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Stochastic Risk and Reliability Assessments of Energy Management System in Grid of Microgrids under Uncertainty

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Abstract

As various renewable energy resources (RERs) are exploited within microgrids (MGs), some important challenges have arisen as regards coping with generation fluctuations. This paper proposes a probabilistic method aimed at achieving optimal coordinated operation in a grid of microgrids under uncertainties of RERs and variable load demand. In the supposed structure based on networked microgrids (NMGs), a two-level strategy is required for guaranteeing efficient coordination between the MGs and distribution network operator (DNO). Another contribution of the paper deals with the flexibility of NMGs in improving the reliability of the whole system. Additionally, the value at risk (VaR) calculations for output results are carried out for different confidence levels with two important methods. In sum, the aim of the paper is to minimize total energy costs considering the environmental effects. To achieve this purpose, the Imperialist Competitive Algorithm (ICA) as a heuristic algorithm is applied to solve the optimal power dispatch problem and the obtained results are compared using the Monte Carlo Simulation (MCS) method. As the input data are modeled under uncertainties, the output results are described with probability distribution function (PDF).

Keywords: Optimal Coordinated Operation, Networked microgrids (NMGs), Reliability Evaluation, Value at Risk, ICA

1. Introduction

As global power distribution systems are developing rapidly, traditional grids are gradually facing a fossil fuels crisis – to which renewable energy resources (RERs) can be an efficient and sustainable response [1]. A microgrid, which consists of distribution sources, storage systems, loads and other control sections, has the advantages of being self-running and energy complementary and having optimal management and coordination control [2, 3].

In recent years, the development of microgrids has gradually trended towards a larger scale with numerous regional characteristics and diverse forms, which create the concept of Grid of Microgrids or Networked Microgrids (NMGs). In [4], the authors use probabilistic forward-backward load flow with the Monte Carlo simulation (MCS) algorithm to achieve optimal management of distributed energy resources (DER) in a multi-MGs structure. The trading of power between the MGs is one of the significant benefits in the NMG structure and satisfies their own local demands. In [5], an interesting energy management system is introduced to enhance the capability of NMGs in achieving economic conditions for both MG owners and the distribution network. In this regard, demand response programs are utilized as powerful tools to mitigate the operation costs of MGs, using particle swarm optimization under possible uncertainties of the network parameters. In [6], an iterative distributed algorithm is used to optimize the operation cost of MGs without considering the impact of the distribution network, which may affect the reliability of satisfaction, especially for consumers. NSGA-II algorithm is utilized in MGs optimal scheduling to fulfill the economic and environmental aims of multi-MGs structure [7]. In providing reliable coordination between the MGs and distribution system operator (DNO) plays a vital role in regulating the generation-load balance in the whole system [8]. The optimal operation problem is supposed as a stochastic bi-level problem in [9, 10], in which the DNO acts as an upper level network for the MGs. A nested energy management system is applied in day-ahead scheduling of networked microgrids [11]. In this energy management strategy, due to the layered privacy structure, customer privacy is preserved. One of the crucial features of smart grids is self-healing, aided by MGs. Arefifar *et al.* [12] proposed a planning model to divide a distribution system into networked MGs for optimal self-healing. Wang *et al.* [13] presented a transformative

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architecture in autonomous mode of NMGs in order to respond to the optimal operation problem and self-healing circumstances through two-layer cyber communication.

One of the important reasons for gravitation from conventional distribution systems to small scale energy zones or MGs is the desire to improve reliability. In the NMG structure power trading between MGs in addition to the main grid means the interruption rate decreases strongly and consumers are burdened with minimum cost detriments. Moreover, the power congestion in distribution lines in the modern NMGs frame is not comparable with that in classical networks. In other words, MGs can deliver electricity between to one another without being concerned about line capacity, because MGs can interconnect through direct lines with low amounts of transacted power compared to classical lines with high power congestion[3]. In [14],the reliability of NMGs are evaluated using the nonsequential Monte Carlo method under uncertainties of generation and load in various operating modes of the proposed structure. In [15], the authors have designed the MGs considering systematic strategy in teh presence of plausible faults in the system. Moreover, they used the concept of NMGs according to the definition of IEEE Std 1547.4 in order to modify the reliability of the whole system under fluctuations of distributed generations (DGs) and loads. In some cases, in order to enhance the reliability of the distribution system, the demand response programs (DRPs) can be beneficial for both consumers and MG owners. In [16], the authors by mitigating the operational limit violations prevent load interruption thereby improving the reliability level of the distribution network. Kopsidas *et al.* [17] have shown that DRPs can efficiently regulate demand scheduling and play an important role in improving the reliability indicators and expected generation costs.

Value at risk (VaR) is the maximum potential loss expected on a portfolio over a given time period, using statistical methods to calculate a confidence level. Usually, risk management is achieved through using so-called risk measures. Recently, the CVaR is used widely in problems relating to electricity markets, because of its coherent risk measure and linear formulation [18]. In light of the aforementioned literature, the contribution of the proposed paper can be summarized as follows:

- In this paper optimal operation of small scale energy sources (SSESs) within small scale energy zones (SSEZs) is proposed. Renewable generations and loads are described by probability distribution functions (PDFs) for a structure based on NMGs. In the proposed structure for microgrids, some MGs are connected together upstream network.

- After obtaining output results in PDF form, the reliability of network is calculated under uncertainty. We use some indices to analyze the reliability of network. Another important discussion in the paper is calculation of Value at Risk (VaR) for output results. VaR calculations are assessed based on a different confidence level.

- In order to achieve optimal operation of microgrids, we used a heuristic algorithm. The objective of the proposed cost function is to minimize the net cost of microgrids, such as power generation cost, power transaction cost, operation and maintenance cost, and pollutant emission cost. Finally,, the results obtained by the proposed method are compared with MCS to show the accuracy of the method.

The remainder of this paper is organized as follows. After presenting the architecture of the considered Networked Migrogrid (NMG) in Section 2, the proposed modeling which covers load modeling, SSEZs' DG units, cost modeling, objective functions and correlated constraints and the solution are presented in Section 3 and Section 4. Numerical results attained through performance tests are presented in Section 5, while some final conclusions are drawn in Section 6.

2. Paradigm Structure of Microgrid

Fig. 1 presents a grid of microgrids with four small scale energy zones (SSEZs). Each one of these SSEZs is a microgrid with local power generation, storage systems, and loads, which can not only exchange their own power with other MGs but also connect to the distribution network in critical situations in order to avoid load shedding in any given time. The SSEZs have bidirectional power exchange with each other and the upstream grid. This structure can be extended to an MG with a large number of SSEZs based on a study case. In [2] a microgrid with three SSEZs is discussed as a study case. In the proposed work, all SSEZs are connected together, but two MGs do not have a direct link with each other (MG1 and MG3). These MGs are connected together with an interface SSEZ (MG4) and power exchanging between MG1-MG3 is performed through MG4 (see green circle right-middle). Similarly, we used a wheeling concept in the proposed structure. In a wheeling system, power flows from one point to another through a third system. This MG has no local load or power generation unit and only transfers power between MG2 and MG3.

