A Methodology to Determine the Firm Capacity of Distributed Generation Units

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***Abstract*— This paper presents a new methodology to determine the firm capacity of distributed generation units (DGs) connected to electrical distribution networks, using the risk analysis tool Value at Risk (VaR). The stochastic nature of wind and photovoltaic generation can be represented through Monte Carlo simulation. These results were used to analyze the impact of DGs on the feeders' peak demand value.**

***Index Terms*—Distributed Generation Units, Firm Capacity, Load Forecasting, Monte Carlo Simulation, Technical Planning, Value at Risk.**

I. INTRODUCTION

Spatial load forecasting (LF) is the process which defines the load on each region of the electrical distribution network, at predetermined time periods [1]. The accuracy of a long term LF (usually with a horizon higher than 1 year) has significant impact on the technical planning of the future distributed generation units (DGs) and of the electrical distribution networks. An overestimated demand results in unnecessary costs with the equipments for system expansion and excessive purchasing of energy in the market, causing financial losses for Distribution Network Operators (DNOs). On the other hand, an underestimated demand can cause fines due to failure to comply the minimum requirements of power quality, the need to purchase energy in the short term market (with higher prices) to supply the energy not forecasted, besides the customers' complaints [2].

LF has becoming an even more complex task with DGs connection in the electrical distribution network, especially when there are wind generators (WGs) and photovoltaic panels (PVs). Such fact occurs as a consequence of the volatility and intermittency of wind speed and solar irradiation profiles, which make stochastic the power dispatched by WGs and PVs [3].

The power dispatched by DGs is commonly treated in the literature through Monte Carlo method [3]-[6], due to its stochastic nature. However, it was not found in the literature a methodology able to determine the firm capacity of DGs, considering a confidence interval, essential to analyze the impact caused by their connection in the maximum demand of the feeders. In this context, this paper proposes a new methodology to determine the firm capacity of DGs, using the risk analysis tool Value at Risk (VaR).

The remainder of this paper is organized as follows: Section II shows the steps of the proposed methodology. Section III presents the stochastic modeling of DGs. The methodology proposed is described in details in the section IV. The results are shown in section V and the conclusions are presented in section VI.

II. PROPOSED METHODOLOGY

The main steps to perform the proposed methodology are:

- Historical data collection of wind speed, solar irradiation and temperature in the studied area.
- Generation of probability density functions (PDFs) of the wind speed and solar irradiation from the mean value and the standard deviation of the historical series.
- Application of Monte Carlo simulation to get the probabilistic model of power dispatched by DGs to electrical distribution networks.
- Application of risk analysis tool VaR to determine the firm capacity of DGs for each analyzed period.
- Application of superposition method to determine the net power at the beginning of the feeders.

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III. DGs' Modeling

In this paper, two kinds of DGs were considered, PVs and WGs. In order to model the power dispatched by DGs, it is necessary to obtain series of historical data of wind speed, solar irradiation and ambient temperature, which are sampled at periods of 1 hour. Thus, five years of real historical data between the years 2010–2014 of the aforementioned variables are used in this study. To organize these datasets and present the results, each month of the year is represented by one business day, which is subdivided into 24 intervals of 1 hour, i.e., the entire year is represented by 288 hourly intervals. Considering a month with 30 days, each time interval has about 150 measurements (30 days per month x 5 years) of each variable (wind speed, solar irradiation and ambient temperature).

A. Wind Generation Modeling

The Weibull PDF is the most used tool to determine the wind speed profile [5]. The Weibull PDF is shown in (1).

$$f(v) = \frac{k}{c} * \left(\frac{v}{c}\right)^{k-1} * e^{-\left(\frac{v}{c}\right)^{k}} \tag{1}$$

Where:

v wind speed (m/s);

c scale parameter (m/s);

k shape parameter (dimensionless).

A Weibull PDF was performed for each 288 time intervals, whose parameters c e k are defined from the mean (μ) and the standard deviation (σ) of the respective historical data interval.

$$k = \left(\frac{\sigma}{\mu}\right)^{-1.086} \tag{2}$$

$$c = \frac{\mu}{\Gamma(1+\frac{1}{k})} \tag{3}$$

Where (Γ) is the Gamma function.

