Analysis of Hourly Impacts of Photovoltaic Systems and Electric Vehicles in a Distribution Network from Deterministic and Probabilistic Approaches

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***Abstract*— The distributed energy resources (DER) are principal actors of the global energy transition. Particularly, photovoltaic (PV) systems and electric vehicle integration can affect electrical networks operation. For this reason, DER penetration impacts in distribution networks must be studied. Nevertheless, most studies analyze the behavior only resource integration at specific times through the only approach. This document compares deterministic and probabilistic results to PV systems and electric vehicles in the IEEE 13 nodes test feeder (three-phase and unbalanced system). An integration scenario is proposed, and each resource is modeled like load profiles and probability distribution functions in PowerFactory software. Three indicators are used to analyze RMS value and unbalance voltage, and total active power losses. Moreover, some errors between the two analyses are calculated. Results indicate that most affections in the parameters occur in hours with high power penetration of PV systems. Regarding a case without integration, that affectation is more representative in Phase C voltage which is the most loaded. In addition, the higher error between the two kinds of analyses exceeds 30% in hour 16 in unbalance parameter.**

Keywords—Deterministic, Electric vehicle, Distribution network, Probabilistic, PV System

I. Introduction

The greenhouse gasses emissions have a direct incidence of global climatic change. These emissions result from fossil fuels in different areas like industry, transport, or electricity production [1]. Due to the above, the political, economic, and environmental sectors have promoted a global energy transition toward less-polluting energy. The Distributed Energy Resources (DER) are an alternative with high technical and environmental potential to replace fossil fuels [2], [3]. These are defined as a group of technologies connected in electrical networks (especially in distribution) that can be conformed to distributed generation sources (e.g., photovoltaic systems – PVS), energy storage, controllable power converters, electrical vehicle (EV), or demand management [4].

DER like PVS and EVs are growing globally. The photovoltaic (PV) energy market increased 115 GW in 2019, reaching 627 GW globally [5]. Predictions indicate that the PVS enabling policy implementation will result in 1250 GW installed in 2030 [6]. On the other hand, 2.1 million electric vehicles were sold out in 2019, which represented 2.6% of the sales of cars. Under a sustainable scenario, the forecasts estimate that 250 million EVs will drive along in 2030 [7].

It is important to note that PVS integration or electric vehicle charging stations (EVCS) might produce impacts in electric network operation, which can be positive or negative according to the electrical network under study, the amount of power generated or consumed, and the location of integrated resources [1], [8]. These affectations are caused majority by power converters [9], control equipment (of generation and demand) [10], and the intermittence of primary renewable resources [11]. For all that, several investigations search to characterize the impacts produced by DER in distribution networks, mainly through probabilistic and deterministic approaches.

The deterministic and probabilistic analyses get the same output parameters (e.g., voltage, current, unbalanced, and power losses). However, the probabilistic analysis considers random variations inherent in a real system and enables hourly inspection, which increases results accuracy level respect the deterministic case [12].

In the literature, various studies aim to analyze the impact of DER integration in distribution networks. For instance, Rezaee *et al.* [1] propose a novel probabilistic methodology to estimate daily voltage impact caused by EV integration to the grid; they consider statistics data and current policies. On the other hand, Angelim and Affonso [13] perform a deterministic study to analyze quality voltage impact due to EV random behavior for a day. Moreover, Tran *et al.* [8] present a probabilistic analysis of the daily impact produced by PVS integration in a distribution network and its possible solutions; the parameters analyzed were frequency, and voltage variations, and voltage unbalance. Also, Rawat and Vadera [14] exhibit a comparison between two probabilistic approaches (Point Estimation Method and Monte Carlo Simulation) to determine PVS, wind turbines, and loads impacts in voltage stability in two distribution networks. Besides, Illindala and Constante [15] investigate the effect of uncertainty in the allocation of PV generation under two scenarios, high and low irradiance (non-Gaussian distribution). They evaluate the impact on voltage magnitude in a distribution system through a probabilistic simulation. Furthermore, Mahanta *et al.* [16] study the impact of the EV charging station loads on the voltage stability, power losses, reliability indices, and economic losses of the distribution network. The complete analysis is performed for six different cases of EV charging station placement.

