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Energy Management Capability in the Reconfigurable Distribution Networks with Distributed Generation for Minimization of Energy Loss

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Abstract: One of the approaches to improve operation indices, such as power loss and reliability, is to smoothen voltage profiles. Energy management of generation units and network reconfiguration are two methods to achieve this. Hence, the latter is presented in this paper in a distribution with distributed generation units. To this end, an objective function is formulated aiming to minimize power loss and enhance the operating situation of the network. This problem is subject to various constraints and limits such as AC power flow equations, operation limits, planning model, and operation model of distributed generations. It is an integer nonlinear optimization problem and is solved using the crow search algorithm and the optimal solution is obtained. Two major innovations of the study include modeling generation units' operation and network configuration mathematical expression of operation indicators. The method is applied to a test system and results demonstrate the high performance of this approach in improving the operation of the network. Finding the solution in less time with a satisfying standard deviation are two advantages of the proposed algorithm. Adopting this method, the network operator can reduce power loss through proper management of distributed generation power and optimal scheduling of switches. Moreover, the obtained voltage profile is more desirable in comparison to that of power flow studies.

Keywords: crow search algorithm; distributed sources; minimization of energy loss; network operation improvement; reconfigurable distribution network

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1. Introduction

1.1. Motivation

Distribution system operators (DSOs) aim to improve the distribution system operation state constantly [1]. The operation indices include items such as low energy loss, smooth voltage profile, and a high-power factor of the distribution substation. In the distribution network, there are various ways to access the desired state of operation [1]. For example, if the network has local resources (resources at the demand site) such as distributed generation (DG), their energy management may considerably enhance the operation indices [2]. Moreover, generally, the distribution network has tie lines. Hence, by implementing the reconfiguration program, it is possible to take steps to improve various technical indices [3] so that it can obtain a low voltage drop by supplying the consumers through the distribution substation via a short path. Following this, a more favorable voltage profile is obtained. In addition, the reduction of voltage drop is proportional to the reduction of power and energy losses [3]. Therefore, system reconfiguration is a desirable program in the distribution network to improve the operating situation. According to the mentioned cases, appropriate energy management of local resources and optimal planning of system reconfiguration can help technical measures to enhance significantly [4,5].

Nonetheless, extracting these cases requires providing a suitable planning-operation formulation for DSO.

1.2. Literature Review

Regarding the operation and planning of the distribution system, numerous studies have been carried out, which are summarized and reviewed as follows. Electric vehicle (EV) parking lots energy management has been discussed [6] so that the operation of parking lots that transact energy among themselves and with the distribution network is properly scheduled and the profit gained by parking lots is increased. To route and schedule storage equipment, a new restoration strategy has been adopted [7] with the aim of reaching acceptable response of the system in the case of severe events. This model was structured in the form of a stochastic problem subject to some constraints. In an attempt to obtain a resilient network when encountering natural disasters, one study [8] incorporated a two-objective linearized resilient structure according to the scheduling of storage system, tie lines, and backup DGs. The authors in [9] optimally planned DGs and distribution automation so that the reliability and operating indicators of the distribution system are enhanced significantly. Automatic voltage control and VAr control besides automatic fault clearance management equipment are involved in the automation infrastructure. The paper also forms an objective function to find the minimum amount of sum of predicted cost of investment, operation, power loss, and reliability. Ref. [10] uses adaptive robust optimization to provide optimal planning of active distribution networks that consist of renewables and flexibility devices such as EV parking lots. Planning of DGs in a probabilistic manner subject to a securable-reliable operation strategy has also been discussed [11]. The authors established the planning scheme in the form of an optimization problem that consists of four different objective functions. The aim is to provide a suitable model for different indicators of the system. Microgrids' energy management has also been discussed [12] when active/reactive power sources are present in the system along with active demand so that various operation indicators including operating, reliability, pollutants, and economic situation of the system are enhanced at the same time. An optimization problem has been structured to this aim, which includes four objective functions to find the optimal values of expected operating cost, pollution amount, energy not supplied, and voltage variation. To enhance reliability of DGs, provide green energy supply, and reach optimal operating status of micro-grids (MGs), one study [13] deals with the MGs operation that relies on energy management strategies. The same is implemented in [14] but its focus is on microgrids and DGs, in which thermal block and the combined heat and power system (CHP) help meet the demand. The total cost, power loss, and voltage deviation related to the microgrid are minimized using the suggested approach. Ref. [15] manages an active distribution system containing virtual power plants that include renewables, storage devices, and EVs parking lots. In [16], DGs and Battery Energy Storage Systems (BESSs) are used simultaneously to improve the reliability of distribution networks. To solve the optimization problem, the Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D) is used to reduce the energy not supplied (ENS) in the 30 and 69-bus distribution networks. The objective functions used in the proposed algorithm include minimization of ENS, reduction of load losses, reduction of load cost, and reduction of voltage drop in the network. In [17], optimal location and sizing of the flexi-renewable virtual power plants (FRVPPs) in the smart distribution network are targeted through proposing a bi-level optimization problem. In the upper-level formulation, the normalized summation of the network's voltage deviation function and annual operation cost is minimized, and it is limited to AC optimal power flow equations. The yearly operating and investment costs of renewable and flexible resources subjected to model of resources in FRVPP framework are minimized in the lower-level problem. In [18], the Equilibrium Optimizer algorithm is applied to the power distribution network reconfiguration (PDNR) for reducing active power loss, enhancing the voltage magnitude, and improving the reliability indices. In [19], the authors consider a mixed-integer linear model for the reconfiguration program in the radial distribution network. This network includes DGs that include constant power. Finally, the taxonomy of recent works is presented in Table 1.

Table 1. Taxonomy of recent work.

Ref.	Model of System Reconfiguration	Model of DG Operation	Energy Loss Minimization	Voltage Limit Model	Model of Power Factor	Model of Lines and Post Capacity
[6]	✗	✗	✗	✓	✗	✓
[7]	✗	✗	✗	✓	✗	✓
[8]	✓	✓	✗	✓	✗	✓
[9]	✓	✓	✗	✓	✗	✓
[10]	✗	✓	✗	✓	✓	✓
[11]	✓	✓	✗	✓	✗	✓
[12]	✗	✓	✗	✓	✗	✓
[13]	✗	✓	✗	✓	✗	✓
[14]	✗	✓	✗	✓	✗	✓
[15]	✗	✗	✗	✓	✓	✓
[16]	✗	✓	✗	✓	✗	✓
[17]	✗	✗	✗	✓	✗	✓
[18]	✓	✗	✗	✓	✗	✓
[19]	✓	Considering un-controllable model	✓	✓	✗	✓
CP	✓	✓	✓	✓	✓	✓

CP: Current paper.

