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New typical power curves generation approach for accurate renewable distributed generation placement in the radial distribution system

Ali Tarraq, Faissal El Mariami, Abdelaziz Belfqih
Laboratory of Energy and Electrical Systems, Ecole Nationale Supérieure d'Electricité et de Mécanique (ENSEM), Hassan II University of Casablanca, Casablanca, Morocco

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ABSTRACT

This paper investigates, for the first time, the accuracy of normalized power curves (NPCs), often used to incorporate uncertainties related to wind and solar power generation, when integrating renewable distributed generation (RDG), in the radial distribution system (RDS). In this regard, the present study proposes a comprehensive, simple, and more accurate model, for estimating the expected hourly solar and wind power generation, by adopting a purely probabilistic approach. Actually, in the case of solar RDG, the proposed model allows the calculation of the expected power, without going through a specific probability density function (PDF). The validation of this model is performed through a case study comparing between the classical and the proposed model. The results show that the proposed model generates seasonal NPCs in a less complex and more relevant way compared to the discrete classical model. Furthermore, the margin of error of the classical model for estimating the expected supplied energy is about 12.6% for the photovoltaic (PV) system, and 9% for the wind turbine (WT) system. This introduces an offset of about 10% when calculating the total active losses of the RDS after two RDGs integration.

Corresponding Author:

Ali Tarraq
Laboratory of Energy and Electrical Systems, Department of Electrical Engineering, Ecole Nationale Supérieure d'Electricité et de Mécanique (ENSEM), Hassan II University of Casablanca
B.P 8118, Oasis, Casablanca, Morocco
Email: ali.tarraq@gmail.com

1. INTRODUCTION

The 26th session of the Conference of the Parties COP26 held in Glasgow concluded that the most sustainable and ecological solution for the green transition is to integrate renewable energy sources into the electricity grid, leading to the launch of the "Green Grids" initiative with the vision of "One sun, one world, one grid" [1]. Previous research has demonstrated that the appropriate integration of renewable distributed generators (RDGs) into the electrical distribution network can have significant economic, technical, social, and environmental benefits [2]. However, the integration of RDGs, particularly wind turbines and solar panels, is challenging due to their intermittency and dependence on climate change. Recent studies recommend incorporating uncertainties in the power generated by these units, which depend on uncertain and continuous variables such as wind speed and solar irradiance [3], [4].

Considering these two variables are stochastic in nature, and continuously follow the weather conditions, constructing a predictive model for a quantity that depends on them, remains a task that is not obvious enough. According to the authors' knowledge, most of the existing long-term predictive models are still limited in terms of predictive capacity, concerning the studies of the optimal planning of RDGs [5], [6]. In most cases, these models only simulate the future evolution of the total daily or monthly power supplied by the wind turbine or solar module. That is, when optimizing the grid placement of wind turbines and/or photovoltaic modules, most authors used a probabilistic approach to predict the possible long-term evolution of the hourly power supplied by these two systems [7], [8].

Consequently, to investigate the optimal integration of RDGs into the RDS for a long-term planning period, most researchers assume only the knowledge of the typical hourly variation in generated power during the day, often illustrated by normalized power curves (NPCs) [9]. On this basis, a probabilistic approach is often conducted to generate NPCs for a predefined geographical location. This provides quasi-realistic information on the future evolution of the overall power system parameters, caused by the RDG insertion. In this way, the electrical distribution system can be more and more controllable, despite its future expansion. Furthermore, to consider weather conditions, researchers propose to generate seasonal or monthly NPCs [10].

However, this approach is still based on the expected power estimation by a discrete probabilistic model, whose accuracy depends on the chosen step size and the available computing capabilities. Others have proposed to aggregate historical data by adopting a multi-scenario approach, such as the K-mean method [9], or the hierarchical agglomerative method [11]. This constitutes a preliminary study aimed at reducing the number of samples by detecting the same events. Nevertheless, this method is also based on the discrete model, which only aims to simplify the computational complexity, without worrying about the accuracy of the generated results [12].