The review allows identifying that the majority of studies consider daily analysis. Although, its scope is limited to a single resource, either distributed generation or EV. Furthermore, these studies use probabilistic or deterministic methods separately to determine the impact produced by DER integration.

Consequently, this document aims to characterize the impact of deterministic (Newton-Raphson) and probabilistic (Monte Carlo) simulation approaches under a scenario that combines PVS and EV in the IEEE 13 nodes distribution network. For that purpose, the two kinds of DER are modeled like probability distribution function (probabilistic approach) and daily load profile (deterministic approach). Then, each load flow is executed; the results of unbalance and RMS voltage, and total active power losses are obtained 24 hours a day. Also, it exposes how to compare results obtained from deterministic and probabilistic approaches to help researchers to plan their studies and to identify the information more relevant within a large amount of data using graphics. For that study, PowerFactory was selected for its practicality in DER modeling, ability to execute deterministic and probabilistic load flow, and its use in other investigations and industries [17]. Additionally, a Python-PowerFactory co-simulation was implemented to speed up load flow and result extraction process.

Section II of this document presents DER modeling in PowerFactory, exposes the study case and the indicators. Section III shows the analysis of the results. Finally, Section IV presents the conclusions of the document.

II. Methodology

This section presents load, PVS, and EV modeling from probabilistic density functions (PDF) and daily profiles to probabilistic and deterministic cases, respectively, which are entered directly in PowerFactory. In addition, study case characteristics and evaluation indicators are described.

A. Loads modeling

Fig. 1 shows daily demand profile curves for residential, commercial, and industrial loads [18], [19], used in the deterministic analysis.

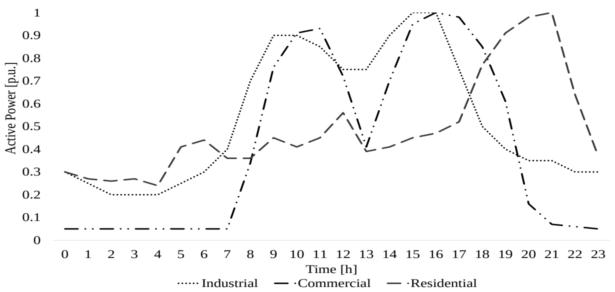


Fig. 1. Daily demand profile curves.

In the probabilistic case, following Jena and Prusty [20], a normal distribution can characterize load behavior where standard deviation corresponds to 5% or 10% of the mean value. For this study, each hour distribution's mean and standard deviation corresponds to the load profile value in that hour and 5% of the mean value, respectively [14], [20]. For instance, for an industrial user with a base power of 385 kW, the normal distributions to 6 and 16 hours have mean values of 115.5 and 385 kW with standard deviations of 5.8 and 19.3 kW, respectively.

B. PV systems modeling

This study has historical irradiance and temperature data measured at the Universidad Industrial de Santander, Bucaramanga, Colombia. These data must be clustered in vectors for each hour where the solar resource is available (e.g., 6:00 – 18:00). In this way, it is possible to define a time characteristic per hour for the two parameters; this process allows defining the PDF. Fig. 2 presents the distributions entered to the software for hour 10 of irradiance and temperature considered all days in a year; the mean values are 650.44 W/m^2 and 25.03 °C, respectively.

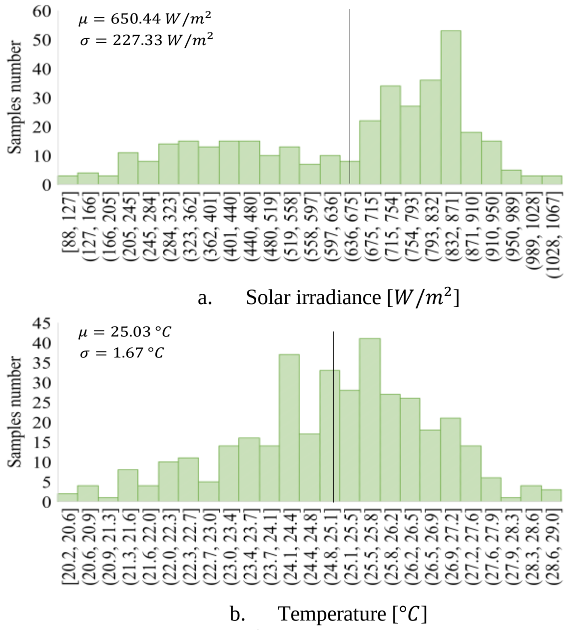


Fig. 2. Distribution for hour 10 (10 a.m. to 11 a.m.).

