IUST Iran University of Science and Technology

Iranian Journal of Electrical and Electronic Engineering

Journal Homepage: ijeee.iust.ac.ir

Research Paper

Optimum Sizing and Placement of Wind Turbines in Distribution Networks Considering Correlation of Load Demand and Wind Power

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Abstract: Optimal placement and sizing of distributed renewable energy resources (DER) in distribution networks can remarkably influence voltage profile improvement, amending of congestions, increasing the reliability and emission reduction. However, there is a challenge with renewable resources due to the intermittent nature of their output power. This paper presents a new viewpoint at the uncertainties associated with output powers of wind turbines and load demands by considering the correlation between them. In the proposed method, considering the simultaneous occurrence of real load demands and wind generation data, they are clustered by use of the k-means method. At first, the wind generation data are clustered in some levels, and then the associated load data of each generation level are clustered in several levels. The number of load levels in each generation level may differ from each other. By doing so the unrealistic generation-load scenarios are omitted from the process of wind turbine sizing and placement. Then, the optimum sizing and placement of distributed generation units aiming at loss reduction are carried out using the obtained generation-load scenarios. Integer-based Particle Swarm Optimization (IPSO) is used to solve the problem. The simulation result, which is carried out using MATLAB 2016 software, shows that the proposed approach causes to reduce annual energy losses more than the one in other methods. Moreover, the computational burden of the problem is decreased due to ignore some unrealistic scenarios of wind and load combinations.

Keywords: Correlation Modeling, Distribution System, Load Demand, Wind Turbine Allocation and Sizing.

Nomenclature

Indices:

i, j	Index of wind clusters
p, q	Index of cluster data
f	Index of lines
g	Index of generation-load scenarios
b	Index of buses
w	Index of wind power clusters
kw	Index of load clusters associated with w-th wind power clusters

Functions:

$d(.)$	Distance between two data points
$U(.)$	Unit step function
max(.)	Maximum-value function
min(.)	Minimum-value function

Constants:

N_b	Total Number of buses
N_f	Total Number of feeders
N_C	Total Number of generation-load scenarios
v_{ci}	Cut-in speed of wind turbine
v_{co}	Cut-out speed of wind turbine
v_r	Rated speed of wind turbine
P_{rated}	Rated power of wind turbine
gp	DG penetration factor

Iranian Journal of Electrical and Electronic Engineering, 2021.
Paper first received 23 June 2020, revised 20 November 2020, and accepted 26 November 2020.
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https://doi.org/10.22068/IJEEE.17.3.1916

W	Number of wind power clusters
$it_{\max}$	Maximum number of iterations
N_{pop}	Number of population
P_{best}	The best position ever visited by a particle
G_{best}	The global best position in the entire swarm
ω	The inertia weight
c_1, c_2	Acceleration constants
$V_{\max}$	Upper limit of bus voltage magnitude
$V_{\min}$	Lower limit of bus voltage magnitude
$I_f^{\max}$	Upper limit of current magnitude of feeder f

Variables:

v	Wind speed
V_b	Voltage magnitude of bus b
I_f	Current magnitude of feeder f
x	A data in a cluster
$d_p^{\max}$	Maximum distance between data of point p and other points of the same cluster
C_i	The cluster number i
N_i	Number of data at cluster i
$\bar{d}_{c_i}$	Average of maximum distance of all data at cluster i
m_i	Center point of cluster i
$d_{c_i}^{\min}$	Minimum distance between two cluster centers related to an IPSO particle.
$V_{g,b}$	Voltage of bus b at scenario g
V_b^E	Expected voltage of bus b
$Pr(C_g)$	Probability of scenario g
P_{loss_g}	Annual network energy loss at scenario g
$P(v)$	Output power of wind turbine at wind speed v
$P_{D,b}$	Load demand at bus b
$P_{DG,b}$	DG installed capacity at bus b
$N_{DG,b}$	Number of DG units installed at bus b

1 Introduction

DUE to the increasing use of electricity in distribution networks, the utilization of distributed generations (DGs) has increased. The use of DGs brings generation resources closer to the load points resulting in power quality improvement, enabling the management of lines' congestion, and reducing the energy losses by optimum power scheduling [1]. To achieve the aforementioned targets, the optimum sizing and placement of DGs in distribution networks are essential.

Generally, DGs can be divided into two groups. The first one is dispatchable units such as conventional fossil fuel DGs with schedulable output powers. The second group is renewable DGs with non-dispatchable output powers, which depend on the stochastic behavior of wind speed or solar irradiance.

1.1 Background and Motivation

The placement issues of dispatchable DGs have been investigated in many types of research. Dynamic programming [2] and simulated annealing algorithm [3] have been used to find the optimum placement and sizing of gas-fired DGs aiming at loss reduction, reliability and voltage profile improvement. Mixed-integer linear programming [4] and genetic algorithm [5] have also been used for dispatchable DGs' sizing and allocation in a distribution system to maximize the total system benefit. However, in the mentioned researches, the maximum capacities of DG units and the peak demand value have been considered as the output power of DG units and the distribution system load, respectively. Considering the peak level of demand for entire periods of planning leads to calculating the power loss more than the actual one. Since electricity consumptions are not fixed at peak value in all periods, the network losses are lower than the calculated one and as a result, placement and sizing of DGs are not optimally carried out.

In [6], the network load has been divided into three levels: low, intermediate and high; then, the problem of locating and sizing fossil fuels DGs has been solved to reduce losses and increase the voltage stability. Although the use of three-level load provides a more accurate calculation of network losses, in practice, due to the different levels of network consumptions, the estimated losses and costs are higher than the actual value. In [7], a multilevel load duration curve (LDC) has been considered. Then, the problem of location and sizing of fixed DGs has been carried out by the triangular fuzzy number method aiming at reducing losses and improving the voltage profile.

Among the various types of DGs, renewable DGs are considered by many countries in terms of numerous benefits if compared to fossil fuels ones. Renewable energy such as wind and solar is not just a short-term solution to energy needs, but a continuous and endless energy source with few environmental impacts.

Unlike fossil-fuelled DGs, the available capacity of renewable DGs is variable. In addition to the high cost of investment, the issue of the uncertain nature of primary resources is a challenge to use renewable DGs. An intermittent generation goes back to the random nature of wind speed and solar irradiance which causes the inability of renewable DGs to supply a stable output [8].

Problems of determining the type, size, and location of renewable DGs aiming at the capital cost [9, 10], minimizing losses [11, 12], and expected energy not served [13] are addressed by researchers.

To consider the stochastic nature of renewable energies, the uncertainty associated with their output powers and available capacities should be modeled with DG placement and sizing problems.