The study presents several significant contributions related to the modeling and optimization of RDGs. Firstly, it addresses the accuracy issue related to NPCs for the first time. Secondly, it introduces a new probabilistic integral formula that can model the uncertainties in wind or solar power, leading to NPCs that are more accurate than the discrete model. Thirdly, it computes the expected power output of a solar system without relying on a specific probability density function (PDF) like the Beta PDF or the log-normal PDF. Finally, the study uses the new integral model to optimize the placement of both photovoltaic distributed generation (PV-DG) and wind turbine distributed generation (WT-DG) in the IEEE 33-bus system, reducing the total daily active power losses of the system.

Apart from this introduction, the rest of this article is composed of four other sections. The second one briefly describes the mathematical basis of the study and the classical documented framework. While the third section presents the proposed new mathematical model of the hourly expected power provided by a photovoltaic (PV) module and that of a wind turbine (WT). Then, the validation of this model is properly described in the fourth section of the paper, through a comparative study with the classical discrete model. Firstly, the comparison is made in terms of the expected total energy delivered by a PV module and that delivered by a WT. Secondly, it is done through an optimization study of the location and size of two different RDGs in the typical IEEE 33-bus RDS of Baran and Wu [13]. The main results and perspectives of the study are presented in the conclusion section.

2. MATHEMATICAL BASIS OF THE STUDY

Let us suppose that the continuous uncertain variable x follows the probability distribution $\mathscr{L}$, and f denotes the probability density function PDF related to $\mathscr{L}$. Hence, each value of x is associated with a theoretical maximum power $P_o(x)$, according to a predefined empirical or theoretical formula. Consequently, the expected total power output during a time segment t can be expressed as (1) [14],

$$P^t = \int_{X_{min}}^{X_{max}} P_o(x) f^t(x) dx \tag{1}$$

where X_{min} and X_{max}, are respectively the minimum and maximum values of the variable x.

Generally, the PDF computation involves the mean and the standard deviation of the observed values of x, in a predefined interval called class, such as (2), (3):

$$\mu^t = \frac{\sum_j^{N_k} x_j}{N_s} \tag{2}$$

$$\sigma^t = \sqrt{\frac{\sum_j^{N_k} (x_j - \mu)^2}{N_s - 1}} \qquad xj \in [xi \,;\, xi+1] \tag{3}$$

where μ^t, σ^t, and N_k are respectively the mean, the standard deviation, and the number of observed values in each interval $[x_i; x_{i+1}]$, for a time segment t. While, N_s is the total number of available observed values, during t. N_s corresponds to the total number of days in each season sa, throughout the period of historical data (HD) collection.

3. GENERAL FRAMEWORK OF THE PROPOSED COMPREHENSIVE MODEL
3.1. Solar power modeling
3.1.1. Maximum solar power calculation

The maximum alternating current (AC) power output of a PV module can be expressed as (4) [15],

$$P_{opv}^{h}(s)=\eta_{conv}\times P_{rpv}\times\frac{s}{s_{stc}}\times\left[1+\eta_{p}\times(T_{c}(s)-T_{stc})\right] \tag{4}$$

where P_{rpv} is the rated power in (Wp), that a PV module can provide under the standard test conditions (STC), i.e., at T_{stc}=25 °C, and s_{stc}=1 kW/m². The coefficients η_p and η_{conv} are respectively the power-related temperature factor expressed in (%/K), and the PV conversion efficiency. T_c denotes the PV cell temperature in °C, which can be computed by (5), (6):

$$T_{c}(s)=T_{amb}+s\times K_{NOCT} \tag{5}$$

$$K_{NOCT}=\frac{NOCT-20}{0,8} \tag{6}$$

where *NOCT* presents the normal operating cell temperature of the PV panel at the STC and the irradiation 0.8 kW/m², and T_{amb} is the ambient temperature, which is assumed to be equal to T_{stc}.