As shown in Fig. 1, the supposed structure consists of various components, including renewable generation, conventional generation, which are flexible components in a microgrid and can be regarded as micro-turbines (MT), fuel cells (FC) and combine heat and power (CHP), and load. There is a single point of connection to an upstream grid called a *point of common coupling* (PCC). LC is the local controller related to units/load. Each LC receives its set points from the MG central controller (MGCC) [19].

3. Probabilistic Modeling of Renewable Resources and Loads

Increasing use of renewable energy resources (RERs) imposes important challenges and concerns in regard of confident access to these resources at any given time. In the case of WTs, in order to achieve a desirable generation rate, initial

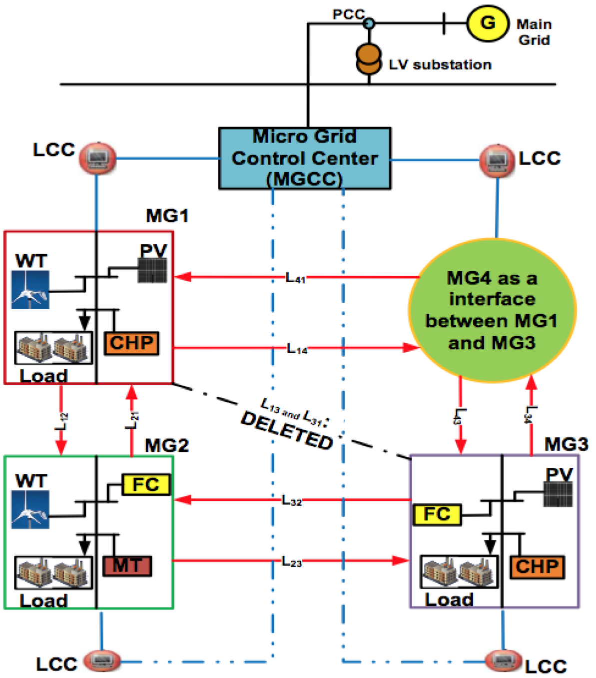


Figure 1: Structure of future smart distribution grid with NMGs

wind speed is the key element in determining power output. For PVs, solar radiation and ambient temperature are key factors in achieving ideal power generation. On the other hand, fluctuations on the demand side pose a challenge to guaranteeing economical operation of NMGs. Taking all the above-mentioned concerns about RERs and loads into account, modeling these MG elements with probability distribution function (PDF) can pave the way for accurate and precise analysis in operational problems. Applying PDF for each element can show a realistic and reliable prospect of optimal operation of MGs.

There are various distribution functions that can be used for modeling the existing intermittency in load demands. In this paper, normal distribution is applied in the modeling process of the loads as follows [20, 21]:

$$f(P_1) = \frac{1}{\sigma_{Pl} \times \sqrt{2\pi}} \exp\left(-\frac{(P_l - \mu_{Pl})^2}{2 \times \sigma_{Pl}^2}\right) \tag{1}$$

For wind generation, Weibull PDF is frequently used in modeling the wind speed [22, 23]:

$$f_v(v) = \begin{cases} 0 & otherwise \\ \frac{\delta}{\alpha} \times \left(\frac{v}{\alpha}\right)^{\delta-1} \times \exp\left(-\left(\frac{v}{\alpha}\right)^{\delta}\right) & v \geq 0 \end{cases} \tag{2}$$

After producing the wind speed samples, we need (3) to convert the samples to wind power according to the wind speed-power curve:

$$P_{G,WT}(v) = \begin{cases} 0 & 0 \leq v \leq v_{ci} \geq v_{co} \\ P_{r,WT} \frac{v - v_{ci}}{v_r - v_{co}} & v_{ci} < v < v_r \\ P_{r,WT} & v_r < v < v_{co} \end{cases} \tag{3}$$

The PV output fluctuates according to the input radiation of the sun. Thus, the location of PVs plays a vital role in generating the electricity, which can easily affect the performance of the whole system especially as poor placement of the solar arrays would hinder the aim of fulfilling demand. In this paper, in order to achieve a confident solution for optimal operation of MGs, beta distribution function [24] is used for radiation sampling and then (4) can convert the radiation samples to the final power output of the PV [25].

$$P_{PV}(R) = \begin{cases} P_{r,PV}\left(\frac{R^2}{R_{STD}R_c}\right) & 0 \leq R \leq R_c \\ P_{r,PV}\left(\frac{R}{R_{STD}}\right) & R_c \leq R \leq R_{STD} \\ P_{r,PV} & R_{STD} \leq R \end{cases} \tag{4}$$

4. Problem Definition

4.1. Cost modeling

Each MG encounters various kinds of costs that affect the total operation cost within the MGs. These costs are as follows: renewable power generation, power transaction, operation and maintenance, and pollutant emission costs.

In terms of power generated within the microgrids, the primary energy cost is the deciding factor in generation cost. Equation (5) describes the generation cost of FC, MT and CHP units, which depend on a constant coefficient of initial energy cost. It is obvious that this coefficient is zero for both WT and Pv:

$$C_{g,unit} = \alpha_\alpha \times P_{g,unit} \tag{5}$$

We can use a $C_g - P_g$ curve to show the direct relation between the generation cost and power for each unit [2]. Another important cost that affects an MG's operation cost relates to operation and maintenance $(O\&M)$ cost. This cost with a coefficient $(K_{O\&M})$ for each unit can be described as:

(6)

Trading of power between MGs as well as between a microgrid and the distribution network is one of the significant contributions of NMGs. The main goal of power exchanging can be divided into two sections: first, creating a generation-load balance within all MGs. The proposed problem in this paper should be optimized on two levels. On the first level each MG using MGCC fulfills demand through receiving data from renewable generation and loads, but MGs cannot afford the power balance between the generation and load because of either a lack of generated power for consumers or extra power that should be consumed at the same time. On the next level, MGs in order to create a power balance have to connect to the DNO and start sharing their powers with each other. The second benefit of power exchanging is mitigating the impact of the distribution network in the generation process. Overall, the major aim of today's SSEZs is to use small scale energy resources to satisfy local loads without involving large distribution grids in the process. A significant point in the proposed structure is the presence of MG4. MG4 operates as an interface area in the network. As we see in Fig. 1 there is no direct connection between MG1 and MG3, but two MGs are linked together through MG4, indirectly. The role of MG4 is to purchase a certain amount of power from an MG (MG1 or MG3) with one particular cost coefficient and to sell the same power to the other MG (MG3 or MG1) with another cost coefficient. In order to explain the transaction cost mathematically, the related formulation of purchased and sold costs of each MG is described as:

$$C_{buy,\,MG} = c_{MG} \times P_{buy,\,MG} \tag{7}$$

$$C_{sell,\,MG} = d_{MG} \times P_{sell,\,MG} \tag{8}$$

According to Fig. 1, the proposed network consists of four MGs, with MG4 considered as an interface microgrid. Each MG has its own cost coefficient for purchasing and selling powers. These costs for MGs are as follows:

$$c = \begin{bmatrix} 0.00 & c_{MG_1-MG_2} & K & c_{MG_1-NW} \\ c_{MG_2-MG_1} & 0.00 & K & c_{MG_2-NW} \\ M & M & M & M \\ c_{NW-MG_1} & c_{NW-MG_2} & K & 0.00 \end{bmatrix} \tag{9}$$

$$d = [c]^T \tag{10}$$

It should be mentioned that the cost coefficient value of MG4 is higher than MG1 and MG2, because MG4 regards losses in lines between MG4-MG1 and MG4-MG3. The cost of power transaction in the network is presented as follow:

$$C_{trans,\,MG} = C_{buy,\,MG} - C_{sell,\,MG} \tag{11}$$

Since an MG cannot buy and sell its sharing power in the market at the same time, we have the following constraints on purchased and sold powers:

$$\begin{cases} if\, P_{g,\,MG} - P_{l,\,MG} > 0 \Rightarrow P_{buy,\,MG} = 0,\ P_{sell,\,MG} > 0 \\ if\, P_{g,\,MG} - P_{l,\,MG} < 0 \Rightarrow P_{buy,\,MG} > 0,\ P_{sell,\,MG} = 0 \end{cases} \tag{12}$$

The generation process always has related environmental effects and each MG emits some pollutants into the air, such as NO_x, SO_2 and CO_2. The pollution cost for each unit can be described as follows:

$$C_{E,\,unit} = \sum_{j=1}^{3} \gamma_j \times \left(\rho_{unit,\,j} \times P_{g,\,unit}\right) \tag{13}$$

Pollution coefficients for each pollutant γ are described in [26].

4.2. Objective function

In our proposed NMG structure, DNO and MGs are considered as distinguished entities with individual objectives to optimize their own operation costs. Our proposed algorithm solves the problem on two levels: On the first level, the optimal solution for the operation cost of each MG is achieved within the MGs separately. In this regard, each MG during the optimization process determines its generation amount of units by taking into account the satisfaction of the load-generation balance. On the second level, after achieving the optimal operation cost of each MG, the MG entities should be coordinated with DNO. Then, DNO plays a significant role in response to the MGs' requests. Overall, it can be stated that the proposed problem is solved with a bi-level algorithm. However, a decision made by one MG could affect the operational planning of other entities, which reflects the fact that none of the MGs can optimize their cost function by changing their decisions from ttime to time [27], [28]. On the other hand, in the proposed networked MGs-based structure, DNO and MGs can run as autonomous entities during some operation hours. The objective function for each MG is as follows:

$$Min\ OF = f_{PG}(s) + f_{PE}(s) \tag{14}$$

$$f_{PG}(s) = \sum_{unit=1}^{9} \left[C_{g,\,unit}(s) + C_{O\&M,\,unit}(s)\right] + \sum_{MG=1}^{3} C_{trans,\,MG}(s) \tag{15}$$

$$f_{PE}(s) = \sum_{unit=1}^{9} C_{E,\,unit}(s) \tag{16}$$

4.3. Problem constraints

The supposed cost function should be solved under important constraints such as equal and unequal limits. The equal constraint of the problem which is called generation-load balance is described as follows:

$$\sum_{unit=1}^{9} P_{g,\,unit}(s) = \sum_{unit=1}^{3} \left[P_{l,\,MG}(s) + P_{trans,\,MG}(s)\right] + P_{loss,\,NW}(s) \tag{17}$$

$$P_{loss,\,NW}(s) = \sum_{i=unit} \sum_{j=unit} P_{g,\,i}(s) B_{ij} P_{g,\,i}(s) + \sum_{i=unit} B_{0i} P_{g,\,i}(s) + B_{00} \tag{18}$$

Besides, there are some unequal constraints for generation and transaction powers as follows:

$$P_{g,\,Min}(s) < P_{g,\,unit}(s) < P_{g,\,Max}(s) \tag{19}$$

$$P_{buy,\,Min}(s) < P_{buy,\,MG}(s) < P_{buy,\,Max}(s) \tag{20}$$

$$P_{sell,\,Min}(s) < P_{sell,\,MG}(s) < P_{sell,\,Max}(s) \tag{21}$$

One of the unequal constraints that operates as a security constraint is transmission of power between MGs as well as between MGs and the external grid.

$$0 < P_{trans,\,MG-MG}(s) < P_{trans,\,Max}(s) \tag{22}$$

$$0 < P_{trans,\,MG-NW}(s) < P_{trans,\,Max}(s) \tag{23}$$

4.4. Reliability evaluation

Reliability assessment is an important part of power systems studies. One of the obvious issues in the gravitation from conventional and large scale systems toward the NMGs is how to deliver reliability improvements. Because renewable resources and load fluctuations are an inseparable feature of microgrids, reliability evaluations encounter great challenges. In this paper, in order to have a more focused reliability assessment, some new indices are presented in the NMGs structure under uncertainties. Therefore, reliability outputs are described in PDF form. One of the reliability indices is loss of load capacity (LOL), which describes the capacity of loss of load (kWh). Let LOL_i be the loss of load obtained for the i^{th} contingency, with a probability of $prob_i$. Then the expected power not served or loss of load expectation (EPNS or LOLE) can be considered as follows:

$$EPNS = \sum_i LOL_i \times prob_i \tag{24}$$

The reliability of the network is then given by eq.(25):

$$EIR = 1 - \frac{EPNS}{P_{l,MG}} \tag{25}$$

The percentage of demand that can be covered by RERs is called renewable energy penetration (REP). At certain given times, a portion of consumer load can be supplied by conventional sources of MGs such as FC, MT, and CHP. This kind of index is called microgrid conventional power penetration (MCPP). The mentioned indices are described as follows:

$$REP = \frac{kWh \text{ renewable energy produced in given time}}{\text{Total } kWh \text{ load demand in given time}} \tag{26}$$

$$MCPP = \frac{\text{Sum of rated power of conventional DGs}}{\text{Average load demand of MG}} \tag{27}$$

Interruption cost is due to customer demand not being met by the utility because of outages in generating units. In this paper, we set the cost of interruption for MGs at 1.75 USD/kWh as described in [29] for household consumption. Total interruption cost in each MG is described as follows:

$$CLOLE_{MG} = 1.75 \times EPNS \tag{28}$$

4.5. Value at risk calculations

For a given time horizon and confidence level β, the value-at-risk at confidence level β is the smallest cost (loss in market value) over the time horizon that is exceeded with probability (no greater than) $1 - \beta$. In this paper two different approaches, namely *historical simulation* and *Variance-Covariance* methods, were used to calculate the VaR for some obtained results. The strength of the Variance-Covariance approach is that the VaR is simple to compute.