In [9], the problem of DGs placement and sizing in a microgrid has been formulated by modeling wind speed, solar irradiance, and load demand by Weibull, beta, and normal distribution functions, respectively. The problem has been solved by the imperialist competitive algorithm and obtained results have been compared with the Monte Carlo simulation method.

In [10], an optimal location and sizing of renewable DGs aiming at minimizing total cost has been modeled by the Monte Carlo method in which the wind speed and load demand are respectively presented by Weibull and normal distribution functions.

In [14], a stochastic distribution feeder reconfiguration problem for systems with wind turbines and fuel cells has been presented. An interactive fuzzy satisfying optimization algorithm based on adaptive particle swarm optimization (APSO) has been employed to solve the problem with multi-objective functions including the total electrical energy losses, the cost of electrical energy generated, the total emissions produced, and the bus voltage deviation. A probabilistic power flow based on the point estimate method has been used to include uncertainty in the wind power output and load demand, concurrently.

In [15], the uncertainty of renewable generations within the distribution reconfiguration problem has been modeled by Monte Carlo simulation. In [16], an optimal location and sizing of renewable DGs aiming at minimizing total power losses has been solved by the ant lion optimization algorithm. Using loss sensitivity factors, the most candidate buses for installing DG has been firstly introduced and the optimization algorithm has been used to deduce the locations and sizing of DG from the elected buses.

The aforementioned references also considered one level (i.e. peak load) or three-level LDC that potentially leads to calculating the loss value much higher than the real one. Also, in a real case that the load demand is low and the renewable generation is high, the aforementioned methods may lead to violation of the thermal limits of lines and/or voltage magnitude limits of buses.

The wind turbine placement problem considering optimal power flow has been presented in [17] in which the total energy losses have been minimized and the net present value associated with the wind turbine investment has been minimized.

In [11, 12], the problem of DG placement and sizing has been formulated as mixed-integer nonlinear programming aiming to minimize the annual energy losses. The proposed method of [11, 12] is based on producing a probabilistic generation-load model that combines all possible operating conditions of the renewable DG units with their probabilities. In [11], the probability of the wind speed states and the load demand states are calculated while they have been assumed to be independent (uncorrelated). In other words, the diurnal and seasonal components of the wind speed and the load demand are neglected. Based on this assumption, the probability of any combination of wind power and load demand can be obtained by multiplying the two related probabilities. In this method, for each wind generation state, all load states are considered to have the same probability while in practice some load states cannot occur for a given amount of wind capacity. As a result, ignoring the correlation between the wind generation states and the load states will increase the computational burden and so not provide the optimal solution.

In [18], an optimal sizing and placement method of a wind farm in a radial distribution network has been presented in which the impacts of forced outages of wind turbines have been considered. To assess this reliability criterion, a sequential Monte Carlo simulation-based technique has been implemented to evaluate the performance of the wind turbines with varying capacities at different locations in the distribution network. However, the uncertainty associated with wind power generation has not been taken into account. A planning method for wind turbines and photovoltaic units based on improved Harris Hawks optimizer using Particle swarm optimization has been presented in [19]. The uncertainties corresponding to the intermittent behavior of photovoltaics and wind turbines power generations have been taken into consideration using probability distribution functions. The objective functions included power loss reduction, voltage improvement, system stability, and yearly economic saving. However, the correlation between renewable generation and load demand has not been considered. In [20], multi-objective particle swarm optimization along with preference order ranking-based approach for placement and sizing of wind and solar-based generation units has been proposed. Uncertainty in solar irradiance, wind speed, and load have been modeled using Monte Carlo simulation where different scenarios have been generated. A priority vector has been implemented for distributed generations and capacitor placement using the analytic hierarchy process to reduce the search space and computational time.

In [21], a method for optimal sizing and placement of battery energy storage systems in the distribution network aiming at minimizing total cost and maximizing reliability index has been proposed. Also, Monte Carlo simulation has been implemented to model the uncertainties associated with load demand as well as the output power of the wind turbines and photovoltaic units. In [22], a two-stage coordinated method for placement of distributed generators such as wind turbines in a microgrid considering the uncertainties corresponding to renewable energy distributed resources has been proposed. The placeman problem has been modeled as a two-stage coordinated stochastic optimization model, where the long-term distributed generator investment has been determined at the first stage and operation decisions have been assigned at the second stage. In [23], a probabilistic method for optimal placement and sizing of wind turbines in distribution networks has been assessed. The objective functions were to reduce loss and improve voltage profile and stability index were the uncertainty of wind generation and the network demand has been modeled based on

Monte Carlo simulation. The result evidenced that the probabilistic method was more realistic and accurate than the deterministic method due to consideration of load and wind generation intrinsic changes with all possible probabilities.

In [24], an optimal wind turbine placement method based on the generation of pseudo-random numbers has been presented. However, the uncertainty corresponding to wind speed and load demand has not been modeled.

In all previous studies of wind turbine placement, no attention has been paid to the correlation between wind power generation and load demand. But as it turns out, there is a significant correlation between these two parameters that can help make the placement problem results more realistic. In [25], a security-constrained unit commitment method considering load and wind uncertainties has been presented. Also, load and wind variability correlations in constructing uncertain intervals aiming at eliminating unlike-to-happen scenarios have been taken into account.

On the other hand, considering all possible states of wind generation and load demand without considering their correlation, the volume of input data in the form of scenarios is very high. It leads to the burden of the computation process where its convergence becomes more difficult.

1.2 Contributions

In this paper, a new approach for modeling the uncertainty associated with the load demand and wind generations, considering their correlation is presented. In the proposed method, the clustering of wind generations and load demands is carried out by the k-means method and the planning optimization is solved by particle swarm optimization (PSO). To this end, a software has been developed in MATLAB 2016 programming environment. In the first step of the software, wind generation data are clustered and in the second step, all load data associated with each wind generation group are clustered. Since considering the correlation between wind generations and load demands significantly reduces the number of clusters, the size and computation burden of the problem will be decreased. Then, by a contribution of different clusters, the optimal placement of DGs with the aim of reducing annual energy losses is achieved. The main contributions of the paper are listed as follows:

- To propose a new method to model the correlation between wind generation data and demand data by creating realistic scenarios.
- To implement the modified k-means clustering method by adopting an integer-based PSO (IPSO) algorithm with the k-means algorithm to achieve the optimum number of data clusters.

1.3 Paper Organization

The rest of the paper is organized as follows: Section 2 describes the proposed hybrid wind generation and load demand modeling approach. Section 3 explains the objective function and constraints of the DG planning problem. Section 4 presents and discusses the results of the case study carried out by using real data to analyze the applicability of the proposed framework. Finally, Section 5 concludes the paper.