1.3. Research Gaps

There are the following research gaps in the field of the distribution network operation:

- To enhance network operation, including reducing energy losses, voltage profile, and other cases, there are various solutions such as energy management of local resources and system reconfiguration. Yet, it is predicted that the use of several different solutions can achieve a favorable operating situation, which has been stated in fewer studies.
- In addition, there are various indices for system operation, for which in most studies, only the bus voltage limit and the capacity of the distribution lines are considered.
- Furthermore, the minimization of energy losses has been considered in fewer studies although there are various indices regarding the network operation, and different indices may not be correlated with each other, meaning that improving a given index may not help the improvement of other index/indices. Therefore, it is necessary to model them simultaneously in the optimization problem.

1.4. Contributions

In this article, to provide a solution to the mentioned cases in Section 1.3, a formulation is presented for system reconfiguration and energy management of DGs in accordance with improving the system operating status. This design is in the form of an optimization problem. Annual energy loss of the network is minimized by the objective function of the problem. Different constraints of the problem include AC power flow equations, the planning model of system reconfiguration and operation of DGs, and the limitations of distribution network operation. Operating constraints include limits on bus voltages, capacity of lines and distribution substation, and power factor of distribution substation. There is an integer nonlinear optimization format for the proposed scheme, so in order to extract an optimized response that has a smaller standard deviation, the crow search algorithm (CSA) is adopted. Finally, the contributions of the article include the following:

- Improving various operation indices such as energy loss, voltage profile, congestion of distribution lines and substations, and power factor of the system with simultaneous use of reconfiguration problem and energy management of distributed generations in the distribution system, and
- Extracting an optimal solution that has a smaller standard deviation in the final response by the CSA, and an optimal solution can be obtained in a lower calculation time.

Objectives of the paper include:

- Improving various operation indices by using DG power management and reconfiguration program.
- Access to the lowest amount of energy losses,
- Extracting almost a flat voltage profile, and
- Extracting the optimal solution with a low standard deviation in the final response.

1.5. Paper Organization

Section 2 describes the formulation of distribution network operation with system reconfiguration and DGs [20–22]. Then, Section 3 explains the process of solving the problem based on CSA. Sections 4 and 5 report numerical results and conclusions, respectively.

2. Mathematical Model

In this section, the formulation of distribution network operation with reconfiguration and DGs [23–25] is expressed. It is an optimal AC power flow of the distribution system considering network loss minimization. Therefore, its formulation is written by:

$$\min \sum_{l \in \varphi_l} 365 \times C_p \times \sum_{t \in \varphi_t} R_l \left(\left(IL_{l,t}^{re+} + IL_{l,t}^{re-} \right)^2 + \left(IL_{l,t}^{im+} + IL_{l,t}^{im-} \right)^2 \right) \tag{1}$$

Subject to:

$$IG_{i,t}^{re} - ID_{i,t}^{re} = \sum_{l \in \varphi_l} AL_{l,i} \left(IL_{l,t}^{re+} - IL_{l,t}^{re-} \right) \qquad \forall i,t \tag{2}$$

$$IG_{i,t}^{im} - ID_{i,t}^{im} = \sum_{l \in \varphi_l} AL_{l,i} \left(IL_{l,t}^{im+} - IL_{l,t}^{im-} \right) \qquad \forall i,t \tag{3}$$

$$R_l \left(IL_{l,t}^{re+} - IL_{l,t}^{re-} \right) - X_l \left(IL_{l,t}^{im+} - IL_{l,t}^{im-} \right) = w_{l,t}^{re} + \sum_{i \in \varphi_i} AL_{l,i} V_{i,t}^{re} \qquad \forall l,t \tag{4}$$

$$X_l \left(IL_{l,t}^{re+} - IL_{l,t}^{re-} \right) + R_l \left(IL_{l,t}^{im+} - IL_{l,t}^{im-} \right) = w_{l,t}^{im} + \sum_{i \in \varphi_i} AL_{l,i} V_{i,t}^{im} \qquad \forall l,t \tag{5}$$

$$ID_{i,t}^{im} = \frac{PD_{i,t} V_{i,t}^{im} - QD_{i,t} V_{i,t}^{re}}{\left(V_{i,t}^{re} \right)^2 + \left(V_{i,t}^{im} \right)^2} \qquad \forall i,t \tag{6}$$

$$ID_{i,t}^{re} = \frac{PD_{i,t} V_{i,t}^{re} + QD_{i,t} V_{i,t}^{im}}{\left(V_{i,t}^{re} \right)^2 + \left(V_{i,t}^{im} \right)^2} \qquad \forall i,t \tag{7}$$

$$PD_{i,t} = P_{i,t}^0 + P_{i,t}^1 V_{i,t} + P_{i,t}^2 (V_{i,t})^2 \qquad \forall i,t \tag{8}$$

$$QD_{i,t} = Q_{i,t}^0 + Q_{i,t}^1 V_{i,t} + Q_{i,t}^2 (V_{i,t})^2 \qquad \forall i,t \tag{9}$$

$$\left(IL_{l,t}^{re+} + IL_{l,t}^{re-} \right)^2 + \left(IL_{l,t}^{im+} + IL_{l,t}^{im-} \right)^2 \le \left(IL_l^{\max} \right)^2 \left(y_{l,t}^{+} + y_{l,t}^{-} \right) \qquad \forall l,t \tag{10}$$

$$\left(V_i^{\min}\right)^2 \leq \left(V_{i,t}^{re+}\right)^2 + \left(V_{i,t}^{im+}\right)^2 \leq \left(V_i^{\max}\right)^2 \quad \forall i,t \tag{11}$$

$$-\overline{w}_l^{re}\left(1 - y_{l,t}^{+} - y_{l,t}^{-}\right) \leq w_{l,t}^{re} \leq \overline{w}_l^{re}\left(1 - y_{l,t}^{+} - y_{l,t}^{-}\right) \quad \forall l,t \tag{12}$$

$$-\overline{w}_l^{im}\left(1 - y_{l,t}^{+} - y_{l,t}^{-}\right) \leq w_{l,t}^{im} \leq \overline{w}_l^{im}\left(1 - y_{l,t}^{+} - y_{l,t}^{-}\right) \quad \forall l,t \tag{13}$$

$$0 \leq IL_{l,t}^{re+} \leq IL_l^{\max} y_{l,t}^{+} \quad \forall l,t \tag{14}$$

$$0 \leq IL_{l,t}^{re-} \leq IL_l^{\max} y_{l,t}^{-} \quad \forall l,t \tag{15}$$

$$y_{l,t}^{+} + y_{l,t}^{-} \leq 1 \quad \forall l,t \tag{16}$$

$$\sum_{l \in \varphi_l}\left(y_{l,t}^{+} + y_{l,t}^{-}\right) = N_{bus} - 1 \quad \forall t \tag{17}$$