Table 1: Mean value of each reliability index in two cases

β	0.95	0.975	0.99	0.999
γ	1.645	1.960	2.326	3.090

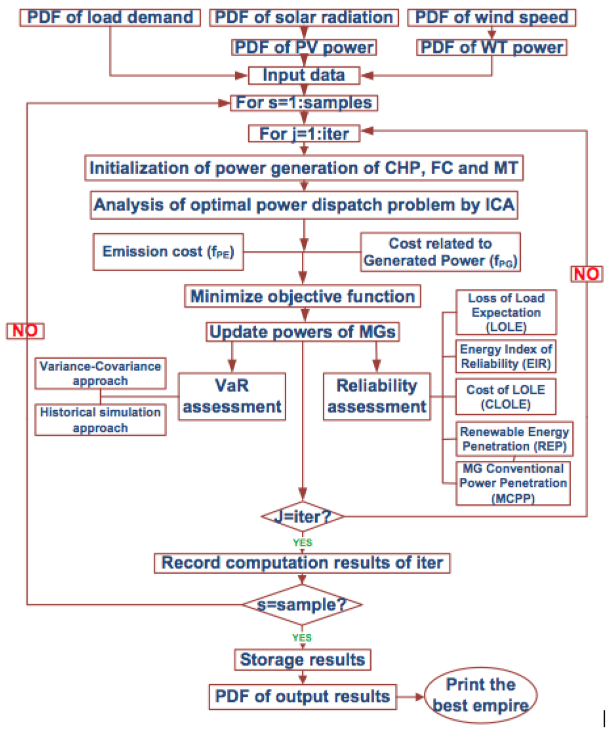


Figure 2: Flowchart of the ICA on probabilistic power dispatch considering reliability and VaR assessments

If conditional returns are not normally distributed, the computed VaR will understate the true VaR. VaR calculation based on Variance-Covariance method is as follows:

(29)

In (29), for a determined parameter (γ) the mean value (Mean) and standard deviation (STD) of γ is calculated. Different values of Z_β considering confidence level (β) are set out in Table 1.

In addition to optimal power dispatch results, the results from reliability assessments are described in PDF form, then under these probabilistic results, VaR assessments can be done for all existing outputs.

4.6. Brief review of ICA

The Imperialist Competitive Algorithm (ICA) introduced in [30] is used here to solve the power dispatch problem. In this algorithm, imperialist countries attempt to dominate other countries and compete strongly with each other to take possession of other countries. During this competition, stronger empires become powerful and the weakest one will collapse. The steps used in the ICA for probabilistic power dispatch considering reliability and VaR assessments can be observed as Fig. 2:

5. Simulation Results and Discussions

Numerical results are presented to illustrate the effectiveness of the proposed dispatching systems. In this section, we show the results obtained through solving the optimal scheduling problem and then the reliability and VaR calculations are illustrated. In this paper, for the given time 2000 samples are used to simulate the uncertainty of the mentioned variables. In an MG the sum of the power generated by micro sources within the same MG determines the total power generation of the MG. Generated power by each MG is described in PDF form. In Table 2 the mean value of power generation and related costs in MGs are represented considering VaR calculation with two different confidence levels: 0.95 and 0.975 using two approaches. In Table 2, generated power of MGs and related costs are analyzed. Table 2 uses mean value and standard deviation, the results are described. The results obtained by the ICA algorithm are compared with the MCS method. The power generated by each MG as well as their related costs are obtained from cost function optimization.

Besides, the results for purchased and sold powers/costs are illustrated in Table 3. In Table 2, the VaR assessments have been carried out based on two different values of confidence level (β), 0.95 and 0.975. VaR calculations have been achieved by approaches, historical (Hist) and variance-covariance (V-C) methods. One of the important points based on results from Table 3 is that the PDF of purchased or sold power/cost may not be in normal distribution function. Hence, in order to calculate VaR, we have used historical approach to assess VaR for confidence level 0.95. As an examination of the results of Tables 2 and 3 two main conclusions are checked, first, transaction purchased power/cost in ICA is lower than MCS and the sold power/cost in ICA is much higher than MCS, respectively. Accordingly, ICA due to its structure manages the transaction power and cost better than MCS and save more energy and cost effectively. Second, transaction VaR for histogram and variance-covariances methods in purchased power/cost in ICA are lower than MCS and for the sold power/cost in ICA is higher than MCS, respectively.

The PDF of total cost of network is shown in Fig. 3. In the figure, sum of pollutant emission cost and operation cost consist of generated power cost, transaction cost and O&M cost create total cost of network. In this figure the value of VaR is described for different values of confidence levels.

In Fig. 3, the VaR values for total cost of the network are calculated for four confidence levels: 0.95, 0.975, 0.99 and 0.999. The Variance-Covariance approach is applied to VaR assessment, because it benefits from normal PDF for the discussed results.

This paper evaluates the reliability of the distribution system including DGs. The stochastic characteristics of photovoltaic and wind power DGs are first studied, and a reliability model for the microgrids with DGs established. The goal of reliability studies in the paper is calculating reliability indices considering the microgrid concept under intermittent behaviors of the distributed energy resources within MGs. VaR analysis can be performed for reliability indices considering different values of confidence levels. In the paper, the following failure rates for MG1, MG2 and MG3 are considered: 0.05, 0.04 and 0.03, respectively. In Table 4 reliability indices are described for the microgrids structure.

As was concluded from Table 4, in the assessment process first the cost function is optimized and then the reliability indices are calculated. Therefore, we can see that the results obtained by ICA in the optimizing process are better than with the MCS method. The loss of load expectation value for MGs calculated by ICA is less than the MCS assessment. Hence, the cost of LOLE using ICA is less compared to MCS.

It should be mentioned that all obtained results are affected if changes are made to the limitations of problem constraints such as power generation limits. For example, In Fig. 4 with decreasing generated power in MGs, the value of LOL will be greater. As mentioned before, MG4 operates as an interface SSER. For example, if MG1 wants to transfer a determined power to MG3, MG4 should receive power from MG1 and deliver the same power to MG3. Fig. 5 illustrates the transaction of power between MG1 and MG3 through MG4 as well as the total transaction of power by MG4 in PDF form.

In order to assess the VaR of MGs reliability, in Fig. 5 the values of VaR for LOLE of each MG are shown based on the different values of confidence levels. In this figure, the assessments of ICA are compared with MCS results. In addition to LOLE calculation, in Table 5 other reliability indices are analyzed based on VaR. In this paper, the optimal power dispatch problem is analyzed considering market operation and reliability.

In order to evaluate the objective function value as described in eq.(13) between the proposed method and MCS, we tested ICA and MCS in the same structure for a smart distribution grid with NMGs (see the Fig. 1). Table 6 reports the obtained value for the cost function (OF) and the implementation time. According to Table 6, the cost function which is the sum of operation, pollution and interruption costs using the heuristic algorithm, the proposed method and its execution time are lower than MCS. This confirms that the ICA is capable of effectively converging the drawbacks of the classic method. As a result, this is an important advantage of the proposed algorithm.