2 The proposed Hybrid Wind and Load Modeling Approach

Usually, the capacity outage probability table (COPT) is used to model the available capacity of wind power plants. COPT contains the capacity levels of wind generations along with the probability of each level. To specify the number and consequently the probability of wind generation levels, data clustering algorithms are commonly used. Since there is a huge number of load data, load data clustering should be accomplished too.

In previous works, wind and load data clustering have been performed separately, assuming independent behavior of them [11, 12]. In this way, the probability of each wind capacity level is the same for all load levels. Since in practice some load levels do not occur for a given wind generation level, the accuracy of these methods is challengeable. To address this challenge, in this paper, at first the wind generation data are clustered to specify generation levels and related probabilities. Then associated load data of each generation level (i.e. the load data synchronized with the wind data of the cluster) are clustered. Using this method, the correlation between load and wind generation data is taken into consideration. In this approach, since all impracticable set of generation-load pairs are omitted, the number of generation-load pairs will be decreased. Also, the numbers of load levels associated with various generation levels will not be equal.

The proposed clustering approach of wind capacity

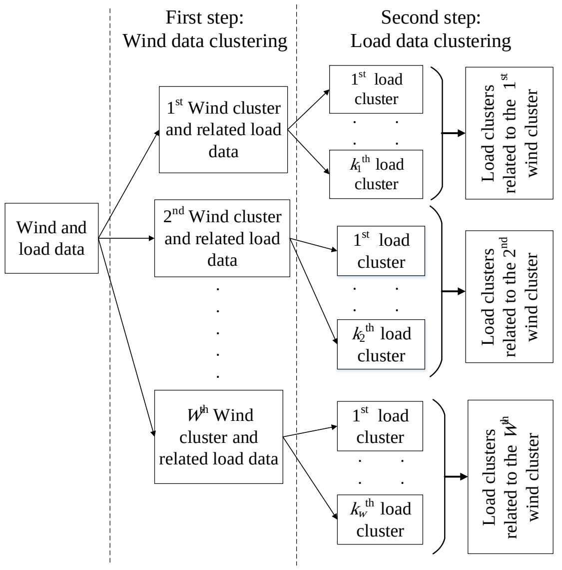


Fig. 1 Wind and load data clustering approach.

and load data is depicted in Fig. 1.

In the first step of Fig. 1, the wind generation data are clustered in W levels, and then the associated load data of *w*-th generation level are clustered in k_w levels. It is important to mention that k_w (for w=1, 2, …, *W*), may have up to W different values while in previous works all k_w were the same.

2.1 Wind Power Clustering

The output power of a wind turbine can be formulated based on wind speed as described in (1) [11].

$$P(v)=\begin{cases}0 & 0\le v\le v_{ci}\\ P_{rated}\times\dfrac{(v-v_{ci})}{(v_r-v_{ci})} & v_{ci}\le v\le v_r\\ P_{rated} & v_r\le v\le v_{co}\\ 0 & v_{co}\le v\end{cases} \tag{1}$$

Regarding wind speed data, the associated turbine output powers are calculated and clustered. After calculating, the wind-generated powers are clustered in several clusters to decrease the computational burden. In this paper, the k-means clustering approach is used for data clustering [18]. In the k-means clustering algorithm, the number of clusters should be defined in advance. It is noted that the lower number of clusters may lead to loss of accuracy and on the other hand, the higher number of clusters may increase the computational burden and decreases the clustering advantages. Thus, to find the optimum number of data clusters, the IPSO method is used.

Each IPSO particle is a candidate solution for the number of data clusters. As the initial particles of the IPSO algorithm, several natural numbers in the closed interval between two and the maximum number of wind power data are randomly produced. These particles are candidate numbers for wind capacity clusters. For each particle, the same numbers of wind power data are randomly selected as the cluster centers. In each iteration of the k-means clustering algorithm, each wind power data is assigned to a cluster that has the minimum distance to the cluster center. After assigning all wind power data to clusters and for the next iteration of the k-means algorithm, the average value of data in each cluster is selected as the new cluster center and again, the data assigning procedure is performed. Data clustering for each IPSO particle is stopped when there are no changes in cluster centers between two consecutive iterations. After stopping the k-means algorithm, the CS index is calculated for each IPSO particle as bellows [19]:

$$d_p^{\max}=\max_{\substack{x_q\in c_i\\ x_q\neq x_p}} d\left(x_p,x_q\right)\quad \forall x_p\in c_i \tag{2}$$

$$\bar{d}_{c_i}=\frac{1}{N_i}\sum_{x_p\in c_i} d_p^{\max} \tag{3}$$

$$d_{c_i}^{\min}=\min_{j\neq i} d\left(m_i,m_j\right) \tag{4}$$

$$CS=\frac{\sum_i \bar{d}_{c_i}}{\sum_i d_{c_i}^{\min}} \tag{5}$$

In (2) to (4), $d_p^{\max}$ is the maximum distance between point p and other points of the same cluster. Additionally, $\bar{d}_{c_i}$ is the average value of $d_p^{\max}$ of all points belonging to the *i*-th cluster. This value shows the diversity of the data of *i*-th cluster. Moreover, $d_{c_i}^{\min}$ is the minimum distance between the *i*-th cluster center and all other clusters' center related to an IPSO particle. The index CS in Eq. (5) shows the ratio between the sum of $\bar{d}_{c_i}$ to the sum of $d_{c_i}^{\min}$ all related to an IPSO particle. The lower value of CS means the lower diversity of the clusters' data and the higher distance of clusters' centers at the same time. Therefore, the objective function of IPSO algorithm, as presented in (6), is to minimize the CS value as the minimum CS value particle is the most desirable particle.

$$OF:\min\left(CS=\frac{\sum_i \bar{d}_{c_i}}{\sum_i d_{c_i}^{\min}}\right) \tag{6}$$

After calculating CS values for all particles in each IPSO iteration, the next position of particles is calculated based on particles personal and global best position and for the new particle set, the wind power data clustering is accomplished. Finally, when the stopping criterion of IPSO is achieved, the wind capacity data are clustered in an optimum number of clusters. It is noted that during the IPSO procedure and after updating particles' position in each iteration, the non-integer particles are rounded to the nearest integer number.

2.2 Load Demand Clustering

For each wind capacity cluster, the associated load data are clustered using the k-means clustering algorithm and IPSO optimization algorithm, as previously described, to produce the generation-load pairs. The probability of each generation-load pair is equal to the multiplication of their own probabilities. The flowchart of the combined wind generation-load data clustering is presented in Fig. 2.

