Performance Enhancement of Distribution Systems via Distribution Network Reconfiguration and Distributed Generator Allocation Considering Uncertain Environment

Mina Naguib, Walid A. Omran, and Hossam E. A. Talaat

Abstract—**The emergence of dispersed generation, smart grids, and deregulated electricity markets has increased the focus on enhancing the performance of distribution systems. This paper proposes a method to reduce the energy loss and improve the reliability of distribution systems by performing distribution network reconfiguration (DNR) and distributed generator (DG) allocation. In this study, the intermittent nature of renewable-based DGs and the load profile are considered using a probabilistic method. The study investigates different annual plans based on the seasonal power profiles of DGs and the load to minimize the combined cost function of annual energy loss and annual energy not served. The proposed method is implemented using the firefly algorithm (FA), which is one of the meta-heuristic optimization algorithms. Several case studies are investigated using the IEEE 33-bus distribution system to highlight the effectiveness of the method.**

Index Terms—**Distributed generator allocation, distribution network reconfiguration, optimal power flow, firefly algorithm, energy loss, reliability.**

I. Introduction

RECENTLY, the deregulation of the electricity markets and the emergence of renewable-based distributed generators (DGs) have gained significant interest. Consequently, local utilities must pay more attention to the efficient planning and operation of the distribution system. Several techno-economical aspects should be considered in the planning and operation of the distribution system while integrating DGs. The technical aspects include protection coordination [1], system reliability [2], voltage profile, energy loss [2], and power quality [3]. Meanwhile, the economic aspects include several costs such as line upgrade [4], energy loss [5], operation and maintenance [5], gas emission [6], and cost related to system reliability [7], [8].

These aspects are considered as the motivation by some researchers to develop the methods that can ensure the efficient planning and operation of the distribution system. One of these methods is the distribution network reconfiguration (DNR). The DNR is performed by changing the status of the system sectionalizing and tie switches. Accordingly, the distribution network configuration is adjusted to achieve specific objectives. Some of these objectives are energy loss minimization [9], load balance [9], voltage profile improvement [10], and system reliability improvement [11]. Another method that can be used to enhance the performance of the distribution system is realized by optimally allocating DGs. Several studies addressed the DG allocation to reduce the total energy loss of the distribution system [12], improve the system reliability [13], and decrease the total system cost [14]. In the mentioned studies, only one method, i.e., DNR or DG allocation, is utilized.

Recently, some studies suggested performing simultaneous DNR and DG allocation to enhance the performance of the distribution system [15]-[27]. The study in [15] considered DG allocation in the reconfiguration problem in order to minimize the energy loss and improve the load balance factor and voltage stability. In [16], the DNR and DG allocation were utilized to enhance the reliability and minimize the operation cost and energy loss. In [17], the DNR was performed in the presence of DGs in order to minimize the energy loss, total harmonic distortion, and voltage unbalance of the distribution system. The study in [18] proposed the DNR problem in the presence of renewable-based DGs to minimize the energy loss. The study in [19] performed simultaneous DNR and DG allocation under peak load conditions to reduce the energy loss and improve the voltage profile. Two long-term planning problems were formulated for the optimal DNR and DG allocation in distribution systems, considering the voltage stability [20] and investment cost of DGs [21].

However, none of those mentioned studies considered the intermittency in the output power of renewable-based DGs or the different annual load profiles. In [22], a fuzzy-based

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approach was utilized to model the uncertainty of the output power and demand of DGs in order to minimize the energy loss considering the voltage stability. In [23], the DNR and the DG allocation were performed to maximize the profits of the DG owner and distribution system operator, considering the uncertainty of power profiles of the load and wind turbines (WTs). Moreover, the DNR and DG allocation were addressed in [24] in order to minimize the energy loss and system operation cost based on the optimal annual configurations and DG allocation plans. The study in [25] presented a state-based DNR strategy using the Markov decision processes considering the uncertainty of the output power of WTs. In this study, an optimal network configuration was obtained for the whole study period to minimize the WT curtailment and load shedding costs. The study in [26] investigated DNR and dispatched energy storage allocation in the presence of the renewable-based DGs. The objective of the study was to enhance the system reliability and to minimize the system operation cost while considering the hourly variation of the renewable energy resources and energy storage. In [27], an hourly-based dynamic DNR was presented considering the uncertainty of output power in the photovoltaic (PV) systems and WTs. The study achieved a reduction in the system operation cost and enhanced the system reliability.

The studies in [22]-[27] were able to model the intermittency in the output power of renewable-based DGs. Some of these studies proposed simultaneous DNR and DG allocation during the study period [22]-[24], while other studies investigated DNR only in the presence of the renewable-based DGs [25]-[27]. Table I summarizes the distribution systems, objectives, data uncertainties, optimization algorithms, and numbers of buses studied in the literature. The table shows that performing both DNR and DG allocation can achieve several benefits, including reducing the system energy loss and system operation cost, and enhancing the system reliability, voltage stability, load balance, and power quality.

