Probabilistic Storage Modeling and Suboptimal Sizing of Renewable Energy Microgrids

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***Abstract*—This paper proposes a novel probabilistic storage modeling and a suboptimal sizing of renewable energy Microgrids. The emergence of renewable energies and distributed systems has been worldwide hastened. Yet, several challenges face this metamorphosis, above all, renewable energy uncertainties which require the integration of storage systems. When the system is undersized, the renewable energy would be dumped, and when it is oversized, the storage would be ineffective. Optimal configurations with probabilistic constraints are then primordial. Therefore, the contribution of this paper is twofold: First, it formulates a novel modeling of energy storage systems by introducing the idleness and counterbalance probabilities; and second, it proposes a suboptimal sizing by maximizing the goodness of fit between the probability density functions of residual power, or the difference between the generation and consumption, and the matching storage output power. Simulations were operated on two Microgrids with distinct parameters, and optimization computing used the Genetic Algorithm toolbox of Matlab.**

***Index Terms*—Energy Storage System, Load Sharing, Optimal Sizing, Probabilistic modeling, Renewable Energy Source.**

I. INTRODUCTION

Electrical energy is indispensable to ensure necessities as well as comfort for human beings. Nonetheless, non renewable energy scarcity, beside the increasing demand and other environmental concerns, have urged us to foresee a modern image for the power grid and for energy resources. Combining renewable energies with a smart grid management, which has been denoted *Smart Grid*, seems to portray perfectly this contemporary image [1]. The *Smart Grid* integrates various renewable energy sources (RES) in order to substitute conventional ones. However, the intermittent characteristic of renewable energy negatively affects the power quality within the grid. Accordingly, the inclusion of energy storage systems (ESS) is primordial to redress these uncertainties which can be exposed on so many levels. ESS's i)-mitigate renewable energy fluctuations, ii)-provide energy during peak hours, iii)-improves power quality, and iv)-ensure operating reserves which enhance the grid reliability. For these purposes, ESS's cover wide ranges of technologies, sizes, and applications such in [2]. Moreover, the rise of Microgrid and miniature Smart Grid applications has furthered distributed architectures including distributed RES and distributed ESS, albeit the boundaries encountering these applications [3] in optimal technical and economical configurations. Similar architectures are foremostly driven by energy cost savings, power quality, and grid reliability. Besides, high penetration of renewable energy require optimal land use, and RES placement which ought to regard climatic conditions correlations. The latter calls for collocating renewable technologies on multiple sites, for instance in [4], authors proved the benefits of collocating wind and solar technologies in the state of Texas.

Effectiveness studies and ESS implementation strategies have been recently discussed in literature [5]–[7] in order to increase the distributed penetration of ESS regarding existing challenges. Particularly, optimal configurations with respect to RES fluctuations are also one of the most crucial studies storage systems. In [8]–[10], authors provide control and sizing procedures of ESS to flatten random features and fluctuations of RESs within the grid.

Furthermore, researchers have recently developed a high awareness toward probabilistic features of energy storage systems. As in [11]–[13], ESS performance and operation are assessed using stochastic features and based on renewable energies behavior. Photovoltaic and wind technologies are mostly considered since they are highly random. However, this research still lacks attention and accuracy which is particularly due to the shortage of data sets and the absence of explicit randomness models.

In this paper, we are performing a suboptimal sizing of ESSs within a Microgrid consisting of a bunch of Virtual Power Plants (VPP) based on uncertainties of RESs and whose the load is shared among VPPs. Besides, for a more scalable system, a VPP is presented as a specified number of RESs with similar properties. The objective function is minimizing the mismatch between the load power and RES output power, whether the latter power is directly delivered from RES or stored in storage systems and which is designated by *residual power*. Our aim is to fit the probability density function

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(p.d.f) of the residual power to the p.s.f of the storage output power. The first density can be drawn from the load and RES powers. However, the second density is conditioned by several constraints that we unfold in our second contribution by introducing the idleness and counterbalance probabilities. Given these entries, one can provide a decent sizing of the Microgrid. The sizing consists of identifying the number of RES units within each VPP, the full capacity energy of each ESS class and the load share allocated to each VPPs. To do so, we control these variables to perform a suboptimal sizing of a given Microgrid. We used annual data of photovoltaic energy outcome, as well as wind energy outcome and load derived from [14]. We adopted the genetic algorithm toolbox GA in Matlab for the optimization computing, we chose the GA since it is more convenient for highly nonlinear functions, which is our case.