It should be noted that the conversion efficiency η_{conv} is obtained by multiplying all factors characterizing the efficiency of the conversion system, which are the mismatch factor, the dirt or soiling coefficient, and the efficiency of the chosen inverter [16]. In this study, η_{conv} is set to 0.9.

3.1.2. Expected solar power output estimation

According to (1), the expected power that a PV module can produce during the hour number *h* is expressed as (7),

$$P_{pv}^{h}=\int_{0}^{1}P_{opv}^{h}(s)\times f_{\beta}^{h}(s)\,ds \tag{7}$$

Substituting (7) into (10), we get:

$$P_{pv}^{h}=\mu_{pv}^{h}\times\left(A+B\times\mu_{pv}^{h}\right)+B\times\left(\sigma_{pv}^{h}\right)^{2} \tag{8}$$

The parameters *A* and *B* could be computed by the following expressions:

$$A=P_{rpv}\times\eta_{conv} \tag{9}$$

$$B=A\times K_{NOCT}\times\eta_{P} \tag{10}$$

where μ_{pv}^{h} and σ_{pv}^{h} are respectively the mean and standard deviation of all available values of solar irradiance during the h^{th} hour. From (8), the expected solar power does not depend, explicitly, on the PDF from which the solar irradiation can be predicted.

3.2. Wind power modeling
3.2.1. Maximum wind power calculation

The maximum power a wind turbine can provide depends on the wind speed measured at the height *h* of its hub. However, the historical wind speed data are collected from an anemometer installed at an altitude called h_o, above the earth. That is, the correction of the hub effect is done through Hellman's exponential law, such that [17]:

$$v=v_{o}\times\left(\frac{h}{h_{o}}\right)^{\alpha} \tag{11}$$

where α is the friction coefficient which depends on the type of land where the installation of the WT is planned, and v_o is the wind speed measured at the altitude h_o.

According to [18], the maximum power that a wind turbine can provide is determined based on the coupling speed v_{cin}, decoupling speed v_{cout}, rated speed v_r, and rated power P_{rw} of the wind turbine, such that:

$$P_{ow}^{h}(v)=\begin{cases} 0 & v\leq v_{cin},\ v\geq v_{cout} \\ P_{rw}\times\frac{v-v_{cin}}{v_r-v_{cin}} & v_{cin}\leq v\leq v_r \\ P_{rw} & v_r\leq v\leq v_{cout} \end{cases} \tag{12}$$

Because of its reduced order, (12) greatly simplifies the development and calculation of the integral in (1). Consequently, the hourly-expected power output of a WT can be easily computed. More details on different reported models adopted in literature are documented in [19].

3.2.2. Expected wind power output estimation

Based on (1), the hourly-expected wind power can be expressed as (13),

$$P_{w}^{h}=\int_{v_{cin}}^{v_{cout}} P_{ow}^{h}(v)\times f_{wbl}^{h}(v)\ dv \tag{13}$$

Substituting (15) into (16), we obtain:

$$P_{w}^{h}=\frac{P_{rw}}{v_n-v_{cin}}\times\left(\mu_{v_{cin}\leq v\leq v_n}^{h}+v_n\times C-v_{cin}\times D\right) \tag{14}$$

where C and D are two probabilistic coefficients, which can be expressed as (15) and (16),

$$C=F_{wbl}^{h}(v_{cout})-F_{wbl}^{h}(v_n) \tag{15}$$

$$D=F_{wbl}^{h}(v_{cout})-F_{wbl}^{h}(v_{cin}) \tag{16}$$

where the quantity $\mu_{v_{cin}\leq v\leq v_n}^{h}$ is the mean of all available samples comprised between v_{cin} and v_n at the h^{th} hour, and F_{wbl}^{h} presents the CDF of the chosen distribution for modeling the wind speed, corresponding to the hour number h.

