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Scenario-Based Design for Multiple Microgrids with High DG Penetration Considering Uncertainty on Demand and Generation Side

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Abstract

In this paper a new scenario-based approach is proposed to design optimized multiple-microgrids considering the uncertainty of load consumption and renewable DGs generation. The proposed method is used to determine the optimal capacity, type, number and location of renewable and controllable distributed generation resources along with the switch optimal location to cluster the traditional distribution network into a set of interconnected microgrids with economic and reliable structured. This study aims to decrease the total design costs including investment and operation costs, system loss cost, air pollution cost as well as the microgrids energy not supplied cost. Different considered objective functions have been modeled using weighted coefficients method as a single-objective nonlinear mixed integer problem. In addition, the uncertainty of the problem input parameters is modeled using scenario generation method, and in order to decrease the computational burden and increase the program execution speed, the backward scenario reduction technique is used. The Cuckoo optimization algorithm is used to optimize the objective function, and also the effect of optimization coefficients on the design problem and the robustness of the proposed algorithm are investigated using sensitivity analysis. Finally, the efficiency and performance of the proposed method are evaluated on the standard 33-bus network and the results show that the proposed method is an effective tool to design interconnected microgrids with consideration of uncertainty.

Keywords

multiple microgrid, reliability, renewable distributed generation, scenario based programming

1 Introduction

Conventional distribution systems (DS) have been designed to have a capacity adequate to meet the demand required at any time, where power flows in one direction to the consumer. Currently, the DS is being impacted by an increasing installation of different types of distributed energy resources (DERs), such as photovoltaic and wind turbines.as well as a wide range of emerging demandside management (DSM) resources, e.g. battery storage and electric vehicles (EVs) [1].

Today, the distribution network designers are being faced to issues including significant load growth, demand cost growth, limited fossil sources, distribution network low reliability due their radiality, and customers' geographic expansion [2]. On the one hand, due to environmental policies, new challenges have emerged in utilizing power generation sources for power system designers, and power system investors have little desire to construct fossil fuel plants [3]. Furthermore, the connection of distributed generation resources to the current distribution networks has not provided the technical and economic benefits for investors, while it was expected that increasing the penetration rate of distributed generation sources would increase the power quality, but due to the power fluctuations caused by voltage and frequency difference in renewable energy resources, the desired results have not been obtained [4].

The increasing penetration of renewable energy resources (RER) and their stochastic behaviors on the one hand and also, sharp fluctuations of electricity prices on the other hand have created substantial challenges for optimal operation of microgrids (MG) [5]. Therefore, the appropriate solution to solve the above-mentioned problems is to create small independent grids or the so-called "microgrids". Microgrid, which is composed of integrating several distributed resources at low and medium voltage levels, is one of the most suitable ways to generate

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power in future distribution networks. According to the definition of the American Energy Agency [6], various references have addressed the microgrids design issues with different perspectives. In [7], an overall overview of the various methods used to design microgrids is presented.

Reference [8] proposed an optimal method in order to design multiple microgrids with respect to the distribution system reliability and security. The main purpose of this paper is to cluster distribution networks into a set of microgrids with consideration of network reliability [9]. In [1], linearization system can be implemented mainly using three techniques, such as sampled sensitivity, Zbus matrix and analytically. The sampled based technique is easier to implement but processing time is slow, while the Zbus matrix method is the more precise linear model, but it is unable to capture non-linear behavior. The analytical method is challenging to implement but its processing time is very quick ensuring the maximum possible precision of linearization. A multi-objective economic approach is proposed to design a unit microgrid taking into account the probabilistic characteristics of renewable distributed generations. Design of self-repair microgrids to tolerate contingencies in distribution network is examined in [10]. In this reference, the distribution network is partitioned into a set of microgrids aiming to minimize system load shedding under standard conditions and operating cost in fault conditions.

Reference [11] is concerned with the zoning of distribution networks in the form of microgrids with the aim of increasing the overall system reliability against natural and rare accidents. This paper presents optimal operational strategies during severe faults with high domain and low probability which is became operational by zoning distribution network into a cluster of microgrids.

Voltage rise is one of the main concerns that can limit the allowed penetration of DG. During high power generation of DG and light load periods (extreme state), there is a high possibility of reverse power flow, and therefore voltage rise, in the distribution feeder. The conventional voltage regulation devices such as on-load tap changers (OLTCs) are not capable of treating these issues completely without aproper coordination with DG. An optimization model is proposed to determine the optimal DG inverter oversize for voltage regulation in the distribution system [12]. Reference [13] proposed an optimal model to design microgrids, taking into account the uncertainty of renewable distributed generations such as wind turbines and photovoltaic systems. In this paper, the objective function involves the installation and operating costs of generation units and the energy storage resources, while the reliability and environmental aspects are not considered. In [14], the microgrid is designed using Graph theories. In this paper, the grid structure design has been investigated using the graphs partitioning theory with regard to system reliability. In [15, 16], the distributed generations are optimally integrated at the medium voltage site of distribution network, and the network adequacy has been investigated using Harmony search algorithm. In addition, in [17], the multiple microgrids [5] are clustered aiming to improve the network controllability and tele-communication aspects.

In this paper, the stochastic operation scheduling of a MG consisting of non-dispatchable resources including WT and PV and dispatchable resources including Phosphoric Acid Fuel Cell (PAFC), Micro-gas Turbine (MT) and electrical storage as Battery Energy Storage System (BESS) is investigated to minimize operation cost and emissions [18]. Although the design of multiple microgrids is reported in the mentioned studies, the design of microgrids considering all economic, technical, environmental and reliability aspects regarding the uncertainty in the design parameters is not reported in previous references. In addition, with respect to the problem type, which is a non-linear and non-convex problem, it is much more desired to employ novel and improved optimization algorithms to achieve more optimal results. To this end, in this paper an optimal and comprehensive approach is proposed with regard to the economical, technical, environmental, and reliability aspects aiming to introduce an economic and reliable structure considering the power exchange between microgrids and upstream network in order to increase the system reliability and reduce the load shedding in islanding mode for multiple microgrids.

The above calculations have been evaluated under the probabilistic environment in which the scenario generation method is used to cover the problem uncertainty. The proposed objective function is optimized using a new intelligent algorithm named Cuckoo optimization algorithm, with the consideration of various network operating and technical constraints.

Fig. 1 shows the microgrids design concepts including DGs placement and microgrids bounding in distribution network.

