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Robust operation of distribution network based on photovoltaic/wind energy resources in condition of COVID-19 pandemic considering deterministic and probabilistic approaches

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ABSTRACT

In this paper, optimal allocation and planning of wind and photovoltaic energy resources are performed in a distribution network with the objective of reducing losses, improving reliability, and minimizing energy generation cost in terms of changes in load consumption pattern during the COVID-19 pandemic condition. The main goal is identifying the best operating point, i.e., the optimal location and size of clean energy resources in the worst load change conditions, which ensures the best network operation in all conditions during the COVID-19 condition via the turbulent flow of water-based optimization (TFWO). First, the deterministic approach is implemented in Hybrid and Distributed cases before and during COVID-19 conditions. The probabilistic approach is performed considering generation uncertainty during the COVID-19 conditions. The results showed better performance in the Distributed case with the lowest losses and higher reliability improvement. Moreover, the losses are significantly reduced and the reliability is improved during the COVID-19 pandemic conditions. The findings indicate that the allocation and planning during the COVID-19 conditions is a robust option in network operating point changes. Also, the probabilistic results showed that considering the uncertainty has increased active and reactive losses (4.67% and 5.82%) and weakened the reliability (10.26%) of the deterministic approach.

1. Introduction

In late 2019, an acute respiratory illness caused by a new COVID-19 called SARS-CoV-2 broke out in Wuhan, China. The virus spread rapidly in Chinese cities and countries. The COVID-19 crisis was initially perceived as a threat to public health but gradually became a global economic threat [1]. In the face of the COVID-19, governments quickly quarantined various environments including residential, commercial, and industrial, and even shut down some industries [1,2]. Residential quarantine has increased the consumption of electricity in the residential sector, which has caused the pattern of electricity consumption in various commercial, industrial and residential sectors to change completely [1,2]. Changes caused by variations in electrical consumption patterns in the context of the COVID-19 have created a major challenge for electricity distribution companies to supply the energy needed by their customers in critical situations and also weakening of the network characteristics. The renewable energy sources (RESs) such as photovoltaic (PV), fuel cell (FC), wind turbine (WT), geothermal power plants, biomass sources can be installed close to the final consumers in the electricity distribution network [3-6]. Presence of the renewable energy sources (RES) in the networks can enhance the reliability and also decrease the losses and also decrease the voltage deviation and improve the voltage stability [7,8]. In addition, the RES power generation is uncertain due to its inherent nature and changing the RESs generation moves the network operating point away from the optimal point. Since the installation location and size of these sources are unchangeable, tools should be sought to use them to bring the network operating point as close to the optimal conditions as possible while receiving the maximum power from the RESs [9,10]. So, with changes in consumption patterns due to the COVID-19 pandemic, we are faced with the challenge of whether locating and determining the RESs size is appropriate for quarantine conditions. Therefore, in the allocation of these resources, all conditions should be considered, including changes in consumption patterns and uncertainties due to the RESs generation [11,12].