Thus, the generation of NPCs can be achieved through the use of formulas (8) and (14), providing a simple and accurate alternative to classical methods that require the discretization of formula (1) into finite elements [20]. This involves calculating the sum or average of expected powers across each element, which is a more complex and less precise approach. While the generation of expected wind power model expressed by (13) depends on the selected probability density function (PDF), the majority of studies recommend the use of the Weibull PDF for modeling wind speed.

3.2.3. Weibull distribution

The performance of wind turbines is greatly affected by the variability of wind speed, which is a stochastic continuous variable. It has been widely acknowledged by previous research works that the Weibull probability distribution accurately describes the wind speed variability [21]. The Weibull PDF with two parameters can be mathematically represented by (17), which is commonly used to model the wind speed probability distribution for wind energy applications.

$$f_{wbl}^{t}(v)=\frac{k}{\lambda}\times\left(\frac{v}{\lambda}\right)^{k-1}\times e^{-\left(\frac{v}{\lambda}\right)^{k}} \qquad v,k,\lambda>0 \tag{17}$$

The corresponding CDF is deduced as (18),

$$F_{wbl}^{h}(v)=1-e^{-\left(\frac{v}{\lambda}\right)^{k}} \tag{18}$$

where k and λ respectively represent the shape end the scale factors, and their estimation is obtained through the use of the following two formulas [9]:

$$k=\left(\frac{\sigma}{\mu}\right)^{-1,086} \tag{19}$$

$$\lambda=\frac{\mu}{\Gamma\left(1+\frac{1}{k}\right)} \tag{20}$$

The computation of μ and σ is carried out using historical data that is non-zero and corresponds to the wind speed of each season. These parameters are estimated by (3) and (2).

4. VALIDATION OF THE PROPOSED MODEL

4.1. Historical data processing and data settings

The present study uses data collected from an urban site located in the city of Basel, situated in the northern part of Switzerland, having a latitude of 47.546944 and a longitude of 7.568918. The data consist of hourly records of wind speed and solar irradiance, which were obtained for a period of six years, from January 1, 2015, to December 31, 2020. The data can be accessed free of cost through an online portal [22].

To facilitate the analysis, the hourly data for each variable (wind speed and solar irradiance) are arranged in a matrix *M*, where each row corresponds to an hour of the day, and each column represents a particular day. Matrix *M* is then divided into four smaller matrices, one for each season, named *S*. Each matrix *S* has 24 rows (corresponding to the 24 hours in a day) and [(6 years) x (number of days per year of each season)] columns. The adopted approach is described in detail through the pseudocode of algorithm 1, which is presented in Figure 1. Additionally, the technical specifications of the solar panel and wind turbine used in the study are listed in Table 1, and the value of Hellman's α exponent is estimated to be 0.1, as reported in [16].

```
Algorithm 1: Pseudocode of the adopted approach
Begin the procedure
Parameter setting
Extraction, processing and seasonal arrangement of HD
Set X = = (Solar HD)  &  Y = = (Wind HD)
If X==1 && Ȳ==1
  sa=1
  For sa = 1:4 do
      h=1
       While  h ≤ 24   do
        μ^h_pv,σ^h_pv and P^h_pv estimation according to  (2), (3) and (8),  h=h+1
     End
  End
Else
   sa=1
   For sa = 1:4 do
      h=1
      While h ≤ 24   do
          μ^h_(vcin≤v≤vn),F^h_wbl(vcin), F^h_wbl(vcout),F^h_wbl(vn) and  P^h_wbl assessement according to (2), (14) and (18),  h=h+1
      End
   End
End
Results displaying and NPCs plotting
End of the procedure
```

Figure 1. Pseudocode of the adopted approach for NPCs generation

Table 1. Technical specifications of the PV module EMMVEE Pvt and the WT, Enercon E-53