In general, the paper contributions are as follows:

- Various types of di stributed generation resources are designed optimally and coordinated.
- The microgrids electrical boundaries are determined using switch placement.

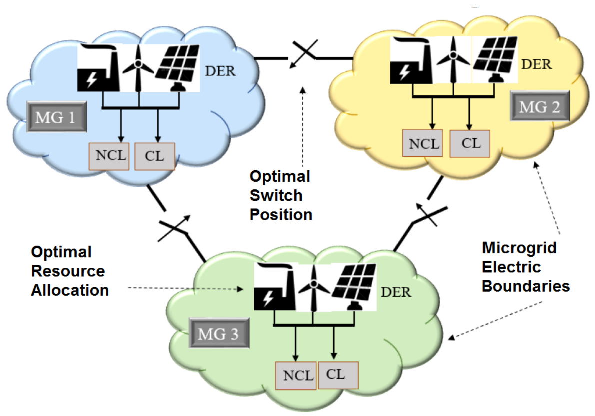

Fig. 1 The concepts of method proposed to design microgrids

- Cost, reliability and air pollution are considered at the same time.
- The load and production uncertainty are modeled using scenario generation method.

A new optimization algorithm called Cuckoo algorithm is employed. In Section 2, the probabilistic modeling of resources as well as the network load consumption is presented. Section 3 describes the proposed methodology formulation. The algorithm used for optimization is reported in Section 4. Section 5 provides and evaluates the simulation results and the overall conclusion is presented in Section 6.

2 The Loads and Resources Probabilistic Modelling

In this section, the uncertain parameters probabilistic modeling using scenario generation method is described.

2.1 Consumption Load

The distribution system demand depends to a large extent on human activities and the time factor. In the theory of probability, the stochastic behavior of parameters could be represented by a probability density function proportional to their behavior in the past. In this paper, the normal distribution is used to model the network load probabilistic behavior [19].

$$F_L\left(p^D\right)=\frac{1}{\sqrt{2\pi}\times\sigma}\exp\left(-\frac{\left(p^D-\mu\right)^2}{2\times\sigma^2}\right) . \tag{1}$$

Where μ represents the load average value, σ is the standard deviation of network load probability distribution, and p^D depicts the microgrids power consumption, where a number is obtained for $F_L(p^D)$ for each p^D. It is worth to notice that the above relation shows the annual peak load.

2.2 Wind Turbine

The wind speed is continuously changing and the exact speed could not be determined for a particular geographic area. Referring to the prior data of wind speed in a particular region, we could obtain a suitable probability function to determine wind speed distribution in that area. In this paper, the Weibull distribution function is used to model the wind variations [20]. Equation (2) shows the general function of Weibull probabilistic function.

$$F_\upsilon\left(\upsilon\right)=\begin{cases}\frac{\partial}{\kappa}\times\left(\frac{\upsilon}{\partial}\right)^{\rho-1}\times\exp\left(-\left(\frac{\upsilon}{\partial}\right)^{\rho}\right) & \upsilon\geq 0\\ 0 & \text{otherwise}\end{cases} . \tag{2}$$

Where ∂ and υ represent the Weibull distribution coefficients and wind speed, respectively.

In a wind turbine, the output power is proportional to the wind speed. Equation (3) represents the wind turbine output in terms of wind speeds, which is approximated by a quadratic function.

$$P_{WT}=\begin{cases}0 & 0\leq V\leq V_{ci} \text{ or } V_{co}\leq V\leq\infty\\ \left(A.V^2+B.V+C\right)P_{WT}^{rate} & V_{ci}\leq V\leq V_r\\ P_{WT}^{rate} & V_r\leq V\leq V_{co}\end{cases} . \tag{3}$$

Where the variables V_{co}, V_r and V_{ci} represent the cut-speed, rated speed and connection speed of wind turbine, respectively, and P_{WT}^{rate} depicts the wind turbine rated power under its rated speed.

2.3 Solar Cell

The solar radiation rate and the air temperature of the ambient where the solar cells are located cause the variability of the generation capacity of solar power resources. In this paper, a beta probability distribution function is used to show the sunlight variation curve [20], in which the general relation between beta distribution and the shape parameters Ω and φ are presented in Eq. (4).

$$F_s\left(S\right)=\begin{cases}\frac{\Gamma\left(\xi+\varphi\right)}{\Gamma\left(\xi\right)+\Gamma\left(\varphi\right)}\times S^{\xi}\times\left(1-S\right)^{\varphi}, & 0\leq S\leq 1\\ 0 & \text{otherwise}\end{cases} \tag{4}$$

$$P_{PV}=P_{STG}\times\frac{G_{ING}}{G_{STG}}\times\left(1+k\left(T_C-T_{ref}\right)\right) . \tag{5}$$

Equation (5) shows the power generated by solar modules under different environmental conditions. The solar module output power is determined according to the above relation. In this relation, k is the thermal coefficient and P_{STG} is the power generated under the rated conditions. G_{ING}, G_{STG} are solar radiations in standard and normal conditions, and T_C and T_{ref} are the temperature around the cell and the standard temperature.

2.4 Combined Heat and Power Generation resources (CHP)

The combined heat and power sources are known as one of the most economical and most efficient power generation sources, which are capable to simultaneously generate electrical power and heat. These resources are made in three types, whereas only the electrical power type is used in this paper. The fuel cost of these units is calculated using Eq. (6) as shown in [21]. In this relation, α, β and γ are the generation cost coefficients of combined heat and power generation units, and PCHP is the source generated power.

$$P_{CHP}(G) = \alpha + \beta.P_{CHP} + \gamma.P_{CHP}^2 \ . \tag{6}$$

2.5 Generation a nd Reduction of Scenarios

Due to the uncertainties in microgrids consumption load and power generation of renewable energy sources such as wind turbines and solar cells, designing microgrids with consideration of the uncertainty has become a major challenge for distribution system designers. In this paper, the scenario generation method is used to cover the uncertainty of system design parameters. In this approach, using the Monte Carlo simulation method, a number of stochastic conditions are generated for system variables based on their probability distribution function and then, the probability of each condition is calculated [22]. Equations (7) to (9) show the extracted samples from probabilistic distributions for load, wind generation, and solar power, respectively, while the sum of their probabilities is equal to one. Eq. (10) shows how to combine samples in order to produce scenarios so that the sum of the generated scenarios probabilities is always equal to one as it can be seen in [10].