In the deterministic case, a daily irradiance and temperature profile are created. In that sense, the deterministic value of each hour corresponds to the mean value of distributions in the same hour.

C. Electric vehicles modeling

This study considers power consumption of EVs like a PDF from the data of the National Household Travel Survey (NHTS) of distance traveled, arrived time, and charge duration available in Angelim and Affonso [13].

Fig. 3 presents the charging probability of an electric vehicle, which is created from the charge time required (Weibull distribution [13]) and arrived time (Normal distribution [13]). This study considers a Nissan Leaf vehicle with a nominal battery capacity of 24 kWh and consumption of 0.24 kWh/km.

The EV load is defined for each hour from PDF, just like for loads and PVS. The electric vehicles are additional charges in the systems; thus, a behavior represented like a normal distribution is assumed. In that case, in Fig. 3, the number of vehicles and charge power determine the mean value of PDF. As proposed by Angelim and Affonso [13], the standard deviation might be equal to 5% of the mean value.

In the deterministic case, the daily load profile is created from the mean values of the distribution.

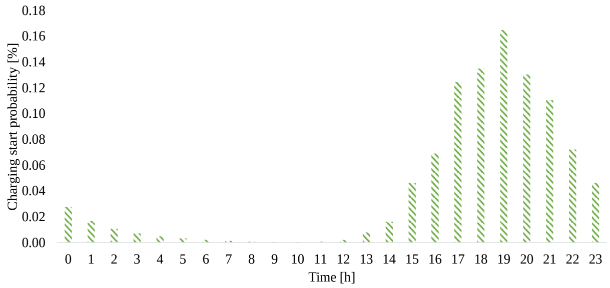


Fig. 3. Charge probability of an electric vehicle for each hour of the day.

D. Study Case

An IEEE 13 nodes test feeder is studied in this work, which has a substation conformed by a 5 MVA – 115/4.16 kV (Δ/Y) three-phase bank of auto-transformer. The grid characteristics are shown in Kerting [21]. Fig. 4 shows the grid single-line diagram.

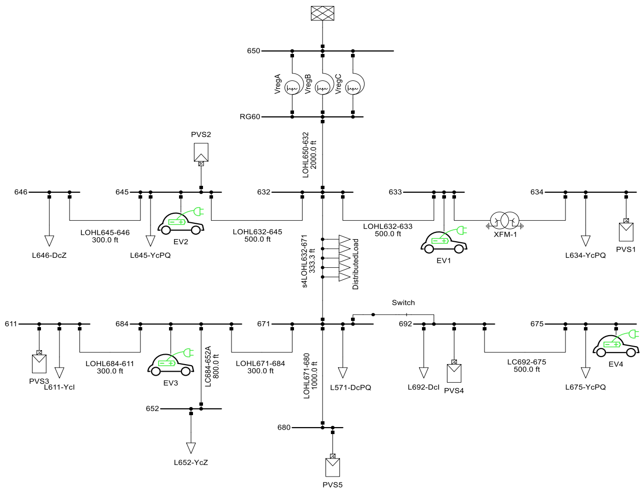


Fig. 4. IEEE 13 nodes in PowerFactory.

Two simulation scenarios are considered in this work; the first one does not have DER penetration and is the reference case; the second combines PVS and EV integration. The PVS and EV capacities installed per node are 1.0 MVA and 0.25 MVA, respectively; thus, the total capacity of each DER is 5.0 MVA (5 nodes) and 1.0 MVA (4 nodes). Fig. 4 shows the nodes of each DER integration.