TABLE I
A COMPREHENSIVE SUMMARY OF STUDIES IN LITERATURE IN TERMS OF PROPOSED METHOD

Reference	Distribution system		Objective						Uncertainty		Optimization algorithm	Bus number
	DNR	DG allocation	Obj1	Obj2	Obj3	Obj4	Obj5	Obj6	U1	U2		
[9]	×	○	×			×			×		Mixed-integer non-linear programming	33, 84
[10]	×	○	×				×				Particle swarm and ant colony	33
[11]	×			×							Self-adaptive clonal selection	69
[12]		×	×						×	×	Mixed-integer linear programming	41
[13]		×		×				×			Simulated annealing	33
[14]		×						×	×	×	Demand response programming	N/A
[15]	×	○	×			×					Ant colony	33
[16]	×	×	×	×				×			Enhanced gravitational search	33, 70
[17]	×	○	×		×	×	×				Antlion optimizer	33
[18]	×	○	×		×						Mixed-integer linear programming	69, 136
[19]	×	×	×				×				Mixed-integer linear programming	33, 69
[20]	×	×	×				×				Cuckoo search	33, 69, 113
[21]	×	×		×				×			Non-dominant sorting genetic	33
[22]	×	×	×				×		×	×	Genetic algorithm	33, 52
[23]	×	×						×	×	×	ε-constrain method	33
[24]	×	×	×		×			×	×	×	Non-dominant sorting genetic	38
[25]	×	○						×	×	×	Markov decision based dynamic programming	33, 123
[26]	×	○		×				×	×	×	Shuffled frog leaping	119
[27]	×	○		×				×	×	×	Mixed-integer linear programming	119

Note: × means covered; ○ means in the presence of DGs without optimal DG allocation; Obj1 means energy loss; Obj2 means reliability; Obj3 means power quality; Obj4 means load balance; Obj5 means voltage stability; Obj6 means system operation cost; U1 means load uncertainty; and U2 means output power uncertainty of DGs.

In addition, few studies proposed simultaneous DNR and DG allocation while considering the intermittency in the output power of renewable-based DGs and the different annual load profiles. Moreover, these studies proposed simultaneous DNR and DG allocation during the study period. However, none of the aforementioned studies investigated the possibility of simultaneous DNR and DG allocation while investigating the impact of further reconfiguration for the distribution system on a seasonal basis. Hence, the main contributions of this paper can be summarized as follows.

1) Developing different annual plans by performing simultaneous DNR and DG allocation based on a specific season and then performing further DNR for the remaining seasons.

2) Modeling the uncertainties of different types of renewable-based DGs and loads using a probabilistic method.

3) Improving the performance of the distribution system by reducing the energy loss and enhancing the system reliability.

II. STRATEGY FOR DEVELOPING SEASONAL PLANS

It is well known that the generation from renewable-based DGs and the system demand is subjected to seasonal variations. In this study, the sizes and locations of DGs are kept fixed once the optimal DG allocation is achieved; however, the DNR is investigated each season. Therefore, the proposed strategy is based on developing different annual plans considering the four seasons of the year. Hence, the plan providing the best performance of the distribution system is to be chosen. To achieve this task, the proposed strategy is divided into two phases.

1) Phase 1 aims to perform simultaneous DNR and DG allocation for the four seasons of the year independently to find the optimal network configuration and the optimal size and location of DGs based on the data of each season. The output of this phase provides four planning options at the beginning of the study period.

2) In phase 2, each planning option is used to complete the annual plans by performing additional seasonal DNRs for the remaining seasons, e.g., an annual plan x consists of simultaneous DNR and DG allocation based on the winter season data and this is followed by further DNRs for the three remaining seasons. Hence, the annual plans are developed, and the system operator can choose the best plan for the whole year. The flow chart of the proposed strategy is shown in Fig. 1, where m = 1, 2, 3, 4; n = 1, 2, 3, 4; seasons 1, 2, 3, 4 represent the winter, spring, summer, and fall, respectively.

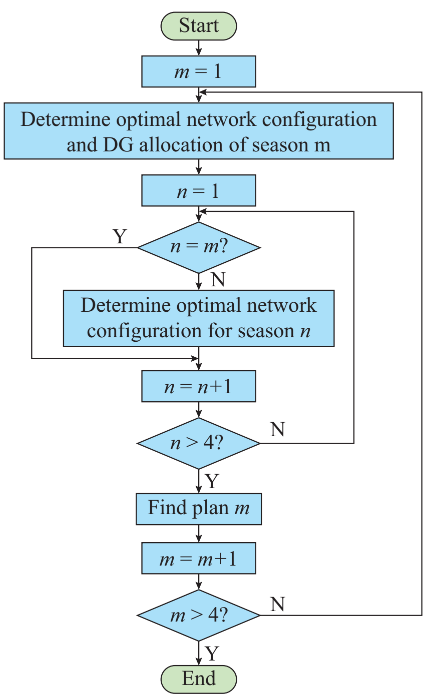

Fig. 1. Flow chart of proposed strategy.

III. Modeling of DGs and Load

In the proposed strategy, the temporal historical load power and weather data related to DGs are used to build a probabilistic model for the demand and generation of the distribution system. The weather data related to DGs are mainly the solar irradiance for PV systems and wind speed for WTs.