$$\begin{gathered}\phi_d = \left\{\left(C_d^1,\psi_d^1\right),\left(C_d^2,\psi_d^2\right),\ldots,\left(C_d^n,\psi_d^n\right)\right\} \\ \psi_d^1+\psi_d^2+\ldots+\psi_d^n=1\end{gathered} \tag{7}$$

$$\begin{gathered}\phi_w = \left\{\left(C_w^1,\psi_w^1\right),\left(C_w^2,\psi_w^2\right),\ldots,\left(C_w^n,\psi_w^n\right)\right\} \\ \psi_w^1+\psi_w^2+\ldots+\psi_w^n=1\end{gathered} \tag{8}$$

$$\begin{gathered}\phi_s = \left\{\left(C_s^1,\psi_s^1\right),\left(C_s^2,\psi_s^2\right),\ldots,\left(C_s^n,\psi_s^n\right)\right\} \\ \psi_s^1+\psi_s^2+\ldots+\psi_s^n=1\end{gathered} \tag{9}$$

$$S = \phi_d \times \phi_w \times \phi_s \tag{10}$$

$$\sum_{S\in N_s} \psi_d + \psi_w + \psi_s = 1 \ . \tag{11}$$

In the above equation, ψ_w, ψ_d and ψ_s represent the probability of possible load conditions, wind turbine and solar modules generations, respectively. In addition, C_w, C_d and C_s depict the numerical amount of values extracted from probability distribution for load, wind turbine and solar generations, respectively, and N_s is the number of the generated scenarios.

It should be noted that in this paper, in order to reduce the computational burden and program execution time, we considered the backward scenario reduction method. The scenario reduction is a way to optimally choose useful scenarios among a set of generated scenarios, which reduces the algorithm execution time and also greatly decreases the problem computational complexity. The backward scenario reduction method steps are described below:

- Generate distance matrix between scenarios as $C(S,S')$
- Select first scenario using Eq. (12)
- Select next scenario and add it to the previous scenario
- Repeat algorithm until sufficient scenarios are selected
- Add the probability of each scenario that is not selected to the probability of the closest selected scenario.

$$S_1 = \arg\left\{\min_{S'\in N_s} \sum_S \psi_s \times C(S,S')\right\} N_s = \{S_1\} \tag{12}$$

$$S_n = \arg\left\{\min_{S'\in N_s} \sum_S \psi_s \times C(S,S'')\right\} N_s \ . \tag{13}$$

More detailed information on available methods for scenario reduction is provided in [23].

3 Problem Formulation

3.1 Economic assessment

In this section, we perform an economic assessment for installation of distributed resources and power switches, including investment and operation costs to design microgrids. It is worth noting that proposed method is a static method in which all investments are made in the first year of the design horizon.

3.1.1 Investment cost

The investment cost of distributed generation resources and switches involves the installation cost and the costs concerned with the land. Equation (14) presents the costs of distributed generation and switches for all scenarios.

$$C_1 = \sum_{s=1}^{N_s}\left(\sum_{i=1}^{N_{DG}} IC_{i,s}^{DG} \times P_{i,s}^{DG} \times \eta_{i,s}^{DG} + \sum_{m=1}^{N_{SW}} IC_{m,s}^{SW} \times \theta_{m,s}^{SW}\right). \quad (14)$$

Where $IC_{i,s}^{DG}$ is the sources construction cost, $P_{i,s}^{DG}$ is the amount of sources generated power and $\eta_{i,s}^{DG}$ is a binary variable to install source i in the scenario s. In addition, $IC_{m,s}^{SW}$ is the switches installation cost and $\theta_{m,s}^{SW}$ is a binary variable to install switch m in scenarios.

3.1.2 Repair and Maintenance Cost

This cost involves the annual costs of the periodic and seasonal repairs associated with installed distributed generation resources and power switches, which is presented by Eq. (15) and is modified using inflation and interest rates as Eq. (16). In Eq. (15), MC_i^{DG} is the resources repair and maintenance cost and $P_{i,s}^{DG}$ shows the sources generated power in scenario s. In addition, MC_m^{SW} is the repair and maintenance cost of installed switches and $\tau_{m,s}^{SW}$ is the switching rate of switch m in scenario s. In Eq. (16), $\ln fR$ and $\ln tR$ represent the inflation rate and interest rate in the operation horizon, respectively.

$$C_2 = \sum_{s=1}^{N_s}\left(\sum_{i=1}^{N_{DG}} MC_i^{DG} \times P_{i,s}^{DG} + \sum_{m=1}^{N_{SW}} MC_m^{SW} \times \tau_{m,s}^{SW}\right) \quad (15)$$

$$CPV(C_2) = C_2 \sum_{s=1}^{N_s}\sum_{t=1}^{T}\left(\frac{1+\ln fR}{1+\ln tR}\right)^t. \quad (16)$$

3.1.3 Operating cost

The operating cost includes the cost of fossil fuel unis, such as he combined heat and power generation units, which is obtained using Eq. (17) in different operational years, and is modified at the different operating horizons as shown in Eq. (18). In these relationships, CG_i^{DG} is generation production cost, $T_{i,s}^{DG}$ is the operation time, and $P_{i,s}^{DG}$ represent the amount of generated power in scenario s.

$$C_3 = \sum_{s=1}^{N_s}\sum_{i=1}^{N_{DG}} T_{i,s}^{DG} \times CG_i^{DG} \times P_{i,s}^{DG} \quad (17)$$

$$CPV(C_3) = C_3 \sum_{s=1}^{N_s}\sum_{t=1}^{T}\left(\frac{1+\ln fR}{1+\ln tR}\right)^t. \quad (18)$$

It is worth noting that renewable resources lack the primary fuel cost and their operating costs are considered only in terms of maintenance and repair costs.

3.2 Technical assessment

This section addresses the technical aspects of microgrid design, including the air pollution cost due to the fossil fuel based distributed generations and the network losses cost.

3.2.1 Air pollution cost

According to the Kyoto treaty and the need to reduce greenhouse gases, consideration of this discussion in microgrids design has become an important goal of designing future distribution networks. In this paper, the cost of air pollution is modeled according to the Eqs. (19)–(20) [24].

$$C_4 = \sum_{s=1}^{N_s}\sum_{i=1}^{N_{CHP}}\left[\zeta_i^{CHP}\exp\left(\delta_i \times P_{i,s}^{CHP}\right)\right] \quad (19)$$

$$CPV(C_4) = C_4 \sum_{t=1}^{T}\left(\frac{1+\ln fR}{1+\ln tR}\right)^t \quad (20)$$

Where ζ_i^{CHP} and δ_i are the coefficients associated with combined heat and power (CHP) units in creating air pollution and $P_{i,s}^{CHP}$ represent CHP units in scenario s. In addition, Eq. (20) calculates the current value of cost caused by air pollution in the operating horizon.