Section II describes the Microgrid structure and formulates the sub-optimization statement; Section III details ESS probabilistic model and its density function considering its limited specifications; and Section IV presents the simulation results. Finally, section V concludes.

II. PROBLEM STATEMENT

A. Assumptions & Notations

Hereafter, several notations and assumptions are adopted as follows:

i The electrical energy E in *(kWh)* is delivered to a load, or drawn from a source, at the rate P which is the electrical power in *(kW)*. The power and the energy are generally joined at the time t by $E(t) = \int_{t-\delta t}^{t} |P(\tau)| d\tau$. P is assumed to be positive if drawn from a source and negative if delivered to a load.

ii For simplification purposes, variables are fixed to specified values in the time period Δt. Therefore, P and E remain constant over Δt: $E(t) = |P(t)|.\Delta t$. Likewise, variables in this paper follows this assumption.

iii For each random variable X, a probability density function (p.d.f) f_X and a cumulative distribution function (c.d.f) F_X are assigned where: $f_X(x) = \frac{d}{dx} F_X(x)$.

iv If X is a continuous random variable with probability density function $f_X(x)$, then, for $c \neq 0$, so is $c.X$ a continuous random variable with p.d.f $f_{c.X}(a) = \frac{1}{|c|} f_X(a.c)$.

v Probability distribution functions in this paper are given by Kernel density estimation over a year.

vi Renewable energy output and load energy are assumed to be independent, thus, the p.d.f of their sum can be given by the convolution of each p.d.f.

B. Renewable Energy Microgrid Structure

The Microgrid is a physical miniature of the power grid that can operate dependently or independently of the power grid. It includes storage devices and energy sources to feed its loads. In this paper, the Microgrid is supplied with different and distributed renewable energy sources (RES) that can be hypothetically combined in distinct Virtual Power Plants (VPP) according to the RES type.

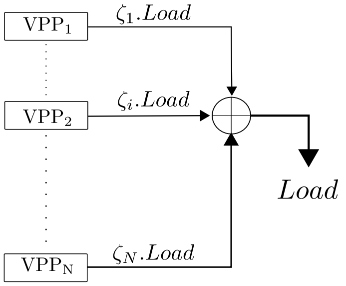

Fig. 1: Microgrid Structure and load sharing among VPPs

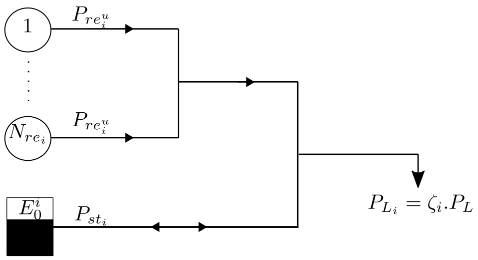

Fig. 2: Power Dispatch within the VPP i

The VPP, as stated by [15], is a cluster of distributed generators, controllable loads, and storage systems aggregated to operate as a unique power plant. A VPP can have multiple connection points and give away energy as efficiently and hassle free, as possible. Herein, a VPP is provided with only renewable energy sources and it is small-scale.

The Microgrid is seen as a collection of N VPPs operating collaboratively to feed a specified aggregate load as in fig.1. To balance the Microgrid, a load share $0 < \zeta_i < 1$ is virtually alloted to each $\mathrm{VPP_i}$ (1).

$$P_L = \sum_{i=1}^{N} P_{L_i} = \sum_{i=1}^{N} \zeta_i P_L \tag{1}$$

where P_L denotes the aggregate load, it takes negative values since it is consumed. P_{L_i} is the assigned load to $\mathrm{VPP_i}$. Also $\sum_{i=1}^{N} \zeta_i = 1$.