The obtained data are converted into a probabilistic model representing each season, which is then used in the optimization algorithm. This model is based on multi-state variables [12] for each type of renewable-based DGs as well as the demand. The details of the modeling of DGs and the load are presented in the following subsections.

A. PV System Modeling

The PV system modeling starts by obtaining the historical solar irradiance over several years at the candidate locations. The full range of solar irradiance values is divided into N_p PV states, where each PV state represents a specific range of solar irradiance. Furthermore, the solar irradiance data are separated into four seasons so that each season can be represented by a probabilistic 24-hour day. Each hour in this day contains the probabilities corresponding to each PV state, which is obtained from the historical data. The output power corresponding to each PV state, using the model in [12], is evaluated at the mid-value of the state range. After calculating the output power of each PV state, a vector $\boldsymbol{A}_p$ containing these power is formed, where the dimension of this vector is $1 \times N_p$. In the next step, a $24 \times N_p$ seasonal probability matrix $\boldsymbol{M}_p$ is formed, where each element of this matrix Pb_p corresponds to the probability of a certain PV state at a specific hour.

B. WT Modeling

The probabilistic model for the output power of WTs is built from the historical wind speed data at the candidate locations. The full range of wind speed is divided into N_w WT states, where each WT state represents a range of the wind speed. Moreover, the wind speed data are separated into four seasons; each season is represented by a probabilistic 24-hour day. Each hour in this day contains the probabilities corresponding to each WT state. The output power corresponding to each WT state is calculated at the mid-value of this state using the output power curve of the WT.

After calculating the output power of each WT state, a $1 \times N_w$ vector $\boldsymbol{A}_w$ containing these power is formed. Also, a $24 \times N_w$ seasonal probability matrix $\boldsymbol{M}_w$ is formed, where each element of this matrix Pb_w corresponds to the probability of a certain WT state at a specific hour.

C. Load Modeling

The load model (LM) is built using the way similar to the PV system and WT models. The historical load data are collected at the same candidate locations. The full range of the load data is divided into N_l LM states, which are stored in a $1 \times N_l$ vector $\boldsymbol{A}_l$ containing the output power of each LM state. Also, a 24-hour seasonal probability matrix $\boldsymbol{M}_l$ is formed, where each element of this matrix Pb_l corresponds to the probability of a certain LM state at a specific hour.

D. Combined Modeling of DGs and Load

Finally, a combined $24 \times N_T$ probability matrix $\boldsymbol{M}_t$ is formed for each season, where N_T is the total number of the combined states and is obtained by:

$$N_T = N_p N_w N_l \tag{1}$$

The probability matrix $\boldsymbol{M}_t$ contains the seasonal combined probability Pb_t of different combined states corresponding to the PV systems, WTs, and the load. This matrix is formed by multiplying each probability element of the matrix $\boldsymbol{M}_p$ with the corresponding row of the matrix $\boldsymbol{M}_w$ and matrix $\boldsymbol{M}_l$ at a specific hour as follows.

$$\begin{cases} M_t(1,1)=M_p(1,1)\,M_w(1,1)\,M_l(1,1) \\ M_t(1,2)=M_p(1,1)M_w(1,1)M_l(1,2) \\ M_t(1,3)=M_p(1,1)M_w(1,1)M_l(1,3) \\ \vdots \\ M_t(1,N_l+1)=M_p(1,1)M_w(1,2)M_l(1,1) \\ \vdots \\ M_t(1,N_lN_w)=M_p(1,1)M_w(1,N_w)M_l(1,N_l) \\ \vdots \\ M_t(1,N_T)=M_p(1,N_p)M_w(1,N_w)M_l(1,N_l) \\ \vdots \\ M_t(24,N_T)=M_p(24,N_p)M_w(24,N_w)M_l(24,N_l) \end{cases} \tag{2}$$

where $M_t(k,h)$ is the combined probability at hour k with combined state h; and $M_p(k,h)$, $M_w(k,h)$, and $M_l(k,h)$ are the probabilities at hour k with state h of the PV, WT, and load, respectively. Figure 2 shows the probabilistic modeling process of DGs and the load.

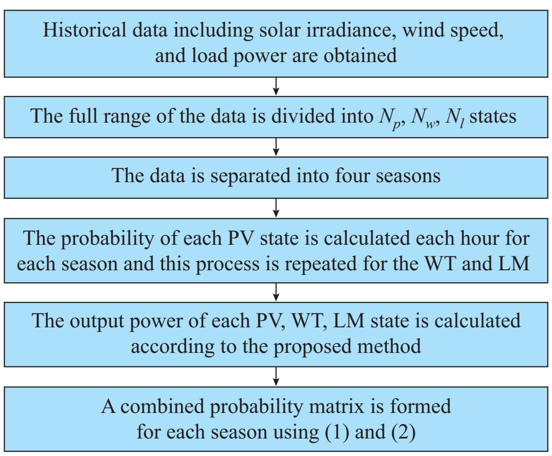

Fig. 2. Probabilistic modeling process of DGs and load.