Equations (4), (5), (6) and (7) model the power profile dispatched by wind generators as a function of the wind speed [7].

$$P = \begin{cases} 0 & 0 \leq V < V_i \\ P_r(A + B * V + C * V^2) & V_i \leq V < V_r \\ P_r & V_r \leq V < V_o \\ 0 & V \geq V_o \end{cases} \tag{4}$$

$$A = \frac{1}{(V_i - V_r)^2}\left[V_i\,(V_i + V_r) - 4V_iV_R\left(\frac{V_i + V_r}{2V_r}\right)^3\right] \tag{5}$$

$$B = \frac{1}{(V_i - V_r)^2}\left[4(V_i + V_r)\left(\frac{V_i + V_r}{2V_r}\right)^3 - (3V_i + V_r)\right] \tag{6}$$

$$C = \frac{1}{(V_i - V_r)^2}\left[2 - 4\left(\frac{V_i + V_r}{2V_r}\right)^3\right] \tag{7}$$

Where:

V wind speed (m/s);

V_i start-up wind speed (m/s);

V_r rated wind speed (m/s);

V_o cut-off wind speed (m/s);

P_r rated power of wind generator (W).

B. Photovoltaic Generation Modeling

Typically, the probabilistic model that best fits the solar irradiation profile of a region is the Beta distribution [8], whose PDF is described in (8):

$$f(r) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha) * \Gamma(\beta)}\left(\frac{r}{r_{max}}\right)^{\alpha-1}\left(1 - \frac{r}{r_{max}}\right)^{\beta-1} \tag{8}$$

Where:

r solar irradiation (kW/m^2);

r_{max} maximum solar irradiation in the period (kW/m^2);

α shape parameter (dimensionless);

β shape parameter (dimensionless).

Analogous to wind speed modeling, a Beta PDF was performed for each 288 time intervals, whose parameters α e β are defined from μ and σ of the respective historical data of solar irradiation.

$$\beta = (1-\mu)\left[\frac{\mu(1-\mu)}{\sigma^2} - 1\right] \tag{9}$$

$$\alpha = \frac{\mu\beta}{1-\mu} \tag{10}$$

Equations (11), (12), (13), (14) and (15) model the power profile dispatched by PVs as a function of the solar irradiation incident on the panels and the ambient temperature [4].

$$T_c = T_a + r\left(\frac{N_{ot} - 20}{0.8}\right) \tag{11}$$

$$I = r[I_{sc} + K_i(T_c - 25)] \tag{12}$$

$$V = V_{oc} - K_v \times T_c \tag{13}$$

$$FF = \frac{V_{mpp} \times I_{mpp}}{V_{oc} \times I_{sc}} \tag{14}$$

$$P_s = FF \times V \times I \tag{15}$$

Where:

T_c	cell temperature (°C);
T_a	average hourly ambient temperature (°C);
N_{ot}	nominal operating temperature of cell (°C);
I	rated cell current (A);
I_{sc}	short circuit current (A);
K_i	current/temperature coefficient (A/°C);
V	module voltage (V);
V_{oc}	open-circuit voltage (V);
K_v	voltage temperature coefficient (V/°C);
FF	fill factor (dimensionless);
V_{mpp}	voltage at maximum power point (V);
I_{mpp}	current at maximum power point (V);
P_s	simulated output power of the PV module (W).

IV. Detemination of DGs' Firm Capacity

In order to determine the power dispatched by DGs, preserving their stochastic nature, the approach proposed in this paper uses Monte Carlo simulation, also known as "Method of Statistical Trials", which is a statistical method used to solve deterministic and stochastic problems based on the generation of random numbers [6].

In this paper, the Monte Carlo method is applied 288 times (one time for each time interval). In each time, the input variables are wind speed PDFs, solar irradiation PDFs and 20,000 random numbers ranging between 0 and 1. The system is modelled as described in section III and, finally, the output variable is an output power PDF of DGs generated from each of the 20,000 simulations. In this way, the probabilistic model of annual power dispatched by DGs consists of 288 PDFs, which will be used as data to define the firm capacity of DGs.

