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Optimization and Placement of DG Resources in the Network to Reduce Line Loading

Farhad Zishan[1] | Ehsan Akbari [2] | Abdolreza Sheikholeslami*[3] | Nima Shafaghatian [4]

Department of Electrical Engineering, Sahand University of Technology, Tabriz, Iran.[1]
Department of Electrical Engineering, Mazandaran University of Science andTechnology, Babol, Iran.[2]
Department of Electrical Engineering, Babol Noshirvani University of Technology, Babol, Iran.[3]
Electrical Engineering Department, Zanjan University, Zanjan, Iran.[4]

Corresponding author's email: asheiikh@nit.ac.ir

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ABSTRACT

Due to the high penetration coefficient of wind and solar energy in the grid and the uncertainty of these sources, we need a possible analysis. This paper contributes to the design, modeling, and planning a distributed generation (DG) network with wind and solar by means of the particle swarm algorithm (PSO) and backtracking search optimization (BSO) algorithm in the IEEE 33-bus network, aiming to minimize The results indicate an adequate performance in a variety of environments, and the presence of distributed wind/solar energy generators decreases network stress by feeding loads locally. These systems (wind and solar) can be used in remote areas without power networks, or even in areas where there is a tendency to use renewable energy despite the presence of a power network. They can also supply the output load for most of the day and night .Probability distribution functions are used, and the outputs are expressed as probability density distribution functions instead of absolute numbers. In addition, there is a high degree of uncertainty regarding the state of the system, which is an associated renewable energy source within the power system elements. By means of the MATLAB software, the proposed method is implemented in order to ensure effectiveness and validate the results**.** Finally, the superiority of the BSO algorithm over PSO will be seen.

NOMENCLATURE

Wind velocity	V_W
Blade radius	R
Blade angle	β
Air density	ρ
Turbine power factor	C_P
Wind velocity scale parameter	K_t
Formation parameter	C_t
Series resistance	R_S
Parallel resistance	R_{SH}
Wind turbine output power	Pw
Radiation-induced current	I_L
Diode current	I_O
Boltzmann constant	k
Electric charge of an electron	q
Ideality factor of a diode	n
Nominal thermal voltage of a cell	v
Beta distribution factors	$\alpha_\beta , \beta_\beta$
Sunlight intensity	R_C
Gamma function	Γ
Mean and standard deviation	μ_s^t and δ_s^t
Open circuit voltage	Voc
Short circuit current	Isc
Ambient temperature	Tc
Weight function	w
Resistance and reactance of airline feeder	X and R

Active and reactive power	Q *and* P

I. Introduction

To date, the issues of optimal operation with the presence of renewable resources and optimizing the production of these resources have become very relevant. Wind and solar power plants are among the most attractive opportunities for investors. The consolidation of a significant amount of power from renewable sources such as the wind and the sun in distribution networks poses significant operational challenges due to the degree of uncertainty involved [1-4]. In order to meet the increasing electricity demand, the most important task of energy distribution companies is to plan the development of sustainable power distribution networks [5-8]. The main goal of distribution network expansion planning is to provide consumers with an acceptable and affordable service [9] while keeping voltage levels and power quality within acceptable limits. In addition, the purpose of a distribution network is to provide power to customers and respond rapidly to changes in their demands. In this vein, it becomes necessary to assess the state of sustainable energy generation with regard to wind and solar (photovoltaic, PV) systems [10-14] in terms of transmission, distribution, and consumption conditions. A distribution network does not have a power plant, but it does have transmission lines that deliver electricity to it. Large power plants create electricity, which is then supplied to distribution networks through transmission lines. Given the urge to minimize coal/gas power plants and the increasing consumption of electricity, there is a need for new generation resources [15-19]. However, the privatization of the power industry has changed the status of power plants from regulative to competitive. The advent of small power plant technologies (clean generation and higher-efficiency power plants) has aided in meeting the current energy demands [20-22]. The conditions of energy markets and geographical conditions completely dictate investors' choices with regard to power plants [23, 24].

Many sectors of distribution networks are nowadays crowded due to the intervention various small scale renewable energy and coal/gas power plants. This, while investment in the generation sector declines [25] and the energy demand rises, as well as the price of electricity, particularly in western Asia, in countries such as in Iran [26]. The goal of the electrical sector is to provide residents and companies with clean, safe, and dependable energy, so it is critical to invest in new technologies that enhance current power systems and usher in a revolution in this industry [27-31]. This will not be possible unless the structure of the distribution network and its control system are fundamentally changed. One solution is the use of distributed generation (DG) resources [32-33]. In recent years, the utilization of DG resources in networks has contributed to improving effectiveness and reliability. Most classical point-to-point methods (e.g., direct methods and derivation-based methods) use computational techniques to arrive at the optimal solution [34]. However, as the problem size and search space increase, finding the solution via classical methods becomes more complicated. Computational intelligence optimization algorithms have been used in various fields, including science, business, and engineering, to solve complex optimization problems. This is due to their ease of use, wide execution capability, and overview. The most popular method is particle swarm optimization (PSO) [35, 36]. PSO is better in terms of solution quality and number of iterations, namely regarding the initial random population, particle upgrades, and the generation of new solutions. However, these methods of collective intelligence are limited by premature convergence and because they are often trapped in local minima. To overcome these issues, these algorithms have undergone different variations, aiming to improve their performance [37]. These methods' principles of operation are inspired by natural genetic evolution, which why they are the most famous example of a genetic algorithm.