IV. Problem Formulation

In general, the energy loss is affected by the network configuration and the sizes/locations of DGs in the distribution system [28]. These also affect the failure rates of the system components, and hence, can impact the system reliability [11]. Thus, the optimization problem is formulated to find the optimal network configuration and sizes/locations of DGs that can minimize the energy loss and the energy not served related to the system reliability. The following assumptions are considered while the optimization problem is formulated.

1) In fault analysis, once the optimal network configuration is achieved based on the optimal system reliability, no further DNR is performed, and the open switches remain unchanged.

2) In fault analysis, each DG is kept connected to its local bus if it has sufficient active/reactive power to supply its local load.

A. Objective Function

The objective of the optimization problem is to perform optimal DNR and DG allocation in order to minimize the seasonal combined cost of energy loss and energy not served C_T, which is expressed as:

$$Obj=\min_{x,DG_P,DG_S}\{C_T\}=\min_{x,DG_P,DG_S}\{C_L+C_R\} \tag{3}$$

$$C_L=\sum_{h=1}^{N_T}\sum_{z=1}^{n_{br}}\sigma I^2(k,h,z)R_zM_t(k,h)\Delta TN_d \tag{4}$$

$$C_R=\sum_{h=1}^{N_T}\sum_{i=1}^{n_b}\rho(k,h,i)P_D(k,h,i)T_{DG}(k,h,i)M_t(k,h)N_d \tag{5}$$

$$T_D(k,h,i)=\begin{cases} \sum\limits_{z\in n_{br}}\lambda_z\cdot SW_z \\ \quad P_{DG}(k,h,i)\ge P_D(k,h,i),\,Q_{DG}(k,h,i)\ge Q_D(k,h,i) \\ \sum\limits_{z\in n_{bru}}\lambda_z\cdot REP_z+\sum\limits_{z\in n_{brd}}\lambda_z\cdot SW_z \\ \quad P_{DG}(k,h,i)<P_D(k,h,i)\text{ or }Q_{DG}(k,h,i)<Q_D \end{cases} \tag{6}$$

where C_L is the seasonal cost of the energy loss, which is calculated by summing the probabilistic cost of the energy loss of branch z at hour k with combined state h for N_d season days; C_R is the seasonal cost of the energy not served, which is calculated by summing the probabilistic cost of the energy not served of bus i at hour k with combined state h for N_d season days; x is a binary variable representing the decision of each branch, which equals to 1 if the branch is connected and 0 otherwise; DG_P is the set of candidate locations where the DGs are installed; DG_S is the number of modules of each DG at each candidate location in the network; n_{br} is the total number of branches; σ is the unit cost of the system power loss; $I(k,h,z)$ is the current of branch z at hour k with combined state h, which is obtained from the optimal power flow analysis; R_z is the resistance of branch z; ΔT is the time step; $T_D(k,h,i)$ is the expected failure time of bus i at hour k with combined state h, which is investigated to check whether the DGs have sufficient power to supply the bus demand or not; n_b is the total number of buses; $\rho(k,h,i)$ is the unit cost of the energy not served of bus i at hour k with combined state h; $P_{DG}(k,h,i)$ and $Q_{DG}(k,h,i)$ are the active and reactive output power from DG_S modules stored in $\boldsymbol{A}_w$ and $\boldsymbol{A}_p$, respectively; $P_D(k,h,i)$ and $Q_D(k,h,i)$ are the active and reactive power of the load stored in $\boldsymbol{A}_l$, respectively; SW_z is the switching time of branch z; λ_z is the failure rate of branch z; n_{bru} is the number of the upstream branches connecting bus i to the substation; n_{brd} is the number of the branches connecting bus i to the remaining downstream buses; and REP_z is the repair time of branch z.

B. Problem Constraints

The following constraints are considered in the optimization problem.

1) Power balance

$$P_{DG}(k,h,i)-P_D(k,h,i)=\sum_{j=1}^{n_b}x_{ij}V(k,h,i)V(k,h,j)Y_{ij}\cdot \cos\{\theta_{ij}-\varphi(k,h,ij)\}\quad \forall k=1,2,\ldots,24,\,h\in N_T,\,i=1,2,\ldots,n_b \tag{7}$$

$$Q_{DG}(k,h,i) - Q_D(k,h,i) = -\sum_{j=1}^{n_b} x_{ij} V(k,h,i) V(k,h,j) Y_{ij} \cdot \sin\{\theta_{ij} - \varphi(k,h,ij)\} \quad \forall k = 1,2,\ldots,24, h \in N_T, i = 1,2,\ldots,n_b \tag{8}$$

where x_{ij} is the binary status of the branch connecting bus i and bus j; $V(k,h,i)$ and $V(k,h,j)$ are the voltage magnitudes of buses i and j at hour k with combined state h, respectively; Y_{ij} is the admittance magnitude of branch ij; θ_{ij} is the admittance angle of branch ij; and $\varphi(k,h,ij)$ is the power angle between bus i and bus j at hour k with combined state h.

2) Bus voltage

$$V_{\min} \le V(i,k,h) \le V_{\max} \tag{9}$$

where $V_{\min}$ and $V_{\max}$ are the minimum and maximum acceptable bus voltages, respectively.