In the context of substations, the firm capacity is defined as the maximum demand that they can supply at any time, considering a contingency criterion (usually based on N-1 rule), when a failure occurs in the biggest substation transformer [9]. This paper defines the firm capacity of DGs as the power that all DGs can inject into the electrical distribution network, considering a specified confidence level (ζ). The firm capacity of DGs can be defined to each 288 analyzed intervals.

In order to determine the DGs' firm capacity, the risk analysis tool VaR was applied. The VaR method represents the minimum return of an investment, considering a confidence level (ζ) and a certain investment horizon [10]. For instance, if the VaR of an investment is equal to US$ 100,000 and ζ = 95%, the financial return will be higher or equal than US$ 100,000 in 95% of the events. An example of PDF with its VaR value considering a confidence level of 95% is presented in Fig 1.

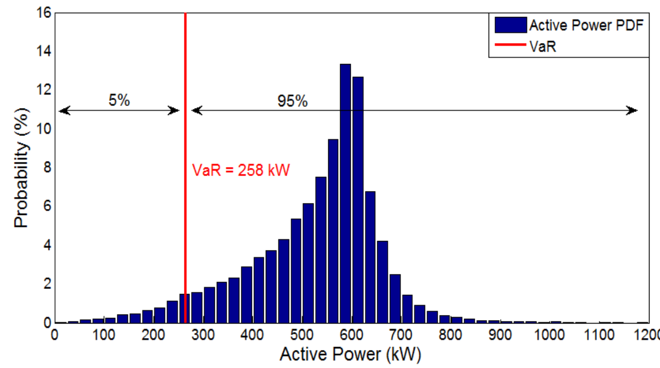

Figure 1 – Power dispatched by DGs (january – 4 a.m.) and its VaR value.

In order to determine the variation of the peak demand in the analyzed feeders, caused by the DGs connection, it will be applied the superposition method, which allows to determinate the net power of a feeder in each 288 intervals from the difference between the load power and the DGs' firm capacity. Based on these results, it can be assessed which DG (or group of DGs) is best suited to be installed in order to reduce the annual peak demand.

V. Results

The new methodology for determination of DGs' firm capacity is the main contribution of this paper, whose database is comprised by real measurements of wind speed, solar irradiation, ambient temperature described in section III and the annual active power (2014) measured at the beginning of two feeders, which are also real. These measurements were obtained from the same region in which data of wind speed and solar irradiation were collected.

In order to apply the methodology and present the results, 3 scenarios with different DGs groups were considered. The first group consists of 50 WGs whose technical specifications are shown in the Table I, totaling 500 kW installed. The second scenario has a group of 4,000 PVs with the data described in Table II, resulting in a total of 1 MWp. And finally, a third scenario with both aforementioned DGs groups. Fig 2 shows the annual firm capacity curve of each of the three scenarios considering the VaR metric with a confidence level of 95%.

TABLE I. Characteristics of the wind turbine available

Wind Generator Features			
Rated power (kW)	Cut in speed (m/s)	Rated Speed (m/s)	Cut out speed (m/s)
10	2,5	12	30

TABLE II. CHARACTERISTICS OF THE PV MODULE AVAILABLE.

Photovoltaic Module Features								
Module characteristics	Watt peak (Wp)	Open circuit voltage (V)	Short circuit current (A)	Voltage at maximum power (V)	Current at maximum power (A)	Voltage temperature coefficient (V/°C)	Current temperature coefficient (A/°C)	Nominal cell operating temperature (°C)
Features	250	38.4	8.79	30.4	8.24	0.33	0.06	46