In [38], the effect of influence of distributed generation with different technologies on annual energy losses is calculated. This includes combined cycles, wind energy, and photovoltaic and solar cells. It is shown that wind energy has the worst behavior with respect to reducing losses, and it is concluded that distributed generation units with reactive power control capabilities have a greater effect on improving the voltage profile and reducing losses in the network. The authors of [39] combine genetic algorithms and particle aggregation to optimize the size and location of scattered products.

In [40], an algorithm for determining the optimal location and size of DGs in distribution networks is introduced. This algorithm is based on a new index that examines the effects of energy sources. The work by [41] offers a way to optimally locate different DG technologies in order to reduce energy losses. Voltage limits, line load capacity, the maximum influence of DG, and steps to increase or decrease DG capacity are among the constraints of the problem. The authors of [42] propose an analytical method for minimizing system losses, which involves installing different types of DGs. To this effect, in addition to the resource capacity, the optimal power factor for the four types of distributed generation resources is determined in order to obtain the greatest reduction in losses. Thereupon, this method studies the types of DGs that can generate or absorb reactive power.

The authors of [43] present a probabilistic method to analyze the steady-state operating conditions of a distribution system with wind and photovoltaic power plants. This method is based on the uncertainty of power system loads and power generation from renewable systems, as well as on a combination of Monte Carlo simulation techniques and linear equations. In [44], the load distribution of a power system is analyzed using a new point estimation method while considering the system's uncertainty, which may arise from a variety of sources such as load or downtime. A new algorithm for the longitudinal differential protection of transmission lines is described in [45], and the imperialist competitive algorithm is employed in [46] for determining the location and size of optimal multiple DGs in a distribution network. In [47], an optimal controlled strategy for multiple distributed generations in a micro grid island is presented. Below are some relevant applications of wind and solar systems in distribution networks [48]:

1. Increasing the average annual growth rate of energy consumption in the country and reducing oil exports
2. Expanding the influence of renewable energy on the energy supply
3. Introducing these technologies into the global energy supply market
4. Backing up the power supply in order to provide power to sensitive loads such as special industrial units during network power outages, as well as improving reliability
5. Reducing the costs associated with the power supply, which can be very expensive in remote areas or due to geographical obstacles
6. Providing the power required by the load during peak hours
7. Providing part of the power required by the base load
8. Reducing environmental pollution

The aforementioned solutions have limited control capabilities due to the lack of a communication infrastructure. Loading transmission lines with distributed generation sources is a common topic of discussion. This paper addresses their placement within the power system to reduce losses and keep the transmission lines free.

The aim of this research is to minimize the density of transmission lines and coordination in systems that integrate DG energy sources and wind and solar energy. The placement of these resources is studied using the PSO algorithm in an IEEE 33-bus network. This article first introduces wind and solar sources, and it delves into losses in networks with DGs. Then, the coordination of these sources and the use of the PSO and BSO algorithm for locating and reducing line loading are discussed. Finally, the results are reviewed and analyzed. Among the most important works of this article:

Results of losses with wind sources
Results of losses with solar sources
Results of losses with hybrid sources
Load rate of lines in optimal condition with wind resources
Load rate of lines in optimal condition with solar resources
Load rate of lines in optimal condition with wind and solar resources
Locating resources with PSO and BSO

II. Research Methodology

A. Wind turbine performance

A wind turbine first converts wind energy into mechanical energy, which is in turn converted into electrical energy by a generator. The active power output from the wind turbine and the input to the generator only depend on changes in the generator's optimum speed. Thus, the output power may be regulated by adjusting the generator's speed. The relation of wind power can be expressed as shown in Equation (1) [18].

$$P_W = \frac{1}{2}\rho\pi R^2 Vw^3 C_P(\lambda, B). \tag{1}$$

Figure 1 show a diagram and power area in terms of wind turbine speed. Wind turbines start moving at cut in velocity and generate electricity up to cut out velocity. Where V_W is the wind speed, R is the blade radius, β is the blade angle, ρ is the air density, and C_P is the turbine power factor, which is a function of λ and β Figure 1 shows the power-speed curve of the wind turbine. Wind turbines start moving at a cut-in velocity and generate electricity up to a cut-out velocity. The type of wind turbine considered in this study is DFIG. Wind velocity is modeled with a Weibull distribution. The Weibull function is a specific state of the gamma distribution which is more flexible than other functions. Moreover, different time frames can be used for long-term measurements. Wind velocity can be characterized by its mode and by random events. The implemented Weibull distribution function is shown in Equation (2) [49]:

$$f(v) = \frac{Kt}{Ct}\left(\frac{V}{Ct}\right)^{Kt-1} * \exp\left[-\left(\frac{v}{Ct}\right)\right]^2 \tag{2}$$

Where Kw is the Weibull wind speed scale parameter, Cw is the Weibull wind speed formation parameter, and V is the wind speed. The turbine output capacity can be determined according to Equation (3) [50-54]:

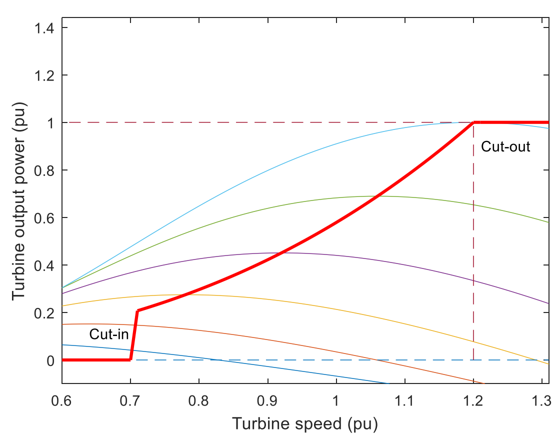


Fig. 1. Wind turbine performance in different areas

$$P_{WTG} = \begin{cases} 0 & \text{if} \quad v < Vi \text{ or } v > V0 \\ P_{rw} \frac{V-Vi}{Vr-Vi} & \text{if} \quad Vi < v < Vr \\ P_{rW} & \text{if} \quad Vr < v < Vo \end{cases} \quad (3)$$

Where $Vi, Vo, and\ Vr$ are the starting speed (cut-in velocity), the cut-off speed (cut-out velocity), and the nominal velocity of the turbine, respectively. Note that v represents the wind velocity.

B. Photovoltaic Cell Modeling

Solar energy is converted into electrical energy by photovoltaic panels and converters. Photovoltaic technology uses semiconductor cells made up of diodes. By radiating light on the cell, voltage and current are produced. The cells combine to form a module that can be modeled as a current source parallel to a diode, as shown in Figure 2. Using the relationships of the solar cell, a general relation can be given, as shown in Equation (4):

$$I = I_L - I_O \left(E^{\frac{q(V+I.Rs)}{nkT}} - 1 \right) - \frac{V+I.Rs}{R_{SH}} \quad (4)$$

In this equivalent circuit, RS and RSH are series and parallel resistors, IL is the radiation current, IO is the diode current, k is the Boltzmann constant parameter, q is the electric charge of one electron, T is the cell temperature, n is the ideal coefficient of the diode, and v is the nominal thermal voltage of the cell. Solar radiation is modeled as a distribution function based on the model presented in [20]. The probability distribution function can show the probable state of the solar radiation phenomenon. Solar radiation has a high degree of uncertainty and changes as a function of several factors such as climate, time, day, month, season, and the orientation of solar cell generators (P_SCG). Sunlight is modeled with the beta distribution function, as shown in Equation (5) [20]:

$$f(R: \alpha_\beta, \beta_\beta) = \frac{\Gamma(\alpha_\beta + \beta_\beta)}{\Gamma(\alpha_\beta)\Gamma(\beta_\beta)} R^{\alpha_\beta - 1}(1-R)^{\beta_\beta} \quad (5)$$

Here, α_(β) and β_(β)are beta distribution factors, and $PSCG$ is the output power is related to solar radiation, which is shown in Equation (6):

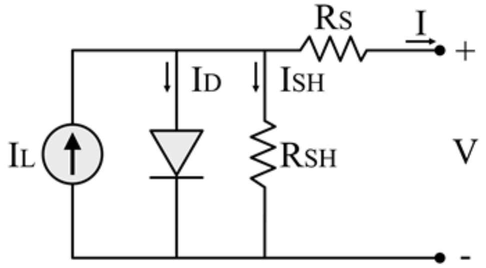


Fig. 2. Circuit equivalent to a solar cell

$$P_{SCG} = \begin{cases} P_{rs} & \text{if } v \le R < R_C \\ P_{rs} \frac{R}{R_{STD} R_C} & \text{if } RC \le R < RSTD \\ P_{rs} & \text{if } R_{STD} \le R \end{cases} \quad (6)$$

RSTD is the radiation intensity under standard conditions (usually 150W/m2), P_rs (usually 1000 W/m2) is the output power of a solar cell, and $PSCG$ is the total output power.

C. Modeling network losses

Determine the number of changes in distribution network losses when DG re-sources are integrated, the load distribution of the network must first be calculated. The purpose determining the load distribution in this context is to analyze the voltage quality at each connection point. The increase in voltage due to the presence of the generator is obtained with Equation (7):

$$\Delta v = \frac{PR+QX}{V} \quad (7)$$

For low-voltage networks, the effect of the resistance is greater than that of the reactance. Therefore, active power is more effective than reactive power in the network. For control purposes, the powers in the network are continuously measured. Implementing a power measurement period and running simulations can be an effective way to minimize losses. Figure 3 shows a part of the distribution feeder and power distribution path. The generators provide active power, but their reactive power capabilities are not used.

The reactive power at bus 1 (a load-bearing bus) can be obtained from Equation (8):

$$Q_{1j} = Q_{2j} + Q_{L1} \quad (8)$$

In this equation, if the reactive power of generator G1 is equal to Q1j, equal to the sum of Q2j and QL1 according to the node law. The same procedure applies to other buses. To achieve optimal loss reduction [21], most operators cannot get the reactive power of DG resources.