3) Branch current

$$I(k,h,z) \le I_{\max,z} \tag{10}$$

where $I_{\max,z}$ is the current ampacity of branch z.

4) Network radiality

$$\sum_{j=1}^{n_b} x_{ij} = n_b - 1 \tag{11}$$

The network radiality constraint for a distribution system composed of n_b buses ensures that only $n_b - 1$ branches must be connected for each configuration. In addition, there are four conditions that are utilized to guarantee that (11) gets feasible (i. e., radial) configurations for the distribution system [24].

V. Implementation of Firefly Algorithm

The firefly algorithm (FA), one of the modern metaheuristic techniques [29], is used to achieve the proposed objective. FAs are influenced by fireflies, an insect that exists in nature. Fireflies produce unique and rhythmic flashes to communicate with each other. These flashes are governed by the inverse square law of the light intensity. Hence, as the distance between two fireflies increases, the flashing brightness decreases, leading to miscommunication between the fireflies. Thus, this flashing brightness can be formulated as the objective function to be optimized. The FA shows superiority over the particle swarm optimization (PSO) algorithm and genetic algorithm (GA) to achieve global solutions [30] due to its robust exploitation capabilities. Another important advantage of the FA is that the movement of the fireflies is not affected by their past positions, thus avoiding obtaining local optimal solutions [30].

Figure 3 presents the implementation of the FA on the proposed method. In *Step 1*, the combined probability matrix for each season is obtained, as described in Section II. In *Step 2*, the FA is initialized by developing an initial population of fireflies. Each firefly contains x, DG_p, and DG_s. In *Steps 3* and *4*, the seasonal cost function of each firefly is calculated using (3)-(6). In *Step 5*, the firefly which has the lowest cost among all fireflies and does not violate the constraints mentioned in (7)-(11), is considered as the best for this iteration. In *Step 6*, the fireflies modify their locations using (12) in order to obtain the best firefly [29]. Then, *Steps 3* to *6* are repeated until reaching the maximum number of iterations T and the obtained optimal solution is stored as in *Step 7*. Finally, *Steps 1* to *7* are repeated S times to ensure the optimal global solution.

$$F_t = F_t + \beta_o e^{\gamma r_{tw}^2}\left(F_w - F_t\right) + \alpha\left(rand - \frac{1}{2}\right) \tag{12}$$

where F_w is the position of the best firefly; F_t is the position of the current firefly; r_{tw} is the cartesian distance between firefly t and firefly w; β_o is the attractiveness when $r_{tw} = 0$; γ is the light absorption coefficient; α is a random coefficient; and *rand* is a random number generator uniformly distributed in [0, 1].

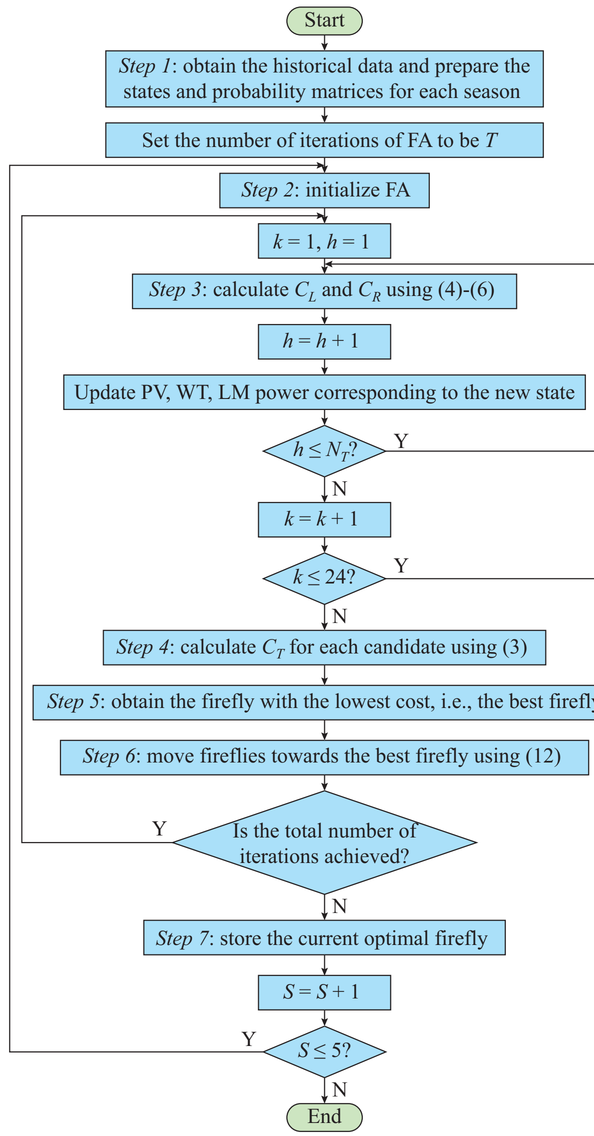

Fig. 3. Implementation of FA in proposed method.