$$0 \leq IL_{l,t}^{im+}, IL_{l,t}^{im-} \quad \forall l,t \tag{18}$$

$$y_{l,t}^{+}, y_{l,t}^{-} \in \{0, 1\} \quad \forall l,t \tag{19}$$

$$\sum_{t \in \varphi_t}\left(y_{l,t}^{+} + y_{l,t}^{-}\right) \leq N_{ch} \quad \forall l \tag{20}$$

$$PG_{i,t} = V_{i,t}^{re} IG_{i,t}^{re} + V_{i,t}^{im} IG_{i,t}^{im} \quad \forall i,t \tag{21}$$

$$QG_{i,t} = V_{i,t}^{im} IG_{i,t}^{re} - V_{i,t}^{re} IG_{i,t}^{im} \quad \forall i,t \tag{22}$$

$$0 \leq PG_{i,t} \leq PG_i^{\max} \quad \forall i,t \tag{23}$$

$$0 \leq QG_{i,t} \leq QG_i^{\max} \quad \forall i,t \tag{24}$$

$$-\tan\left(\cos^{-1}\left(PF^{\min}\right)\right)PG_{i,t} \leq QG_{i,t} \leq \tan\left(\cos^{-1}\left(PF^{\min}\right)\right)PG_{i,t} \quad \forall i,t \tag{25}$$

Equation (1) describes the objective function that deals with the minimization of annual energy losses. In Equation (1), the term $\sum_{l \in \varphi_l} \sum_{t \in \varphi_t} R_l\left(\left(IL_{l,t}^{re+} + IL_{l,t}^{re-}\right)^2 + \left(IL_{l,t}^{im+} + IL_{l,t}^{im-}\right)^2\right)$ for calculating the network energy loss in a day or the operation horizon is 24 h. However, this term is multiplied by $365 \times C_p$. The number 365 denotes the number of days of a year [26]. Additionally, as the consumption behavior of all days of a year in the distribution network is not the same, the term C_p has been used, which is known as the coincidence factor, and it is around 70% for distribution level [27]. Moreover, real and imaginary terms of the current flowing through lines include two positive and negative components, each of which determines the direction of current in the distribution lines [28]. The reduction of losses is proportional to the reduction of the current passing through the distribution lines. The reduction in the current of the distribution lines also leads to a reduction in the voltage drop of the lines, which results in a favorable voltage profile. In other words, the minimization of energy losses and the minimization of the voltage deviations function are in the same direction, that is, the reduction of losses corresponds to the reduction of the voltage deviations function. However, in multi-objective optimization, it is necessary that the changes of different objective functions in terms of increase and decrease are in the same direction. This issue is not established between energy losses and voltage deviations, so it is not necessary to provide multi-objective optimization. Simply said, the minimization of losses will lead to the improvement of the profile.

Constraints (2) and (3) also represent real and imaginary current balance equations in each bus and each hour, which can be achieved using Kirchhoff's current law (KCL) [28–31]. In addition, equations of real and imaginary terms of the drop in the distribution lines are given by limits (4) and (5). Moreover, real and imaginary terms of the current injected to loads in each bus can be calculated based on (6) and (7) [28,32–34]. It is worth mentioning that in this problem, the constant power–current–impedance model has been chosen for the load. Therefore, the terms PD and QD can be calculated based on (8) and (9), respectively. Based on these relationships, it can be said that the load changes according to the voltage magnitude.

The technical constraints of the distribution network are expressed in (10) and (11) [28,35–37]. These constraints include the limits of line current [19] and bus voltage [19], which are presented in (10) and (11), respectively. It should be noted that the variables y^+ and y^- are binary variables that show the state of the lines. In other words, if y^+ and y^- are equal to 1 and 0, respectively, the distribution line is intact and the current flows from bus i to bus j. Moreover, if y^+ and y^- are equal to 0 and 1, respectively, this means that the distribution line is standing and the current flows from bus j to bus i. However if y^+ and y^- are both 0, the distribution line is out of circuit due to the operation of its switch [19].

Constraints (12) and (13) show the limitations on real and imaginary terms of auxiliary variable w in the line voltage drop equations. The term w must be 0 at the moment the line is connected, but if the line is disconnected, the voltage drop equation governing it should be removed. According to (4) and (5), the right side of these equations is 0 if the line is connected; therefore, based on the two mentioned cases, the value of w must be a value that is established in sufficient freedom to eliminate the voltage drop equation. In addition to this, the real and negative components of the real current should not have a value at the same time, therefore constraints (14) to (16) are used for this purpose. Constraint (17) also represents the configuration of the radial distribution system [8]. In such a system, there are fewer distribution lines than buses [8]. Finally, constraints (18) and (19) express the type of variables of imaginary components of current and y^+ and y^-, respectively. Constraint (20) expresses the limitation on the number of operations of breakers during the operation horizon. In other words, based on this constraint, the number of switching of breakers during the operation horizon is limited.

The equations governing DGs are stated In constraints (21) to (25). It is worth mentioning that the active and reactive power of DGs are also considered in the presented equations. Therefore, the relationship between DG's active/reactive power, its voltage, and current are given by (21) and (22) [28]. Constraints (23) and (24) also express the limits of active and reactive production power of DGs, respectively [10]. Finally, Equation (25) expresses the power factor limit of the DGs [28].

The proposed scheme is as optimization formulation. The optimization model includes objective function [38–47]. Moreover, it contains the different constraints [48–56]. To consider the optimization problem in a network, the grid should include smart devices [57–65]. These systems are based on telecommunications equipment [66–73].

3. Problem Solution Procedure

Concerning the fact that the formulated problem using Equations (1)–(25) has a mixed integer nonlinear programming (MINLP) structure, this model includes nonlinear formulation [74–76]. The CSA has been adopted to address the problem and find solutions thanks to the advantages of CSA such as high speed and reliable solutions, particularly the low amount of standard deviation [77]. The details of the algorithm can be referred to in Algorithm 1.

Constraints of the problem in the form of penalty functions are involved in the objective function [78], in which μ.max(0, $a - b$) is used for constraint $a \leq b$. Also note that $\mu \geq 0$ denotes a Lagrangian multiplier. Constraints (19), (23), and (24), and μ help find the optimal decision variables using the CSA. These variables include y^+, y^-, PG, and QG. Equality constraints of the problem assist to find the rest of the variables. This article adopts the forward-backward approach and solves AC power flow equations [79]. Eventually, the variables are used to formulate the fitness function.