6. Conclusion

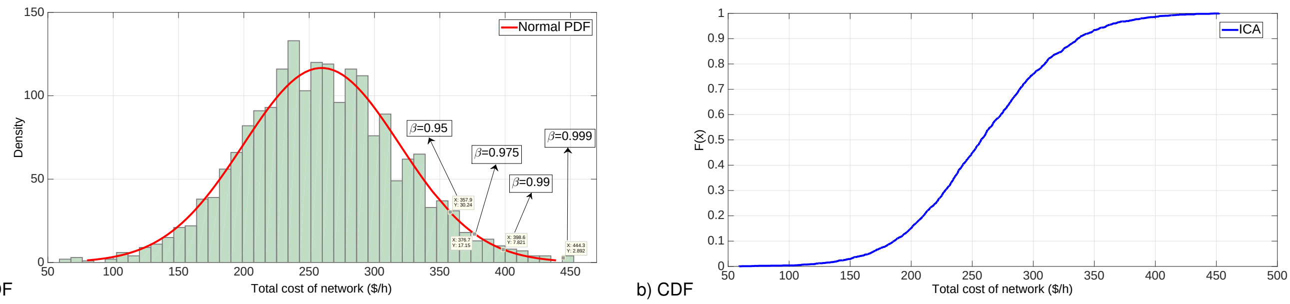
In this paper a framework is proposed for optimal power dispatch in interconnected NMGs considering reliability and market operation of MGs. The uncertainty in MGs components such as SSERs and load are modeled and simulated by numerical analysis. In addition to reliability evaluations of MGs operations, the VaR assessment is used to show the risk of some output results. Historical and variance-covariance methods are two methods, which have been applied to obtain the value of risk for studied outputs. In or-

Table 2: Statistical analysis of powers and their related costs in MGs and VaR calculations

Type		**ICA**			**MCS**		
		MG1	**MG2**	**MG3**	**MG1**	**MG2**	**MG3**
Power	**Generation**	μ : 544.04	μ : 627.05	μ : 585.88	μ : 541.88	μ : 625.20	μ : 582.52
	kW	ρ : 90.34	ρ : 90.11	ρ : 69.99	ρ : 93.52	ρ : 88.57	ρ : 70.08
	VaR	β : 0.95:690.08	β : 0.95:777.50	β : 0.95:695.61	β : 0.95:696.17	β : 0.95:770.04	β : 0.95:696.76
	Hist	β : 0.975:711.80	β : 0.975:798.35	β : 0.975:714.18	β : 0.975:715.90	β : 0.975:788.79	β : 0.975:712.17
	VaR	β : 0.95:692.65	β : 0.95:775.27	β : 0.95:701.01	β : 0.95:695.73	β : 0.95:770.89	β : 0.95:697.79
	V-C	β : 0.975:721.10	β : 0.975:803.66	β : 0.975:723.06	β : 0.975:725.19	β : 0.975:798.79	β : 0.975:719.87
Cost	**Generation Cost**	μ : 34.45	μ : 117.17	μ : 64.05	μ : 34.39	μ : 116.82	μ : 63.34
	$/h	ρ : 7.28	ρ : 13.08	ρ : 9.19	ρ : 7.16	ρ : 13.14	ρ : 9.23
	VaR	β : 0.95:47.29	β : 0.95:138.04	β : 0.95:79.88	β : 0.95:47.06	β : 0.95:137.20	β : 0.95:79.18
	Hist	β : 0.975:48.55	β : 0.975:140.07	β : 0.975:82.15	β : 0.975:48.67	β : 0.975:139.77	β : 0.975:81.64
	VaR	β : 0.95:46.42	β : 0.95:138.70	β : 0.95:79.17	β : 0.95:46.19	β : 0.95:138.44	β : 0.95:78.53
	V-C	β : 0.975:48.71	β : 0.975:142.82	β : 0.975:82.06	β : 0.975:48.42	β : 0.975:142.58	β : 0.975:81.44

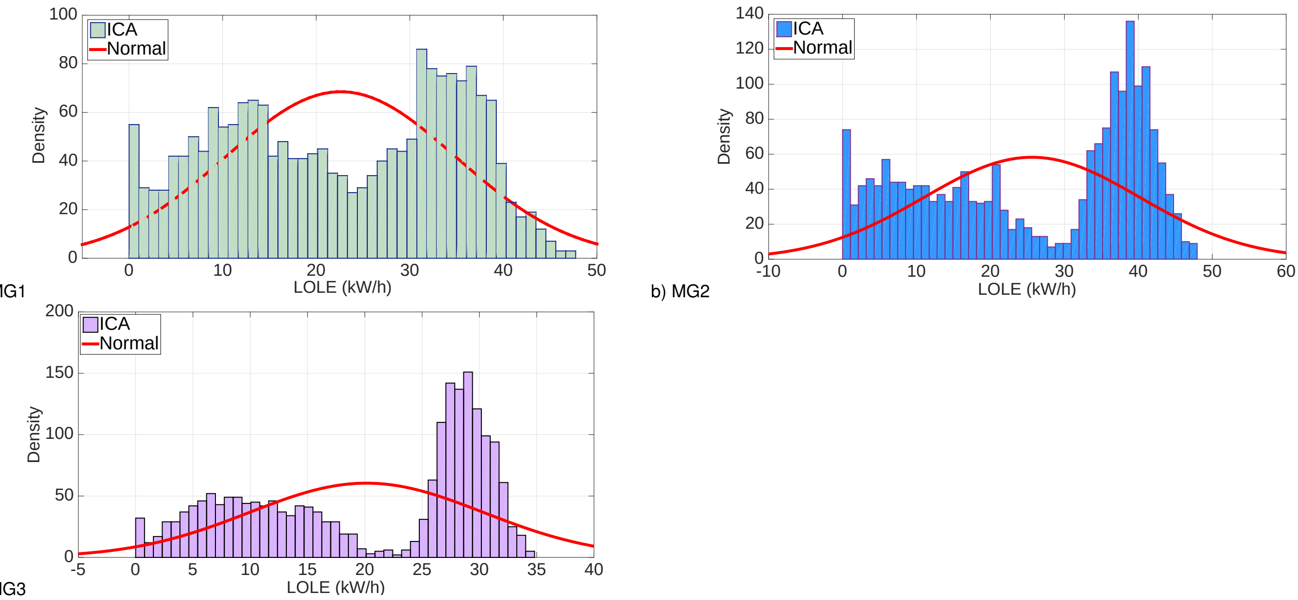
Table 3: Statistical analysis of transaction powers and costs in MGs and VaR calculations