VI. Results and Discussion

The effectiveness of applying the FA to the proposed method is investigated and it is compared with other optimization algorithms. This is done by performing simultaneous DNR and DG allocation under peak load and DG generation conditions. Then, the implementation of annual plans considering the uncertainties in the output power of DGs and the load is investigated. The proposed method is tested on the 12.66 kV IEEE 33-bus distribution system with a peak demand of 3.7 MW and 2.3 Mvar. The operation power factor of all DGs is set to be 0.85 lag [24]. In addition, the voltage boundaries are set in the range of 0.95 p.u. to 1.05 p.u.. The simulation parameters are presented in Table II and the optimization process is repeated five times to ensure the random initialization of the FA and to ensure the global optimal solution. A different number of iterations (100, 500, 1000, and 5000) are examined to ensure the convergence of the objective function. The convergence curve of the FA is monitored, and based on that, the maximum number of iterations T is specified to achieve a reasonable convergence of the objective function.

TABLE II
SIMULATION PARAMETERS

Parameter	Variable	Value
FA parameter	T	1000
	S	5
	α	0.8
	γ	1
	β_o	0.25
Reliability parameter [36]	SW_z	0.5 hour
	REP_z	6 hours
Energy loss cost [11]	σ	0.02 $/kWh

A. Case 1

In this case, the FA is benchmarked with different optimization algorithms, including harmony search algorithm (HSA) [31], GA [31], redefined genetic algorithm (RGA) [31], and PSO [32]. The simultaneous DNR and DG allocation method is applied once to the studied distribution system under the peak load and DG generation conditions. The base energy loss of the distribution system is 202 kW at the default network configuration with switches 33, 34, 35, 36, and 37 open and without using DGs.

The minimization of the power loss is considered as the main objective of this case, similar to the studies in [31], [32]. Table III shows the results obtained after performing simultaneous DNR and DG allocation using different optimization algorithms.

TABLE III
OPTIMAL SOLUTIONS AND SYSTEM ENERGY LOSS OF DIFFERENT ALGORITHMS

Algorithm	Open switch	DG generation (MW)	Power loss (kW)
FA	7, 9, 13, 25, 31	0.4 (17), 0.8 (25), 0.4 (14)	71.00
HSA	7, 14, 10, 32, 28	0.52 (32), 0.55 (31), 0.58 (33)	73.05
GA	7, 10, 28, 32, 34	1.9633 (N/A)	75.13
RGA	7, 9, 12, 32, 29	1.774 (N/A)	74.32
PSO	7, 14, 11, 32, 27	0.64 (31), 0.49 (32), 0.51 (33)	96.86

Note: the numbers in the () represent the bus number.

The results show that the FA achieves the better power loss reduction for the studied distribution system under peak load and DG generation conditions compared with the other algorithms.

B. Case 2

For this case, the solar irradiance and wind speed data are obtained for two years during the interval of 2012-2014 [33]. It is assumed that the PV systems and WTs can be separately installed at three different buses with an overall penetration level of 30% to avoid reverse power flow.

The solar irradiance data are divided into 10 states ($N_p = 10$) starting from 0.05 kW/m^2 with a step size of 0.1 kW/m^2. Meanwhile, the output power for a 250 W monocrystalline PV module [34] is calculated using the model in [12]. Hence, $\boldsymbol{A}_p$ can be calculated. Figure 4 shows an example of hourly solar irradiance data in winter for a 2-year study period. The wind speed data are divided into 11 states ($N_w = 11$) starting from 0.5 m/s with a step size of 1 m/s. To calculate $\boldsymbol{A}_w$, the output power curve of a 100 kW WT module shown in Fig. 5 is used [35]. Figure 6 shows an example of hourly wind speed data in winter for the 2-year study period. The load is modeled using the per unit load data presented in Fig. 7 [12].

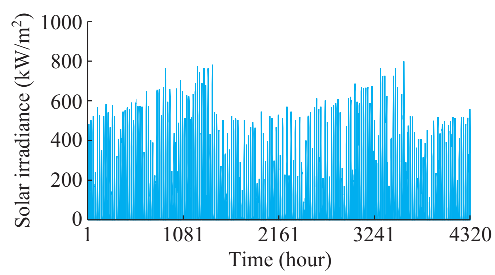

Fig. 4. Hourly solar irradiance data in winter during 2-year study period.

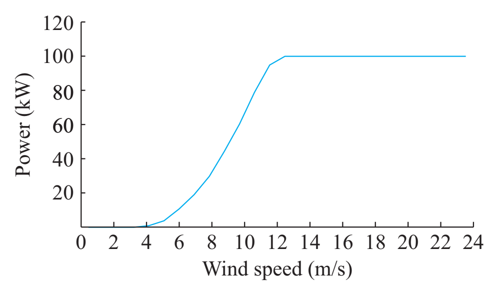

Fig. 5. Output power curve of WT.

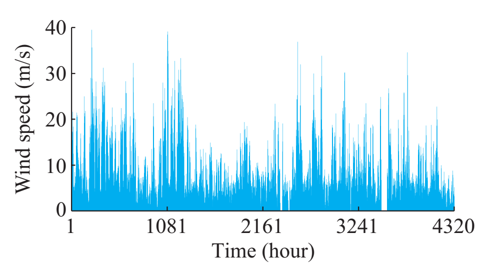

Fig. 6. Hourly wind speed data in winter during 2-year study period.

