at 13.2 kV. The power consumption of the users (loads) is calculated based on the average consumption over a one year period.

Figure 2 shows the single-line diagram of the LV network. In general, it is the network modeled in PowerFactory.

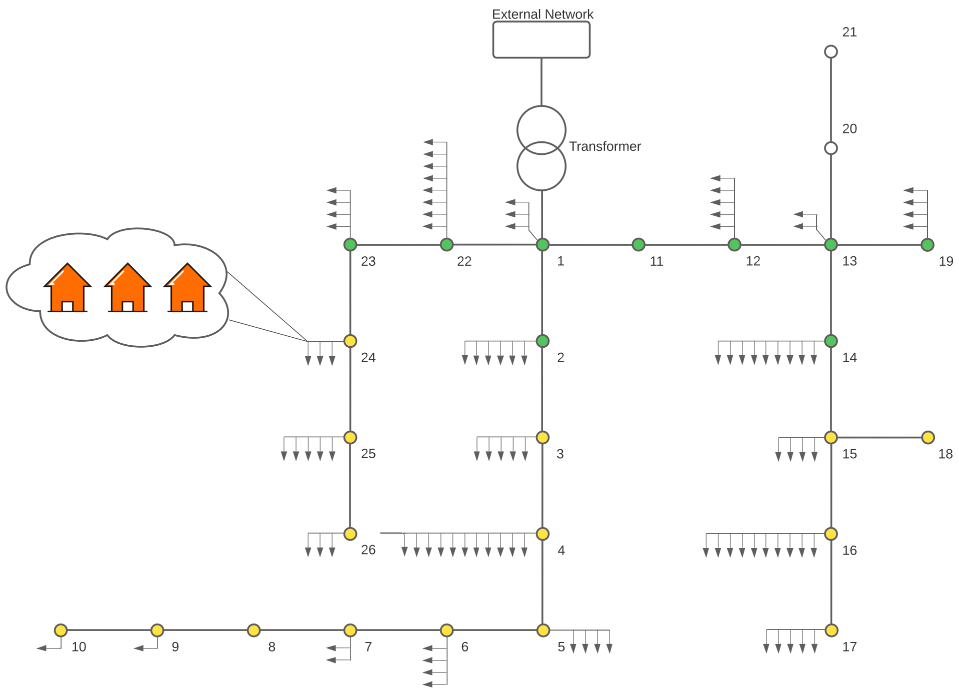


**Figure 2.** Reference LV electrical network.

### 2.2. DERs modeling

In this study, where the focus is not on harmonic propagation, current sources are selected as the modeling approach for DERs. PowerFactory offers this option, and it is employed to model PVS and EVs. However, due to the lack of available information regarding the harmonic distortion of loads, no specific model is chosen for their harmonic modeling. The following details provide an overview of the modeling considerations for each element.

#### 2.2.1. PVS harmonic modeling

PVS systems include power converters, which are switched devices that produce harmonics, given that, those should be considered and modeled as harmonic sources. PowerFactory allows the definition of a current source through a harmonic spectrum. In this case, the harmonic spectrum is entered in PowerFactory through its *Unbalanced, Phase Correct harmonic sources* option. The above means that the magnitudes and phases can be defined for the available harmonic injections at integer and non-integer harmonic orders.

The spectrum for each odd order and each network phase (A, B, or C) is as follows: For magnitude, it is entered as the result of the quotient between the harmonic order's current and the fundamental frequency's current; for phase angle, it is entered as the result of subtracting from each order's angle, the product between the harmonic order and the fundamental frequency's angle.

The information on the harmonic spectrum for this study is selected after the study of Martínez-Peñaloza and Osma-Pinto [22], who states the existence of a relationship between the harmonic distortion level produced by a PVS and the solar irradiance level. The authors conduct a study in an LV electrical network and provide data that allows them to characterize PVS systems [22]. Given that, three sets of current source models are defined with $x \leq 300$ [W/m$^2$]; 300 [W/m$^2$]$< x \leq 600$ [W/m$^2$] y $x > 600$ [W/m$^2$], with $x$ as the solar irradiance level.