PV module specifications		WT specifications	
Parameter	Value	Parameter	Value
Rated power (P_{rpv})	290 Wc	Rated power (P_{rw})	800 kW
Temperature coefficient rated power (η_p)	0.43 %/K	Hub height (h)	60 m
NOCT	47 °C	Rated wind speed (v_r)	13 m/s
		Decoupling speed (v_{cout})	34 m/s
		Coupling speed (v_{cin})	3 m/s

4.2. Comparative study

4.2.1. Comparison of the generated NPCs

In Figure 2, the difference between the seasonal NPCs generated by the proposed and classical discrete models is depicted. The proposed model shows a significant difference in terms of the generated daily energy (E_d) as compared to the classical model. Figures 2(a) and 2(b) illustrate the seasonal NPCs of the solar panel generated by the proposed and classical models, respectively. On the other hand, Figures 2(c) and 2(d) demonstrate the seasonal NPCs of the wind turbine generated by the proposed and classical models, respectively.

Furthermore, Table 2 exhibits the energy estimation gap between the proposed and classical models. The table shows the average daily energy (E_m) deduced by dividing the total annual energy (E_a) over 365 days. The energy estimation gap between the models becomes more visible when comparing the energy estimated by each model. For instance, the proposed model records an annual overestimation of 47.6 kWh/year for solar energy, which translates to a margin of error ε_m of approximately 12.6%. Similarly, for wind energy, the proposed model introduces an underestimation of annual energy, with a margin of error of 9%. Therefore, an optimal planning study of renewable distributed generation integration in a power system based on the classical discrete model may lead to inaccurate results due to the significant mismatch in the obtained results.

