Article

Uncertainty Costs Optimization of Residential Solar Generators Considering Intraday Markets

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Abstract: The uncertainty of solar generation and the bull market are unavoidable in energy dispatch. The purpose of this research is to validate an uncertainty cost function of residential photovoltaic energy in a real microgrid by varying the number of auctions in intraday markets. Therefore, the following procedure is proposed. First, the variability of photovoltaic generation is quantified through Monte Carlo simulations. Second, a statistical function calculates the variability costs of photovoltaic generation. Third, the uncertainty costs are estimated by varying intraday auction markets. Other complementary services are added to the network, such as battery exchange stations for electric vehicles, demand response loads, market power restrictions, and energy storage systems, which are estimated as total costs in an index ranking. The total costs are optimized in a benchmark microgrid and take complimentary services as a black box. Only the uncertainty costs of residential solar generators are discriminated. The main findings were that (1) the uncertainty costs have an error of less than 0.0168% compared to the Monte Carlo simulations and that (2) the uncertainty costs of solar generation are reduced with a decreasing trend to a more significant number of auction markets in intraday markets.

Keywords: electric markets; photovoltaic generation; Monte Carlo simulations

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1. Introduction

The greater diffusion of renewable energies mitigates the environmental deterioration caused by greenhouse gases due to conventional electricity generation (Gen) [1]. Power microgrids (MGs) are complex because they face uncertainties such as demand forecasts, electric vehicles (EVs), battery swapping stations (BSSs), market price (MP) variability, and renewable energy forecasts [2–7]. Gen is strongly influenced by the variability of electricity market (EM) prices, which seek to minimize operating costs using energy sources such as the solar power [8]. Furthermore, pivotal agents and monopolies should be reduced because they produce market power. Traditionally, the Herfindahl Hirschman index and the Residual Supply Index have been used to monitor EMs [9].

The prediction of photovoltaic (PV) energy has been extensively studied with Monte Carlo simulations [8]. However, the lack of reliable information on solar Gen makes energy delivery less efficient. Weather conditions such as unpredictable winds prevent forecasts from being accurate. In such a scenario, uncertainty is inherent and cannot be eliminated in planning [8]. Additionally, energy is available in Ems, where agents can buy and sell power [10]. Intraday markets (IMs) present an additional complexity that should be responsible for mismatches in scheduling on the day of operation. These imbalances are produced by changes in the forecasts of the load or PV Gen [11].

The regularization of the electric generators that are involved in energy dispatch must be studied in more detail. The user is given reliability, and study on the reserves that allow absorbing market volatilities is imperative. The literature suggests planning with multiple agents to reduce greenhouse gas costs, separately evaluating operating

expenses and revenues obtained in markets, and assessing the demand curve [10,12,13]. Another approach takes price information from a real EM to conduct energy dispatch planning [14]. However, the adequate number of IM auctions and their relationship with (PV) Gen remains undefined [11].

The main objective of this research is to evaluate the various residential solar Gen curves of an electrical MG, which is the basis for energy dispatch [15]. Gen overestimation and underestimation deviations must be adjusted using a statistical function [8]. The variations are quantified and compared with Monte Carlo simulations [16]. Once the uncertainty costs (UCs) are estimated, UCs due to deviations in the energy dispatch of the MG are evaluated [8]. The solution strategy uses the variable neighbourhood search-differential evolutionary particle swarm optimization (VNS-DEEPSO) algorithm in two stages: the first one optimizes the economic benefits of the MG, and the second one optimizes the IMs [17]. This algorithm was selected due to its high performance in smart MG optimization problems [18].

The evaluations of the revenues from solar Gen were conducted by taking 500 representative scenarios out of 5000 [14]. The costs were collated with the results obtained from the Monte Carlo simulations, yielding an error between $7 \times 10^{-5}\%$ and 0.0168% for one day of operation. The prices of uncertainty are evaluated by varying the IM auctions. It is ascertained that with greater number of auctions, the imbalances in the scheduling of solar Gen decrease.