A. Resources Uncertainty

There are several uncertainties throughout the distribution network, including changes in network load and the accidental output of power equipment. With the use of renewable energy sources, which have a variable nature, the uncertainty of power systems has increased even more. This poses many challenges with regard to the design and planning of these systems. Analytical load distribution can help to calculate the voltage of the nodes and the power of the branches under certain defined conditions, but it is not able to consider the uncertainty of the network parameters. Because wind and solar power are completely random and probabilistic, the amount of electrical power they generate during the day or night is completely variable. The optimal location of solar and wind resources in a distribution

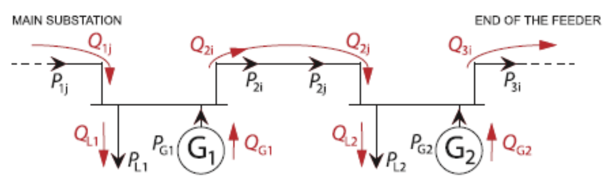


Fig. 3. Example of power distribution [21]

network is obtained by considering seasonal loads and changes in weather conditions, such as the solar radiation level and wind velocity. De-spite the uncertainty, the beta distribution for solar resources can be expressed as shown in Equation (9) [53-55]:

$$\begin{cases} f_s^t(s) = \frac{\Gamma(a^t+B^t)}{\Gamma(a^t).\tau(B^t)} * (s^t)^{a^{t-1}} * (1-s^t)^{B^{t-1}} \\ \quad \text{for } a^t > 0 \quad , B^t > 0 \end{cases} \tag{9}$$

Where Γ represents the gamma function, a and B is parametric quantities, $f_s^t(s)$ i is the radiation intensity, and δ_s^t and μ_s^t are the mean and standard deviation, respectively. The wind distribution formulation is as follows:

$$\begin{cases} f_v^t(v) = \frac{k^t}{c^t} * \left(\frac{v^t}{c^t}\right)^{k^{t-1}} \\ \exp * \left(\frac{v^t}{c^t}\right)^{k^{t-1}} \quad \text{for } c^t > 0, k^t > 0, k^t > 0 \end{cases} \tag{10}$$

Where k^t , wind velocity scale parameter, and c^t is the formation parameter. These are calculated according to Equations (11). Generation capacity of the solar system is calculated, as according to Eq (12).

$$k^t = \left(\frac{\delta^t}{\mu_v^t}\right)^{-1.086}, c^t = \frac{\mu_v^t}{\Gamma(1+\frac{1}{k^t})} \tag{11}$$

$$P^t_{PV=\sum_{g=1}^{Ns} PG_{PV} * P_S(s_g^t)} \tag{12}$$

This equation is used to distribute the wind velocity and radiation level throughout the day and night by considering the variable daily load consumption and, as a result, the potential power generated by the solar cell or wind turbine. This is done by integrating the potential density function. Thus, 〖PG〗_PV and P_(S) are calculated, as shown in Equation (13).

$$P_S(s_g^t) = \begin{cases} \int_0^{s_g^t+s_{g+1}^t)/2} f_s^t(s)ds & \text{for } g = 1 \\ \int_{s_{g-1}^t+s_g^t)/2}^{s_g^t+s_{g+1}^t)/2} f_s^t(s)ds & \text{for } g = 2 \ldots\ldots (N_s-1) \\ \int_{s_{g-1}^t+s_g^t)/2}^{\infty} f_s^t(s)ds & \text{for } g = N_s \end{cases} \tag{13}$$

$$PG_{PVg(s_{ag})=NPvmodel*FF*Vg*Ig}$$

The current, voltage, and temperature of the panel are determined as follows:

$$\begin{cases} Ig = \mathrm{Sag}((\mathrm{Isc} + \mathrm{Ki}(\mathrm{Tc}-25)) \\ \mathrm{Vg} = \mathrm{Voc} - \mathrm{Kv} * \mathrm{Tcg} \\ Tcg = T_A + Sag(\frac{Not-20}{.8}) \end{cases} \tag{14}$$

The efficiency of each solar panel is calculated according to (15):

$$FF = \frac{V_{MPP} * I_{MPP}}{Voc * Isc} \tag{15}$$

I_{MPP} and V_{MPP} are the maximum voltage and current of each panel. Losses P_{Loss} are calculated according to Equation (16):

$$PLoss = \frac{\sum_{t=1}^{Nt}\sum_{i=1}^{N1} \frac{r_i((P_{D,i+1}^t)^2 + ((Q_{D,i+1}^t)^2}{(V_{i+1}^{t\;2})}}{Nt} \tag{16}$$

$P_{D,i+1}^t$ and $Q_{D,i+1}^t$,are the active and reactive power, V_{i+1}^t is the bus voltage, and Nt is the number of bus lines.

B. Objective Function

For the sake of stability and security, as well as to improve the power quality, several limits are established for the voltage and current across the lines, as well as for the losses. Hence, the above-mentioned constraints imply an optimization problem. To solve the problem with the one-objective optimization method, the variable weighting technique is used (Equation (17)). The goals of the optimization problem are to minimize the average annual power losses, maximize the voltage stability index, and minimize the network security index. Traditionally, a multi-objective problem is reconstructed into a single-goal optimization one via the weight accumulation method, as the objective functions depend on the location, size, and type of renewable DGs. Thus, a multi-objective performance index can be formulated [55]:

$$F = f\left(\sum_{i=2}^{Nb}\sum_{j\in type} PDG_{i,j} * ni * Li\right) = w1 * sPLos_a - w2 * VSF_a + w3 * NSIa \quad wi = [0,1] \tag{17}$$

$PDG_{i,j}$, is the bus injection capability and w is the weight function. Indicators are used to assess voltage stability. Buses in the transmission or distribution network are very fast And effective tools for measuring off-line voltage stability Status of buses Voltage stability index VSF proposed in for each bus-i in the time segment's' can be displayed as follows Nb is the total number of network buses. It is assumed that Bass-1 is located in the main distribution post. . The network will become more stable. VSF is calculated according to Equation (18):

$$SFa = \frac{\sum_{t=1}^{Nt}\sum_{i=2}^{Nb} VSF_{i+1}^t}{N_t(N_b-1)} \quad , VSF_{i+1}^t = (2_{i+1}^t - V_i^t) \tag{18}$$