The probability of each hourly load is considered to be unity. The reliability parameters and energy loss cost of this case are presented in Table II. The branch failure rate, switching time, and repair time are obtained from [36] while the energy loss cost and the energy not served cost are obtained from [11]. The energy not served cost corresponding to different expected failure time ($60T_D$) for a typical distribution system is shown in Fig. 8.

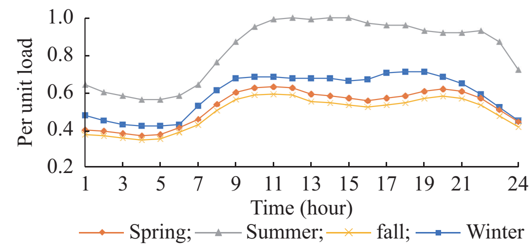

Fig. 7. Per unit load data.

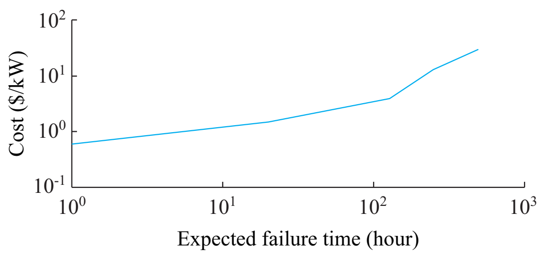

Fig. 8. Energy not served cost.

In this case, five different annual plans are presented described as follows.

1) Plan 1: performing simultaneous DNR and DG allocation based on the data of winter followed by performing DNR for each of the remaining seasons.

2) Plan 2: performing simultaneous DNR and DG allocation for the data of spring followed by performing DNR for each of the remaining seasons.

3) Plan 3: performing simultaneous DNR and DG allocation for the data of summer followed by performing DNR for each of the remaining seasons.

4) Plan 4: performing simultaneous DNR and DG allocation for the data of fall followed by performing DNR for each of the remaining seasons.

5) Plan 5: performing simultaneous DNR and DG allocation once for the whole year without performing DNR.

These plans are compared with the base case of the default network configuration and without using any DGs.

To compare the results of different plans, the annual cost reduction *ACR* is calculated as:

$$ACR = \frac{C_{base} - C_N}{C_{base}} \times 100\% \tag{13}$$

where C_{base} is the annual cost without DNR or DG allocation, i.e., base case; and C_N is the annual cost of each plan. Table IV presents the optimal network configurations and DG sizes/locations for each of the five plans. Besides, the annual costs corresponding to each plan are shown in Fig. 9, and a comparison among the *ACR* of each plan is shown in Fig. 10.

TABLE IV
OPTIMAL NETWORK CONFIGURATIONS AND DG SIZES/LOCATIONS FOR EACH PLAN

Season	Plan 1			Plan 2			Plan 3			Plan 4			Plan 5		
	Open branch	PV generation (MW)	WT generation (MW)	Open branch	PV generation (MW)	WT generation (MW)	Open branch	PV generation (MW)	WT generation (MW)	Open branch	PV generation (MW)	WT generation (MW)	Open branch	PV generation (MW)	WT generation (MW)
Winter	10, 14, 16, 25, 33	0.23 (15), 0.17 (16), 0.08 (6)	0.1 (26), 0.2 (22), 0.3 (20)	8, 13, 20, 27, 30	Same DG sizes/ locations of spring		8, 12, 20, 28, 30	Same DG sizes/ locations of summer		8, 12, 20, 25, 30	Same DG sizes/ locations of fall		14, 16, 20, 21, 27	0.29 (15), 0.22 (17), 0.22 (11)	0.20 (27), 0.20 (28)
Spring	8, 14, 20, 26, 30	Same DG sizes/ locations of winter		9, 13, 15, 28, 33	0.19 (14), 0.11 (8), 0.19 (17)	0.2 (26), 0.3 (31), 0.3 (28)	6, 11, 13, 33, 37	Same DG sizes/ locations of summer		8, 14, 16, 33, 28	Same DG sizes/ locations of fall				
Summer	4, 16, 24, 34, 33	Same DG sizes/ locations of winter		8, 13, 20, 26, 31	Same DG sizes/ locations of spring		9, 14, 16, 26, 33	0.07 (9), 0.32 (8), 0.16 (11)	0.1 (28), 0.3 (27), 0.1 (29)	8, 14 17, 25, 33	Same DG sizes/ locations of fall				
Fall	6, 15, 11, 27, 34	Same DG sizes/ locations of winter		8, 14, 20, 26, 31	Same DG sizes/ locations of spring		8, 14 15, 28, 33	Same DG sizes/ locations of summer		10, 14, 16, 33, 26	0.10 (8), 0.35 (16)	0.4 (22), 0.2 (28), 0.2 (20)			

Note: the numbers in the () represent the bus number.