Algorithm 1: Steps of the CSA

(1) Find those parameters that can be set, this includes the population size or number of crows (N), maximum iterations ($iter_{max}$), awareness probability (AP), and flight length (fl)
(2) Initialize the position and crows' memory in a random way
(3) Assess the value of the objective function as per Step 2
(4) Update the crows' positions

```
for iteration = 1:iter_max
  for i = 1:N
    Select a crow randomly (e.g., crow j)
    Specify a random number between [0, 1] for jth crow, i.e., r_j
      if r_j ≥ AP
      position (i, iteration + 1) = position (i, iteration) + r_j × fl × {memory
      (i, iteration) − position(i, iteration)}
        Check the feasibility of positions of individual crows
      else
      position (i, iteration + 1) = a random value for the position between its
      minimum and maximum values
      end
  end
  Evaluate the objective function based on the new position date
  Update the crows' memory
    if fitness (position (i, iteration + 1)) is better than
      fitness (position (i, iteration))
      memory (i, iteration + 1) = position (i, iteration + 1)
    else
      memory (i, iteration + 1) = memory (i, iteration)
    end
end
```

4. Numerical Results

4.1. Problem Data

Figure 1 depicts the standard IEEE 69-bus radial distribution system adopted in this article [80]. The base voltage and power of the system are 12.66 kV and 1 MW, and its minimum and maximum permissible voltage limit is [0.9, 1.05] p.u. [81–85]. In addition, the network has 68 main lines, which are represented by the solid line in Figure 1. This network also includes 5 tie lines to reconfigure the network, which are presented with dashed lines in the figure. There is a breaker on each line. Each main line is located between bus n and n + 1, and the breaker on this line is marked with number n. For example, the breaker on the line between buses 15 and 16 is marked with the number 15. In addition, the tie lines are located between the buses (11, 43), (13, 21), (15, 46), (27, 65), and (50, 59), and the breakers on these lines are identified by numbers 69, 70, 71, 72, and 73. The data of distribution lines and distribution substations and peak data of P^0 and Q^0 are extracted from [80]. The hourly amount of P^0 and Q^0 can be found by multiplying the daily curve of the load factor and peak values of P^0 and Q^0. The daily load factor curve is drawn in Figure 2 [28]. Parameters P^1 (Q^1) and P^2 (Q^2) are assumed to be 20% and 10% of P^0 (Q^0), respectively. N_{ch} is considered to 5.

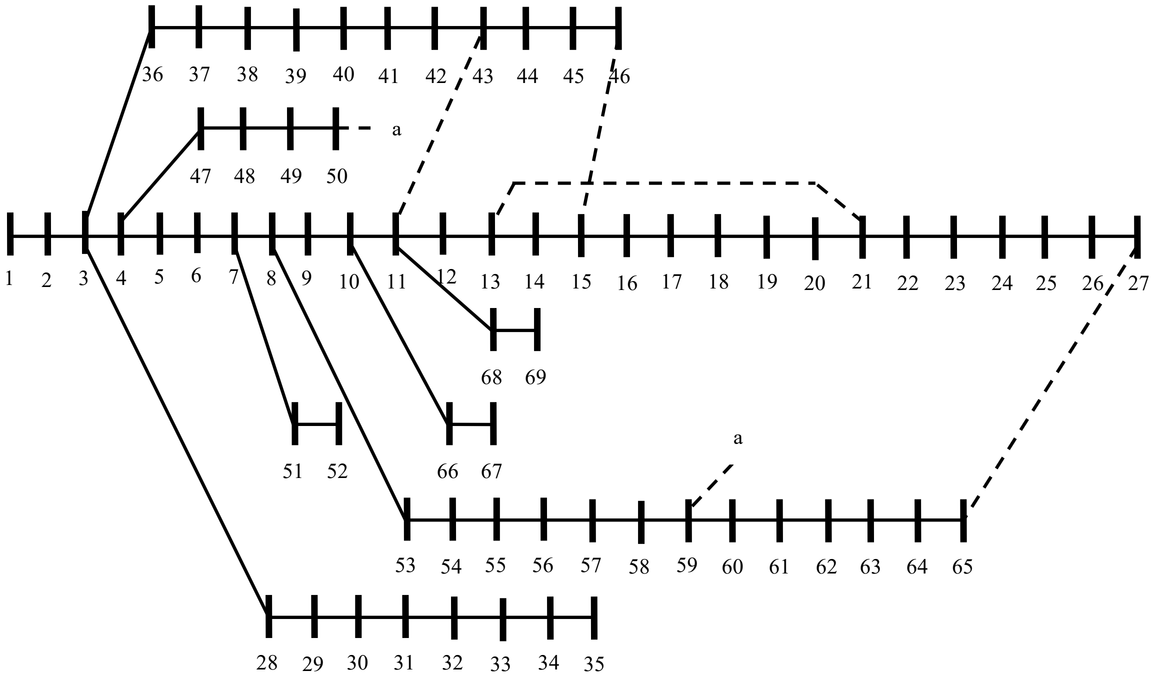

Figure 1. Diagram of the test 69-bus radial distribution system [80].

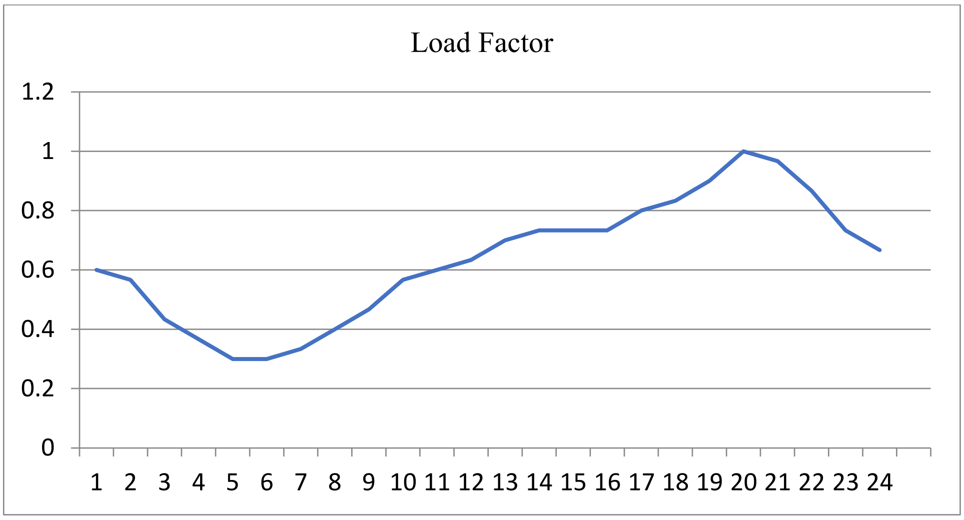

Figure 2. Daily curve of load factor [80].

This article incorporates wind turbine and solar cells as two kinds of renewable energy generation equipment. It is noteworthy that the generation output of wind turbine and solar cells relies on wind speed and solar irradiance, respectively [26]. Obviously, the output generation of these units is time-variant as the wind speed and irradiance varies over time. Hence, the expressions of their maximum capacity are time-variant [26]. Daily curves of generation power rates for the wind system and solar panel are drawn respectively in Figures 3 and 4 [86], and their maximum capacity is calculated by multiplying these curves by the nominal capacity of this type of DGs. It is assumed that these resources do not participate in reactive power control and were used only for energy generation purposes based on standard IEEE1547 [87]. Their capacity is equal to 700 kW, the wind turbines are located on buses 20, 27, 54, and 65, and the solar cells are placed on buses 34, 38, and 46. Moreover, in the said network, there is a DG of 4000 kW and 1000 kVAr in bus 60, which is a diesel generator. Additionally, the minimum power factor allowed for the said network is set to 0.9.