Type		**ICA**			**MCS**		
		MG1	**MG2**	**MG3**	**MG1**	**MG2**	**MG3**
Related to Power	**Purchased**	μ : 51.93	μ : 81.28	μ : 73.95	μ : 58.04	μ : 89.39	μ : 82.39
	Power, kW	ρ : 88.81	ρ : 121.33	ρ : 103.61	ρ : 95.85	ρ : 127.54	ρ : 111.26
	VaR, Hist	β : 0.95:250.29	β : 0.95:341.90	β : 0.95:283.13	β : 0.95:263.79	β : 0.95:356.65	β : 0.95:316.57
	Sold Power	μ : 93.73	μ : 87.38	μ : 64.11	μ : 87.68	μ : 78.63	μ : 57.19
	kW	ρ : 115.67	ρ : 123.76	ρ : 98.17	ρ : 112.90	ρ : 118.14	ρ : 93.37
	VaR, V-C	β : 0.95:335.32	β : 0.95:355.02	β : 0.95:277.23	β : 0.95:330.14	β : 0.95:330.86	β : 0.95:261.35
Related to Cost	**Purchased**	μ : 9.66	μ : 14.99	μ : 13.85	μ : 10.90	μ : 16.60	μ : 15.52
	Cost, $/h	ρ : 7.28	ρ : 13.08	ρ : 9.19	ρ : 7.16	ρ : 13.14	ρ : 9.23
	VaR, Hist	β : 0.95:46.58	β : 0.95:63.91	β : 0.95:54.83	β : 0.95:49.99	β : 0.95:68.20	β : 0.95:61.60
	Sold Cost	μ : 17.53	μ : 16.39	μ : 12.19	μ : 16.33	μ : 14.63	μ : 10.82
	$/h	ρ : 21.84	ρ : 23.47	ρ : 18.73	ρ : 21.22	ρ : 22.26	ρ : 17.76
	VaR, V-C	β : 0.95:63.51	β : 0.95:66.59	β : 0.95:53.34	β : 0.95:61.39	β : 0.95:63.50	β : 0.95:49.03



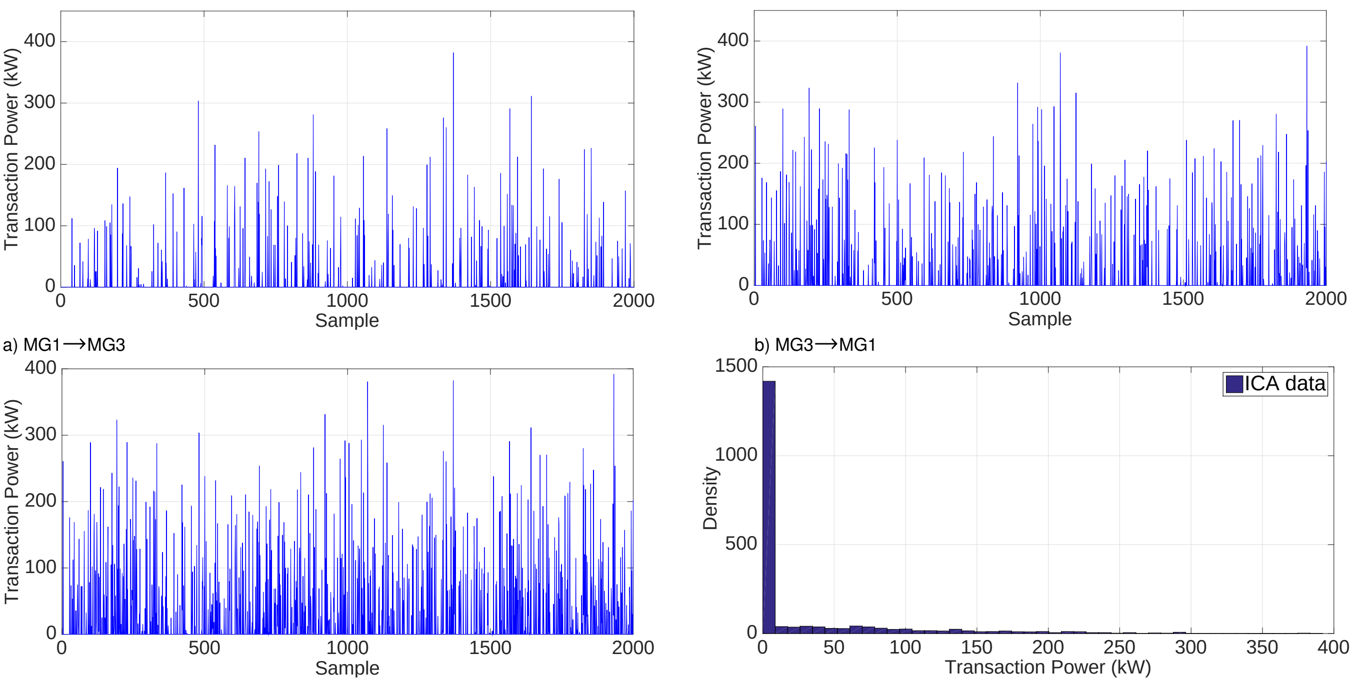
a) PDF b) CDF

Figure 3: PDF and CDF of total cost of network considering VaR assessment



a) MG1 b) MG2 c) MG3

Figure 4: PDF of LOLE of MGs using ICA



a) MG1⟶MG3 b) MG3⟶MG1 c) Total Transaction power of MG4 d) PDF of Total Transaction power of MG4

Figure 5: PDF of transaction power through MG4 using ICA

Table 4: Reliability indices of the proposed network

Method	#MG	LOLE kW/h	EIR pu	REP pu	MCPP pu	CLOLE $\$/h$
	1	17.99	0.9998	0.45	1.08	31.48
ICA	2	17.49	0.9999	0.23	1.19	30.61
	3	17.38	0.9999	0.15	1.53	23.41
	1	34.57	0.9996	0.44	1.05	60.50
MCS	2	38.81	0.9997	0.22	1.16	67.93
	3	36.62	0.9997	0.15	1.48	64.09

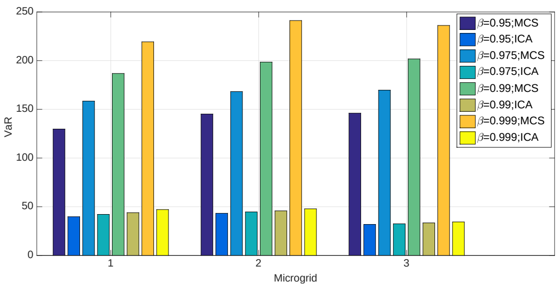


Figure 6: VaR assessments for LOLE in MGs using ICA

der to analyze the optimal operation of microgrids, ICA as a heuristic algorithm is applied in the optimization process. The objective of the proposed cost function is to minimize the net cost of microgrids under load fluctuations and DGs uncertainty. The MCS method is used to compare the results. The presented simulation results show the effectiveness of the proposed model in terms of reducing total energy costs considering operational constraints.

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References

[1] M. S. Mahmoud, M. S. U. Rahman, F. M. A. L. Sunni, Review of microgrid architectures-a system of systems perspective, IET Renewable Power Generation 9 (8) (2015) 1064–1078.

[2] N. Nikmehr, S. N. Ravadanegh, Optimal power dispatch of multi-microgrids at future smart distribution grids, IEEE Transactions on Smart Grid 6 (4) (2015) 1648–1657.

[3] N. Nikmehr, S. Najafi-Ravadanegh, Reliability evaluation of multi-microgrids considering optimal operation of small scale energy zones under load-generation uncertainties, International Journal of Electrical Power & Energy Systems 78 (2016) 80 – 87.

[4] H. Haddadian, R. Noroozian, Multi-microgrids approach for design and operation of future distribution networks based on novel technical indices, Applied Energy 185, Part 1 (2017) 650 – 663.