The formulation of losses while considering generation and reactive power is expressed below [56]:

$$PG_{ss}^t + \sum_{i=2}^{Nb}\sum_{j\in type} PDG_{i,j} * ni * Li - \sum_{i=2}^{Nb} P_{Di}^t - PLoss^t = 0, QG_{ss}^t + -\sum_{i=2}^{Nb} Q_{Di}^t - QLoss^t = 0 \tag{19}$$

Eq. (23) is considered in the distribution network:

$$\sum_{i=2}^{Nb}\sum_{j\in type} PDG_{i,j} * ni * Li \le \sum_{i=2}^{Nb} P_{Di}^t \tag{20}$$

Where PG_{ss}^{t} and QG_{ss}^{t} are the active and reactive power fed by the substation at a given time, and Plosst and Qlosst are the active and reactive power losses at a given time PSO algorithm, whose full details are reported elsewhere [57], was implemented in this research.

C. Backtracking search optimization algorithm (BSOA)

Backtracking search optimization algorithm is introduced in [30-31]. This algorithm uses the jump operator during the search to avoid getting stuck in local optima during the first iterations while obtaining new solutions. The main components of BSOA-based design, i.e., initialization, selection, mutation, reproduction, and selection, are described. There will be a random generation (PoP) initialization phase at the edge boundaries:

$$
\begin{aligned}
&\text{for } i = 1:\text{PopSize}\\
&\text{for } j = 1:\text{D} \qquad\qquad (21)\\
&\text{PoP}(i,j) = \text{PoPmax}(j) - \text{rand}/\\
&(\text{PoPmax}(j) - \text{PoPmin}(j))\\
&\text{end}\\
&\text{end}
\end{aligned}
$$

In relation (21), Pop Size and D are the maximum population size and the dimensions of the population set. The algorithm with selection, mutation and reproduction is the following steps:

$$
\begin{aligned}
&\text{Define mixrate}\\
&\text{oldPoP} = \text{oldPoP}(\text{randperm}(\text{PopSize}),:);\\
&\text{map} = \text{zeros}(\text{PopSize}, \text{D});\\
&\text{if rand} < \text{rand},\\
&\text{for } i = 1:\text{PopSize}, \qquad\qquad (22)\\
&u = \text{randperm}(\text{D});\\
&\text{map}(i, u(1:\text{ceil}(\text{mixrate} * \text{rand} * \text{D}))) = 0;\\
&\text{end}\\
&\text{else}\\
&\text{for } i = 1:\text{PopSize},\\
&\text{map}(i, \text{randi}(\text{D})) = 0;\\
&\text{end}
\end{aligned}
$$

III. The System under Study and result

The single-line diagram of the studied system (IEEE 33-bus network) [58-59] is shown in Figure (4), and the model information is shown in the Appendix. The set under study comprises a combination of the aforementioned resources, along with their quantity and location. There are several Properties in power systems, including changes in network load and the accidental output of power equipment.

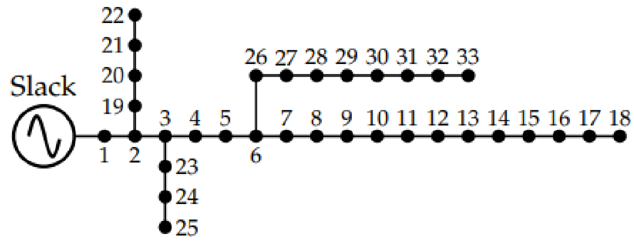


Fig. 4. IEEE standard model of a 33-bus distribution network

With regard to the performance of the system for a 24-hour period, the probability distribution program of solar and wind power plant is shown in Figures 5 and 6, and the information of these models is given in Tables 1 and 2. Due to the relatively small asymmetry, the probability distribution of the resources is relatively symmetric and may be approximated by a normal distribution. If it has a relatively large and positive symmetry, the probability distribution will tend to be in one direction (left or right). In this case, it cannot be approximated to a normal distribution. Data sometimes creates a curve that does not have a natural distribution, i.e., its two ends are not symmetrical. When there is no fit between the two ends of the curve, the curve is skewed.

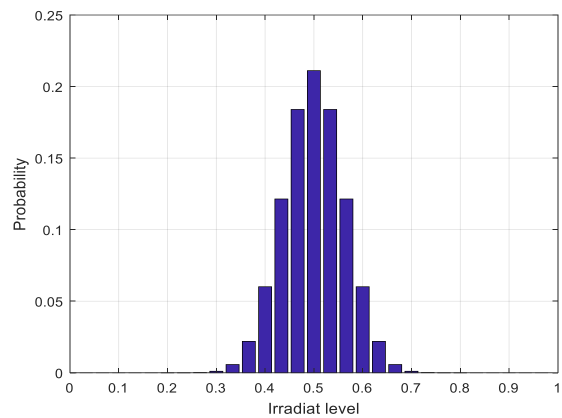


Fig. 5. Probability distribution of solar power (monte carlo methods) [59]