This article presents the following structure: In Section 2, works related to the present investigation are compared. Section 3 presents the mathematical formulation of the UCs and the formulation of the objective cost function of the MG. Section 4 offers the case study, Section 5 shows the results, and Section 6 outlines the main conclusions of this investigation.

2. State of the Art

In the literature, studies on smart MGs that optimize resources are reviewed [19]. Most of the works propose the improvement of the services of the steady demand and the generators [6,19,20] so that users can participate in demand response (DR) programs [21]. They can also collaborate with flexible load management by improving their consumption habits [15,22,23]. Energy storage systems (ESSs) promise to provide further flexibility to stakeholders, who can buy off-peak energy hours and sell it during peak hours [4,10,17,23]. EMs benefit from previous integration that also facilitates the penetration of renewable resources such as solar energy [8,15]. In the case of IMs, the auction numbers play an essential role in the planning of energy dispatch [11].

This research focuses on the comparison of the storage systems (SSs) with batteries, IMs, and solar energy UCs (SEUCs), as shown in Table 1. SSs with batteries include different models of ESSs and residential EVs (REVs). The models in the table are listed below. Model 1 consists of an aggregator that performs transactions between ESSs and MPs, while Model 6 appraises the interaction between providers and users [4]. Model 2 evaluates the revenues from buying and selling in the market [6]. Model 3 suggests evaluating consumption patterns and their interaction with electricity prices [24]. Model 4 shows the incentives of IMs for intermittent generators, which can participate through meritocracy [25–31]. Model 5 estimates deviations in the energy dispatch due to EV uncertainty [8]. Model 7 encourages the participation of programs with DR; in addition, Model 8 includes IMs [19,20].

Table 1. Review of electrical MGs.

No	SS	IM	SEUC	Comments
1	Yes	No	No	MG with RS, REV, MP, DR, ESS, and Gen [4]
2	No	No	No	Include DR and Gen [6]
3	No	No	No	Include ESS and Gen [24]
4	No	Yes	No	Include DR and Gen [25]
5	No	No	Yes	Include REV and Gen [8]
6	Yes	No	No	Smart grid with DR [29]
7	No	No	No	Include DR and Gen [19]
8	No	Yes	No	Include DR and Gen [20]
9	Yes	No	No	Include ESS, demand, and Gen [26]
10	Yes	No	No	Include DR, Gen, ESS, and EV [22]
11	No	No	No	Include DR and Gen [21]
12	No	No	No	Include RS, MP, Gen, demand, and ESS [27]
13	Yes	No	No	Include RS, Gen, ESS, and REV [30]
14	No	No	No	Include DR, Gen, ESS, and REV [31]
15	No	No	No	Include DR, Gen, and ESS [12]
16	No	No	No	Include DR, Gen, and ESS [32]
17	Yes	Yes	Yes	MG with RS, REV, MP, DR, ESS, REV, BSS, and Gen(This proposal belongs to this paper)

Model 9 uses ESSs and predicts demand and Gen [26]. Model 10 enables load reduction [22]. Model 11 encourages competitiveness in EMs between DR and Gen [22]. Model 12 combines renewable sources (RSs), such as a PV panel and ESSs, to reduce CO₂ emissions [27]. Model 13 schedules the commissioning of thermal power plants, which reduces gas emissions and operating costs. Additional vehicles, wind and photovoltaic generators, and ESSs are connected to the grid. In addition, Model 14 schedules the load when faced with uncertainty regarding the future price. Model 15 reduces both costs and environmental emissions by using hybrid systems with batteries and wind and solar generators. Model 16 formulates distributed energy resources, with the energy reserve capacity and coordination of the operation with renewable resources and cogeneration. Model 17, which is the model proposed in this research, turns out to be the most complete. It has an aggregator managing the MG's resources, including RS, REV, MP, IM, DR, ESS, REV, BSS, and Gen [5,7,14,28]. In addition, the MG has restrictions that prevent the appearance of monopolies, pivotal agents, and a minimum supply of demand. [9,13]. Furthermore, the mathematical formulation of the uncertainty caused by deviations in solar energy dispatch is stated [8,15]. The costs of the MG are optimized using the VNS-DEEPSO algorithm, which presents the best performance in a similar MG [17,18].