3.2.2 The loss cost

The electrical network loss is one of the most important technical indicators to evaluate the distribution network quality. System loss calculation requires running the power flow program on the studied system. In this paper, the backward-forward power flow method has been used as a reliable and suitable method for high-resistivity distribution networks [25]. Due to the problem probabilistic modeling, the system loss is also presented probabilistic using scenario generation method in Eq. (21), and the current cost of loss is calculated using Eq. (22).

$$C_5 = \sum_{s=1}^{N_s}\sum_{b=1}^{N_b}\left(R_b \times I_{b,s}^2\right) C_{loss} \quad (21)$$

$$CPV(C_5) = C_5 \sum_{t=1}^{T}\left(\frac{1+\ln fR}{1+\ln tR}\right)^t. \quad (22)$$

Were R_b is the network line resistant, $I_{b,s}^2$ is the lines current and C_{loss} is the dollar per kilowatt cost of energy loss.

3.3 Reliability Assessment

One of the most important goals to convert radial distribution networks into a set of interconnected microgrids is the need to increase the distribution networks reliability level. Due to the distribution networks radial structure and the low reliability of these networks, clustering the distribution networks as a set of interconnected microgrids improves the network subscribers' reliability [25]. The proposed method also assesses the distribution system reliability which is discussed in the following.

3.3.1 Cost of energy not supplied

Energy not supplied is one of the most important indicators to evaluate distribution networks reliability, which provides complete information about the behavior and performance of system. This indicator shows the amount of power loss due to the contingencies at network lines, which is calculated annually. It is important to note that this paper assumes that faults only occur at network lines and other network equipment is 100 % reliable. Eq. (23) represents the subscribers interruption cost for different scenarios, whose current cost is calculated using Eq. (24) for different years of operation.

$$C_6 = \sum_{s=1}^{N_s} \left\{ \begin{array}{l} \sum_{b=1}^{N_b} C_{\text{int}} \times \lambda_b \times L_b \times P_{b,s}^{D} \times \sum_{res=1}^{N_{res}} P_s^{res} \times T_s^{res} \\ + \sum_{rep=1}^{N_{rep}} P_s^{rep} \times T_s^{rep} \end{array} \right\} \tag{23}$$

$$CPV\left(C_6\right) = C_6 \sum_{t=1}^{T} \left(\frac{1+\ln fR}{1+\ln tR} \right)^t . \tag{24}$$

Where λ_{23} is the lines failure rate, L_b is the length of distribution network lines, PBD is the power amount of interrupted load, and C_{int} is the cost of each subscriber outage per kWh. In addition, P_s^{res} and T_s^{res} represent the amount of interrupted power due to repairs and repairs time.

3.4 Objective function and problem constraints

In general, the objective function consists of three parts including economic cost, technical cost, and reliability cost, which are shown using Eqs. (25) to (27). The optimization aims to minimize the total mentioned costs at the same time with respect to the different system constraints. The problem main variables including the placement and sizing the different types of distributed generation resources, as well as the optimal location of switches in order to determine the electrical grid boundaries, as shown in Fig. 2.

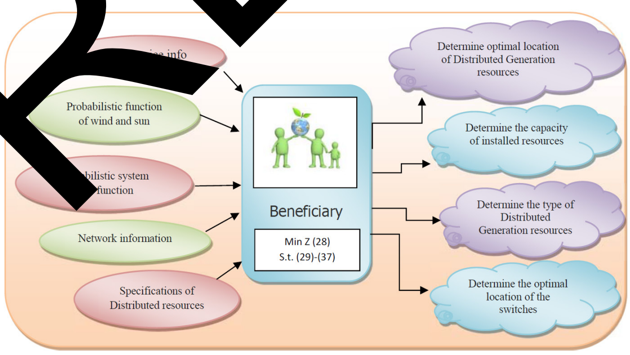

Fig. 2 The decision diagram to design microgrids

The considered objective functions have converted into a single objective function using weighted coefficients method [26].

$$F(1) = C_1 + CPV(C_2) + CPV(C_3) \tag{25}$$

$$F(2) = CPV(C_4) + CPV(C_5) \tag{26}$$

$$F(3) = CPV(C_6) \tag{27}$$

$$Z = W_1 \times F(1) + W_2 \times F(2) + W_3 \times f(3) . \tag{28}$$

Where $F(1)$, $F(2)$ and $F(3)$ represent economic objective function, technical and environmental objective function, and reliability objective function of the problem, respectively. The weighted coefficients method is used to combine these three functions to a unit objective function as shown in Eq. (28).

The optimization problem is carried out under various operational and technical constraints. In this paper, the problem constraints include the allowed range of buses voltages, the allowed range of feeders' current, the maximum number of DGs, each source capacity range and the power equilibrium constraint for each microgrid, as well as the power flow equations, which are formulized using constraints (29) to (34) and Eqs. (35) to (37). Constraint (29) indicates the permitted voltage range for network buses, while in this paper, the allowed range of bus voltages is considered to be between 0.95 and 1.05. In addition, the network lines allowed current is limited using constraint (30). Constraint (31) shows the maximum amount of distributed generation resources to be installed in the distribution network and the constraints (32) to (34) present the allowed range to install CHP units, solar cells and wind turbines. In addition, Eq. (35) imposes the power equilibrium constraint to the created microgrids, which makes the microgrids to be completely independent and stand-alone. Finally, Eqs. (36) and (37) show the power flow equations.