As shown in Fig. 2, two subsections have been marked in two rectangles. The left subsection, surrounded by a dash-dotted rectangle, shows the wind generation clustering procedure and the right side one, surrounded by a dotted rectangle, shows the clustering procedure of load data related to each wind cluster.

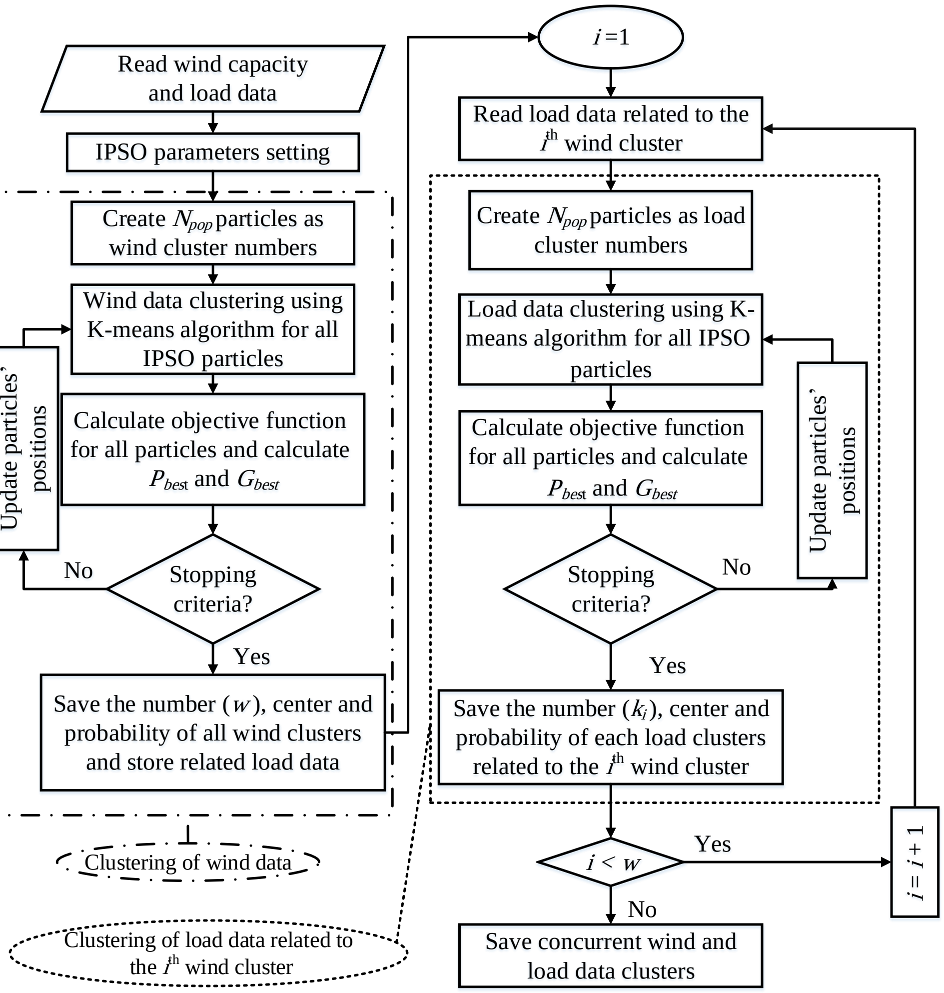


Fig. 2 Wind and load data clustering flowchart.

3 Problem Formulation and Optimization Technique

In this paper, the objective function of the optimal allocation of wind turbines in distribution systems is to minimize the annual energy loss. In the following, the objective function (OF) and constraints are described.

3.1 Objective Function

In order to compare the result of this study with previously published work, the same objective function as considered in [11, 12] is considered in this paper. Therefore the objective function of this paper is to minimize the annual energy loss that is formulated in (7):

$$OF : \min\left(\left[\sum_{g=1}^{N_c} P_{loss\,g} \times \Pr\left(C_g\right)\right] \times 8760\right) \tag{7}$$

The average value of power loss is equal to the sum of all generation–load scenarios' power loss multiplied by their own probability. To achieve the annual energy loss in (7), the average value of power loss is multiplied by 8760.

3.2 Constraints

The constraints of each solution candidate are DG penetration limit, voltage magnitude limit of busses, and the current limit of lines. For each candidate solution, load flow is performed to obtain the voltage of buses and currents of lines in all scenarios.

3.2.1 DG Penetration Limit

To avoid the difficulties raised by high DG penetration in distribution networks, such as protection problems, maximum DG installed capacity should be lower than a predefined value (gp) percentage of the maximum load of the network [20]. DG penetration limit is formulated as below:

$$\sum_{b=1}^{N_b} P_{DG,b} \le gp \times \sum_{b=1}^{N_b} P_{D,b} \tag{8}$$

3.2.2 Buses Voltage Magnitudes Limits

The voltage magnitude limit of buses is described by (9). This constraint ensures that the voltage magnitudes remain within their permissible ranges.

$$V^{\min} \le V_b \le V^{\max} \qquad \forall b \in N_b \tag{9}$$

3.2.3 Lines Current Limits

Lines current in all situations should be less than the cable's maximum allowable current (i.e. cable's thermal limit). The Line's current limit is presented in (10).

$$I_f \le I_f^{\max} \qquad \forall f \in N_f \tag{10}$$

3.3 Optimization Technique

In this paper, the application of the proposed uncertainty modeling approach, designated for the wind generation and load demand, is evaluated through determining the optimum size and location of the wind turbines within the distribution system in terms of an IPSO optimization problem.

It is noticeable that after updating the particles' position along with the IPSO procedure, non-integer particles are substituted by the nearest integer number. The flowchart of the wind turbines' allocation is depicted in Fig. 3.

4 Numerical Results

The presented problem of this paper aims to minimize

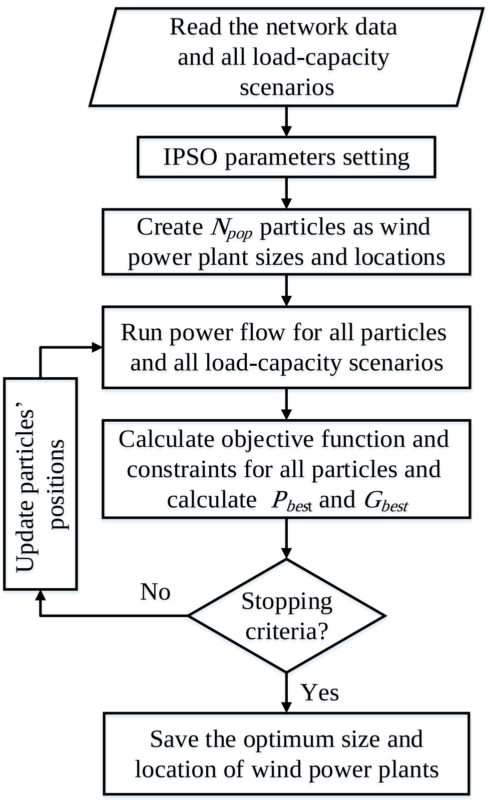


Fig. 3 Flowchart of the wind turbines' allocation in the distribution system.

the annual energy loss of the distribution system. Additionally, the results of the proposed method are compared with ones achieved by other methods in terms of accuracy as well as the computational burden.