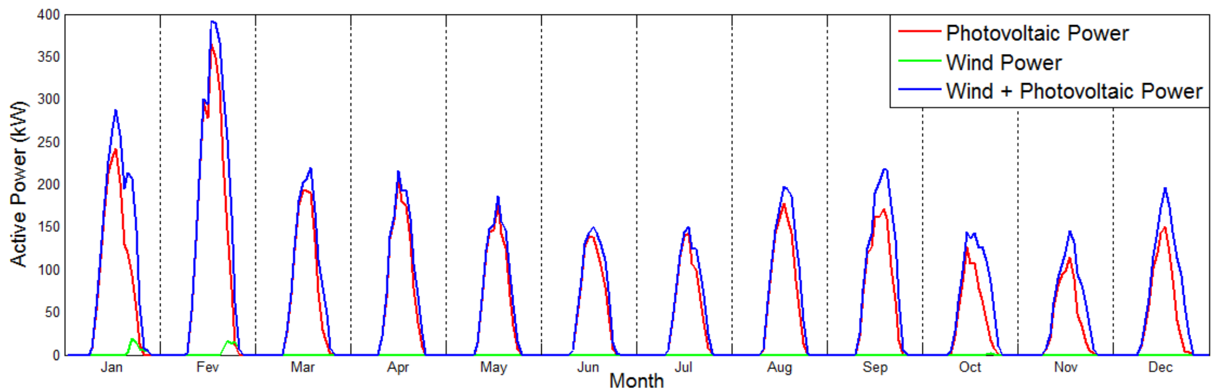

Figure 2 – Annual firm capacity curve of DGs.

Note that the firm capacity of the group that has both types of DGs cannot be directly calculated by the sum of firm capacity of the PVs group and the WGs group, as can be seen in Fig 2. This feature occurs due to the fact that VaR value of each time interval is calculated by the PDF percentile built from 20,000 Monte Carlo simulation results (example in Fig 1), taking into account that in each of these simulations, the power value generated by DGs is obtained by the sum of power output of PVs and WGs, this causes in various simulations that the WGs (which hardly alone have firm capacity in the study region) contribute to the group's power production, resulting in a significant increase in the firm capacity of DGs (PVs + WGs) in relation to the scenario in which only have PVs. Given these facts, it is remarkable that a diversified matrix can supply an electrical system with more reliability.

Based on the firm capacity profiles shown in Fig 2 and the real feeders' load profile (feeder 1 and feeder 2), it was performed a study about the influence of DGs in the feeder's peak demand value, obtained from the application of the superposition method. The study considered 3 cases for each feeder: case 1 corresponds to the feeder with no connected DGs, case 2 represents the feeder with PVs connected to the electrical distribution network. The feeder with PVs and WGs connected is represented by case 3. The scenario with only WGs was not considered because they do not have a significant impact on the peak demand value. The annual demand profile of feeder 1 and feeder 2 considering the three above cases are shown in Fig 3 and Fig 4, respectively.

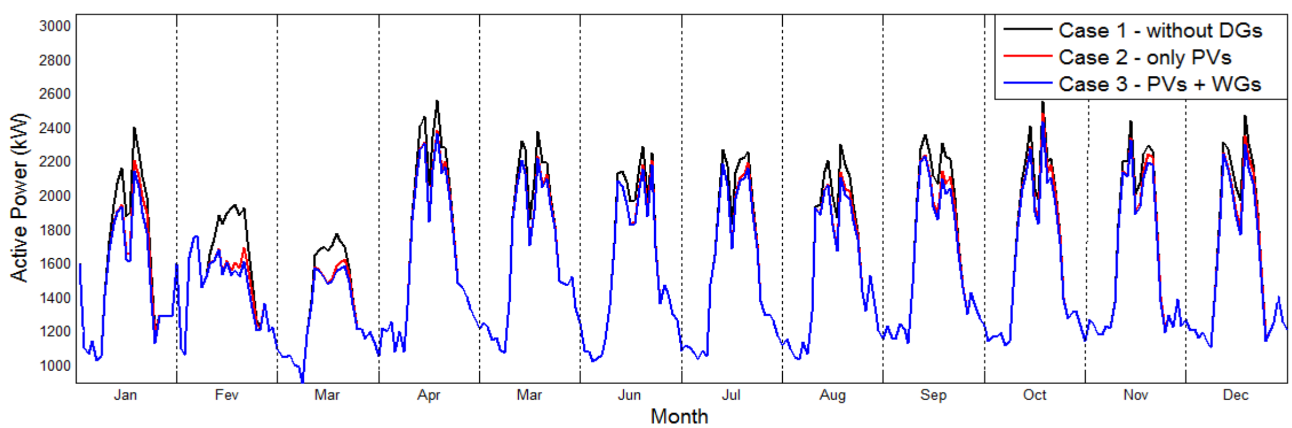

Figure 3 –Annual demand profile of feeder 1 for different DGs groups.