A VPP i consists of $N_{\mathrm{re_i}}$ renewable energy sources with similar characteristics and one storage system whose capacity is E_0^i as illustrated in *fig.2*. Regarding strong correlations among RESs of a technology over a small geographical area, RESs are assumed then to deliver the same power $P_{re_i^u}$ (2).

$$P_{\mathrm{re_i}} = N_{\mathrm{re_i}}.P_{\mathrm{re_i^u}} \ , \tag{2}$$

where $P_{\mathrm{re_i}}$ is the aggregate renewable energy rate available within the i-th VPP and takes positive values since it is generated.

Storage systems are implemented in order to reach the power balance, in other words, to meet the demand within the grid at each time t. A perfect scheme is given for each VPP by (3):

$$P_{\mathrm{re_i}}(t) + P_{\mathrm{st_i}}(t) + P_{\mathrm{L_i}}(t) = 0 \tag{3}$$

where $P_{\mathrm{st_i}}$ is the storage power output, it is positive if drawn from the ESS and negative otherwise. Hence, the power balance in the overall grid is given by (4):

$$\sum_{i=1}^{N} \{P_{re_i}(t) + P_{st_i}(t) + P_{L_i}(t)\} = 0 \tag{4}$$

However, the aforesaid scheme is not fully reached over time. We denote by $P_{\mathrm{rs_i}}$ the residual power that cannot be provided by the i-th VPP with respect to its load share as in (5):

$$P_{\mathrm{rs_i}}(t) = P_{\mathrm{L_i}}(t) + P_{\mathrm{re_i}}(t) \tag{5}$$

$P_{\mathrm{rs_i}}$ is positive if the VPP generates more energy than needed, hence it is stored, and negative otherwise, hence it is discharged from the ESS.

C. Sub-Optimization Statement

Renewable energy sources are non-dispatchable and storage units have limited energy and power ratings. Therefore, the power balance is only accomplished with whether over-sized storage units or renewable sources. In both cases, energy should be evacuated somewhere or wasted. Herein, we aim to reach the optimal size without oversizing the units, as to benefit from the overall installed renewable capacity, nor undersizing them, as to augment the renewable energy integration within the grid.

Since our intent is to compensate this residual power using a storage system, $P_{\mathrm{rs_i}}$ should be very close to $P_{\mathrm{st_i}}$ which can be probabilistically translated into the sub-optimization statement (6).

$$min_{\mathbf{U}} \quad \sum_{i=1}^{N} \left[\int_{\mathbb{R}} |f_{rs_i}(P) - f_{st_i}(P)|^2 dP \right]^{(1/2)} \tag{6}$$

in which $\mathbf{U} = [u_i]_{i=1}^{N}$ is a $1 \times 3N$ column vector containing control variables, u_i is defined for each VPP as:

$$u_i = [E_i^0 \quad N_{re_i} \quad \zeta_i]. \tag{7}$$

$f_{\mathrm{rs_i}}$ is the p.d.f of the residual power $P_{\mathrm{rs_i}}$, and $f_{\mathrm{st_i}}$ is the p.d.f of the storage output power $P_{\mathrm{st_i}}$ within $\mathrm{VPP_i}$.

The residual power $P_{\mathrm{rs_i}}$ of $\mathrm{VPP_i}$ is the sum of the RESs output powers within the VPP and the associated load portion. Moreover, they are assumed to be independent, the p.d.f of the residual power is given by the convolution of the p.d.f of RES output powers $f_{\mathrm{re_i}}$ as in (8).

$$f_{\mathrm{re_i}}(P) = \frac{1}{N_{\mathrm{re_i}}} f_{\mathrm{re_i^u}}(N_{\mathrm{re_i}}.P) \tag{8}$$

and the p.d.f of load power $f_{\mathrm{L_i}}$ as in (9):

$$f_{\mathrm{L_i}}(P) = \frac{1}{\zeta_i} f_{\mathrm{L}}(\zeta_i.P) \tag{9}$$

Therefore, $f_{\mathrm{rs_i}}$ is given in (10).

$$f_{\mathrm{rs_i}}(P) = \frac{1}{\zeta_i.N_{\mathrm{re_i}}} f_{\mathrm{re_i^u}}(N_{\mathrm{re_i}}.P) * f_{\mathrm{L}}(\zeta_i.P) \tag{10}$$

Furthermore, formulating the p.d.f of storage output power $f_{\mathrm{st_i}}$ certainly depends on the residual power, but it inheres in the storage characteristics. It is deployed in the next section.