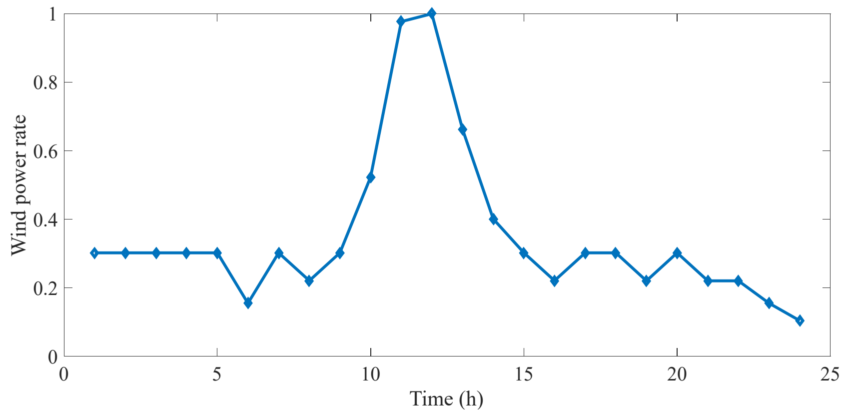

Figure 3. Average daily curve of wind unit power rate [86].

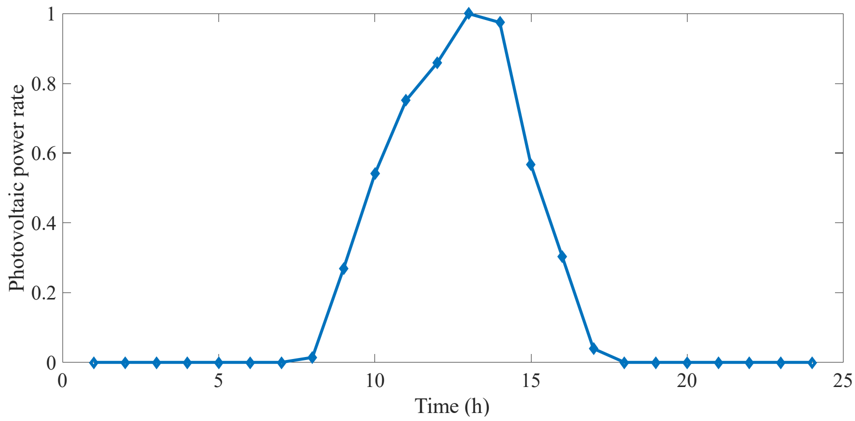

Figure 4. Average daily curve of PV unit power rate [86].

4.2. Results

It is noteworthy that the mentioned problem is a mixed-integer nonlinear optimization problem. Therefore, this article used the CSA algorithm to solve it. Population size and maximum number of iterations to reach convergence were set to 80 and 5000, respectively. The rest of the parameters were extracted from [77].

A. Case studies

In this section, three case studies were carried out:

- Case 1: Power flow studies (in a network without DGs and without applying reconfiguration)
- Case 2: Power flow studies in the presence of DGs
- Case 3: Reconfiguration the distribution network with DGs

B. Evaluation of reconfiguration

Reconfiguration results for the 69-bus distribution network are presented in Table 2. In this table, the open switches of the network are specified. Based on this table, the function of each switch will change every hour. This is due to the change in load. With the changes in the amount of load, there is a possibility of increasing the power loss. Thus, the function of the switches is changed until a suitable path for feeding the loads is obtained in order to minimize energy losses. In addition, five switches are open at any moment. This case is due to compliance with constraint (17) that keeps the distribution system in a radial form.

Table 2. Open switches at each hour.

Hour	Open Switches	Hour	Open Switches	Hour	Open Switches
1	15, 44, 56, 63, 72	9	3, 11, 14, 21, 41	17	46, 47, 56, 63, 72
2	15, 44, 56, 6, 72	10	11, 13, 22, 23, 72	18	14, 15, 46, 47, 56
3	15, 11, 41, 63, 55	11	9, 13, 24, 43, 48	19	12, 14, 15, 57, 72
4	13, 43, 48, 63, 72	12	5, 11, 40, 47, 56	20	14, 15, 56, 70, 72
5	6, 14, 22, 47, 56	13	3, 13, 41, 43, 44	21	12, 47, 56, 57, 72
6	11, 40, 46, 54, 63	14	9, 13, 19, 56, 70	22	12, 13, 20, 47, 56
7	40, 47, 56, 63, 57	15	3, 9, 17, 36, 57	23	14, 47, 71, 72, 73
8	3, 16, 41, 63, 56	16	35, 44, 56, 63, 57	24	13, 55, 57, 71, 72

C. Evaluation of daily curve of DGs power

The daily power curves of individual DGs for total active power of wind systems, solar systems, active power of diesel generators, and reactive power of the diesel generator are shown in Figures 5–8. The variation of DGs active power follows the load factor curve. However, the changes in active power of wind turbines and solar cells are proportional to wind speed or irradiance. Accordingly, the changes will be different from the load factor curve. In some hours, the active power of solar systems is zero, which is because the amount of solar radiation is zero. In addition, Figure 8 depicts the daily reactive power curve of the diesel generator, which follows the load factor curve. Nonetheless, in Case 3, in some time periods, the reactive power changes do not follow the load factor curve.

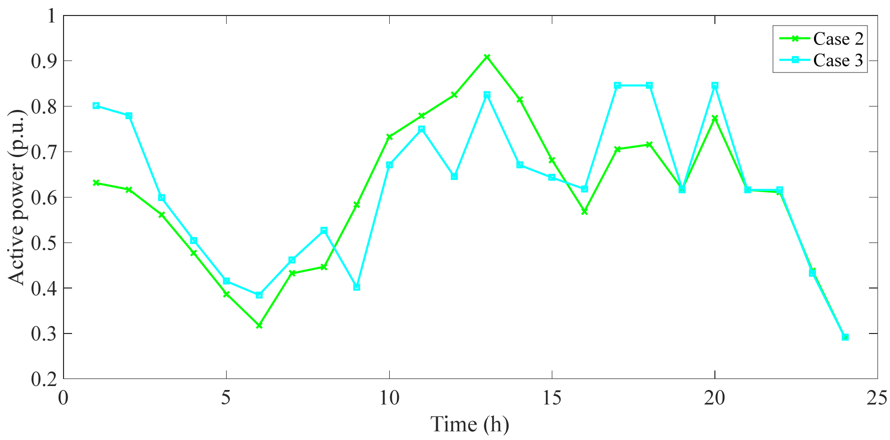

Figure 5. Daily curve of total wind power.