$$V_{n,s}^{\min} \le V_{n,s} \le V_{n,s}^{\max} \quad \forall s \in N_s \tag{29}$$

$$I_{b,s} \le I_{b,s}^{\max} \quad \forall s \in N_s \tag{30}$$

$$\sum_{i=1}^{N_{DG}} P_i^{DG} \le P^{\max} \quad \forall s \in N_s \tag{31}$$

$$P_{CHP}^{\min} \le P_{CHP} \le P_{CHP}^{\max} \quad \forall s \in N_s \tag{32}$$

$$P_{PV}^{\min} \le P_{PV} \le P_{PV}^{\max} \quad \forall s \in N_s \tag{33}$$

$$P_{WT}^{\min} \le P_{WT} \le P_{WT}^{\max} \quad \forall s \in N_s \tag{34}$$

$$\sum_{n=1}^{N_{MG}} P_{i,n}^{DG} = \sum_{l=1}^{N_L} P_l^D + \sum_{b=1}^{N_b} P_b^{loss}, \quad \forall i \tag{35}$$

$$-P_{t,s}^D + \sum_{i \in N_{DG}} P_{i,t,s,}^{DG} = V_{j,t,s} \sum_{b \in Nb} Y_b . V_{k,t,s} \cos\left(\delta_{j,t,s} - \delta_{k,t,s} - \theta_{jk}\right) \tag{36}$$

$$-Q_{t,s}^D + \sum_{i \in N_{DG}} Q_{i,t,s,}^{DG} = V_{j,t,s} \sum_{b \in Nb} Y_b . V_{k,t,s} \sin\left(\delta_{j,t,s} - \delta_{k,t,s} - \theta_{jk}\right) . \tag{37}$$

Where V_n depicts the bus voltage and n_{lb} shows the current flows through line b. In addition, Y_b is the line admittance, δ_j and δ_k are the voltage angles of buses i and j. Q, $P_{i,t,s,}^{DG}$ and P_b show the installed DGs generated active and reactive power, the network active and reactive power consumption and loss, respectively [21].

4 Optimization Algorithm

According to the problem objective function, which is a non-linear and non-convex model with a large number of binary variables and integers, obviously it is not possible to use mathematical methods to solve the problem. Hence, in this paper, the Cuckoo algorithm is used to optimize the objective function [26].

Similar to other evolutionary algorithms, the Cuckoo algorithm begins with a primitive population (a population composed of cuckoos). These cuckoos have a number of eggs that dump them in the nests of host birds. Some of these eggs, which are more similar to host birds eggs, have a greater chance to hatch and become mature cuckoos, while other eggs are identified and destroyed by the host birds. The amount of grown eggs shows that region nests are appropriate. The more eggs in one area are able to live and survive, the more profits are allocated to that area. Therefore, the location in which the largest number of eggs survived is the parameter that Cuckoo algorithm intends to optimize. The cuckoos look for the best location to maximize their survived eggs. When chickens hatch out and become mature cuckoos, form societies and groups. Each group has its own residence area to live. The best residence area among all groups is the next destination of other cuckoos groups. All groups migrate toward best current area. Each group settles in a region close to the current best location. Considering the number of eggs that each cuckoo lays and cuckoos distance to the current optimal region, some egg laying radius is calculated. Then, cuckoos begin to lay eggs in nests within the egg laying radius. This process continues until the best location for egg laying (most profit) is obtained. This optimal location is where the most numbers of cuckoo come together.

One of the most important problem modeling parts is to determine the input vector for intelligent algorithms variables. The proposed input vector for the Cuckoo algorithm in order to simultaneously model the DGs and Switch location is shown in Fig. 3. As can be seen, the algorithm input vector consists of two parts: the first part is composed of two separate parts to determine the optimal location as well as the optimal capacity of the distributed generation resources. In addition, the second part shows the location and number of switches to determine the microgrids electrical boundaries. It is worth to notice that in this paper, all buses and lines are considered as the candidate points to install DGs and switches.

One of the most important features of the Cuckoo algorithm is the possibility of global search, in addition to local search, which allows finding the problem optimal overall solution. In addition, this algorithm has a less convergence time than other metaheuristic algorithms. The flowchart illustrated in Fig. 4 depicts the proposed algorithm to design microgrids under uncertainty using the Cuckoo optimization algorithm.

5 Simulation and Results

In this paper, in order to validate the proposed approach performance, a 33-bus standard distribution network is used to implement the proposed method [27]. The costs associated with the construction and operation of resources and switches are obtained from [28-30]. Also, the forecasted load demand and market price profiles are illustrated in Fig. 5 (a) and 5 (b) respectively. The used demand profile is divided into three various periods namely low load period (00:00 AM to 6:00 AM), off-peak period (6:00 AM to 3:00 PM) and peak period (3:00 PM to 12:00 PM) [31]. It is worth noting that the design horizon for the proposed problem is considered to be 10 years.

This paper aims to optimally design the multiple microgrids in an intelligent distribution grid, taking into account the economic, technical and environmental aspects and

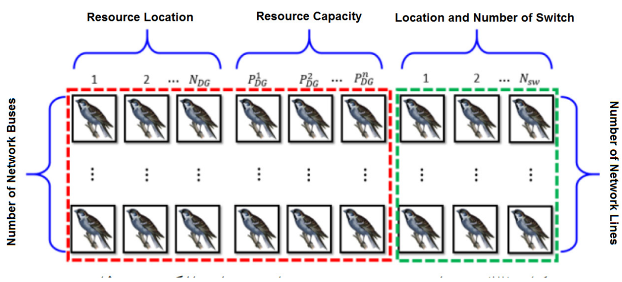

Fig. 3 The proposed input vector for Cuckoo algorithm

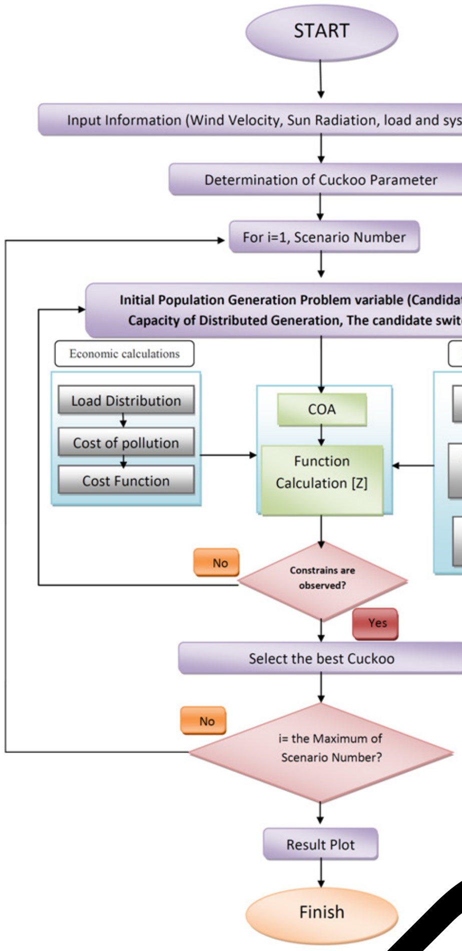

Fig. 4 The proposed algorithm flowchart.