3. Mathematical Formulation

The mathematical models are presented in two sections. The first section establishes the UCs for solar Gen. The second section formulates the objective function for the MG.

3.1. Uncertainty Costs of Photovoltaic Generation

The irradiance distribution (G) is represented using a probability function (f_G), where the parameter (λ) is the mean, and the parameter (β) is the standard deviation [33]. The distribution for intraday solar radiation curves can be adjusted as follows.

$$f_G(G) = \frac{1}{G\beta\sqrt{2\pi}} \cdot e^{-\frac{(\ln(G)-\lambda)^2}{2\beta^2}}; 0 < G < \infty \quad (1)$$

In solar panels, the power that is generated depends on the reference irradiance R_C . The irradiance can be represented by quadratic or linear behavior, as depicted below [33].

$$f_G W_{PV}(G) = \begin{cases} W_{PV_r} \cdot \frac{G^2}{G_r R_C}, & 0 < G < R_C \\ W_{PV_r} \cdot \frac{G}{G_r}, & G > R_C \end{cases} \quad (2)$$

The overestimation $C_{PV,o,i}$ or underestimation $C_{PV,u,i}$ represents the deviations in the binding dispatch and IMs. The variable $W_{PV,i}$ represents PV generators i and the available power, while the power programmed by the aggregator is represented by $W_{PV,s,i}$.

$$UCF = C_{PV,u,i}(W_{PV,s,i} - W_{PV,i}) + C_{PV,o,i}(W_{PV,i} - W_{PV,s,i}) \quad (3)$$

3.2. Objective Function of Microgrid

The smart MG is represented in Figure 1, which has a bidirectional flow of information. The following tasks are undertaken: buying and selling energy in IMs, charging and discharging ESSs, charging and discharging batteries from a BSS, and charging and discharging EVs. Other elements that comprise the MG are the distributed generators (DGs) and load with DR [5,7,14,28]. In addition, the smart MG considers restrictions such as the Herfindahl–Hirschman concentration index and the index of the three most prominent bidders to avoid monopolies and pivotal agents [9]. There is also the demand welfare, which ensures a minimum consumption of the demand [13].

Figure 1. Structure of the electrical microgrid.

The MG model operates in a black box. Information is taken from a real MG, in which the input variables are calculated, and the MG model calculates the benefits obtained as presented below [14]. The profits of the network are represented by P , periods are represented by t , scenarios are represented by s , the probability of the occurrence of each scenario is characterized by Pr , N_s is the maximum number of scenarios, and T is the maximum number of periods.

$$MG_{Total}^{Intraday+1} = \sum_{s=1}^{N_s} \left(\sum_{t=1}^{T=Ti} P_{(t,s)} + \sum_{t=Ti+1}^{T=2Ti} P_{(t,s)} + \sum_{t=iTi+1}^{T=24} P_{(t,s)} \right) \cdot \text{Pr}(s) \quad (4)$$

$\{Ti, 2Ti, \dots, 24\} \in \mathbb{Z}$

The deviations in the dispatch of solar energy will appear in each of the intraday periods. The UCs are calculated for each period, where N_{PV} represents the maximum number of PV Gen units.