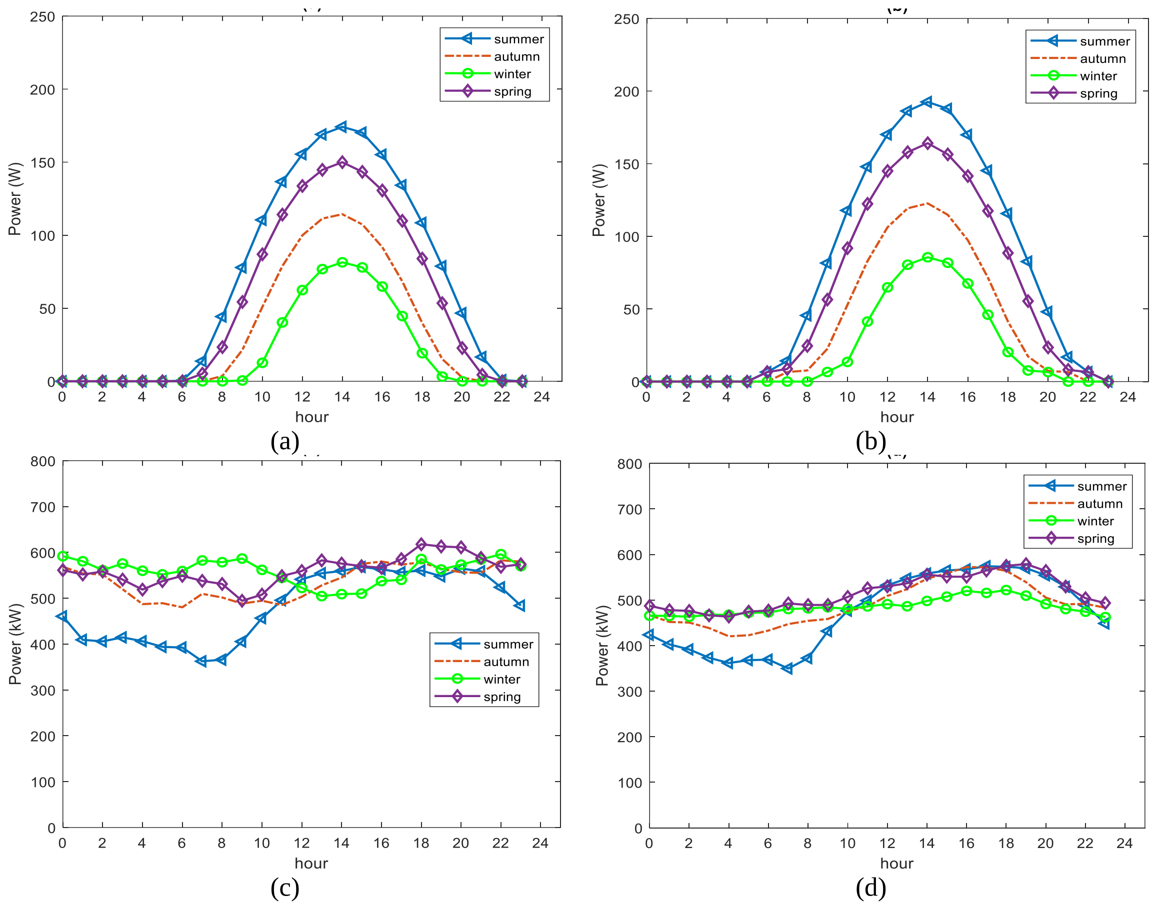


Figure 2. Seasonal NPCs of the solar panel, (a) generated by the proposed model, (b) the classical model, and seasonal NPCs of the WT, (c) generated by the proposed model, and (d) the classical model

Table 2. Solar and wind expected energy estimated by the proposed model and by the classical model

	Solar expected energy (kWh)								WT expected energy (MWh)							
	Proposed model				Classical model				Proposed model				Classical model			
	win	spr	sum	aut	win	spr	sum	Aut	win	spr	sum	aut	win	spr	sum	aut
E_d	0.8	1.3	1.6	0.5	0.9	1.4	1.8	0.6	12.9	13.4	11.6	13.4	11.8	12.4	11.3	11.6
E_a	378.3				425.9				4680				4297.8			
E_m	1				1.2				12.8				11.8			
ε_m	**12.6 %**								**9 %**							

4.3.2. Numerical example: optimal RDG's grid integration

In order to provide evidence for the previous statements, an optimization study is presented in which the optimal location and size of two different RDGs are searched for in a power system. The system under consideration is the IEEE 33 bus system of Baran and Wu [23], which is a commonly used benchmark system in the field of power systems. By performing this study, the accuracy of the proposed model can be evaluated in comparison to the classical discrete model.

a. Problem formulation and resolution techniques

The first RDG is a PV-based system with a number of N_{pv} solar panels, of the brand EMMVEE Pvt 290 Wp, while the second is based on the Enercon E-53 wind turbine. Both RDGs are selected as Type I, i.e., they are only capable of providing active power. This optimization study aims at estimating the offset in the real loss reduction index RLI that can be committed using the discrete model, compared to the proposed comprehensive model. Only, the uncertainties related to renewable sources are taken into account.

The objective function chosen for this study can be expressed as (30),

$$\min \qquad \mathrm{RLI}=\frac{P_{l_{wdvc}}}{P_{l_{wodvc}}} \tag{30}$$

where $P_{l_{wodvc}}$ and $P_{l_{wdvc}}$ are respectively the total active losses without and with RDGs, computed by (31), (32):

$$P_{l_{wdvc}}=\frac{\sum_{sa=1}^{4}\left[\left(\sum_{h=1}^{24} P_{l_{sa}}^{h}\right)\times N_{d_{sa}}\right]}{8760} \tag{31}$$

$$P_{l_{wodvc}}=\sum_{l=1}^{N_l} R_l\times I_l^2 \tag{32}$$

where $P_{l_{sa}}^{h}$ is the sum of active losses during hour h at season sa, and $N_{d_{sa}}$ presents the number of days corresponding to the season number sa during the whole *HD* collection period. Similarly, R_l and I_l, are respectively the resistance and current per branch.