PowerFactory executes a PLF for specific conditions of generation and demand that are entered for a specific hour. For that reason, the user must set for each hour of the day the PDF (parameter, use, and type) for each component, activation and deactivation of the elements defined for each scenario, and extraction of the results. This process could be tedious and time-consuming; for that reason, this work uses Python for automating the assignation of PDFs, execution of PLF, and extraction of resulting data for each hour.

E. Indicators

The characterization of DER integration starts from the analysis and estimation of parameters. Moreover, it is possible to consider metrics for evaluating such integration impact in electrical networks [22]. TABLE **1** presents the indicators used for this study which were calculated based on the information supplied by PowerFactory: nodal voltage variation (IV_A, IV_B, e IV_C), voltage unbalance (VUF), and active power losses (P_{loss}). Altogether, five (5) parameters are considered in this study. In the probabilistic case, each parameter is formed by a 10000 data sample population.

TABLE 1. EVALUATION INDICATORS

Ref.	No.	Equation	Justification
[23]	1	$IV = \frac{v_i with\ DER}{v_i without\ DER} - 1$	Shows the DER integration impact in the voltage of the i-th system node.
[24]	2	$VUF = \frac{V^-}{V^+} * 100$	Calculates the grid voltage unbalance.
[25]	4	$P_{loss} = \sum (P_{import} - P_{consumption})$	Ploss indicates the grid total electrical power losses percentage.

III. Results

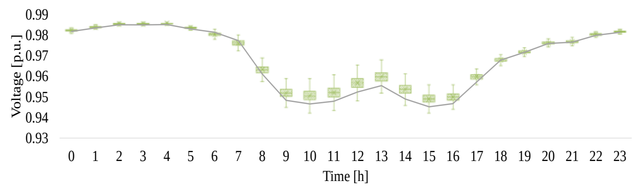
This section presents the results obtained from both probabilistic and deterministic simulations to identify similarities and differences between both approaches. Such results correspond to nodal voltage indicator per phase, voltage unbalances, and total network active power losses.

A. Voltage

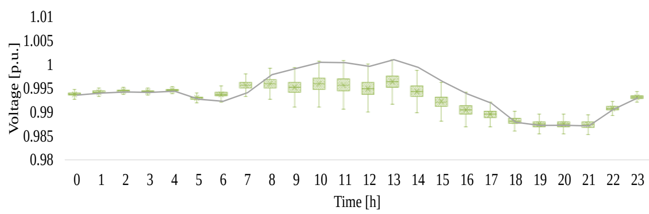
Voltage parameter results are analyzed for each phase in the nearest node to the transformer (632). Additionally, another node analysis enables creating a heat map that represents the voltage behavior in the complete grid.

Fig. 5 shows the Node 632 voltage results variation between deterministic (trend line) and probabilistic (box plot) approaches for the DER integration scenario. The voltage of this node is different in each phase because of the network's own unbalance. Moreover, Phase B is the least charged, and its voltage takes values around 1 p.u. due to PVS power injection. On the other hand, Phases B and C exhibit considerable voltage drops in daytime hours due to PVS integration in an adjacent node (645). The deterministic value is minor to the probabilistic mean value (min. 0.945, max. 0.985 p.u) in Phase A; whereas, it is major (min. 0.94, max. 0.984 p.u.) in Phase C.

When comparing results, deterministic values are out of the interquartile range in daytime hours (6 a.m. to 6 p.m.), although most are within the maximum and minimum distribution values in the three phases. Furthermore, the interquartile range increases in hours of PVS power injection because of the variability of irradiance and temperature. Due to deterministic analysis does not consider these variations, it cannot correctly represent the trend of the sample population.



Phase A



Phase B

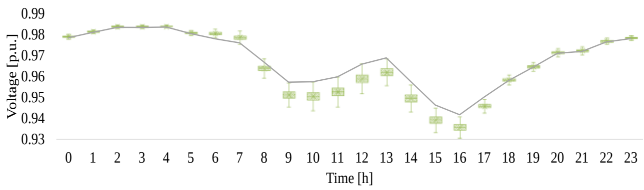


Fig. 5. Comparison of deterministic and probabilistic voltage results in node 632 during a day.