III. STORAGE PROBABILISTIC MODELING

A. State of Charge

As regards storage systems, the state-of-charge χ_i in $(\%)$ is the common measure associated to these systems. It represents the percentage of the available energy in the ESS. For VPP_i, it is defined as in (11).

$$\chi_i(t) \triangleq \frac{E_{\mathrm{st_i}}(t)}{E_i^0} \times 100 \tag{11}$$

where $E_{\mathrm{st_i}}$ is the energy storage level and E_i^0 is the nominal storage capacity. E_i^0 is actually degrading over time, which is beyond the scope of our paper, thus, we restrain our study to a constant nominal capacity. $\chi_i(t)$ can also be expressed by (12).

$$\chi_i(t) = \chi_i(t - \Delta t) - 100 \times \frac{1}{E_i^0} \int_{t-\Delta t}^{t} P_{\mathrm{st_i}}(\tau) d\tau \tag{12}$$

where $P_{\mathrm{st_i}}$ is the storage power output and it is given by:

$$P_{\mathrm{st_i}} = \begin{cases} -P_{\mathrm{rs_i}} & \text{if } P_{\mathrm{st_i}}^- \leq |P_{\mathrm{rs_i}}| \leq P_{\mathrm{st_i}}^+ \\ P_{\mathrm{st_i}}^- & \text{if } P_{\mathrm{rs_i}} \leq P_{\mathrm{st_i}}^- \\ P_{\mathrm{st_i}}^+ & \text{if } P_{\mathrm{st_i}}^+ \leq P_{\mathrm{rs_i}}. \end{cases} \tag{13}$$

where $P_{\mathrm{st_i}}^-$ and $P_{\mathrm{st_i}}^+$ are the lower and upper bounds of $P_{\mathrm{st_i}}$. We denote by $\chi_i'(t) = \dfrac{\chi_i(t) - \chi_i(t - \Delta t)}{\Delta t}$ the rate of χ_i in $\%/h$ and which is given by its derivative over the time interval Δt. χ_i' can be then given by (14).

$$\chi_i'(t) = -\frac{P_{\mathrm{st_i(t)}}}{E_i^0} \tag{14}$$

Our objective is to formulate $f_{\mathrm{st_i}}$ given $f_{\mathrm{rs_i}}$. This formulation is based on some assumptions that are expounded in what follows to construct $f_{\chi_i'}$ and then conclude $f_{\mathrm{st_i}}$.

B. Assumptions

1) Existence: We assume that a non-negative and Lebesgue-integrable function $f_{\chi_i'}$ exists such that $f_{\chi_i'}$ is the p.d.f of the random variable χ'.

$$f_{\chi_i'}(x) = \Pr(\{t \in \mathbb{R} : \chi_i'(t) = x\}) \tag{15}$$

2) Equivalence to the residual power: A Storage unit is mainly provided with the residual renewable energy after feeding the load. Also, it supplies this stored energy to the load when the renewable energy is unable to cover the demand. Thus, $f_{\chi_i'}$ depends strongly on the p.d.fs of the RES outputs and the corresponding load portion in each VPP.

$$f_{\chi_i'}(x) \sim f_{\mathrm{rs_i}}(P) \tag{16}$$

3) Boundaries: $P_{\mathrm{st_i}}$ is bounded, hence:

$$\exists \kappa_1, \kappa_2 \in [-100, +100] \qquad \kappa_1 \leq \chi'_i \leq \kappa_2 \tag{17}$$

κ_1 and κ_2 are two reflective boundaries. In other words: $\lim\limits_{x \to \kappa_1^-} f_{\chi'_i}(x) = \lim\limits_{x \to \kappa_2^+} f_{\chi'_i}(x) = 0$.