#### 2.2.2. EVs harmonic modeling

The same current source model used in the PVS is also applied for EV harmonic characterization. In this case, the difference lies in the harmonic spectrum that is defined for the model.

In accordance with Caro et al. [23], the state of charge of an EV's battery has an impact on the EV's harmonic distortion level. Information provided by the ElaadNL laboratory from the Netherlands indicates that for a Nissan Leaf EV, the $THD_i$ remains relatively constant until the final hour of the charging process and then increases linearly during that hour. Based on this insight, two sets of current source models are defined in this study, categorized by the level of current distortion. The first set corresponds to $THD_i$ values below 4.3% for charging times exceeding one hour, while the second set includes $THD_i$ values ranging from 4.3% to 15% specifically for the last hour of the charging process.

The PowerFactory current source model utilized for EV (and PVS) enables the integration of current source models by inputting the magnitude and phase for each harmonic frequency across the three phases of the system. The magnitude of each harmonic frequency is expressed as a function of the fundamental frequency, and the phase angle for each frequency is defined as the difference between the angle for a given frequency and the product of the same harmonic and the angle of the fundamental frequency. The provided data was processed and organized from a file supplied by the ElaadNL laboratory.

### 2.2.3. Uncertainty considerations in load, PVS, and EVs modeling

This study utilizes historical solar irradiance and ambient temperature data for each hour during a year. To consider the uncertainty, the data is grouped into vectors for hours with solar resource availability (6:00 – 18:00), defining an hourly time for both parameters. That is, all the values of irradiance and temperature for the same hour of all days of the year are grouped in a vector. Subsequently, normal distributions based solar irradiance and ambient temperature profiles are created, as mentioned in the Section 2.3 while explaining Algorithm 3.

For EV, distance traveled and charging initiation times are derived from the National Household Travel Survey (NHTS), and their probability distribution functions were developed by Angelim and Affonso [24].

The distributions suggest that most users return home around 6 PM to charge their vehicles. Since this study considers an hourly approach, probability distributions for each hour were needed. The process involved determining the vehicle's connection time based on traveled distance. Samples from the distributions were then used to calculate the energy required for charging and obtain the charging time, constructing a distribution for charging hours.

Multiplying probabilities from these distributions by the number of vehicles (Table 1) allows to determine the number of vehicles out of the total (20 in this case) charging for specific durations and at specific arrival times. A code routine (Algorithm 2) randomly assigned arrival times and charging duration to vehicles, generating profiles with each vehicle having a designated time to start charging and a specific charging duration.

For both vehicles and residential loads, an hourly normal distribution was assigned for each hour, with the mean as the power consumption or charging power and a standard deviation of 5% of that mean [25]. In that sense, during the execution of the harmonic-probabilistic load flow, the input values are sampled from the aforementioned distributions.

## *2.3. Co-simulation for probabilistic-harmonic load flow*

PowerFactory provides capabilities for conducting separate analyses of probabilistic and harmonic load flows. However, within the software itself, it is not possible to perform a combined analysis that integrates both probabilistic and harmonic aspects, despite the individual strengths of each analysis. This limitation restricts the possibilities of conducting harmonic analysis studies that incorporate uncertainties within the network being studied. To overcome this limitation, a co-simulation procedure can be employed as a viable approach.

Co-simulation is a generalized principle about coupling models from multiple software in a common simulation environment. PowerFactory enables multiple coupling options through MATLAB, libraries of dynamic external links, applied programming interfaces (API), and open platform communication [26]. In this case, Python is selected because of the simplicity of the commands for communicating with PowerFactory.

The integration of Python with PowerFactory facilitates task automation within the software. While PowerFactory can execute harmonic load flow analyses for specific generation and demand conditions at a single time step, configuring the parameters for each resource and each hour of the day, activating or deactivating elements for each scenario, and extracting results can become tedious, particularly when dealing with numerous scenarios and DERs. To streamline this process, this paper utilizes Python for automating tasks such as parameter assignment, harmonic load flow execution, and result extraction for each hour of the day. Python effectively handles the assignment of parameters, executes the harmonic load flow, and automates the result extraction process. Furthermore, Python automatically determines the location and capacity of DERs for each analysis scenario, further enhancing the efficiency and effectiveness of the analysis workflow.