Fig. 6 presents the voltage variation index – IV (Indicator 1 – Table 1), which analyzes the variation between the base case and the integration scenario. Because of system design, three nodes are not connected to Phase A (611, 645, and 646), and two nodes are not connected to Phase B (611 y 684). In the probabilistic results, the higher variation happens in hours with the most solar resource, and Phase C has the greater affectation with a maximum of 2% in Node 611.

The deterministic results maintain a similar trend, but with a higher value of up to 3% at midday. The integration of EV capacities defined for this study case does not cause voltage affectations regarding the operation condition without DER neither of the two approaches.

The nodes furthest from the transformer (611, 671, 680, 684, 692) show higher affectation when integrating DER. Such affectation is more noticeable in the biphasic and monophasic nodes (684, 611) and in the node that supplies a significant and continuous load in the system (634).

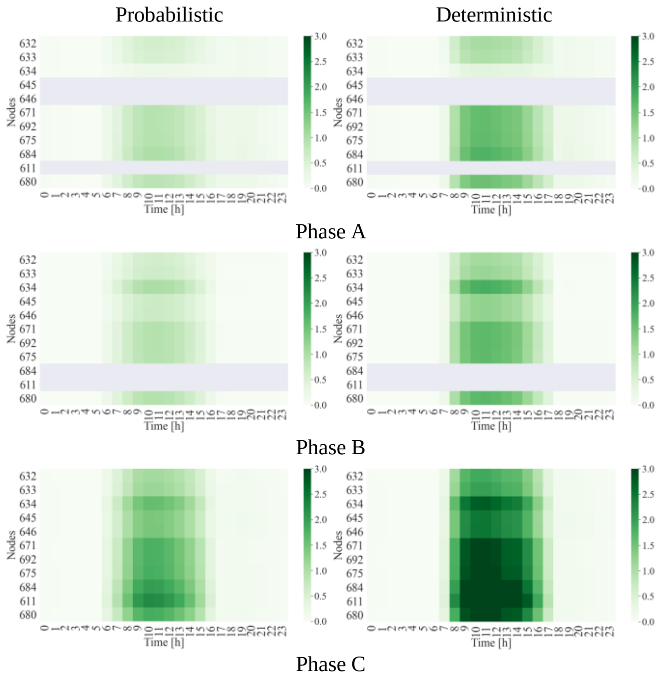


Fig. 6. Voltage Indicator.

B. *Voltage unbalance*

Indicator 2 (Table 1) allows calculating the voltage unbalance in three-phase nodes, such as Node 632. This node is placed in the circuit's head and supplies to all system branches (2-phase and 3-phase).

Fig. 7 relates the hourly voltage unbalance for the DER integration scenario. The boxplot exposes the probabilistic results and the continuous line, the deterministic ones. The interquartile range is increased when PVS injects power into the grid. In the afternoon, the interquartile range decreases, but the voltage unbalance value reaches its maximum (0.82% deterministic and 1.15% probabilistic). The above occurs because most loads (unbalanced industrial and commercial loads) from branches connected to this node have their demand peaks at this time.

The most important differences between the distributions mean and the deterministic value appears in hours with highly solar resource; nevertheless, deterministic values are within the maximum and minimum sample population values in most of twenty-four intervals. The high variability of solar irradiance and temperature do that probabilistic voltage unbalance increase in value, and the deterministic data does not appear within its distribution during hours 14 to 17. In this respect, the deterministic analysis does not allow to infer about the variations in sequence voltages caused by PVS power variation.