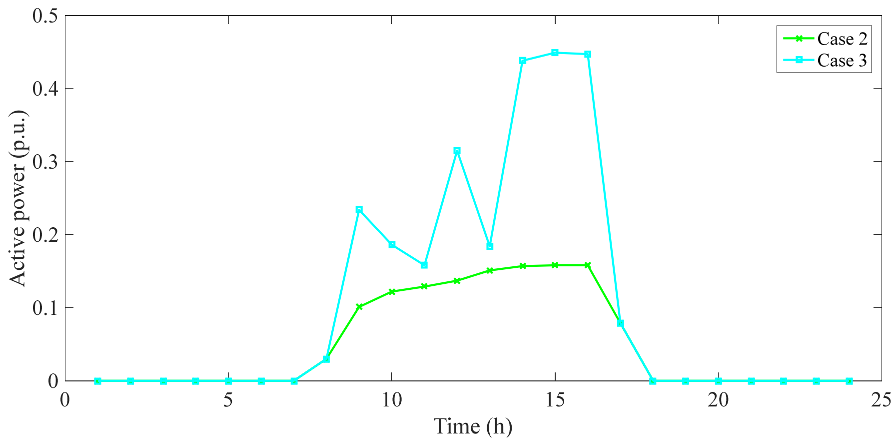

Figure 6. Daily curve of total PV power.

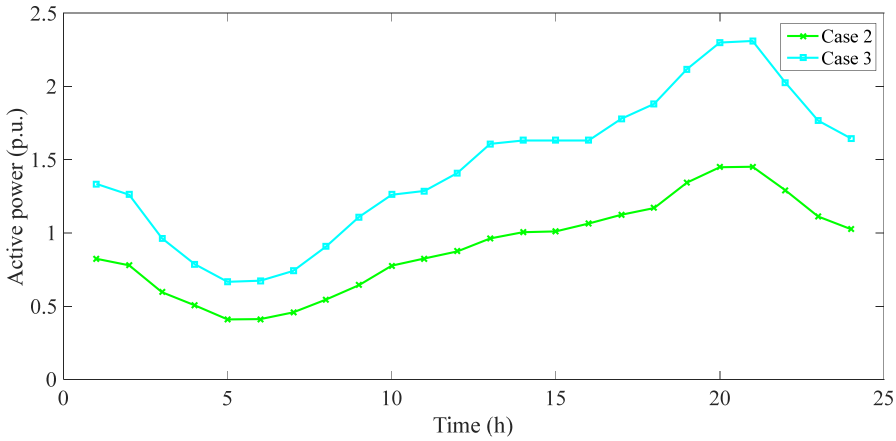

Figure 7. Daily curve of total active power of diesel generator.

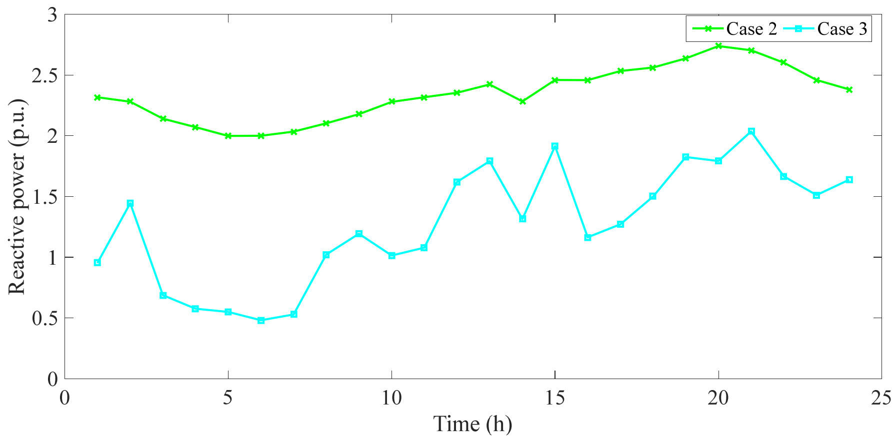

Figure 8. Daily curve of total reactive power of diesel generator.

Based on Figures 5–7 the active power of wind systems, solar systems, and diesel generators in Case 3 is generally more than that of Case 2. This is because the reconfiguration of the network increased the power fed by these sources. The occurrence of such conditions is in accordance with this fact that the paper assumes that DGs are able to control their power. In other words, in optimal energy management, local elements similar to sources located at the consumption points are expected to control their power. Therefore, the paper assumes constant power DGs. In this paper, the upper boundary of control power of DGs is proportional to wind speed or irradiation. Nevertheless, according to Figure 8, the reactive power of the diesel generator is reduced in Case 3 compared to Case 2. Note that the DG is located on Bus 60, and the magnitude of voltage of this bus based on power flow studies [79] is around 0.93 p.u. Hence, the presence of only one DG on this bus cannot increase the voltage magnitude to 1 p.u. Hence, the DG is not expected to play the role of voltage regulator; therefore, this bus remains as a PQ bus. In addition, by performing the reconfiguration program in Case 3, the distance between bus 60 and the upstream network may not be reduced; hence, its voltage becomes higher compared to that of Case 1. In the following, the DG lowers its reactive power to prevent any high overvoltage. Nonetheless, note that active power of the Dg has increased in Case 3. In such conditions, if reactive power of the DG is not reduced, higher overvoltage is more probable in the network.

D. Evaluation of network indices

The network indices are shown in Figures 9–13 which respectively represent the daily curve of the apparent power of the distribution substation (located in the slack bus or bus 1), the voltage profile of the 69-bus distribution network at the peak load hour (20:00), the daily curve of voltage of bus 65 (the reason is the low voltage of bus 65 in Case 1 based on Figure 10), the daily curve of network losses, and station power factor value.

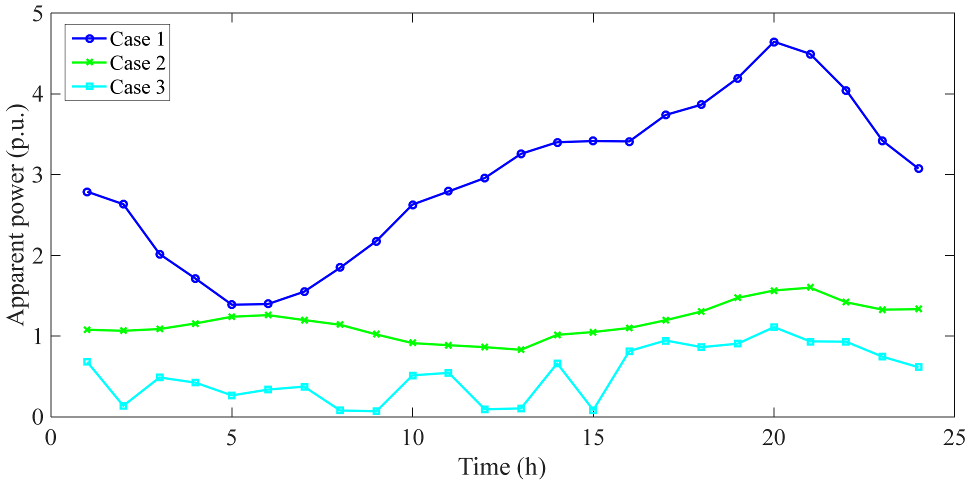

Figure 9. Daily curve of apparent power of distribution substation in bus 1.