The PowerFactory harmonics functions are noteworthy as they enable the analysis of harmonics in the frequency domain. These functions are capable of handling unbalanced, three-phase networks, making it possible to study non-characteristic harmonics (such as 3rd-order, even-order, and inter-harmonics), unbalanced harmonic injections, and harmonics in non-symmetrical networks. Moreover, the software performs harmonic load flow calculations for all frequencies for which harmonic sources are defined.

The algorithm for the harmonic-probabilistic load flow in Python can be divided into three "sub-algorithms," named Algorithm 1, Algorithm 2, and Algorithm 3.

Algorithm 1 is in charge of importing the needed libraries, declaring the lines for the linking between the two software, reading input information (such as values imperative for calculations), scenarios, and harmonic spectrum external files.

**Algorithm 1:** Importing, defining, and reading

**Input:** Libraries, path
**Output:** Element vectors, empty vectors
**Define** Python file path
**Import** random, pandas, numpy, math
**Import** powerfactory
$app \leftarrow powerfactory.GetApplication()$
app.Show()
$grid \leftarrow app.ActivateProject('ProjecName')$
$elements \leftarrow app.GetCalcRelevantObjects('*.Elm')$
$emptyVector \leftarrow elements.loc\_name$
$scenarios \leftarrow excelFileScenarios$
$pvsCurrentSource \leftarrow excelFileharmonicSpectrum1$
$evCurrentSource \leftarrow excelFileharmonicSpectrum2$
$loadsmatrix \leftarrow nominalPowerAndNames$
$nodesAndLines \leftarrow nominalCurrentsAndLines$

Algorithm 2 is responsible for creating the EV load profiles based on users' behavior. This part of the algorithm receives previously defined vectors associated with the number of EVs arriving to start the charging process at a particular time and the time a number of EVs takes to complete the charge. Based on that information, the code randomly combines the vectors and creates a different profile for each EV, where the hour each vehicle arrives to start charging and how many hours it takes to be charged are stipulated. Note that in 2 $A$ refers to the length of the $carsNumberPerDutation$ vector, $B$ to the length of the $carsNumberArrival$ vector, and $C$ to the length of the $numberOfVehicles$ vector.

Finally, Algorithm 3 contains the core about the harmonic - probabilistic load flow. The Python script is composed of three "for" loops that iterate over the number of scenarios, the hours of the day, and the number of samples defined for analysis, respectively. As in the probabilistic case, Python reads an Excel file to determine which items are active in each scenario.

The next operation is to take a defined number $n$ of samples from the distributions created in the previous analysis. Two Python libraries (Numpy and Random) allow characterizing and sampling

**Algorithm 2:** Creating EV profiles

**Input:** numberOfVehicles,chargeDuration, carsNumberPerDuration, arrivalHour, carsNumberPerArrival
**Output:** EV load profiles
**for** *i=0* **To:** *A*
**do**
⌊ randomly assign a charging duration for each vehicle
**for** *i=0* **To:** *B*
**do**
⌊ randomly assign an arrival time for each vehicle
**for** *i=0* **To:** *C*
**do**
⌊ create a profile for each vehicle with an assigned arrival time and load duration

normal distributions for loads and EVs. Because a defined PDF does not describe the irradiance and temperature distributions, the same $n$ samples are taken directly from the values that make up the distribution. In summary, a number $n$ of samples is taken for each input parameter of DERs and the process is repeated for each hour of the day.

Next, the current source models must be configured for each DERs. The harmonic spectrum is assigned according to the defined current sources. The information is read from Excel files and then assigned to the models in PowerFactory from Python. The commands used to define the models in PowerFactory are: *"FCS[NumVE].ifreqs"*, *"FCS[NumVE].ka"*, and *"FCS[NumVE].ca_phase"* .