4) Idleness Probability: When a storage unit reaches one of the two boundaries, it remains idle ($\chi'_i = 0$) by triggering the charging or discharging process. In particular, when the storage pumps all its energy at κ_2 rate, it is fully discharged ($\chi'_i = 0$), and then $\chi'_i \neq 0$ if and only if it starts charging again. We denote by ϕ_i^{id} the *idleness probability* which is the probability mass at $x = 0$:

$$\phi_i^{id} \triangleq f_{\chi'_i}(0) \triangleq \Pr(\{t \in \mathbb{R} : \chi'_i(t) = 0\}) \tag{18}$$

and since $\int_{-\infty}^{+\infty} f_{\chi'_i} = 1$, we can write:

$$\int_{-\infty}^{0^-} f_{\chi'_i}(x)dx + \int_{0^+}^{+\infty} f_{\chi'_i}(x)dx + \phi_i^{id} = 1 \tag{19}$$

5) Counter-Balance Probability: A storage system should evacuate the whole energy that it has received to maintain its equilibrium. Thus, the daily total energy drawn from/to the storage unit must average zero.

By definition, the expected value is:

$$\mathbb{E}[\chi'_i] \triangleq \int_{\kappa_1}^{\kappa_2} x.f_{\chi'_i}(x)dx = 0 \tag{20}$$

We place a virtual load which discharges the storage at its maximal rate κ_2, hence, ϕ_i^{cb} the *probability of counter-Balance* defined as:

$$\phi_i^{cb} \triangleq f_{\chi'_i}(\kappa_2) \triangleq \Pr(\{t \in \mathbb{R} : \chi'(t) = \kappa_2\}) \tag{21}$$

the probability of the storage virtual inability to evacuate what it has received considering its boundaries, it is given by:

$$\int_{\kappa_1}^{\kappa_2^-} x f_{\chi'_i}(x) + \phi_i^{cb}.\kappa_2 = 0 \tag{22}$$

C. Probabilistic Storage Model

With the former assumptions, we can build $f_{\chi'_i}$ as:

$$f_{\chi'_i} = f_{\mathrm{rs_i}}.\Pi_{\kappa_1,\kappa_2}(x) + \phi_i^{id}.\delta_0(x) + \phi_i^{cb}.\delta_{\kappa_2}(x) \tag{23}$$

where $\delta_a(x)$ is the Dirac function defined as follows:

$$\forall\, a \in \mathbb{R} \quad \delta_a(x) = \begin{cases} 1 & \text{if } x = a; \\ 0 & \text{Otherwise.} \end{cases}$$

And $\Pi_{a,b}(x)$ is the rectangle function defined as follows:

$$\forall\, a < b \in \mathbb{R} \quad \Pi_{a,b}(x) = \begin{cases} 1 & \text{if } a \leq x \leq b; \\ 0 & \text{Otherwise.} \end{cases}$$

where ϕ_0 is the *idleness probability* or the mass probability at $x = 0$:

$$\phi_i^{id} = 1 - \int_{\kappa_1}^{0^-} f_{\chi'_i}(x)dx - \int_{0^+}^{\kappa_2^-} f_{\chi'_i}(x)dx - \phi_i^{cb} \tag{24}$$

wnd ϕ_i^{cb} is the *counter-balance probability* or the mass probability at $x = \kappa_2$:

$$\phi_i^{cb} = -\frac{\int_{\kappa_1}^{\kappa_2^-} x f_{\chi'_i}(x).xdx}{\kappa_2}\ , \tag{25}$$

Finally:

$$f_{\mathrm{st_i}}(P) = E_i^0.f_{\chi'_i}(E_i^0.x) \tag{26}$$

Given the objective function in (6), we are minimizing the idleness and counterbalance probabilities since they are the values at which the two densities of the residual and the storage might differ, also, they represent probabilities of storage abnormalities.

IV. SIMULATION AND RESULTS

The unfolded sizing methodology was tested according to one Microgrid containing two VPPs. A photovoltaic VPP and a wind one. Therefore, two storage classes are considered, we assigned each type to one VPP. In fact, differences between storage classes derive from their chemical, thermal, and mechanical features. Operating conditions, such as operating bounds and response time, result from natural characteristics of the storage material and also from additional constraints regarding the state-of-health of the storage system.