4.1 Simulation Data

To evaluate the effectiveness of the proposed method, the well-known IEEE 33-bus distribution test network, shown in Fig. 4, has been considered [21]. Since the hourly load data is needed for the studies of the paper and this data is not available for the IEEE 33-bus distribution test system, the real historical load data pertaining to a specific feeder of Iran's distribution network, located in Mazandaran province, has been used. Since the peak load of the mentioned feeder is 8.73 MW and 5.40 MVAr, while the same data for the IEEE 33-bus distribution test system are 3.90 MW and 2.30 MVAr [21], the maximum active and reactive powers of all nodes of the IEEE 33-bus test system are multiplied by $\left(\frac{8.73}{3.90}\right)$ and $\left(\frac{5.40}{2.30}\right)$, respectively.

Wind turbine characteristics are given in Table 1.

It is assumed that the wind turbines are operated under a unity power factor [11].

The IPSO parameters are given in Table 2.

In this case study, all busses are candidates for wind turbines installation. Thus, 33 decision variables are assigned to the candidate buses for DG installation. The structure of the IPSO candidate solution is presented in Fig. 5.

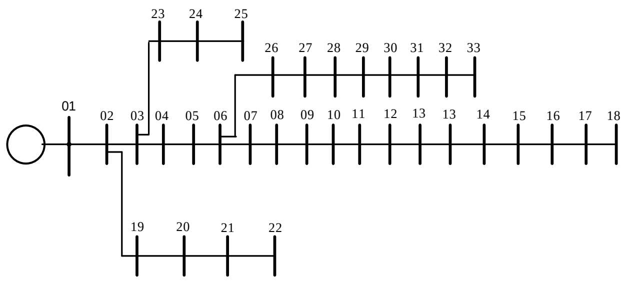


Fig. 4 IEEE 33-bus test system.

Table 1 Wind turbine characteristics.

Parameter [unit]	Value
Rated power [MW]	0.66
Cut-in speed [m/s]	4
Rated speed [m/s]	14
Cut-out speed m/s]	25

Table 2 PSO algorithm parameters.

Setting parameters	Value
N_{pop}	100
$it_{\max}$	100
c_1, c_2	1.4
ω	0.72

$$\boxed{N_{DG,1}}\boxed{N_{DG,2}}\cdots\boxed{N_{DG,16}}\boxed{N_{DG,17}}\cdots\boxed{N_{DG,32}}\boxed{N_{DG,33}}$$

Fig. 5 Structure of the IPSO candidate solution.

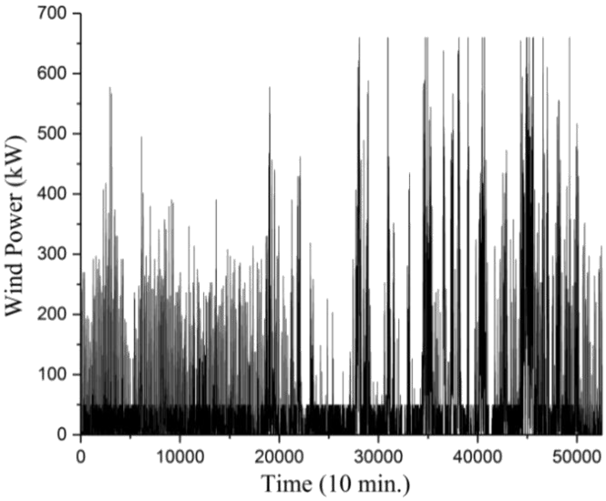


Fig. 6 Structure of the IPSO candidate solution.

Table 3 Cluster data of available output power of each wind turbine.

Cluster number	The output power of the cluster center [kW]	The output power of the cluster center [pu]	Probability [%]
1	3.6	0.00548	41.21
2	30.6	0.046	30.16
3	78	0.11	6.54
4	142.7	0.21	5.75
5	210.8	0.32	6.06
6	280.4	0.42	4.35
7	352.48	0.53	2.93
8	438.33	0.66	1.69
9	543	0.82	0.78
10	660	1	0.53

The maximum penetration of DG in the distribution system is set at 40% [22]. According to this limitation, the maximum installed capacity of the wind turbines in the network is 3.49 MW. As the nominated power of selected wind turbines is 660 kW, each variable in Fig. 5 can be an integer value in the range of [0, 5] while the sum of variables pertaining to a particle should not exceed 5. As a result, the maximum possible capacity for the wind turbine installation in each candidate bus, as well as the entire network, is obtained 3.3 MW.

4.2 Wind and Load Clustering

The wind speed data has been provided from wind speed measurements by 10-minutes intervals in a region of Iran. The wind speed is converted to the available power output based on the power-speed curve of the wind turbine, which is graphically depicted in Fig. 6.

As previously mentioned, the k-means clustering method is used to cluster the wind power data. The resultant clusters pertaining to the available output power of each wind turbine are presented in Table 3.

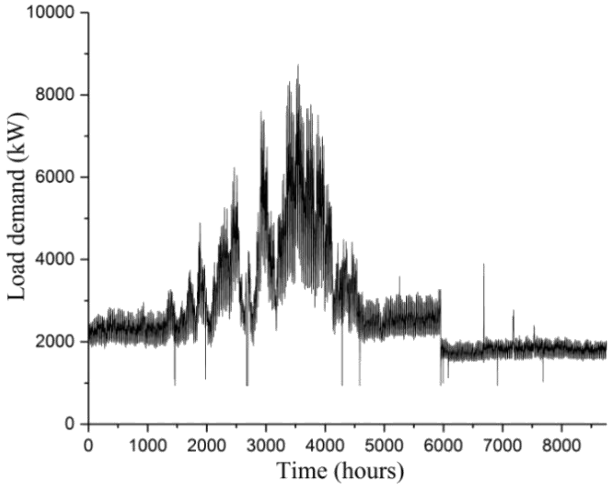


Fig. 7 Hourly load demand data in a year.