The study presented in this paper employs a direct approach algorithm for the computation of load flow to estimate the current value of I_l [24]. The method used in this study is known to be efficient in solving power system problems. The authors have used this method to evaluate the basic case, where the total real losses $P_{l_{wodvc}}$ are estimated to be 202.6 kW. The direct approach algorithm has been preferred over other conventional methods owing to its superior accuracy and computational efficiency in solving complex power system problems.

The set of inequality constraints chosen include: the nodal voltage limit according to (33), and the RDG capacity limit according to (34), while the power balance (35), presents an equality constraint.

$$0.95\ \mathrm{pu} \leq V_b \leq 1.05\ \mathrm{pu} \tag{33}$$

$$P_{pv}+P_{wt} \leq 0.25 \times \sum_{L=1}^{N} P_L \tag{34}$$

$$P_s+P_{pv}+P_{wt} = \sum_{L=1}^{N} P_L + P_l \tag{35}$$

where N is the number of system busses, and P_s, P_l and P_L are respectively the power taking from the system at the slack bus, the total real losses, and the power demand of the L^{th} node. The powers P_{pv} and P_{wt} are respectively, the size of the PV based RDG and the wind turbine based RDG. The locations of the two RDGs (PV_{loc} and WT_{loc}) have to lie between 2 and N.

In this study, the chosen optimization algorithm is the famous particle swarm optimization (PSO). According to [25], this algorithm and its new versions are among the most adopted in the literature. More details on this algorithm and on its implementation for a power system can be found in [26]. In this paper, the PSO algorithm is applied for a set of 20 populations with 100 iterations for 10 trials, in the case of both models. Each population *Pop* is a vector of four elements such that:

$$\mathrm{Pop} = \left[PV_{loc}, WT_{loc}, P_{pv}, P_{wt}\right] \tag{36}$$

b. Results discussion

In this study, the simulations are done with an Intel ® Core™ i5-3320M CPU @ 2.60GHz (4 CPUs), and a RAM memory of 6 GB, in the MATLAB programming environment. According to Table 3, the discrete model introduces a shift of about 10% in terms of RLI. According to this table, the PSO with the classical model refuses the integration of the WT into the grid. Herein, location 15 and size 31 kW are randomly generated. Moreover, the algorithm proposes the installation of 3097 solar panels in node number 8. With land constraints, the PV system will be very bulky and the operating cost could be very penalizing. Consequently, the PSO gives inconsistent and impractical results with the classical discrete model.

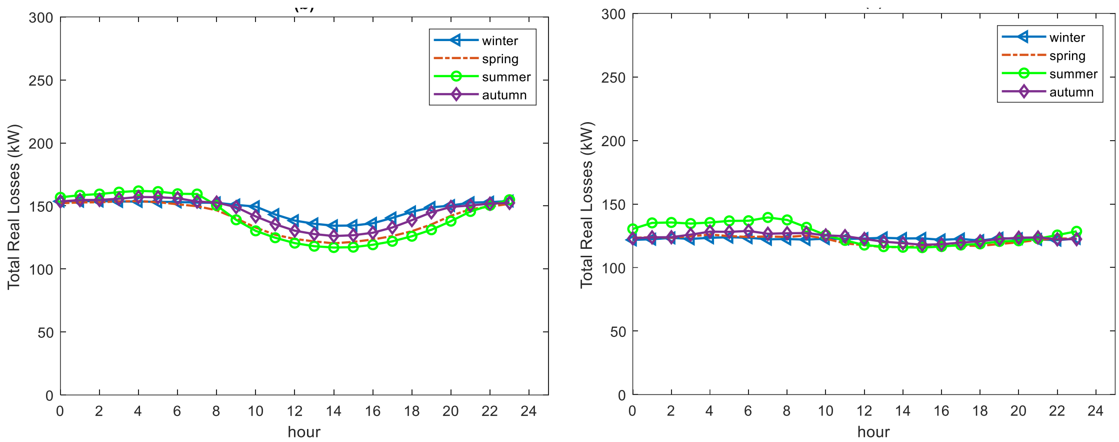
Using the comprehensive model, the generated results are more concrete. To reach a minimal RLI, the algorithm proposes the integration of one Enercon E-53 wind turbine at bus 30. Moreover, a PV system with 445 EMMVEE solar panels is proposed to be incorporated at node number 17.