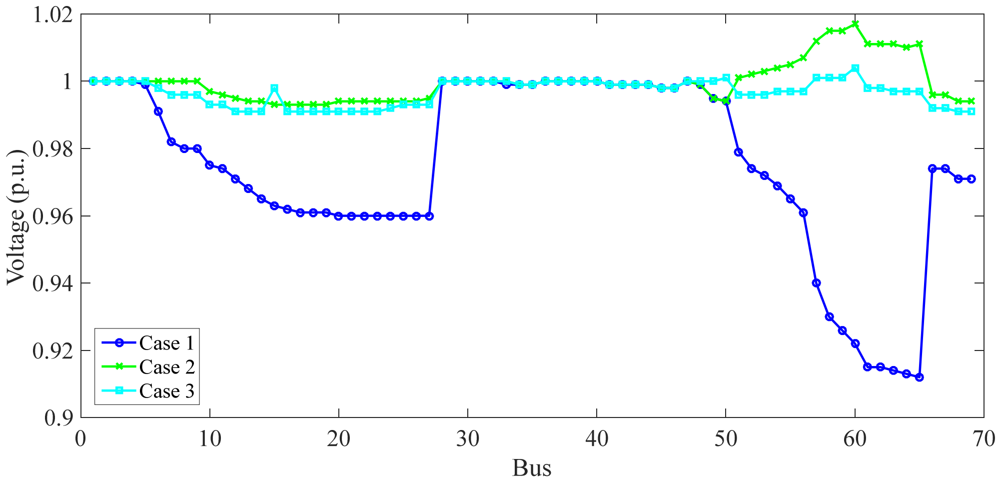

Figure 10. Voltage profile at peak load hour (20:00).

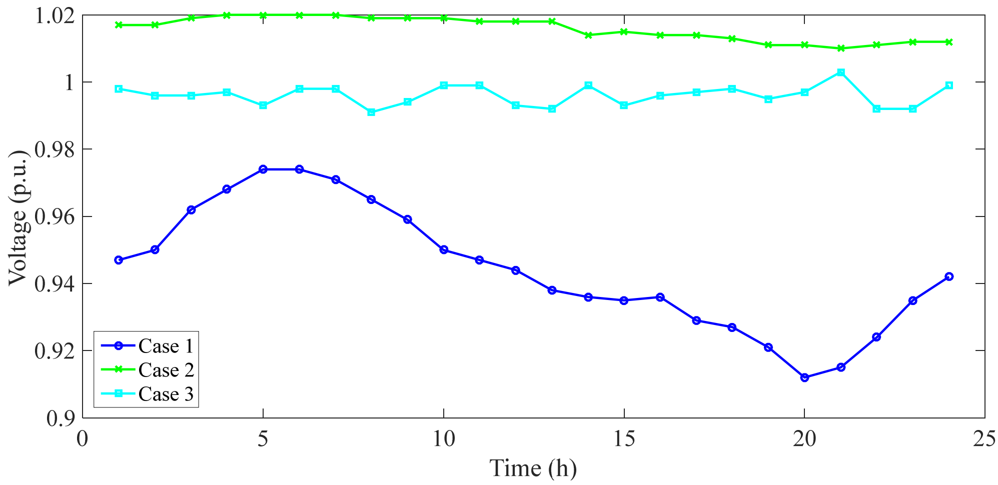

Figure 11. Daily curve of voltage of bus 65.

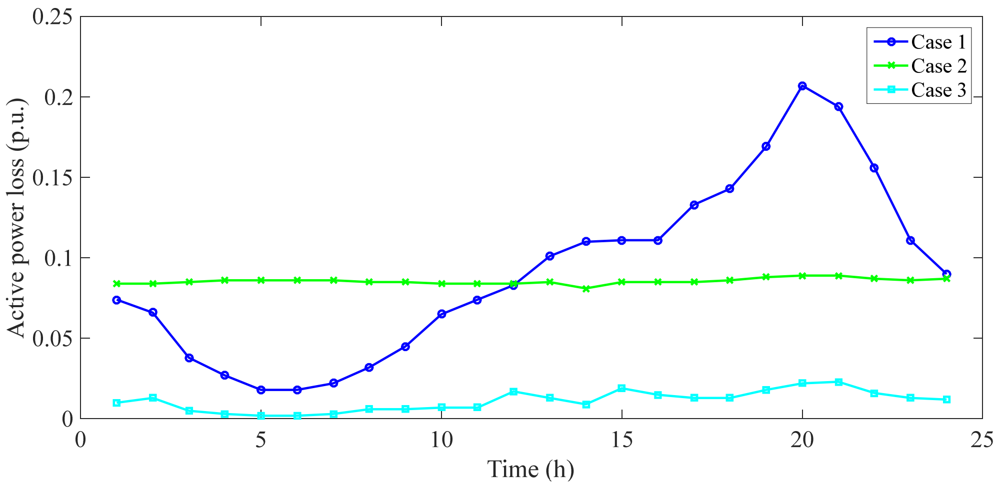

Figure 12. Daily curve of total active loss of the network.

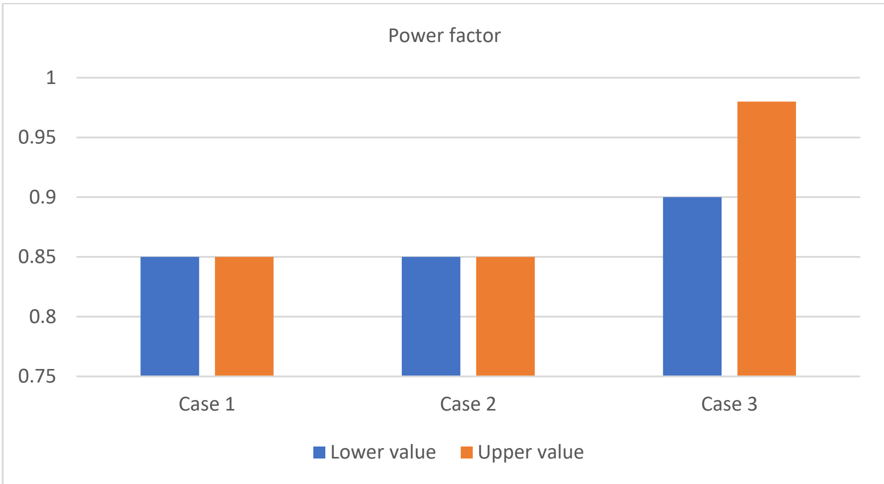

Figure 13. Lower and upper values of station power factor in different cases.