Finally, the command Case1 = app.GetFromStudyCase("ComHldf") and Case1.Execute() executes the harmonic load flow for each selected sample. The process iterates for 24 hours and all scenarios. The results are extracted in comma-separated values (CSV) files. Note that in Algorithm 3, $S$ refers to the number of scenarios, $C$ to the number of current sources, $H$ to the amount of hours a day, $L$ to the number of loads, $V$ to the number of vehicles, $P$ to the number of PVS, and $M$ to the number of samples.

Figure 3 illustrates the process implemented through algorithms. The red squares denote processes exclusively executed in PowerFactory without Python intervention. Python-developed procedures are encapsulated in blue and orange squares, showcasing primary "for" loops iterating over scenarios, hours, and samples. The green squares denote Python processes organized within each algorithm. Dotted arrows symbolize the flow of instructions between PowerFactory and Python during the simulation.

The figure reveals that to execute the probabilistic analysis, initial modeling of DERs and the network is required manually in PowerFactory. Additionally, the definition and manual assignment of current source models for their respective elements (PVS and EVs) are essential. Subsequently, within Python, the interface between the two software applications is initiated using Algorithm 1. Following this, EV distributions are generated through Algorithm 2.

As Algorithm 3 is executed, iterations commence across scenarios, instructing Python to determine the status (connected/disconnected) of elements in each scenario (refer to 1). At this juncture, instructions activating current sources for active elements in each scenario are transmitted. For every scenario, iterations are conducted for each hour of the day. During each hour, samples are drawn from normal distributions and irradiance data, both specific to the corresponding hour. Subsequently, for each sample, a harmonic load flow is conducted, automatically adjusting the harmonic spectra of current sources in PowerFactory based on Python-derived values for each sample. Calculated results are then stored for each sample, hour, and scenario.