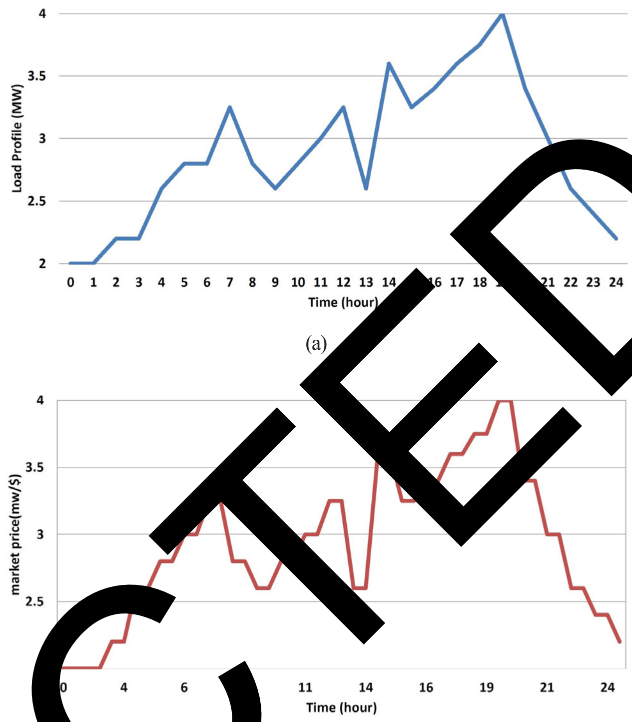

Fig. 5 (a) The forecasted daily load demand (b) electricity price curves.

the uncertainty in the distribution system design parameters. The microgrids design problem is carried out as optimal location of renewable DG resources and controllable power generation sources simultaneous with switch location in energy distribution network in order to determine microgrids electrical boundaries. The proposed model is static in which all investments are made in the first year and determination of a year to construct resources is not a decision variable. Cuckoo optimization algorithm has been used as one of the most powerful and newest metaheuristic algorithms to optimize the problem objective function. To cover the uncertainty, a scenario generation method is employed to reduce the computational burden and program runtime using the backward scenario reduction technique.

Including the weighted coefficients in the problem objective function depends on the network designers' policies and strategies, and depending on their goals and priorities, they could have different values between zero and one. In this paper, sensitivity analysis is used to determine the exact impact of optimization coefficients and weighted coefficients on the intended problem.

Table 1 shows the results obtained for optimal placement and sizing of DG resources as well as the switch location for microgrids boundaries based on the obtained average values from probability distribution. According to Table 1, three microgrids are selected for this particular system, and three DG resources are allocated to each microgrid. Three types of DG power resources include solar cells, wind turbines and CHP units are considered for each microgrid.

In addition, Table 2 shows different objective functions optimal values for three different modes of DG resources penetration index (PI). The resources penetration rate is defined as the ratio of the resources installed capacity to the network consumption. According to Table 2, it is clear that with increased penetration of distributed generation resources, the investment and operational costs may increase, while this may improve the technical indicators and system reliability.

Fig. 6 (a) shows the network voltage profile in the both traditional and the multiple microgrids based structures.

Table 1 Optimal placement of distributed generation source

Kind of source	Location (Bas)	Capacity (KW)
Sources of electricity and heat production	12, 19, 33	200, 150, 175
Wind Turbine	4, 9, 30	125, 100, 75
Solar Cell	17, 24, 27	50, 100, 75
The switch	1, 6, 25	--

Table 2 Problem objective function for microgrid design

objective functions	objective functions Amounts ($)		
	PI = 100 %	PI = 75 %	PI = 50 %
Investment cost	2.25846	1.17388	8.12694
maintenance cost	3.8617	8.5792	7.4648
Cost of operation	5.8977	3.6619	4.5091
Cost of air pollution	664.7	1913.7	2846.3
The cost of casualties	6.1084	6.3198	3.5297
Cost of reliability	4.591	6.6425	1.8846
Total cost	9.45786	2.41335	5.394405

According to Fig. 6 (a), the voltage variations of different network buses are much less than that of the traditional one and the voltage level is under different loadings within its allowed range, thus, the system power quality has been improved. Therefore, the proposed method increased the voltage stability margin of the distribution network and prevented the voltage collapse phenomenon in the distribution network.

In addition, Fig. 6 (b) depicts the network loss diagram in two conventional and restructured conditions. According to Fig. 6 (b), in the case where the distribution network is designed as a set of interconnected microgrids, the system loss is greatly reduced, which improves the system technical specifications such as reducing the current passing through lines, and thus, reducing investment costs in distribution feeders, as well as postponing the distribution network upgrade. Reducing the system loss may increase the distribution lines equipment life span and decrease the distribution system operating cost.

Fig. 7 shows a single-line diagram of 33-bus standard distribution network which the proposed method is implemented on. According to Fig. 7, the network is divided into three interconnected microgrids, while each microgrid could be available for different operators and private owners. In addition, they could be isolated from the main network in the case of fault occurrence and continue to operate independently. The number and type of distributed generation resources are specified and their optimal capacity is determined using the proposed algorithm.

In this paper, regarding the increase of sensitive loads at the distribution network level and the need for increased reliability in the distribution system, a great deal of effort has been devoted to improve the distribution network reliability by optimal location of DG resources as well as clustering the distribution network into a set of interconnected microgrids. By changing the weighted coefficients corresponding to the system loss function from 0 to 1, various degrees of system loss could be obtained, which depends on the operational policies and distribution network planners decisions. The exact value of weighted coefficients and their effects on the design problem is determined using sensitivity analysis.

In this study, the energy not supplied index is used as an indicator to evaluate the system reliability. Fig. 8 shows the amount of network energy not supplied in microgrid-based and conventional conditions for different design years. As can be seen, in the case where the distribution networks are designed as a set of multiple microgrids, the amount of energy not supplied significantly reduced due to the splitting the distribution network into smaller parts. It is worth to notice that the reliability assessment is carried out under uncertainty conditions.