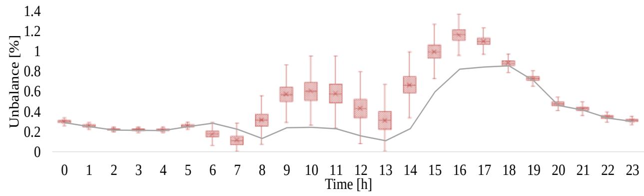
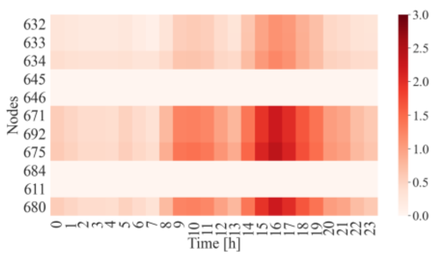


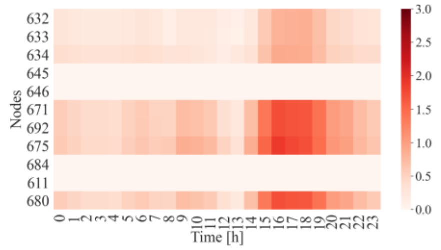
Fig. 7. Comparison of deterministic and probabilistic voltage unbalance results in Node 632 during a day.

Fig. 8 shows the comparison between probabilistic and deterministic voltage unbalance results during a day and for all the nodes. None of the nodes exceeds the 3% value, which is propitious for DER integration, on account of such value is the established limit in the IEEE Std. 1159 [26] from 2009. The higher unbalance percentages are presented in the nodes farthest from the transformer (671, 675, 680, 692) because most of the loads placed in these areas are monophasic, biphasic, or triphasic unbalanced. Due to predominant loads are industrial, greater voltage unbalance coincides with the loads demand peak (Hour 16).

The heat map of unbalance error shows that the nodes farthest from the transformer present the most considerable variations between the probabilistic and deterministic approaches, reaching values over 30%. Moreover, it is shown that in Node 632, the more significant difference occurs in the afternoon hours. The above is consistent with the exposed in Fig. 7.



a. Probabilistic approach



b. Deterministic approach

c. Error [%]

Fig. 8. The voltage unbalance in grid nodes during a day and error calculation.

C. *Power losses*

Fig. 9 shows the boxplot for network total active power losses during a day. Again, PowerFactory calculates this value (Indicator 3, Table 1) directly. The highest losses occur in Hour 16 because of the load demand peak of the loads with the greater demand in the systems (commercial and industrial ones). Additionally, the loss values are not above 110 kW at any time of the day, and PVS contributes to such value reduction. In daytime hours, the interquartile range increases due to PVS power injection; however, deterministic value is within maximum and minimum distribution boundaries in all the hours during a day. In the proposed scenario for EV integration, the power losses do not exhibit considerable increases.

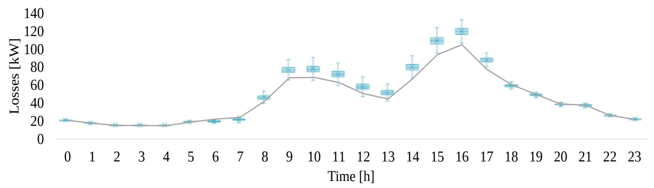


Fig. 9. Comparison of deterministic and probabilistic results of active power losses.

IV. Conclusions

This study shows an hourly result comparison between probabilistic and deterministic approaches when SFV and EV are integrated into an IEEE 13 nodes distribution network. Three indicators characterize the impact in voltage unbalance, voltage effective value, and power losses.

The higher variations between the two approaches in the analyzed parameters occur in great solar resource hours. The distributions' interquartile range increases in such hours, and its mean value is separated from the deterministic value. The voltage unbalance, and power losses exhibit the more significant error in Hour 16, with 33% y 8.7% values, respectively. The above is caused by the relation of these parameters with demand variation, which is strongly influenced by commercial and industrial loads.

When comparing deterministic and probabilistic approaches, it is possible to infer that a deterministic simulation is not reliable enough for analyzing the three parameters when PVS are integrated. For example, the deterministic analysis does not consider the sequence voltage variations due to PVS power changes. For this reason, probabilistic analysis is recommended. Finally, results show that the integration of the EV capacity defined for this study does not cause representative affectations in the studied parameters.

This study enriches discussion about the importance of choosing the analysis approach for studying DER integration in distribution networks.

Finally, for future work, it is recommended to consider power quality parameters in probabilistic studies, for example, the levels of harmonic distortion of DER. In addition, DER's probability density functions with a higher level of detail could also be used for each hour.

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