Based on Figure 9, the apparent power of the distribution substation in Cases 2 and 3 is less than that of Case 1, and the reduction rate is higher in Case 3. Moreover, Figure 10 depicts the peak load hour voltage profile, where the voltage profile in Case 3 is smoother and flatter than the other study cases. This indicates a lower voltage drop in Case 3. Figure 11 shows the daily voltage curve of bus 65, based on which it can be seen that the voltage changes at different hours for Cases 2 and 3 are low. However, in Case 3, the voltage time curve is always close to 1 p.u. This indicates a lower voltage drop in Case 3. Moreover, Figure 12 depicts the time losses of the network, where Case 3 obtains the lowest losses per hour. Figure 13 reports the minimum and maximum values of the power factor of the distribution substation for different study cases. In Cases 1 and 2, the amount of active and reactive power of the network is affected by the load. Since the power factor of loads is around 0.85 according to [80], the power factor of the distribution substations for Cases 1 and 2 is around 0.85. However, in Case 3, distributed generations can change the amount of active and reactive power requested from the distribution substation, therefore the power factor in this case can change between 0.9 and 0.98.

E. Evaluation of objective function

Table 3 lists objective function values for different study cases. As seen, the annual energy loss is the highest in Case 1, but the reconfiguration of the mentioned distribution system with DGs has caused a sharp reduction in the annual energy loss from 802 MWh to 97 MWh. Moreover, in Table 4, the state of convergence of the problem by different solvers such as CSA, krill herd optimization (KHO) [88], gray wolf optimization (GWO) [89], teaching-learning-based optimization (TLBO) [90], and particle swarm optimization (PSO) [78] have been reported. The population size and the maximum convergence iterations for these algorithms are 80 and 5000, respectively. In addition, Refs. [77,78,88–90] were referred to to choose the parameters of the algorithms. To calculate the standard deviation of the final response, each of the mentioned algorithms finds the solution of the problem 30 times. As per the table, the CSA obtains 97.455 MWh for the objective function in 2936 convergence iterations. This iteration corresponds to a computing time of 128 s. However, other algorithms extract more than 99.8 MWh for the objective function. Moreover, their convergence iterations and computing time are more than 3500 and 170 s, respectively. Therefore, CSA can extract the optimal solution in a shorter period than other algorithms. Furthermore, in this algorithm, the lowest standard deviation of the final response, i.e., 0.96%, is obtained. Hence, the dispersion of their responses in different iterations is the minimum compared to other algorithms.

Table 3. Annual energy loss (objective function value).

Case	Annual Energy Loss (MWh)
1	802.27
2	748.97
3	97.455

Table 4. Convergence status of the problem based on different solvers.

Solver	Annual Energy Loss (MWh)	Convergence Iteration	Convergence Time (s)	Standard Deviation (%)
CSA	97.455	2936	128	0.96
KHO	99.874	3567	174	1.48
GWO	104.032	3974	198	1.97
TLBO	109.257	4367	241	2.34
PSO	113.228	4822	287	2.79

5. Conclusions

The current study states the electricity distribution networks reconfiguration in the presence of DGs. The mentioned problem was in the form of an optimization problem, whose objective function is to minimize annual energy losses. Additionally, the constraints of the problem included power flow equations, the constraints of DGs, technical limitations of the network, and the reconfiguration planning model. In this model, constant power–current–impedance load models were assumed. The mentioned problem was mixed-integer nonlinear, and was solved by the CSA. Eventually, according to the numerical results, the mentioned solution algorithm was able to obtain the most optimal solution in terms of the number of convergence iterations and low computation time. Moreover, it has the lowest dispersion in its final response, where the standard deviation of its final response is around 0.96%. In the proposed scheme, there are changes in the performance of switches mounted on each distribution line every hour in order to minimize annual energy losses. DGs produce high active and reactive power; hence, the consumers are supplied locally and the power loss is minimized. Further, reducing the apparent power of the distribution substation, smoothing the voltage profile, reducing the voltage drop in the distribution lines, and reducing the power and energy losses is achievable when optimal reconfiguration of the distribution network is opted for along with reaching the optimal performance of DGs compared with network power flow studies. Therefore, in the proposed scheme, the energy losses will be reduced by about 700 MWh compared to the power flow studies. In addition, a smoother voltage profile is obtained in the proposed scheme compared to the power flow studies.

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Nomenclature

Indices and sets	
i	Index of bus
l	Index of line
t	Index of time step
φ_i	Set of network buses
φ_l	Set of distribution lines
φ_t	Set of time steps
Variables	
IL^{re+}, IL^{re-}	Positive and negative terms of real part of current flow through the line in per-unit (p.u.)
IL^{im+}, IL^{im-}	Positive and negative components of imaginary part of current flow through the line (p.u.)
IG^{re}	Real part of current generation by DGs (p.u.)
IG^{im}	Reactive part of current generation by DGs (p.u.)
ID^{re}	Real part of the consumption current (p.u.)
ID^{im}	Imaginary part of the consumption current (p.u.)
PG	Active power generation by DGs (p.u.)
QG	Reactive power generation by DGs (p.u.)
PD	Consumption active power (p.u.)
QD	Consumption reactive power (p.u.)
V^{re}	Real part of the voltage (p.u.)
V^{im}	Imaginary part of the voltage (p.u.)
V	Voltage magnitude (p.u.)
w^{re}	An auxiliary variable in equation of real part of voltage drop (p.u.)
w^{im}	An auxiliary variable in equation of imaginary part of voltage drop (p.u.)
y^+, y^-	Binary variables for determining the status of lines and current flow through them
ΔI^{re}	Real part of deviation of line current (p.u.)
Constants	
C_p	Coincidence factor
N_{ch}	Maximum number of switching
R	Resistance of line (p.u.)
X	Reactance of line (p.u.)
P^0, P^1, P^2	Coefficients of active load curve
Q^0, Q^1, Q^2	Coefficients of reactive load curve
IL^{max}	Maximum capacity of line (p.u.)
V^{max}	Maximum magnitude of voltage (p.u.)
V^{min}	Minimum magnitude of the voltage (p.u.)
N_{bus}	Number of buses
PG^{max}	Maximum active power of DGs (p.u.)
QG^{max}	Maximum reactive power of DGs (p.u.)
PF^{min}	Minimum power factor
$\overline{w}^{re}$	Maximum value of w^{re} (p.u.)
$\overline{w}^{im}$	Minimum value of w^{im} (p.u.)

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