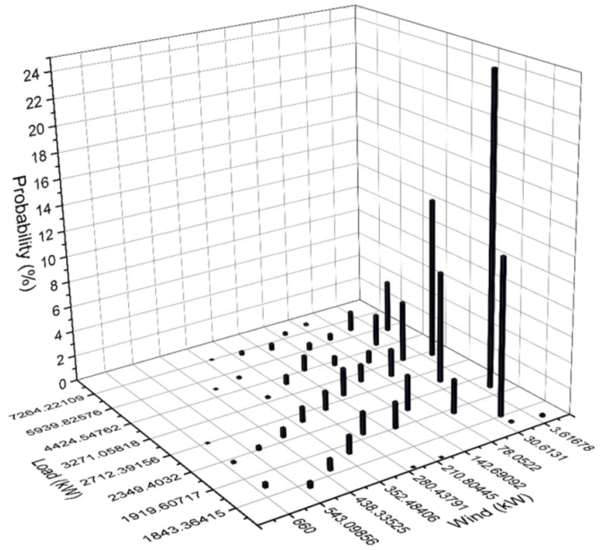


Fig. 8 Wind-load clusters and their probability when their correlation is considered.

The hourly load demand data of the mentioned region has been depicted in Fig. 7.

To cluster the load demand data, the load data corresponding to each wind cluster is firstly determined. Then, each group of load data is clustered via the k-means method. The resultant wind-load clusters along with their occurrence probability are depicted in Fig. 8, in which the X-axis is related to the wind capacity with center of wind power clusters and the Y-axis is related to load demand; the probability of simultaneous occurrence of corresponding wind and load clusters are shown in Z-axis.

The wind-load clusters and their occurrence probability are also presented in Table 4. Regarding to Table 4 and Fig. 8, the total number of load and wind clusters are 43, in which 2 to 6 load cluster are designated to each wind cluster. The number of load clusters depends on the diversity of load demand data

Table 4 Data of wind generation and their corresponding load demand clusters.

Cluster number	Wind generation		Load demand power		Wind-load clusters probability [%]
	Cluster center [kW]	Probability [%]	Cluster center [kW]	Probability [%]	
1	3.6	41.2	951.81	0.4757	0.25
2			1996.66	58.80	24.26
3			3097.59	30.68	12.66
4			5227.67	10.04	4.14
5	30.6	30	953.5	0.46	0.13
6			1843.36	40.66	12.23
7			2494.438	29.1	8.75
8			3271.06	15.97	4.80
9			4426.84	8.46	2.55
10			6067.78	5.35	1.60
11	78	6.5	1887.73	41.01	2.68
12			2742.44	33.87	2.21
13			4197.15	14.84	0.97
14			5959.64	7.85	0.51
15			7662.84	2.43	0.16
16	142.7	5.75	2063.43	48.41	2.78
17			3001.09	24.40	1.40
18			4307.07	13.30	0.76
19			5939.83	9.92	0.57
20			7561.96	3.97	0.23
21	210.8	6	935.30	0.19	0.01
22			1919.60	34.27	2.07
23			2730.16	36.35	2.20
24			4424.55	20.53	1.24
25			6794.53	8.66	0.52
26	280.4	4	935.30	0.53	0.05
27			1959.95	40.94	1.80
28			2706.06	34.90	1.51
29			4303.87	16.8	0.73
30			6806.16	6.83	0.29
31	352.48	2.9	1875.60	48.64	1.42
32			2530.67	40.85	1.19
33			4089.37	4.67	0.14
34			5031.47	5.06	0.15
35			7264.22	0.78	0.02
36	438.33	1.69	1854.43	53.38	0.90
37			2437.55	43.91	0.74
38			4785.656	2.71	0.04
39	543	0.78	1833.35	59.42	0.47
40			2349.40	40.58	0.33
41	660	0.537	1861.16	70.21	0.38
42			2312.29	25.53	0.14
43			2712.39	4.26	0.02

corresponding to the wind data in each wind cluster.

The difference of load clusters number in various wind clusters shows that the best number of generation–load pair scenarios is not achieved by multiplying their own states number. Also the same for scenarios' probabilities.

The advantage of the proposed method is considering the correlation between the wind output power and load demand, resulting in realistic scenarios, that reduces the number of the scenarios and also the burden of computation.

To compare the result of the proposed method with the one in other clustering methods in which the wind output power and load demand are separately clustered, the hourly load demand has been separately clustered and the results have been given in Table 5.

According to Tables 3 and 5, if the correlation between wind power and load demand are neglected [11], the results are 80 clusters, which are depicted in Fig. 9 along with their occurrence probability.

In Fig. 9, the center of clusters and their probabilities are not the same as the ones given in Fig. 8 (or Table 4). By comparison, it can be concluded that: 1) the probability of each load cluster is not a constant value for all wind clusters; 2) some of the clusters created based on [11] has a zero probability of occurrence in practice. In addition, there are some clusters that have been neglected while they have a considerable probability of occurrence. For example, let consider the state of Fig. 9, in which wind power and load demand are 660 kW (i.e. 1 pu) and 6962.12 kW (i.e. 0.8 pu), respectively, with the probability of 1.31%. However, according to Table 4, the probability of this state is zero. Also, the state in which the wind power and load demand are 660 kW (i.e. 0.216 pu) and 7561.96 kW (i.e. 0.87 pu) respectively, has the occurrence probability of 0.23% in Table 4. However, in the probability multiplying

Table 5 Cluster data of load demand.

Cluster number	The demand of load cluster center [kW]	[pu]	Probability [%]
1	954.01	0.10	0.53
2	1723.70	0.19	21.7
3	2079.243	0.24	25.6
4	2565.40	0.29	22.5
5	3227.88	0.37	13.5
6	4238.10	0.48	8.9
7	5511.828	0.63	4.8
8	6962.12	0.8	2.47

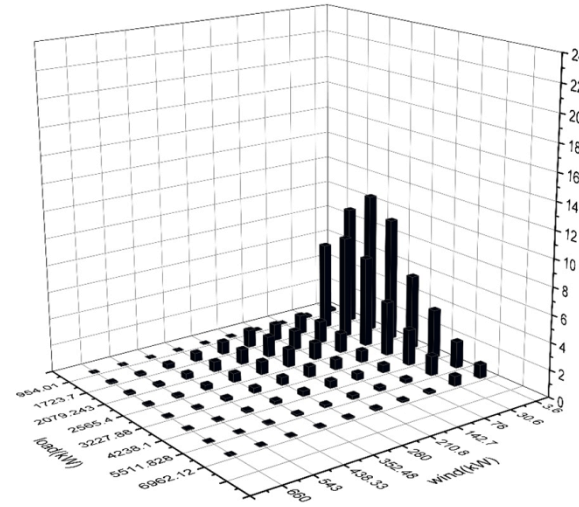


Fig. 9 Wind-load clusters and their probability without considering their correlation.

method, the occurrence of this state is neglected.