Accordingly, Figure 3 how's the difference between the hourly seasonal profiles of the total active losses in the IEEE 33 bus system, by adopting the classical model (cf. Figure 3(a)), and by adopting the proposed model (cf. Figure 3(b)).

Thus, by adopting the discrete model, the total active losses are overestimated by about 10%. After a large number of runs, it is obvious that this gap is mainly due to the discretization of the formula (1). In fact, this shift is intolerable when it concerns studies dealing with the optimal integration of RDGs in the electrical distribution network, taking into account the uncertainties related to the wind or solar power generation.

Table 3. Obtained results for both models

	Solar DG			WT DG			RLI
	PV_{loc}	Ppv (kW)	Number	WT_{loc}	Pwt (kW)	Number	
Proposed model	17	129	445	30	800	1	0.61
Classical model	8	898	3097	15	31	0	0.71



(a) (b)

Figure 3. Hourly profiles of total active losses by (a) applying the proposed model and (b) the classical model

5. CONCLUSION

The present study proposes a comprehensive probabilistic model for the generation of seasonal NPCs of PV and WT systems, which considers uncertainty associated with these renewable sources. The model is validated through a numerical example, and the results indicate that the expected solar power does not explicitly depend on a specific PDF.

The case study further demonstrates that the discrete expected power model introduced a considerable shift in the estimation of the energy supplied by a solar panel or a wind turbine, with an average error of 12.9% and 9%, respectively. These findings highlight the importance of using a comprehensive probabilistic model that captures the stochastic nature of renewable energy sources and incorporates the relevant uncertainties in the system. Furthermore, the results suggest that the use of a discrete model can have a significant impact on the accuracy of studies aimed at the optimal integration of RDGs in the RDS, particularly when considering uncertainties related to wind speed and solar irradiation.

As the authors note, climate change introduces new challenges to the accurate modeling of wind speed, and a more precise distribution could replace the widely used Weibull's distribution. The authors recommend the adoption of the proposed comprehensive model in future studies for the optimal integration of RDG into the RDS, particularly when incorporating uncertainties related to the WT and PV power output. The use of such a model could improve the accuracy of predictions and facilitate the efficient integration of RDG into the grid, ultimately contributing to a more sustainable and resilient power system.

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BIOGRAPHIES OF AUTHORS

Ali Tarraq was born in Safi, Morocco. He received the M. Eng. degree in industrial engineering from the University of Cadi Ayyad (UCA), National School of Applied Sciences, ENSA of Safi, Morocco, in 2010. Currently he is a PhD student in electrical engineering at the National School of Electricity and Mechanics, ENSEM of Casablanca, Morocco. His current research interests include distributed generation based renewable energy, and smart grids applications. He can be contacted at email: ali.tarraq@gmail.com.

Faissal El Mariami is an engineer, PhD and holder of university HDR accreditation. He is a professor qualified to direct research and member of the RECS research team at the National School of Electricity and Mechanics ENSEM (Hassan II University). Electrical networks stability and protection coordination are the center of his interest. He can be contacted atemail: f_elmariami@yahoo.fr.

Abdelaziz Belfqih is an engineer, PhD and holder of university HDR accreditation. He is a professor qualified to direct research and member of the RECS research team at the National School of Electricity and Mechanics ENSEM (Hassan II University). His research subjects focus on electrical networks and smart grids. He can be contacted at email: a-belfqih@hotmail.com.