$$\begin{aligned}
 UC_{Total}^{Intraday+1} = & \sum_{s=1}^{N_s} \left(\sum_{t=1}^{T=Ti} \left(\sum_{j=1}^{N_{PV}} C_{PV,u,ju} (W_{PV,s,i} - W_{PV,i}) \right) + \dots \right. \\
 & \dots \sum_{t=Ti+1}^{T=2Ti} \left(\sum_{j=1}^{N_{PV}} C_{PV,u,ju} (W_{PV,s,i} - W_{PV,i}) \right) + \dots \\
 & \dots + \sum_{t=iTi+1}^{T=24} \left(\sum_{j=1}^{N_{PV}} C_{PV,u,ju} (W_{PV,s,i} - W_{PV,i}) \right) + \dots \\
 & \dots + \sum_{t=1}^{T=Ti} \left(\sum_{j=1}^{N_{PV}} C_{PV,o,ju} (W_{PV,i} - W_{PV,s,i}) \right) + \dots \\
 & \dots \sum_{t=Ti+1}^{T=2Ti} \left(\sum_{j=1}^{N_{PV}} C_{PV,o,ju} (W_{PV,i} - W_{PV,s,i}) \right) + \dots \\
 & \dots + \sum_{t=iTi+1}^{T=24} \left(\sum_{j=1}^{N_{PV}} C_{PV,o,ju} (W_{PV,i} - W_{PV,s,i}) \right) \Bigg) \\
 & \{Ti, 2Ti, \dots, 24\} \in \mathbb{Z}
 \end{aligned} \quad (5)$$

The objective function is defined as minimizing the costs of uncertainty for the dispatch of solar energy minus the benefits obtained in the MG, which is optimized by using the VNS-DEEPSO algorithm.

$$\text{minimize } Z_{Total}^{Intraday+1} = UC_{Total}^{Intraday+1} - MG_{Total}^{Intraday+1} \quad (6)$$

4. Case Study Presentation

The case study is presented in two sections. The first section shows the statistical data used to evaluate the costs of uncertainty, and in the second one, the MG is given.

4.1. Residential Solar Generators

The power that is generated daily is taken from [14], where the energy for residential solar panels is considered. Figure 2 shows the power supply for 500 representative scenarios.

Figure 2. Residential PV generators in 24 h, data from [14].

The UC function must be validated using Monte Carlo simulations with which random irradiance values are obtained by assuming the proportionality between the irradiance and the generated power. Solar radiation parameters are considered according to solar radiation distribution frequency functions, as shown in Table 2 [34]. The penalties for overestimation and underestimation are considered [8].

Table 2. Solar generation parameter, data from [34].

Symbol	Parameter	Value
W_{PVr}	PV Gen source (MW)	100
G_r	Nominal irradiance (W/m ²)	775
R_C	Irradiance of reference (W/m ²)	116
$W_{PV,\infty}$	Maximum power Gen (MW)	150
N	Number of iterations	100,000
$W_{PV,s,i}$	Scheduled PV Gen (MW)	100
$C_{PV,u,i}$	Penalty for underestimation (USD/MW)	300
$C_{PV,o,i}$	Penalty for overestimation (USD/MW)	700

The solar radiation values in Figure 2 are the basis for calculating the mean and standard deviation of each hour. The obtained values are summarized in Tables 3 and 4.

Table 3. Mean and standard deviation between 8 and 14 h.

Symbol	8	9	10	11	12	13	14
β	0.0965	0.0710	0.0673	0.0887	0.1030	0.1069	0.1121
λ	2.3059	3.7685	4.4929	4.8512	5.0494	5.1577	5.2085

Table 4. Mean and standard deviation between 15 and 21 h.

Symbol	15	16	17	18	19	20	21
β	0.0965	0.0710	0.0673	0.0887	0.1030	0.1069	0.1121
λ	2.3059	3.7685	4.4929	4.8512	5.0494	5.1577	5.2085

4.2. Objective Function of Microgrid

MG is located in Portugal and comprises 17 solar Gen units, 5 dispatchable units, 34 REVs, 2 ESSs, an external electricity service provider, and 90 users who actively participate in DR programs [35,36]. The distribution transformer is 160 kVA and connects to a medium and low voltage line of 30 kV/400 V–230 V [37]. The five dispatchable units comprise four DGs and an external solar generator. The transformer is connected to 25 buses [37]. Additionally, MG can transfer energy with intraday markets [11]. It also has penalties for costs of uncertainty in the Gen of solar energy, market power restrictions, and constraints on the minimum supply of energy for demand [9,13,15]. MG is optimized using the VNS-DEEPSO algorithm, which improves MG in the first stage and MIs in the second stage, as shown in Figure 3 [17,18].

Figure 3. Solar generators in the electrical microgrid [14].