Both of the above-mentioned situations may result in inaccuracy and errors for the optimum solutions of DG sizing and placement problem. Nevertheless, in the proposed method, these situations are abandoned.

4.3 Wind Turbines Sizing and Allocation

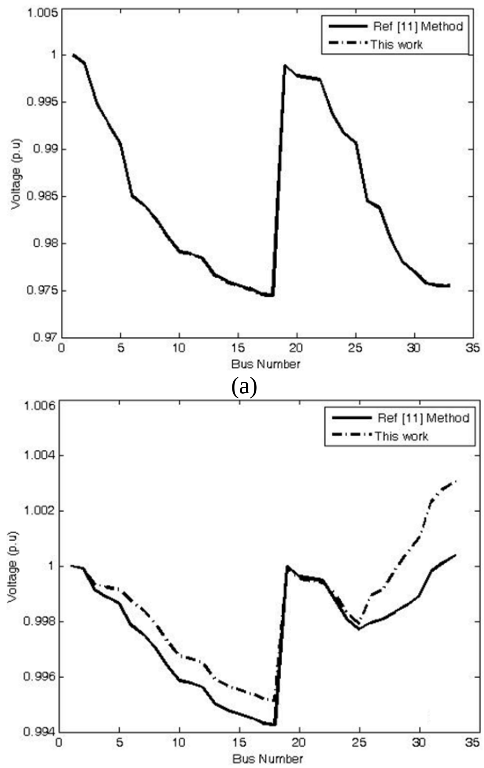
To evaluate the efficiency of the proposed method, the wind turbines sizing and placement problem aiming at annual energy loss minimization has been carried out using the proposed method and the one presented in [11]. The obtained comparative results are presented in Table 6. To better evaluate of two methods, the annual energy loss has been also calculated based on the data given in Table 5 while no DGs are installed. In the second state simulation, the results are based on the method and objective function of [11] while the required data is given from the combination of data in Tables 3 and 5. The value of annual energy losses in the second and third states have been calculated based on the data given in Table 4.

The obtained results illustrate that the objective function and the annual energy loss values obtained via the proposed method are 25.76% and 12.5% less than the ones calculated in [11], respectively.

The voltage profiles of the network resulted by two methods have been drawn in Fig. 10. The voltage profiles correspond to the two clusters in which the maximum voltage drops and voltage rise occur.

Table 6 Simulation results.

Case No.	Description	DG Capacity (Bus No.)	O.F. Value [MWh]	Annual energy losses, [MWh]
1	No DGs	0 MW	–	346
2	By method of [11]	2× 0.66 MW (18) 1× 0.66 MW (31) 2× 0.66 MW (32)	330	280
3	This paper	1× 0.66 MW (18) 2× 0.66 MW (31) 2× 0.66 MW (32)	245	245



(b)

Fig. 10 Voltage profile of the network in a) maximum voltage drop state and b) maximum voltage rise state.

In Fig. 10 (a), maximum voltage drop happens when the wind output power and load demand are 3.6 kW and 5227 kW, respectively. Regarding the Fig. 10 (b), the maximum voltage rise occurs when the wind output power and load demand are 660 kW and 1800 kW, respectively. As shown, the voltage magnitudes are kept within the allowable limits in both methods.

The expected value of the voltage at the system buses in the two states of before and after installing the wind turbines have been calculated based on (11) and graphically shown in Fig. 11. The result shows that by sitting and sizing of wind turbines based on the proposed method, the voltage profile is improved.

$$V_b^E = \sum_{g=1}^{N_c} \Pr\left(C_g\right) \times V_{g,b} \qquad \forall b \in N_b \tag{11}$$

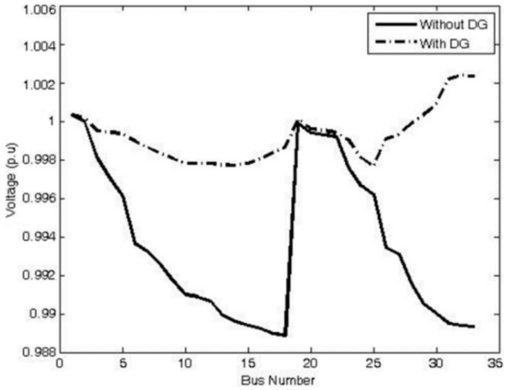


Fig. 11 Expected voltage value profile of the network before and after wind turbines installation.

5 Conclusion

This paper presented a new approach for simultaneous uncertainty modeling of wind power and load demand. Using k-means and IPSO algorithms, the real data of wind speed and load consumption have been clustered employing the proposed method.

Afterward, the results have been used to find the optimum sizing and placement of wind turbines in distribution networks. To evaluate the efficiency of the proposed method, the obtained results have been compared with ones achieved by one of the prevalent methods.

The comparison evidenced that the proposed method leads to a better solution with 12.5% lower annual energy losses. Also, the number of simulation states has been reduced by 46% leading to a considerable reduction in computation time.

References

[1] S. C. E. Jupe, P. C. Taylor, and A. Michiorri, "Coordinated output control of multiple distributed generation schemes," *IET Renewable Power Generation*, Vol. 4, No. 3, pp. 283–297, May 2010.

[2] N. Khalesi, N. Rezaei, and M. R. Haghifam, "DG allocation with application of dynamic programming for loss reduction and reliability improvement," *International Journal of Electrical Power & Energy Systems*, Vol. 33, No. 2, pp. 288–295, Feb. 2011.

[3] J. M. Nahman and D. M. Peric, "Optimal Planning of Radial Distribution Networks by Simulated Annealing Technique," *IET Renewable Power Generation*, Vol. 23, No. 2, pp. 790–795, May 2008.

[4] S. Porkar, P. Poure, A. Abbaspour-Tehrani-fard, and S. Saadate, "Optimal allocation of distributed generation using a two-stage multi-objective mixed-integer-nonlinear programming," *European Transactions on Electrical Power*, Vol. 21, No. 1, pp. 1072–1087, Jan. 2011.

[5] H. Falaghi, C. Singh, M. R. Haghifam, and M. Ramezani, "DG integrated multistage distribution system expansion planning," *International Journal of Electrical Power & Energy Systems*, Vol. 33, No. 8, pp. 1489–1497, Oct. 2011.

[6] B. Poornazaryan, P. Karimyan, G. B. Gharehpetian, and M. Abedi, "Optimal allocation and sizing of DG units considering voltage stability, losses and load variations," *International Journal of Electrical Power & Energy Systems*, Vol. 79, pp. 42–52, Jul. 2016.