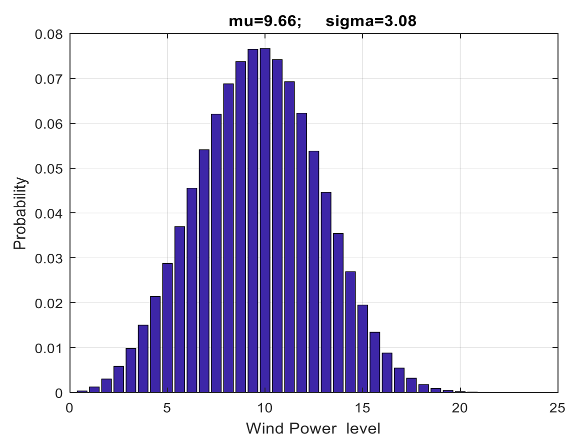


Fig. 6. Probability distribution of wind power (monte carlo methods) [59]

In Table 1, a comparative summary of the literature on the protection of smart grids and MGs has been presented. The summarized literature review shows that a research gap exists in developing a new study for MG protection using the DS-DOCRs that takes into account N-1 contingency-based network topologies and corresponding selectivity constraints. This research aims to fill this gap. Indeed, using the DS-DOCRs, as a specified characteristic, would be useful to mitigate the challenges of the protection system's speed in [4].

TABLE 1
PARAMETERS STUDIED IN THE SOLAR SYSTEM

Photovoltaic system power	200W
Maximum voltage	28.36V
Maximum current	7.76 A
Open circuit voltage	36.96V
Short circuit current	8.38 A
Flow on temperature factor	Ki = 0.00545
Voltage on temperature factor	Kv = − 0.1278

TABLE 2
WIND SYSTEM INFORMATION [59]

Minimum wind speed	5 m/s
Maximum wind speed	20 m/s
Average wind speed	9 m/s
Generation capacity	250 kW

Figure 7 shows the proposed per-unit load value for the four seasons. Note that the load peaks occur many times at noon and during the night.

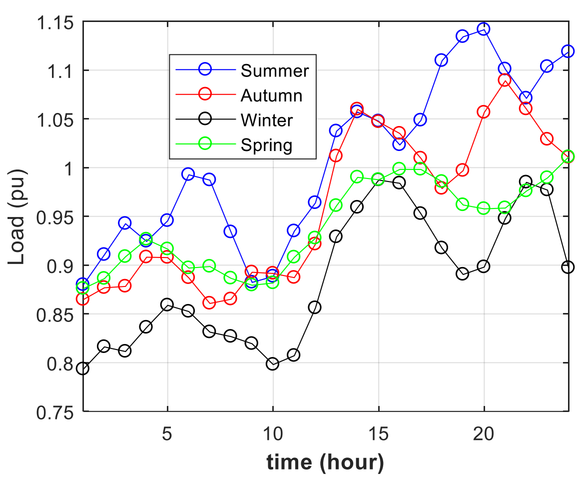
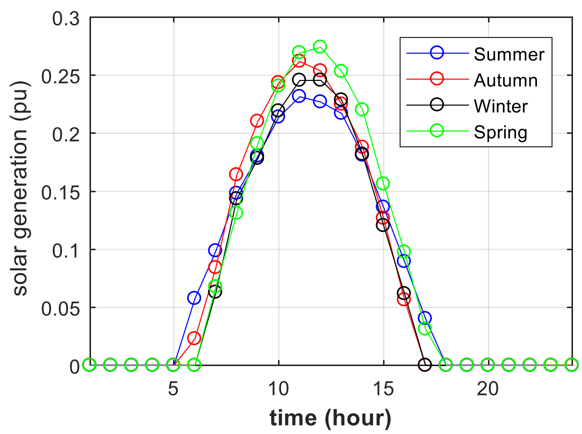
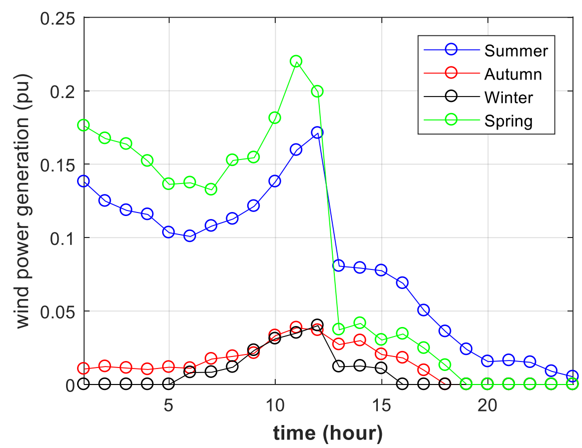


Fig.7. Load for a season of the year for DG resources

In the first stage, the PSO algorithm is used to find locate wind power plants. As an optimization issue, the mode estimation problem requires deliberate and restricted performance. Figure 8 shows the power generation of wind and solar power plants throughout a day. The variable loads and generators are considered to be fixed variables, and the distributed generation resources are regarded as variable modes. The results regarding losses with wind, solar, and hybrid sources are shown in Figures 9, 10, and 11, respectively. Figure 12 shows the convergence diagram for locating three wind power plants.