The results demonstrate the positive impact of performing the simultaneous DNR and DG allocation on the cost related to energy loss and reliability. Furthermore, the results show that the results of the annual cost reduction corresponding to plans 1-4, where seasonal DNRs are performed, are significantly higher than that of plan 5. Hence, presenting annual plans based on the seasonal DNRs leads to a significant reduction in the system operation cost. However, performing additional DNR, i. e., monthly or weekly, will add more switching costs and thus affect the overall system operation cost. Moreover, for the studied distribution system, plan 3 provides the highest *ACR* corresponding to different annual costs compared with those of the other plans. This indicates that for the studied distribution system, performing the simultaneous DNR and DG allocation based on the season with the higher demand, i. e., summer, followed by performing DNR for the remaining seasons, leads to a higher reduction of the combined cost.

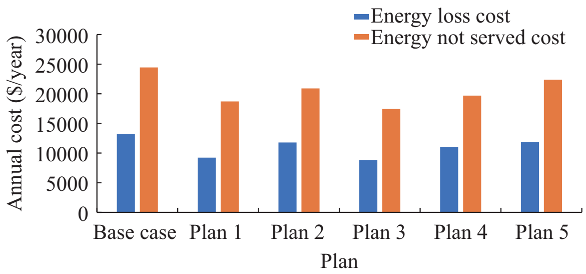

Fig. 9. Annual cost of each plan.

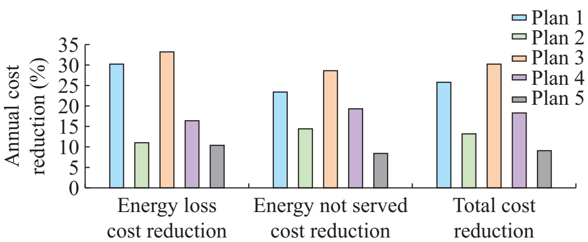

Fig. 10. Annual cost reduction of each objective plan.

The daily voltage profile based on the season is investigated as well, where the voltage of each node is multiplied by its corresponding probability resulting in a probabilistic daily voltage. Figures 11 to 14 show the probabilistic daily voltage profile for each season corresponding to plan 3 compared with the base case.

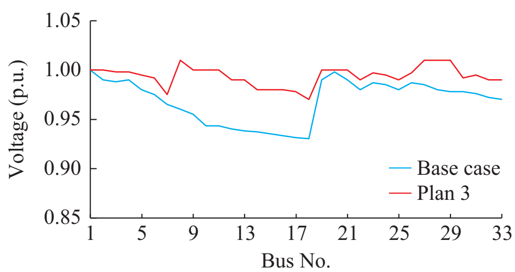

Fig. 11. Probabilistic daily voltage profile for plan 3 in winter.

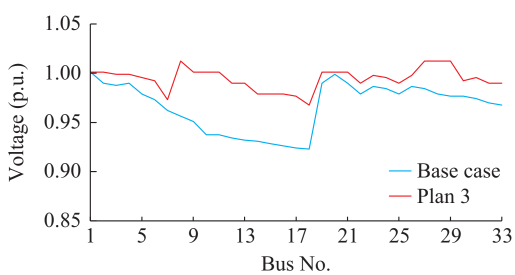

Fig. 12. Probabilistic daily voltage profile for plan 3 in spring.

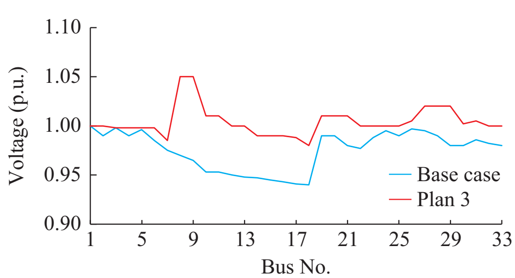

Fig. 13. Probabilistic daily voltage profile for plan 3 in summer.

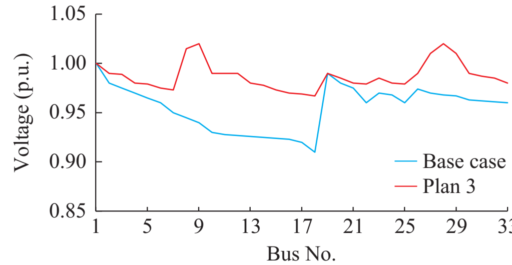

Fig. 14. Probabilistic daily voltage profile for plan 3 in fall.

It can be clearly observed that the proposed method is able to maintain the daily voltage profile within acceptable limits for the studied distribution system for all buses under different loading conditions.

VII. Conclusion

In this study, DNR and DG allocation are used to enhance the performance of distribution systems. The purpose of the study is to develop annual plans that minimize the combined costs of the energy loss and the energy not served related to the system reliability. The proposed method considers the uncertainties in the output power of the DGs and the system demand using a combined probabilistic model. The method is applied to the IEEE 33-bus distribution system using the FA.

The study shows that simultaneous DNR and DG allocation can significantly reduce the combined costs. Moreover, the voltage profile is improved. The study shows that considering the seasonal changes in the network configuration while developing annual plans can lead to better network performance than implementing only the DNR or DG allocation for the whole year. The study also shows that performing simultaneous DNR and DG allocation for the season with the highest demand followed by performing the DNR for the remaining seasons produces the optimal results. Accordingly, it is recommended that the system operators develop different seasonal plans to compare their results before deciding on the optimal sizes/locations of DGs and the network configuration.

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