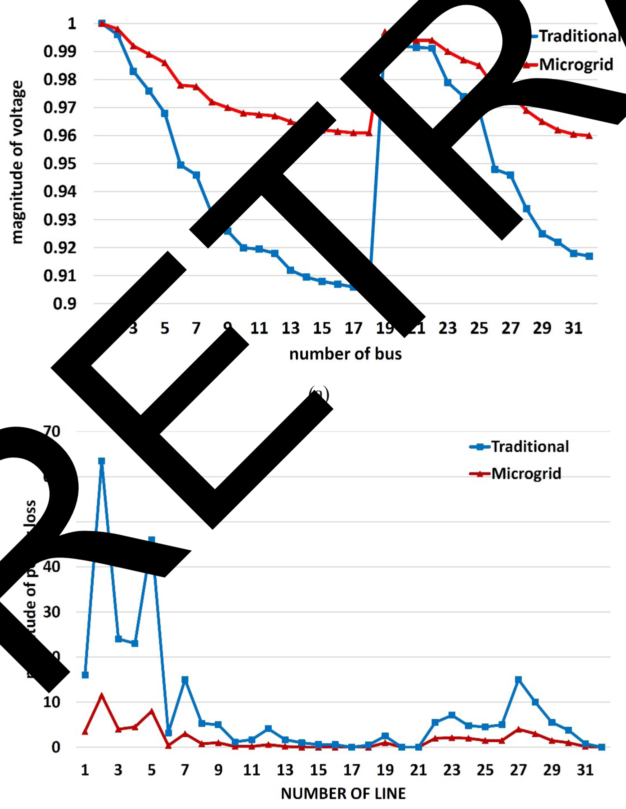

Fig. 6 (a) Network voltage profile (b) System total loss

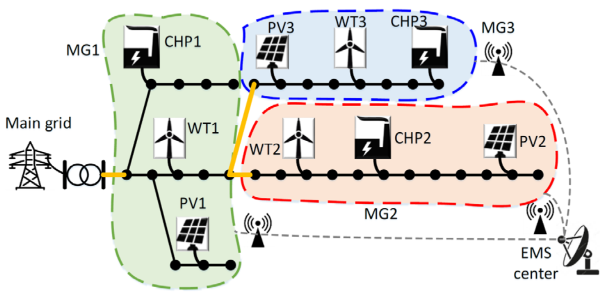

Fig. 7 DG optimal location and multiple microgrids boundaries

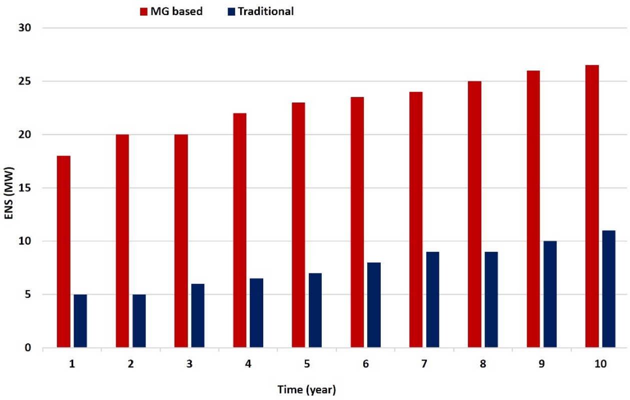

Fig. 8 Energy not supplied values along design horizon

Fig. 9 (a) shows probability diagram of the system energy not supplied index for different scenarios. In distribution networks reliability assessment, the failure rate and repair rate are assigned to each network line, and then, the reliability indicators are calculated based on the faults occurred on each feeder. Fig. 9 (b) shows the probability distribution of the air pollution caused by fossil fuel sources. In addition, Fig. 9 (c) shows the probability distribution of microgrids design total cost including the investment cost of resources and switches, operating cost, loss and air pollution costs as well as energy not supplied cost for different scenarios.

To illustrate the overall design cost, the expected value that is extracted from probabilistic diagram obtained from scenarios is used, which indicates the most probable condition for microgrids design cost. Due to the problem probabilistic modeling, the microgrid design is robust against system variables uncertainty, and the proposed method shows more flexibility to the network operators in different operating conditions. Since the renewable resources power generation depends on these resources environmental conditions, scheduling these resources based on the average value obtained from the probabilistic distribution make the network design robust against weather changes and these resources generation fluctuations. This increases the microgrids reliability in both grid-connected and islanding modes.

Considering that different solutions are obtained for each scenario in scenario-based planning, selection of a single solution among the obtained solutions has become one of the decision makers' challenges. In practice, the average or expected value obtained from the probabilistic distribution of uncertain variables is used for the distribution system planning, which has the highest probability to other scenarios.

However, in recent years various methods are proposed to reduce the risk of costly scenarios [12]. In this paper, we used the sensitivity analysis method to examine the effect of weighted coefficients on system design quantity. In this method, the problem is performed for various values that weighted coefficients could have, and the best design in terms of obtained quantities is the optimized weighted coefficient.