(a)



(b)

Fig. 8. Power generation after implementing the PSO algorithm throughout the day in a year with four seasons: (a) Hourly solar power generation and (b) wind power generation in the studied period

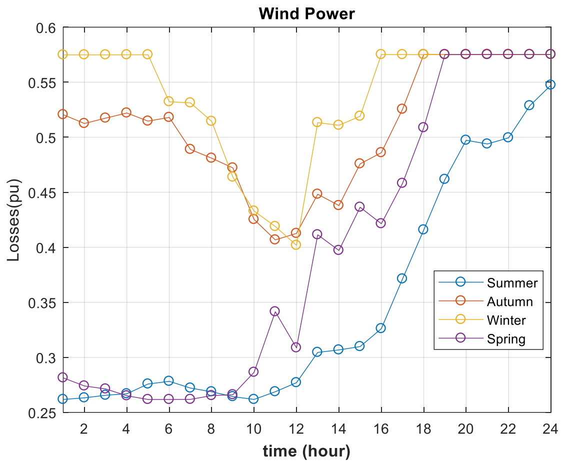


Fig. 9. Results of losses with wind sources

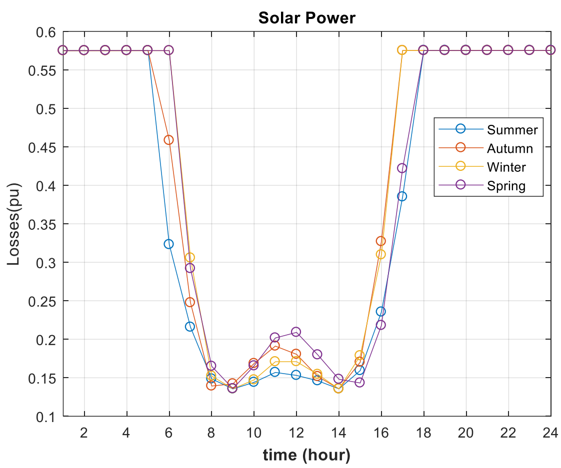


Fig.10. Results of losses with solar sources

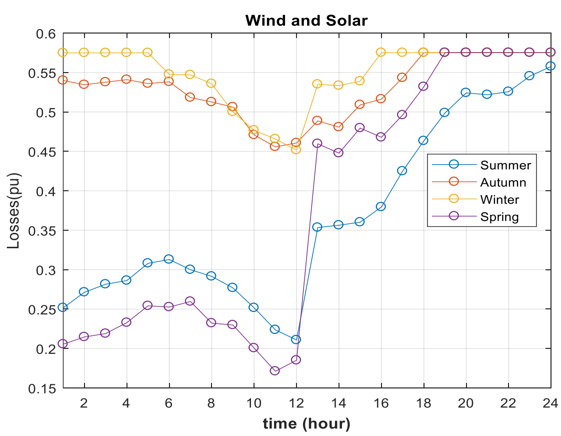


Fig.11. Results of losses with hybrid sources

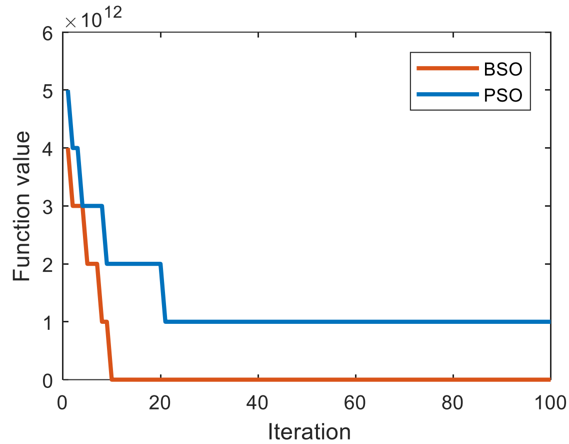


Fig.12. Convergence of the algorithms

Distributed generation resources usually reduce the feeding path, which reduces network losses. A load-proportional DG is installed at the desired location according to the relationship between the loss formulation and the reduced injection capacity. In fact, the effect of these sources is on the voltage and loss profiles, and these two components are closely related. The presence of DGs, as they feed loads locally, also reduces network load (Figure 13) and frees up the different line capacity, which is one of the advantages of these resources. However, some lines may be overloaded if the design is not adequate. Normally, DG reduces line current by feeding part of the network load. However, de-pending on the size and condition of the network, it is possible for the DG current to flow in the opposite direction. If the DG is larger than its loads, part of its current will return to the post. This may not be a problem unless the flow through the post is greater than the conductor capacity. However, this can occur under certain conditions, one of which is the release of loads after the DG due to unpredictable errors. If the DG size is large and the network is designed based on the same assumptions as traditional networks, it may face overcurrent issues. Figures (14, 15) show the load of lines with solar and hybrid resources. Note that, with the hybrid system, the line release space is significantly different than that of the previous two modes. The three wind resources are placed at nodes 30, 24, and 13 of the IEEE 33-bus network. More wind and solar resources were also tested, and their locations are shown in Tables 3 to 5.