Load and weather annual data had been taken from System Advisor Model SAM developed by NREL [14] for the site Morocco, Casablanca Nouasser whose the latitude and longitude coordinates are $33.37°$ and $-7.58°$ respectively. Data is given in hourly basis over one TMY (*Typical Meteorological Year*).

The Load peak power is $24.5443kW$ in the studied site as in *fig.*3. The maximum output power for the PV unit (VPP1) is $3.76906kW$ and for the wind unit (VPP2) is $1.85737kW$ as in *fig.*4, values are placed on the left side of the graph since the power is generated. The choice of renewable energy sources characteristics are given by the SAM [14] as typical residential sources.

Within the simplistic studied scenario, we had not included the aforesaid storage features, and we limited our simulation to two storage classes I and II, regardless their types and their performances and we only specified their operating bounds κ_1 and κ_2 (Table I) as in the equation **(17)** and which indicate the maximum rates of the sate of charge and discharge.

Cumulative distribution functions of load *fig.3* and VPP units *fig.4* powers were estimated adopting the Kernel smoothing function estimate for univariate and bivariate data (*ksdensity*) of Matlab, for further information, refer to Matlab Help.

To run the optimization procedure, we have used genetic algorithm toolbox of Matlab.

TABLE I: Characteristics of Storage Classes

	Storage I (VPP1)	Storage II (VPP2)
κ_1	$-25\ (\%/h)$	$15\ (\%/h)$
κ_2	$-20\ (\%/h)$	$15\ (\%/h)$

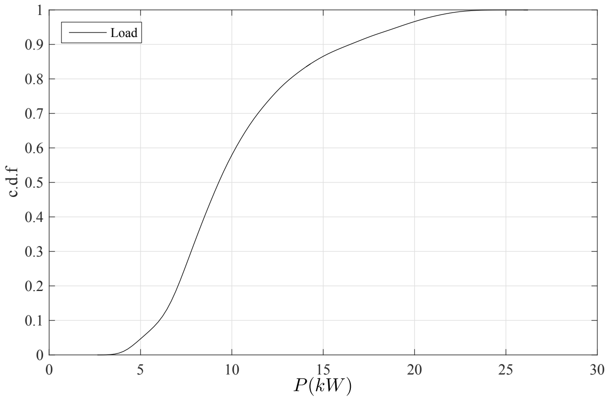

Fig. 3: The cumulative distribution of the load power ($\int f_{\mathrm{L}}$)

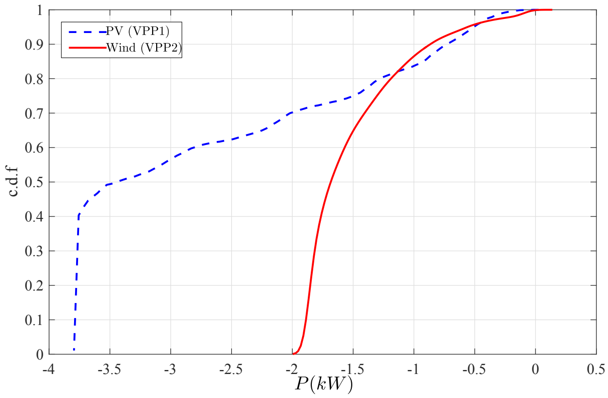

Fig. 4: The cumulative distribution of the generated power of the two RES units ($\int f_{\mathrm{re}_1^{\mathrm{u}}}$ and $\int f_{\mathrm{re}_2^{\mathrm{u}}}$)

Optimization results are given in Table II. According to the GA toolbox, to feed the mG with two VPPs, the suboptimal scheme suggests that for the PV one should be embedded with three PV units, whereas the Wind one could involve two Wind Units. This allocation abides by a load share of 77% PV to 23% Wind. With this load share, a capacity of $16kWh$ of class I and $5kWh$ of class II are to be installed to correct the renewable energy fluctuations and maintain the production output as smooth as possible.

In fact, these results seem reasonable since the studied site has more solar potential and then favored to receive PV rather than wind energy sources. Moreover, with an important installed capacity of PV, it is natural that the corresponding storage class should be installed in an important capacity.