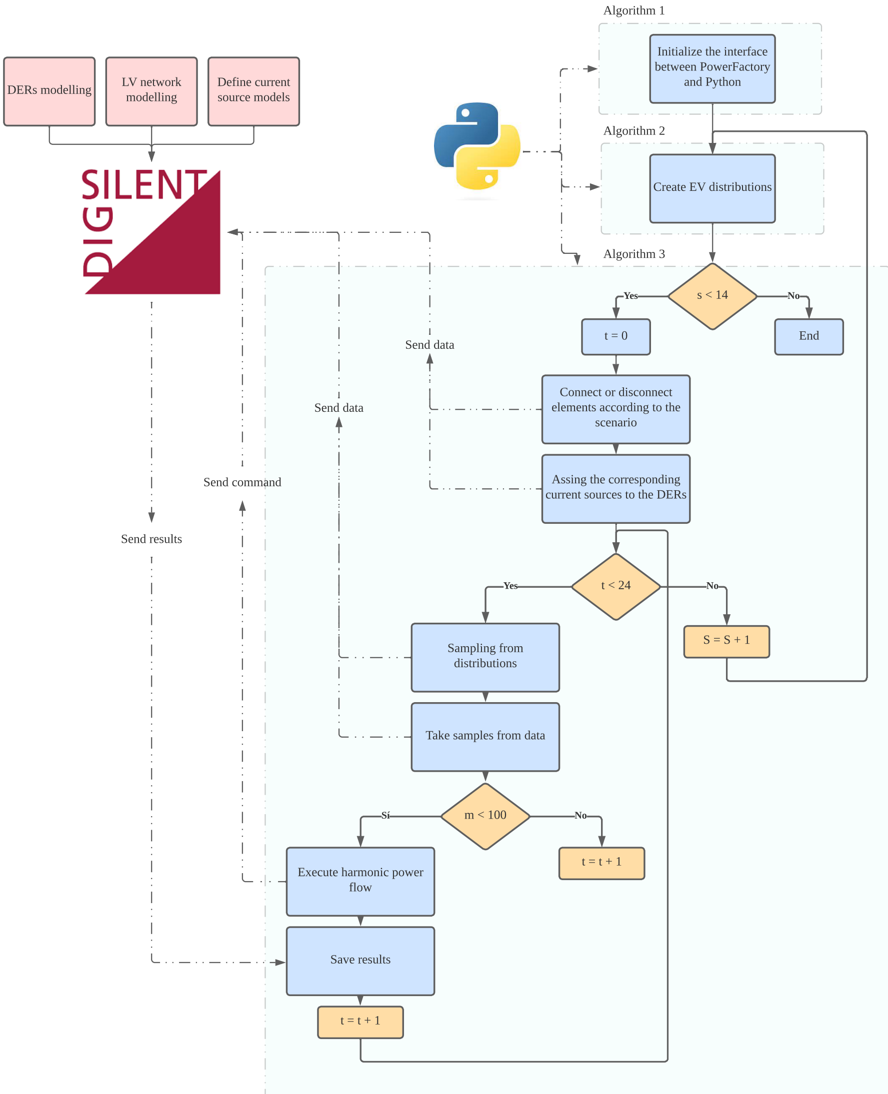


**Figure 3.** Flow chart of the harmonic - probabilistic load flow.

**Algorithm 3:** Probabilistic-harmonic load flow

```
Input: loadProfiles, evProfiles, hSpectrums, itdistributions, scenarios, valuesFundamental
Output: THD_i, THD_i
load ← loadProfiles
for s=0 To: S
do
    for e=0 To: E
    do
        if elementName ∈ elements then
            element ← active;
        else
            element ← inactive;
        currentSources ← app.GetCalcRelevantObjects('*TypHmcurr');
        for c=0 To: C
        do
            csPV ← cs1;
            csEV ← cs2;
        case1 ← app.GetFromStudyCase('ComHldf');
        for i=0 To: H
        do
            for l=0 To: L
            do
                loadpowerAtFundamental ← randomValueNormalDistribution
            for v=0 To: V
            do
                evpowerAtFundamental ← randomValueNormalDistribution
            for p=0 To: P
            do
                read irradiance data
                pvirradianceAtFundamental ← randomValueIrradianceDistribution
            for m=0 To: M
            do
                load.plini ← loadpowerAtFundamental;
                ev.plini ← loadpowerAtFundamental;
                pvs.ghi ← pvirradianceAtFundamental;
                if ev = active then
                    if m = x then
                        csev ← evharmonicspectrum1;
                    else
                        csev ← evharmonicspectrum2;
                if pvs = active then
                    if irradiance ≤ 300 then
                        cspvs ← pvharmonicspectrum1;
                    else if irradiance > 300 and irradiance ≤ 600 then
                        cspvs ← pvharmonicspectrum2;
                    else
                        cspvs ← pvharmonicspectrum3;
                case1.Execute()
                comRes ← app.GetFromStudyCase('ComRes');
                define results and write a csv per phase
                comRes.Execute()
                read results per phase and calculate THD and TDD per phase
            write three-dimensional THD matrix (samples, elements, and hours).
    export matrix per scenario into an Excel file
```

## 2.4. DERs integration scenarios

The DERs integration scenarios are aimed to cover different possibilities of resources integration, that is, integration individually, in a group, in locations close (C, green nodes in Figure 2), far (F, yellow nodes in Figure 2), and distributed (D, it includes all nodes) to the transformer, and with two different levels of penetration based on the number of users (20 or 40) with DERs in the network.

The information on the number of connected elements and their installed capacity in each scenario

**Table 1.** DERs integration scenarios.

| No | Users | Location | Element | | Capacity (kW) | |
|---|---|---|---|---|---|---|
| | | | PVS | EV | PVS | EV |
| 0 | 0 | | | | | |
| 1 | 20 | C | X | | 20x2.5 | |
| 2 | 20 | C | | X | | 20x7.4 |
| 3 | 20 | F | X | | 20x2.5 | |
| 4 | 20 | F | | X | | 20x7.4 |
| 5 | 20 | D | X | X | 20x2.5 | 20x7.4 |
| 6 | 20 | D | X | | 20x2.5 | |
| 7 | 20 | D | | X | | 20x7.4 |
| 8 | 40 | C | X | | 20x2.5 | |
| 9 | 40 | C | | X | | 20x7.4 |
| 10 | 40 | F | X | | 20x2.5 | |
| 11 | 40 | F | | X | | 20x7.4 |
| 12 | 40 | D | X | X | 20x2.5 | 20x7.4 |
| 13 | 40 | D | X | | 20x2.5 | |
| 14 | 40 | D | | X | | 20x7.4 |