5. Results and Discussion

The results are presented in two sections. In the first section, the UCs for residential solar energy Gen are validated, while in the second one, the UCs are estimated by varying the IMs of the MG.

5.1. Uncertainty Costs with Residential Solar Generators

The validation uses Monte Carlo simulations to determine the histograms of irradiance and solar power generated with the underestimated and overestimated costs of solar radiation, as shown in Figure 4.

Figure 4. Histograms of (a) irradiance and (b) solar power generated. (# means 10^4).

Penalties due to UCs are determined, and UCs are calculated while solar Gen varies (Figure 5).

Figure 5. Monte Carlo simulations for (a) UC function histogram and (b) evaluation of UCs by varying solar power. (# means 10^4).

Finally, the UCs are evaluated for each hour using Monte Carlo simulations and the UC function. In the Monte Carlo simulations, the value is obtained with the average of the estimated values MC_{PV} [38]. The costs for underestimation and overestimation are used [33] as shown below.

$$AC_{PV} = E[C_{PV,u,i}(W_{PV,s,i}, W_{PV,i})] + E[C_{PV,o,i}(W_{PV,o,i}, W_{PV,i})] \quad (7)$$

The estimated error when evaluating the Monte Carlo functions and the UC function is summarized in Tables 5 and 6. The error is in the range between $7 \times 10^{-5}\%$ and 0.0168%. This research differs from previous works in which the uncertainty costs of renewable energies per day had been evaluated; in this research, a set of intraday evaluations per hour is carried out. For comparative purposes, the highest error reported in each research is taken, in which the error of 0.0168% is more exact than the errors obtained for 0.0615% from [39], 0.0343% from [16], and 0.072% from [33]. This means that this investigation contains the error closest to zero.

Table 5. The estimated error between 8 and 14 h.

Symbol	8	9	10	11	12	13	14
MC_{PV} (\$)	64,698	68,525	63,725	58,465	55,843	54,220	53,375
AC_{PV} (\$)	64,695	68,524	63,723	58,460	55,842	54,215	53,383
e (\$)	0.0049	4×10^{-4}	0.0026	0.0099	0.0027	0.0088	0.0151

Table 6. The estimated error between 15 and 21 h.

Symbol	15	16	17	18	19	20	21
MC_{PV} (\$)	69,920	68,526	63,726	58,465	55,844	54,216	53,374
AC_{PV} (\$)	69,920	68,524	63,723	58,460	55,842	54,215	53,383
e (\$)	7×10^{-5}	0.002	0.0047	0.0091	0.0041	0.0022	0.0168

5.2. Uncertainty Costs Varing Intraday Markets in the Microgrid

The uncertainty from the solar energy dispatch is due to the underestimation and overestimation of the power. The MG model considers the UCs for solar Gen with 2, 3, 4, and 6 IMs. The auctions are taken in symmetrical times; for example, in the case of three intraday markets, the auctions are conducted every 8 h, as shown in [11]. The uncertainty

costs due to overrating and underestimating the solar energy dispatch are reduced with a more significant number of intraday markets, as shown in Figure 6.

Figure 6. UCs of PV generators varying IMs.

6. Conclusions

The uncertainty in energy distribution planning is inevitable and can have minor impacts on the planning of electrical microgrids. This research quantified the uncertainty of the solar generation of an electric microgrid and validated the methodology using Monte Carlo simulations. The relative error of the uncertainty cost estimation function for the solar energy generation obtained values in the range between $7 \times 10^{-5}\%$ and 0.0168%. In addition, the authors evaluated the effect of intraday markets in an optimization case of an electrical microgrid. It was found that the costs of uncertainty for the generation of the solar energy decrease when the number of intraday markets increases, thus considering symmetrical daily auction periods. For example, in the case of three intraday markets, the auctions are carried out every 8 h. The aggregator improved the economic management of the network with a more significant number of intraday markets. Future works should evaluate other sources of clean energy such as micro-hydroelectric plants and wind turbines. Such studies must also assess the effect of the implementation of intraday markets with non-symmetrical daily auction periods on the costs of uncertainty.

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