TABLE II: Optimization Results (u_1 and u_2)

	E^0 (kWh)	N_{re}	ζ
VPP1={PV, Storage I}	15.88	3	0.7728
VPP2={Wind, Storage II}	5.1526	2	0.2275

Fig.5 and *6* plot the residual energy and the storage c.d.fs for PV and Wind respectively. As shown in the second graph, storage systems wouldn't exceed the operating bounds (Table. I), otherwise, their c.d.fs follows the pattern of the residual power in each VPP.

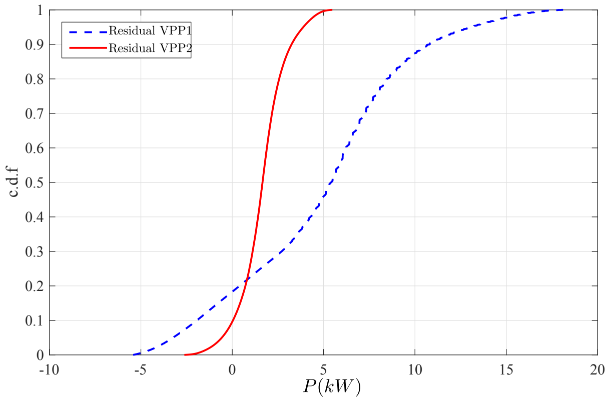

Fig. 5: The cumulative distribution of the residual power for VPP1 and VPP2 ($\int f_{\mathrm{rs}_1}$ and $\int f_{\mathrm{rs}_2}$)

TABLE III: Idleness and counter-balance Probabilities for Storage units ϕ^{id} and ϕ^{cb}

	Storage I	Storage II
Idleness Probability ϕ^{id}	0.2323	0.2504
probability ϕ^{cb}	0.2315	0.2479

In addition, Table III shows the idleness and counter-balance probabilities for each storage class that can also be noticed in the *fig.6*. Obviously, the two storage classes remain idle or are disused for long periods, even though it is optimized.

The idleness and counter-balance probabilities are intuitive features of any storage system since they act as auxiliary devices. However, in renewable energy Microgrids, their function goes beyond back-up devices to reach a vital place.

V. CONCLUSION

The futuristic energy context involves a high penetration of Renewable Energy as well as incorporating disparate renewable energy sources in order to inter-mitigate their weaknesses. It is certainly a varied scenario, albeit rather insufficient without including Energy Storage systems.

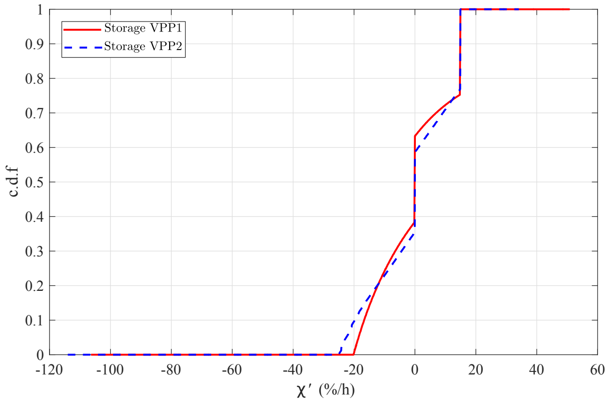

Fig. 6: The cumulative distribution of the storage for VPP1 and VPP2 ($\int f_{\mathrm{st}_1}$ and $\int f_{\mathrm{st}_2}$)

Our contribution mainly consists in finding an optimum scheme of the load sharing and storage capacity among Virtual Power Plants within renewable energy Microgrids. We have insisted on their probabilistic aspect since it widely affects the reliability of the mG. Also, finding the accurate size of the installed renewable energy, as well as corresponding energy storage systems, independently on the economic aftermath is quite intricate and not largely investigated. Herein, we gave a new approach to estimate the irregularities of storage systems which is, to a great extent, contingent to the associated renewable energy source and the demand. Our optimization statement tended to minimize the idleness and the counterbalance states of storage classes which are negatively reflected on he technical and economical conditions of the storage systems.

The objective function and constraints are to be improved in order to include more configurations. This could concern more characteristic properties of storage units to polish the storage p.d.f. In addition, we aim to increase the number of Microgrids, of VPPs and to diversify energy storage systems types.

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