is presented in Table 1, where the "X" means that the DER is integrated into that scenario. For example, in Scenario 5, the two DERs are integrated into the network. Likewise, the installed capacity columns allow identifying that in Scenario 5, there are twenty (20) users with 2.5 kW of PVS, and the same twenty (20) users each have an EV with a charging power of 7.4 kW. For its part, in Scenario 12, forty (40) users each integrate a PVS capacity of 2.5 kW, and those same forty (40) users also each integrate an EV with a charging power of 7.4 kW.

The installed capacities of the elements mentioned in the previous paragraph are specified to know the effects experienced by the network in a context of real integration, in which the total installed capacity increases as more users integrate each one of the DERs, and not when each user increases their own installed capacity over time. Therefore, a unique value is used for each element, and all users are assumed to integrate that same value. The PVS capacity was determined so that each user integrated 10 PVS each of 250 W (which, in the two cases of integration, allows having an installed PVS capacity of approximately 50% and 100% of the TRF capacity). The Nissan Leaf's charging power determines the capacity of each EV. Choosing 20 and 40 users that makeup DERs is based on the fact that, in a natural context, 20% and 40% of the total 98 network users had the opportunity to integrate resources.

## 3. Results

This section presents the simulation results for $THD_v$ (Eq. 3.1) and $THD_i$ (Eq. 3.2), from specific register nodes in the network according to the proposed scenarios. The harmonic distortions are computed from the simulation results according to the respective expressions. The results are presented as heat maps and boxplots to show the results' population for each time step and for each registration node.

$$THD_v = \frac{\sqrt{\sum_{h=2}^{\infty}(V_h)^2}}{V_1} \tag{3.1}$$

$$THD_i = \frac{\sqrt{\sum_{h=2}^{\infty}(I_h)^2}}{I_1} \tag{3.2}$$

Figure 4 shows the $THD_v$ for Scenario 1, Node 2, and the 24 hours in a day. In such a scenario, PVS are integrated into the transformer's nearest area, which the node under study is part of. It can be seen that the $THD_v$ values only appear during PVS power generation since there are no other harmonic sources defined in the grid in such operating conditions. $THD_v$ mean values oscillate around 0.05 %, and even if there are values reaching over 0.10%, the 75% of the data are under 0.06%.

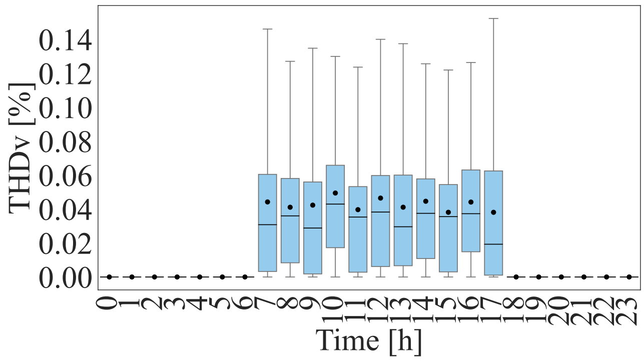


**Figure 4.** $THD_v$ boxplot for Scenario 1, Node 2, and 24 hours

Figure 5 shows the $THD_i$ for Scenario 1, Node 2, and the 24 hours a day. In this case, $THD_i$ mean values are around 5% for PVS power injection hours.