[5] N. Nikmehr, S. Najafi-Ravadanegh, A. Khodaei, Probabilistic optimal scheduling of networked microgrids considering time-based demand response programs under uncertainty, Applied Energy 198 (2017) 267 – 279.

[6] D. Gregoratti, J. Matamoros, Distributed energy trading: The multiple-microgrid case, IEEE Transactions on Industrial Electronics 62 (4) (2015) 2551–2559.

[7] Z. Pooranian, N. Nikmehr, S. Najafi-Ravadanegh, H. Mahdin, J. Abawajy, Economical and environmental operation of smart networked microgrids under uncertainties using nsga-ii, in: 2016 24th International Conference on Software, Telecommunications and Computer Networks (SoftCOM), 2016, pp. 1–6.

[8] N. Nikmehr, S. Najafi-Ravadanegh, Optimal operation of distributed generations in micro-grids under uncertainties in load and renewable power generation using heuristic algorithm, IET Renewable Power Generation 9 (8) (2015) 982–990.

[9] Z. Wang, B. Chen, J. Wang, M. M. Begovic, C. Chen, Coordinated energy management of networked microgrids in distribution systems, IEEE Transactions on Smart Grid 6 (1) (2015) 45–53.

[10] Z. Wang, B. Chen, J. Wang, J. kim, Decentralized energy management system for networked microgrids in grid-connected and islanded modes, IEEE Transactions on Smart Grid 7 (2) (2016) 1097–1105.

[11] A. Hussain, V. H. Bui, H. M. Kim, A resilient and privacy-preserving energy management strategy for networked microgrids, IEEE Transactions on Smart Grid PP (99) (2016) 1–1.

[12] S. A. Arefifar, Y. A. R. I. Mohamed, T. H. M. EL-Fouly, Comprehensive operational planning framework for self-healing control actions in smart distribution grids, IEEE Transactions on Power Systems 28 (4) (2013) 4192–4200.

[13] Z. Wang, B. Chen, J. Wang, C. Chen, Networked microgrids for self-healing power systems, IEEE Transactions on Smart Grid 7 (1) (2016) 310–319.

[14] Z. Bie, P. Zhang, G. Li, B. Hua, M. Meehan, X. Wang, Reliability evaluation of active distribution systems including microgrids, in: 2013 IEEE Power Energy Society General Meeting, 2013, pp. 1–1.

[15] S. A. Arefifar, Y. A. R. I. Mohamed, T. H. M. EL-Fouly, Optimum microgrid design for enhancing reliability and supply-security, IEEE Transactions on Smart Grid 4 (3) (2013) 1567–1575.

[16] A. Safdarian, M. Z. Degefa, M. Lehtonen, M. Fotuhi-Firuzabad, Distribution network reliability improvements in presence of demand response, IET Generation, Transmission Distribution 8 (12) (2014) 2027–2035.

[17] K. Kopsidas, A. Kapetanaki, v. levi, j. milanovic, Optimal demand response scheduling with real time thermal ratings of overhead lines for improved network reliability, IEEE Transactions on Smart Grid PP (99) (2016) 1–1.

[18] M. Asensio, J. Contreras, Stochastic unit commitment in isolated systems with renewable penetration under cvar assessment, IEEE Transactions on Smart Grid 7 (3) (2016) 1356–1367.

[19] M. Hemmati, N. Amjady, M. Ehsan, System modeling and optimization for islanded micro-grid using multi-cross learning-based chaotic differential evolution algorithm, International Journal of Electrical Power & Energy Systems 56 (2014) 349–360.

[20] S. Conti, S. Raiti, Probabilistic load flow using monte carlo techniques for distribution networks with photovoltaic generators, Solar Energy 81 (12) (2007) 1473–1481.

[21] N. Nikmehr, S. N. Ravadanegh, Solving probabilistic load flow in smart distribution grids using heuristic methods, Journal of Renewable and Sustainable Energy 7 (4) (2015) 043138.

[22] S. Kamalinia, M. Shahidehpour, Generation expansion planning in wind-thermal power systems, IET generation, transmission & distribution 4 (8) (2010) 940–951.

[23] N. Nikmehr, Heuristic probabilistic power flow algorithm for microgrids operation and planning, IET Generation, Transmission & Distribution 9 (2015) 985–995.

[24] K. Clement-Nyns, E. Haesen, J. Driesen, The impact of charging plug-in hybrid electric vehicles on a residential distribution grid, IEEE Transactions on Power Systems 25 (1) (2010) 371–380.

[25] M. Aien, M. Rashidinejad, M. Fotuhi-Firuzabad, On possibilistic and probabilistic uncertainty assessment of power flow problem: A review and a new approach, Renewable and Sustainable Energy Reviews 37 (2014) 883–895.

[26] H. Wu, X. Liu, M. Ding, Dynamic economic dispatch of a microgrid: Mathematical models and solution algorithm, International Journal of Electrical Power & Energy Systems 63 (2014) 336–346.

[27] S. A. Arefifar, A.-R. M. Yasser, T. H. El-Fouly, Optimum microgrid design for enhancing reliability and supply-security, IEEE Transactions on Smart Grid 4 (3) (2013) 1567–1575.

[28] J. Wu, X. Guan, Coordinated multi-microgrids optimal control algorithm for smart distribution management system, IEEE Transactions on Smart Grid 4 (4) (2013) 2174–2181.

Table 5: VaR calculations for Reliability indices of the proposed network

Confidence	β=0.95						β=0.975					
Methods	**ICA**			**MCS**			**ICA**			**MCS**		
MG	**MG1**	**MG2**	**MG3**	**MG1**	**MG2**	**MG3**	**MG1**	**MG2**	**MG3**	**MG1**	**MG2**	**MG3**
LOLE	39.78	43.25	31.79	129.73	145.21	146.09	42.14	44.65	32.47	158.49	168.27	169.69
REP	0.84	0.46	0.26	0.85	0.46	0.26	0.98	0.52	0.30	0.98	0.53	0.31
CLOLE	69.61	75.69	55.63	227.03	254.12	255.66	73.74	78.14	56.82	277.36	294.46	296.96

Table 6: Comparison of results in two methods

Method	**Cost Function**	**Execution time,** s
ICA	259.50	346
MCS	267.18	5641

[29] R. Yokoyama, T. Niimura, N. Saito, Modeling and evaluation of supply reliability of microgrids including pv and wind power, in: Power and Energy Society General Meeting-Conversion and Delivery of Electrical Energy in the 21st Century, 2008 IEEE, IEEE, 2008, pp. 1–5.

[30] E. Atashpaz-Gargari, C. Lucas, Imperialist competitive algorithm: an algorithm for optimization inspired by imperialistic competition, in: 2007 IEEE Congress on Evolutionary Computation, 2007, pp. 4661–4667.

[31] A. Y. Saber, G. K. Venayagamoorthy, Efficient utilization of renewable energy sources by gridable vehicles in cyber-physical energy systems, IEEE Systems Journal 4 (3) (2010) 285–294.