[7] M. Esmaeili, M. Sedighizadeh, and M. Esmaili, "Multi-objective optimal reconfiguration and DG (Distributed Generation) power allocation in distribution networks using Big Bang-Big Crunch algorithm considering load uncertainty," *Energy*, Vol. 103, pp. 86–99, May. 2016

[8] R. H. A. Zubo, G. Mokryani, H. S. Rajamani, J. Aghaei, T. Niknam, and P. Pillai, "Operation and planning of distribution networks with integration of renewable distributed generators considering uncertainties: A review," *Renewable and Sustainable Energy Reviews*, Vol. 72, pp. 1177–1198, May. 2017.

[9] N. Nikmehr and S. Najafi-Ravadanegh, "Optimal operation of distributed generations in micro-grids under uncertainties in load and renewable power generation using heuristic algorithm," *IET Renewable Power Generation*, Vol. 9, No. 8, pp. 982–990, Nov. 2015.

[10] A. Soroudi, R. Caire, N. Hadjsaid, and M. Ehsan, "Probabilistic dynamic multi-objective model for renewable and non-renewable distributed generation planning," *IET Generation, Transmission & Distribution*, Vol. 5, No. 11, pp. 1173–1182, Nov. 2011.

[11] Y. M. Atwa and E. F. El-Saadany, "Probabilistic approach for optimal allocation of wind-based distributed generation in distribution systems," IET Renewable Power Generation, Vol. 5, No. 1, pp. 79–88, Jan. 2011.

[12] Y. M. Atwa, E. F. El-Saadany, M. M. A. Salama, and R. Seethapathy, "Optimal renewable resources mix for distribution system energy loss minimization," *IET Renewable Power Generation*, Vol. 25, No. 1, pp. 360–370, Feb. 2010.

[13] G. Muñoz-Delgado, J. Contreras, and J. M. Arroyo, "Multistage generation and network expansion planning in distribution systems considering uncertainty and reliability," *IET Renewable Power Generation*, Vol. 31, No. 5, pp. 3715–3728, Sep. 2016.

[14] A. R. Malekpour, T. Niknam, A. Pahwa, and A. K. Fard, "Multi-objective stochastic distribution feeder reconfiguration in systems with wind power generators and fuel cells using the point estimate method," *IET Renewable Power Generation*, Vol. 28, No. 2, pp. 1483–1492, May. 2013.

[15] W. Guan, Y. Tan, H. Zhang, and J. Song, "Distribution system feeder reconfiguration considering different model of DG sources," *International Journal of Electrical Power & Energy Systems*, Vol. 68, pp. 210–221, Jun. 2015.

[16] E. S. Ali, S. M. Abd Elazim, and A. Y. Abdelaziz, "Ant Lion optimization algorithm for optimal location and sizing of renewable distributed generations," *Renewable Energy*, Vol. 101, pp. 1311–1324, Feb. 2017.

[17] P. Siano and G. Mokryani, "Evaluating the benefits of optimal allocation of wind turbines for distribution network operators," *IEEE System Journal*, Vol. 9, No. 2, pp. 629–638, Jun. 2015.

[18] S. Maity, S. Paul, H. Karbouj, and Z. Hussain Rather, "Optimal sizing and placement of wind farm in a radial distribution network considering reliability, operational, economic and environmental factors," *IEEE Transactions on Power Delivery*, Early Access, Oct. 2020.

[19] M. R. Elkadeem, M. Abd Elaziz, Z. Ullah, S. Wang, and S. W. Sharshir, "Optimal planning of renewable energy-integrated distribution system considering uncertainties," *IEEE Access*, Vol. 7, pp. 164887–164907, Oct. 2019.

[20] P. Gangwar, S. N. Singh, and S. Chakrabarti, "Multi-objective planning model for multi-phase distribution system under uncertainty considering reconfiguration," *IET Renewable Power Generation*, Vol. 13, No. 12, pp. 2070–2083, Sep. 2019.

[21] H. B. Yamchi, H. Shahsavari, N. T. Kalantari, A. Safari, and M. Farrokhifar, "A cost-efficient application of different battery energy storage technologies in microgrids considering load uncertainty," *Journal of Energy Storage*, Vol. 22, pp. 17–26, Apr. 2019.

[22] Z. Li, Y. Xu, S. Fang, and S. Mazzoni, "Optimal placement of heterogeneous distributed generators in a grid-connected multi-energy microgrid under uncertainties," *IET Renewable Power Generation*, Vol. 13, No. 14, pp. 2623–2633, Oct. 2019.

[23] A. Naderipour, S. A. Nowdeh, P. B. Saftjani, Z. Abdul-Malek, M. W. B. Mustafa, H. Kamyab, and I. F. Davoudkhani, "Deterministic and probabilistic multi-objective placement and sizing of wind renewable energy sources using improved spotted hyena optimizer," *Journal of Cleaner Production*, In Press, Nov. 2020.

[24] S. Zergane, A. Smaili, and C. Masson. "Optimization of wind turbine placement in a wind farm using a new pseudo-random number generation method," *Renewable Energy*, Vol. 125, pp. 166–171, Sep. 2018.

[25] B. Hu, L. Wu, and M. Marwali, "On the robust solution to SCUC with load and wind uncertainty correlations," *IEEE Transactions on Power Systems*, Vol. 29, No. 6, pp. 2952–2964, 2014.

[26] S. Das, A. Abraham, and A. Konar, "Automatic clustering using an improved differential evolution algorithm," *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, Vol. 38, No. 1, pp. 218–237, Jan. 2008.

[27] G. P. Papamichail and D. P. Papamichail, "The k-means range algorithm for personalized data clustering in e-commerce", *European Journal of Operational Research*, Vol.177, No. 3, pp.1400–1408, Mar. 2007.

[28] S. K. Injeti and N. P. Kumar, "A novel approach to identify optimal access point and capacity of multiple DGs in a small, medium and large scale radial distribution systems," *International Journal of Electrical Power & Energy Systems*, Vol. 45, No. 1, pp. 142–151, Feb. 2013.

[29] K. D. Mistry and R. Roy, "Enhancement of loading capacity of distribution system through distributed generator placement considering techno-economic benefits with load growth," *International Journal of Electrical Power & Energy Systems*, Vol. 54, pp. 505-515, Jan. 2014.

[30] A. M. Tahboub, V. R. Pandi, and H. H. Zeineldin, "Distribution system reconfiguration for annual energy loss reduction considering variable distributed generation profiles," *IEEE Transactions on Power Delivery*, Vol. 30, No. 4, pp. 1677–1685, Aug. 2015.

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