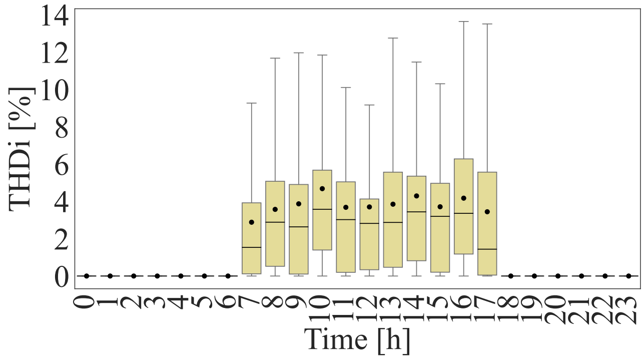


**Figure 5.** $THD_i$ boxplot for Scenario 1, Node 2, and 24 hours.

Figure 6 shows the $THD_v$ for Scenario 2, Node 2, and the 24 hours a day. It can be seen that the values of the $THD_v$ increase in the night hours when EVs are mainly integrated, reaching maximum values over 0.5%.

It can be seen that the interquartile range of harmonic distortion maintains a similar proportion across all hours due to the normal distributions from which the harmonic distortion data in the harmonic load flow was generated.

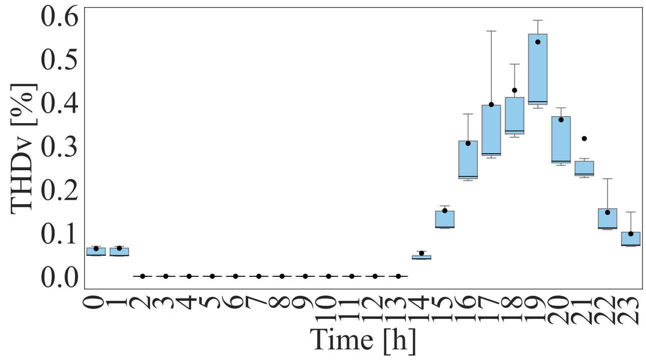


**Figure 6.** $THD_v$ boxplot for Scenario 2, Node 2, and 24 hours.

Regarding the $THD_i$ in the case of EVs integration, Figure 7 shows that the maximum values reach around 2.5% in hour 19. In the hours where there is no EVs integration, the $THD_i$ values are also 0% since no harmonic sources are defined for these operating conditions.

In particular, the box plots corresponding to the EV integration scenarios show that the average values of the total harmonic distortions are located, in some cases, outside the interquartile range; more precisely, they are located near the quartile and/or the upper whisker of the box. On the other hand, it is observed that the medians in these cases are located close to the lower quartile and/or the lower whisker of the boxes. The above is caused by the randomness of the EV harmonic distortion data, in which some outliers can influence the mean value, but most of the data is below that value; for example, in the case of $THD_v$, even when the average maximum value is located near 0.6%, most of the data is actually below 0.4%.

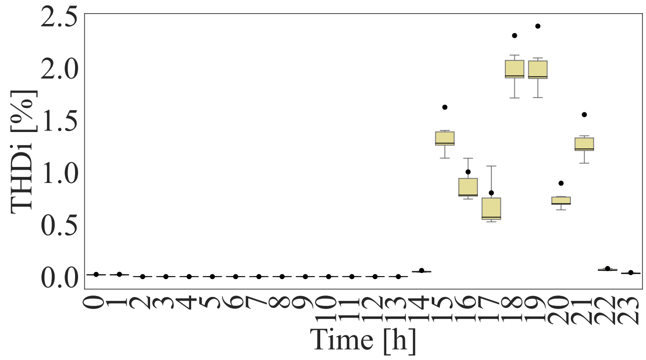


**Figure 7.** $THD_i$ boxplot for Scenario 2, Node 2, and 24 hours.

Figures 8 and 9 show the heat maps for $THD_v$ and $THD_i$, respectively, in all scenarios, the 24 hours a day, and the Node 16. The maps are intended to show the harmonic distortion behavior due to different DERs penetration levels and locations in the grid.

The values are notorious in all cases where some DER is integrated; however, in terms of $THD_v$, the values are higher in scenarios where VEs are integrated and reaches 0.5%. In the case of $THD_i$, the highest values are between 2.5% and 3% and occur in the scenarios and hours in which PVS and EVs are integrated. The total harmonic distortion values are higher in scenarios 7 to 14 because more DERs are integrated into the network. Moreover, the effects are more noticeable in scenarios with the integration of DERs in a zone far from the transformer, which is where Node 16 belongs.