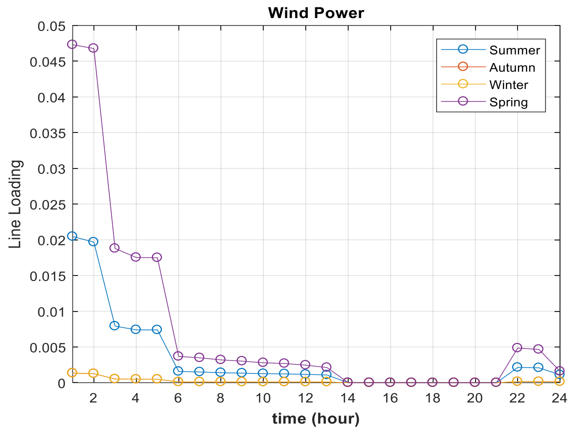


Fig. 13. Load rate of lines in optimal condition with wind resources

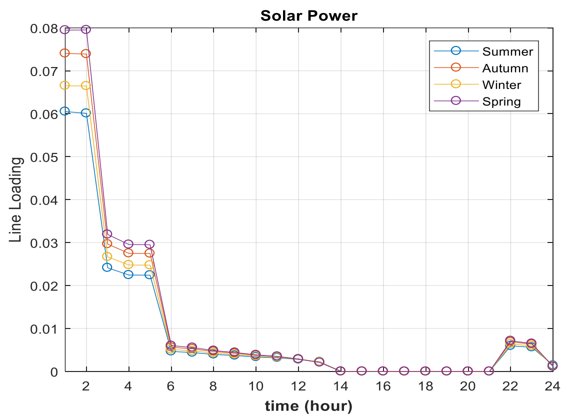


Fig.14. Load rate of lines in optimal condition with solar resources

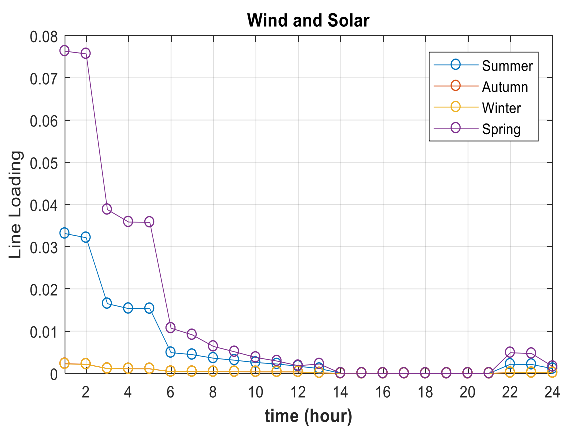


Fig. 15. Load rate of lines in optimal condition with wind and solar resources

TABLE 3
LOCATING WIND RESOURCES IN THE 33-BUS NETWORK

Number of wind resources	Locating resources with BSO	Locating resources with PSO
3	13-24-30	11-24-30
4	4-24-27-30	4-24-27-30
5	7-13-14-29-32	7-13-14-29-32

TABLE 4
LOCATING SOLAR RESOURCES IN THE 33-BUS NETWORK

Number of solar resources	Locating resources sources with BSO	Locating resources with PSO
3	13-24-30	13-24-30
4	11-13-17-27	11-15-17-27
5	13-14-27-29-32	13-14-27-29-30

TABLE 5
LOCATING HYBRID RESOURCES IN THE 33-BUS NETWORK

Number of hybrid resources	Locating resources with BSO	Locating resources with PSO
3	13-24-30	13-24-30
4	11-13-17-27-32	11-16-17-27-32
5	7-13-27-29-32	7-13-27-29-31

IV. Conclusions

The utilization of renewable energy sources, which have a fluctuating nature, has increased the unpredictability of power networks, which poses a number of challenges to their design and development. This study presented the calculation of the probability density function for networks with loads and wind and solar sources with variable output, thus contributing to the minimization of the u coordination in network load and unintentional power equipment output. Sustainable wind and solar power systems were located using the particle swarm optimization algorithm. In this study, the effect of distributed generation on a 33-bus network was analyzed. The optimal location of solar and wind resources was determined by considering seasonal loads and changes in weather conditions such as solar radiation level and wind speed. The coordination of these sources was based on the PSO and BSO algorithms, aiming to reduce the line load. The results show acceptable performance under various conditions, and the presence of DGs reduces network load because they feed loads locally. The optimal results of resources with two algorithms were compared and showed close answers. These systems can be used in remote areas without power grids or even in areas where, despite the existence of a power grid, there is a tendency to use renewable energy. It is presented for future research in this field:

• Reducing voltage fluctuations to achieve the maximum production power from DG sources

• Improving line losses by using compensators

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Farhad Zishan was born in Ardabil, Iran, 1985. He received the B.Sc. degree in Electrical Power Engineering from Islamic Azad University, Ardabil, Iran, in 2014and M.Sc degrees in Electrical Power System, from 2015 to 2017. In 2020, I entered the PhD course in power electricity at Sahand University of Technology. His research interests include renewable energy, distributed generation, optimization and power system .

Ehsan Akbari received the MSc degree from Mazandaran University of Science & Technology (MUST), Babol, Iran, in electrical power engineering in 2014. His research interests include power quality and distribution flexible AC transmission systems (DFACTS), application of power electronics in power systems, power electronic multilevel inverters, smart grids, harmonics and reactive power control, and renewable energy systems.

Abdolreza Sheikholeslami was born in Iran. He received the B.Sc. (Hons.) degree in electrical engineering from Mazandaran University, Babolsar, Iran, in 1979, and the M.Sc. and Ph.D. degrees in electrical power engineering from the University of Strathclyde, Glasgow, U.K., in 1978 and 1989, respectively. He has been an Associate Professor with the Department of Electrical and Computer Engineering, Babol Noshirvani University of Technology, Babol, Iran, since 2009. His current research interests include power electronic, power quality, harmonics, smart grids, and renewable energy.

Nima Shafaghatian received his M.S. degree from Zanjan University and is currently studying Ph.D there. He has authored two articles in the well-known Journals, published by IET and Springer. He has also published two books on renewable energy and the relationship between industry and academia subjects. In addition to studying Ph.D, He is a lecturer at Al-Ghadir University in Zanjan and offers courses in electrical installations, smart home design and specialized language of electricity. His research interests include microgrids, distributed generation and electricity market.