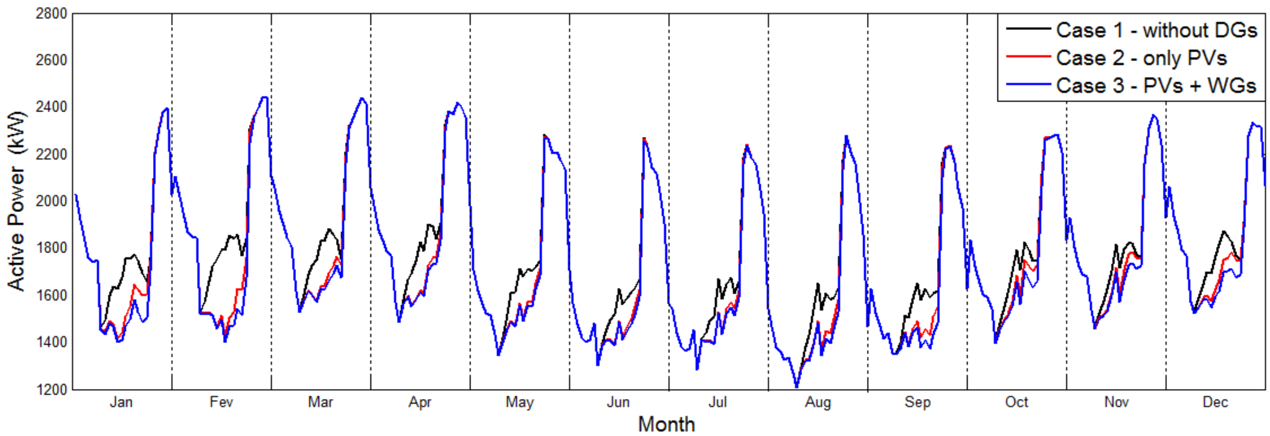

Figure 4 – Annual demand profile of feeder 2 for different DGs groups.

From Fig 3, it is possible to note that occurs a decrease in the maximum annual demand on the feeder when DGs are connected to the electrical network (case 2 and case 3). Table III shows the annual maximum demand of the feeder 1 and its variation in relation to case 1.

TABLE III. MAXIMUM ANNUAL DEMAND OF FEEDER 1.

Case	Maximum Annual Demand of Feeder 1	
	Maximum Demand (kW)	Variation (kW)
Case 1	2562	0
Case 2	2481	-81
Case 3	2433	-129

From Table III, it is possible to prove that the influence of WGs on the peak demand's variation is very significative when also have PVs on the feeder 1. Furthermore, it should be noted that such variation only occurs due to the fact that the peak demand of this feeder happens in the afternoon, a period that has a good level of solar irradiation; in other words, there is power dispatched by the PVs.

In contrast, the feeder 2 has demand peaks at night, thus, it is observed that there is no reduction in the maximum demand with the insertion of DGs. This fact occurs as a consequence of there is no solar irradiation during this period. Table IV shows the annual maximum demand of the feeder 2 and its variation in relation to case 1.

TABLE IV. MAXIMUM ANNUAL DEMAND OF FEEDER 2.

Case	Maximum Annual Demand of Feeder 2	
	Maximum Demand (kW)	Variation (kW)
Case 1	2444	0
Case 2	2444	0
Case 3	2444	0

VI. CONCLUSION

The developed methodology proposes to apply the risk analysis tool VaR in order to determine the DGs' firm capacity and, consequently, the variation of the maximum demand in a distribution feeder caused by the connection of DGs. The proposed methodology can be used in technical and economical studies, applied to electrical distribution networks. Furthermore, the proposed method also can be used as an economic analysis tool for customers who have a binomial tariff structure (power and energy terms), being possible to ascertain the profitability obtained from the reduction of contracted demand, managing the risks based on the confidence level (ζ) and checking what kind of DGs is more adequate to be integrated into the consumer unit.

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