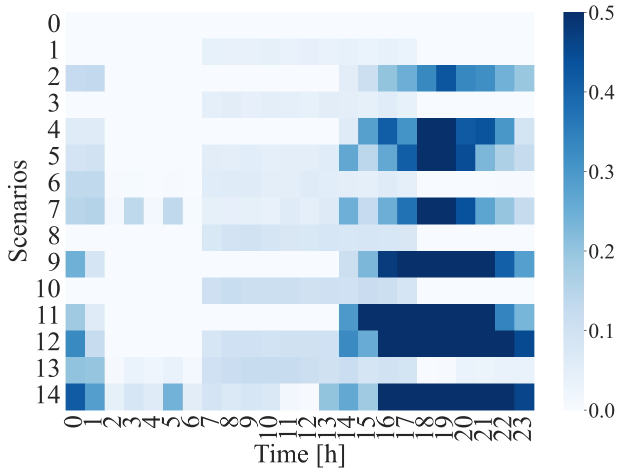


**Figure 8.** $THD_v$ heatmap for Node 16, 24 hours, and all scenarios.

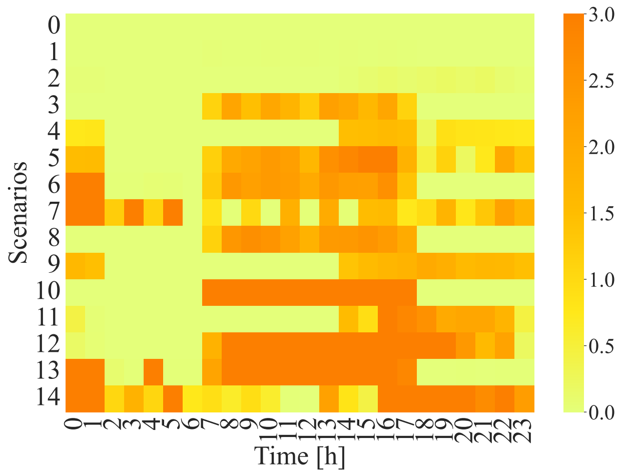


**Figure 9.** $THD_i$ heatmap for Node 16, 24 hours, and all scenarios.

## 4. Conclusions

This research introduces a methodology that leverages the harmonic load flow tool in the PowerFactory simulation software and employs Python to develop a probabilistic harmonic load flow analysis. This approach enables the consideration of uncertainties associated with the integration of DERs in distribution networks, utilizing predefined harmonic spectra. Such a simulation-based approach addressing harmonic distortion is relatively scarce in the existing literature.

The results demonstrate that harmonic distortion levels in voltages and currents primarily manifest during the hours when each resource is integrated, with EVs exhibiting higher $THD_i$ values. Furthermore, it is observed that variability in input data can significantly influence the distributions observed in the output data. These findings underline the importance of considering uncertainties and variability in DER integration studies and highlight the potential impacts on harmonic distortion levels within the electrical network.

The proposed procedure presents challenges in terms of the harmonic distortion modeling, which is constrained by the data available for a specific distributed resource. In simpler terms, knowledge of the harmonic spectrum of electric vehicle loads and photovoltaic solar systems is essential. Acquiring such data for a specific element can be currently intricate, emphasizing the need for increased sharing of such measurements in the literature. Another challenge lies in the potential increase in computational cost as the PowerFactory-modeled network size, connected elements, and the number of samples (proportional to iterations) considered in the analysis grow. Nevertheless, this drawback can be mitigated by refining the form and structure of the proposed code or by utilizing simulation tools with greater computational power.

## Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

## Acknowledgments

The authors wish to thank the School of Electrical, Electronics, and Telecommunications Engineering and the Vice-Principalship for Research and Extension of Universidad Industrial de Santander (Project 3718).

## Conflict of interest

All authors declare no conflicts of interest in this paper.

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