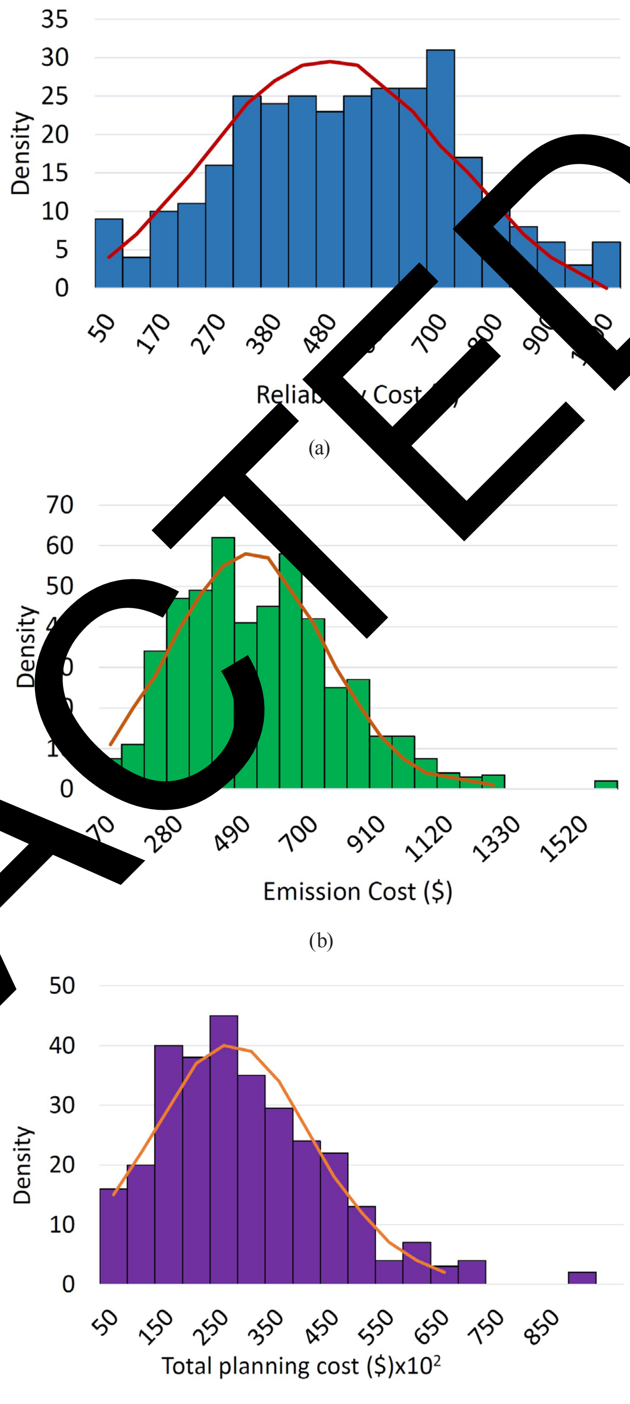

Fig. 9 (a) The probability distribution of energy not supplied. (b) The probability distribution of total design cost. (c) The probability distribution of microgrids design total cost.

Table 3 shows the impact of weighted coefficients different values on the total cost of the network design. According to Table 3, taking into account all the coefficients may reduce the system total cost. Therefore, designing the microgrids with consideration of all economic, technical and environmental aspects as well as reliability may reduce the network design total cost, while all the three coefficients are considered equal to 1 in this paper. In addition, Table 3 shows the results obtained from sensitivity analysis of weighted coefficients on microgrids boundaries. As is shown, as the network reliability weight is higher the microgrid number increases, while its ultimate value in this particular network is equal to 6. In addition, as the economical part weight is higher, the microgrids numbers reduces toward a single microgrid, in other words, small microgrids are more reliable and large microgrids are more economic.

In order to illustrate the efficiency and performance of the optimization algorithm used in solving the proposed problem, the Cuckoo algorithm convergence curve is compared with other conventional optimization algorithms (Genetic Algorithm and Particle Swarm Optimization Algorithm) in Fig. 10. As can be seen, the proposed algorithm has a remarkable superiority to the other two algorithms in terms of convergence speed and obtained

Table 3 Effect of weight coefficients on Micro grid design

W1	W2	W3	Switch location	Cost ($)
0	0	1	5, 12, [illegible] 26	68560.5
0	1	0	1, 7, 25	66327.7
0	1	1	1, 3, 11, 25	59789.5
1	0	[illegible]	1	53454.5
1	0	1	[illegible] 7, 26	53664.8
1	[illegible]	0	1, [illegible]	47456.4
1	1	1	1, 6, 25	45786.9

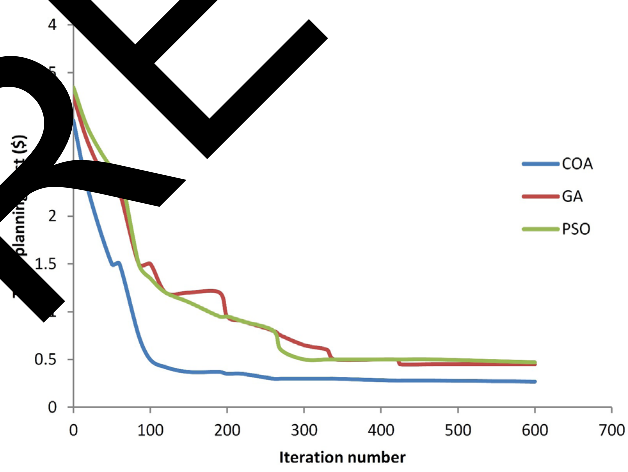

Fig. 10 The proposed algorithm convergence curve

values. This is due to the two local and global explorers in cuckoo optimization algorithm which achieve the more desired value in less time.

It is worth to notice that in the scenario-based approach, selecting the final scenario among the generated scenarios is an important issue. In general, three risk-averse, risk-neutral and risk-taking strategies could be defined for this problem. The risk-taking strategy seeks the lowest possible cost, so that it chooses the scenario that imposes the lowest cost. In contrast, the risk averse-strategy aims to reduce the system technical risk which may increase the design costs. Therefore, in risk-taking strategy, the scenario with the highest cost (the most expensive network) is chosen as the ultimate scenario. Finally, the risk-neutral strategy is the interstitial state of the two mentioned strategies, which selects the most probable scenario as the final scenario. In this paper, we utilized a risk-neutral strategy to find the final scenario (single solution).

In general, the economic and reliability assessments results show that although investment costs are increased in the case where the conventional distribution network is splitted into a set of multiple networks, the decrease of reliability and technical costs due to the loss reduction and voltage profile improvement is far greater which reduces the entire system cost. According to the obtained results, the best way to design microgrids is to consider three different system aspects at the same time, which imposes the least cost to the distribution system designers. Depending on the planners and grid owners' risk-taking or risk-averse policies, different conditions of weighted coefficients could be selected regarding their needs and the microgrid characteristics.

6 Conclusion

In this paper, a non-linear mixed integer planning model is proposed to economic and reliable design of multiple microgrids taking into account the uncertainties in load consumption and renewable resources power generation. The proposed method is used to determine the location, number, type and capacity of renewable and controllable DGs as well as to determine the microgrids electrical boundaries in intelligent distribution networks. In this paper, the scenario generation method is utilized to cover the system parameters uncertainties and the backward scenario reduction method is used to reduce the scenarios in order to increase the computational speed. The results show that clustering the distribution network into a set of interconnected microcircuits improves the economic, technical and reliability specifications of the distribution network. In this study, the sensitivity analysis has been used to illustrate the effect of weighted coefficients on the microgrid design. The results show that by changing the different functions weighted coefficients, the obtained structure for microgrids may be extensively changed, while the optimal selection of these coefficients depends on the microgrids owners' policies. Since the proposed method is comprehensive and considers the system parameters uncertainties, it is an effective tool to design future distribution networks as interconnected microgrids taking into account system uncertainties.

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