[32] T. Niknam, F. Golestaneh, A. Malekpour, Probabilistic energy and operation management of a microgrid containing wind/photovoltaic/fuel cell generation and energy storage devices based on point estimate method and self-adaptive gravitational search algorithm, Energy 43 (1) (2012) 427–437.

[33] Y. Xiang, J. Liu, Y. Liu, Robust energy management of microgrid with uncertain renewable generation and load, IEEE Transactions on Smart Grid 7 (2) (2016) 1034–1043.

[34] M. C. Bozchalui, C. A. Cañizares, K. Bhattacharya, Optimal energy management of greenhouses in smart grids, IEEE Transactions on Smart Grid 6 (2) (2015) 827–835.

[35] C. Chen, S. Duan, T. Cai, B. Liu, G. Hu, Smart energy management system for optimal microgrid economic operation, IET renewable power generation 5 (3) (2011) 258–267.

[36] Y. Zhang, N. Gatsis, G. B. Giannakis, Robust energy management for microgrids with high-penetration renewables, IEEE Transactions on Sustainable Energy 4 (4) (2013) 944–953.

[37] E. Crisostomi, M. Liu, M. Raugi, R. Shorten, Plug-and-play distributed algorithms for optimized power generation in a microgrid, IEEE Transactions on Smart Grid 5 (4) (2014) 2145–2154.

[38] S. Paudyal, C. A. Canizares, K. Bhattacharya, Optimal operation of distribution feeders in smart grids, IEEE Transactions on Industrial Electronics 58 (10) (2011) 4495–4503.

[39] M. C. Bozchalui, C. A. Cañizares, K. Bhattacharya, Optimal operation of climate control systems of produce storage facilities in smart grids, IEEE Transactions on Smart Grid 6 (1) (2015) 351–359.

[40] R. Allan, R. Billinton, A. Breipohl, C. Grigg, Bibliography on the application of probability methods in power system reliability evaluation, IEEE Transactions on Power Systems 14 (1) (1999) 51–57.

[41] R. Billinton, M. Fotuhi-Firuzabad, L. Bertling, Bibliography on the application of probability methods in power system reliability evaluation 1996-1999, IEEE Transactions on Power Systems 16 (4) (2001) 595–602.

[42] S. A. Arefifar, A.-R. M. Yasser, T. H. El-Fouly, Optimum microgrid design for enhancing reliability and supply-security, IEEE Transactions on Smart Grid 4 (3) (2013) 1567–1575.

[43] J. A. Martinez-Velasco, G. Guerra, Parallel monte carlo approach for distribution reliability assessment, IET Generation, Transmission & Distribution 8 (11) (2014) 1810–1819.

[44] S. Bahramirad, W. Reder, A. Khodaei, Reliability-constrained optimal sizing of energy storage system in a microgrid, IEEE Transactions on Smart Grid 3 (4) (2012) 2056–2062.

[45] S. Wang, Z. Li, L. Wu, M. Shahidehpour, Z. Li, New metrics for assessing the reliability and economics of microgrids in distribution system, IEEE Transactions on Power Systems 28 (3) (2013) 2852–2861.

[46] C. J. Booth, G. P. Kurpis, The new IEEE standard dictionary of electrical and electronics terms, IEEE New York, USA, 1993.

[47] Q. Wang, A. Yang, F. Wen, J. Li, Risk-based security-constrained economic dispatch in power systems, Journal of Modern Power Systems and Clean Energy 1 (2) (2013) 142–149.

[48] H. K. Nunna, S. Doolla, Multiagent-based distributed-energy-resource management for intelligent microgrids, IEEE Transactions on Industrial Electronics 60 (4) (2013) 1678–1687.

[49] Z. Wang, B. Chen, J. Wang, C. Chen, Networked microgrids for self-healing power systems, IEEE Transactions on Smart Grid 7 (1) (2016) 310–319.

[50] J. Ni, Q. Ai, Economic power transaction using coalitional game strategy in micro-grids, IET Generation, Transmission & Distribution 10 (1) (2016) 10–18.

[51] M. Fathi, H. Bevrani, Adaptive energy consumption scheduling for connected microgrids under demand uncertainty, IEEE Transactions on Power Delivery 28 (3) (2013) 1576–1583.

[52] M. Fathi, H. Bevrani, Statistical cooperative power dispatching in interconnected microgrids, IEEE Transactions on Sustainable Energy 4 (3) (2013) 586–593.

[53] A. K. Marvasti, Y. Fu, S. DorMohammadi, M. Rais-Rohani, Optimal operation of active distribution grids: A system of systems framework, IEEE Transactions on Smart Grid 5 (3) (2014) 1228–1237.

[54] Z. Wang, B. Chen, J. Wang, M. M. Begovic, C. Chen, Coordinated energy management of networked microgrids in distribution systems, IEEE Transactions on Smart Grid 6 (1) (2015) 45–53.

Nomenclature

α, β	Shape and scale parameters of Weibull function
α_α	Constant value of units
γ_j	Price coefficient of pollutant j
μ_{PL}	Mean value of load power
v	Wind speed [m/s]
ρ_{PL}	Standard variation of load power
$\rho_{unitl,j}$	Emission factor of pollutant j at units
B_{ij}, B_{i0}, B_{00}	Losses coefficients
C_{buy-MG}	Cost of purchased power by MGs
$C_{E,unit}$	Pollution cost of units
$C_{g,unit}$	Power generation cost for units
C_{MG}, d_{MG}	Purchased and sold powers cost coefficients

$C_{O\&M,unit}$	Operation and maintenance cost of units coefficients
$C_{sell-MG}$	Cost of sold power by MGs
$C_{Trans,NG}$	Cost of transaction power by MGs
$CLOLE_{MG}$	Total interruption cost in each MG
EIR	Index of reliability
$EPNS$	Loss of load expectation
$f_{PE}(s)$	Cost function related to pollution emission in sample s
$f_{PG}(s)$	Cost function related to generated power in sample s
$K_{O\&M,unit}$	Operation and maintenance cost coefficients
LOL_i	Loss of load of the ith contingency
$MCPP$	Microgrid Conventional Power Penetration
OF	Objective Function
$P_{buy,MG}$	Purchased power by each MG
$P_{g,MG}$	Generated power in each MG
$P_{g,unit}$	Generated power for units
$P_{G,WT}$	Generated power by wind turbine
$P_{loss,NW}(s)$	Network power losses in sample s
P_{pv}	Generated power by PV $[kW]$
$P_{r,PV}$	Rated power of PV [kW]
$P_{r,WT}$	Rated power of wind turbine [kW]
$P_{sell,MG}$	Sold power by each MG
$P_{trans,MG}(s)$	Transaction power of a MG in sample s
R	Solar irradiance [W/m^2]
R_c	A certain radiation point, usually set to 150 [W/m^2]
R_{STD}	Solar radiation in the standard conditions usually set to 1000 [W/m^2]
REP	Renewable Energy Penetration
V_{ci}	Wind turbine cut-in speed [m/s]
V_{co}	Wind turbine cut-out speed [m/s]
v_r	Operation and maintenance cost coefficients
P$_i$	Load power
X	Vector of uncertain input variables
Y	Vector of uncertain output variables