Allocation of distributed generation sources in the networks has been...
The placement of renewable units is investigated in Ref. [20] using a minimization via an enhanced coyote optimization algorithm (COA). Lightning attachment procedure optimization (LAPO) is applied in multi-objective teaching-learning-grey wolf optimizer with the objective of losses and voltage deviation reduction. The placement of renewable wind resources in the network with the goal of losses reduction and voltage profile and stability enhancement. The placement of renewable units in the network is evaluated in Ref. [25] considering the power market according to the optimal sitting and sizing of DGs. In Ref. [24], allocation of combined heat and wind units aimed losses and voltage deviations reduction and reliability improvement using PSO. The placement of renewable units in the network is evaluated in Ref. [23] for power generation using a modified sine-cosine algorithm (MSCA). The allocation of wind energy resources in Refs. [28, 29] is presented in the network with aim of loss reduction and voltage stability enhancement with the uncertainty of wind unit power based on different approaches. The PSO is considered in Ref. [13] for WT units sitting and sizing in the networks to minimize the losses and cost. Lightning attachment procedure optimization (LAPO) is applied in Ref. [14] to solve the placement problem of WT aimed energy losses reduction. The electric field optimization algorithm (EFOA) is used in Ref. [15] for sitting and sizing the WTs aimed at losses and voltage deviation minimization in the network. In Ref. [16], the moth-flame algorithm is proposed to solve the network reconfiguration and photo-voltaic and wind units placement aimed at reliability enhancement. The multi-objective PSO is developed in Ref. [17] to optimal placement of renewable energy resources in the network with the goal of losses reduction and voltage profile and stability enhancement. The placement of renewable energy units is studied in Ref. [18] via a cuckoo search algorithm (CSA) with the objective of losses reduction. The sitting and sizing of renewable units are evaluated in Ref. [19] for losses and voltage deviation minimization via an enhanced coyote optimization algorithm (COA). The placement of renewable units is investigated in Ref. [20] using a multi-objective teaching-learning-grey wolf optimizer with the objective of minimizing the losses and voltage deviation. The particle swarm optimization (PSO) is applied for placement and sizing the renewable units for losses reduction in Ref. [21]. The PSO is applied to enhance the voltage stability and losses minimization in Ref. [22]. The GA is performed to minimize the losses in Ref. [23] considering the power market according to the optimal sitting and sizing of DGs. In Ref. [24], allocation of combined heat and wind units aimed losses and voltage deviations reduction and reliability improvement using PSO. The placement of renewable units in the network is evaluated in Ref. [25] for power generation using a modified sine-cosine algorithm (MSCA). The allocation of wind energy resources in Refs. [28, 29] is presented in the network with aim of loss reduction and voltage stability enhancement with the uncertainty of wind unit power based on different approaches.

| Reference | Optimization objectives | PV | WT | DG | Uncertainty | Probabilistic (P)/Deterministic (D) | COVID-19 effect | Solution approach |
|-----------|-------------------------|----|----|----|-------------|-------------------------------------|----------------|------------------|
| [13]      | Loss and cost           | ✓  | x  |    | ✓  | D         | D                              | PSO             |
| [14]      | Energy loss             | x  | ✓  | ✓  | ✓  | D         | x                              | LAPO            |
| [15]      | Loss and voltage deviation | x  | ✓  | ✓  | x  | D         | x                              | EFOA            |
| [16]      | Loss and reliability    | ✓  | ✓  | ✓  | ✓  |             | x                              | MFO             |
| [17]      | Loss, voltage profile and voltage stability | ✓  | ✓  | ✓  | ✓  | D         | x                              | PSO             |
| [18]      | Loss                    | ✓  | ✓  | ✓  | ✓  |             | x                              | CSA             |
| [19]      | Loss and voltage deviation | x  | ✓  | ✓  | ✓  | D         | x                              | ECOA            |
| [20]      | Loss, voltage deviation and stability | ✓  | ✓  | ✓  | ✓  | D         | x                              | MOHTLBGWO       |
| [21]      | Loss                    | ✓  | ✓  | ✓  | ✓  |             | x                              | PSO             |
| [22]      | Loss and voltage stability | ✓  | ✓  | ✓  | ✓  | D         | x                              | PSO             |
| [23]      | Cost                    | ✓  | ✓  | ✓  | ✓  |             | x                              | TS-PSO          |
| [24]      | Loss, voltage stability and cost | x  | ✓  | ✓  | ✓  | D         | x                              | MFO             |
| [25]      | Reliability             | ✓  | ✓  | ✓  | ✓  | P          | x                              | GA              |
| [26]      | operating costs         | ✓  | ✓  | ✓  | ✓  | P          | x                              | PSO             |
| [27]      | Loss, voltage deviation and voltage stability | ✓  | ✓  | ✓  | ✓  | P          | x                              | ISH             |
| [28]      | Loss and voltage stability | ✓  | ✓  | ✓  | ✓  | P          | x                              | ISH             |
| [29]      | System cost             | ✓  | ✓  | ✓  | ✓  | P          | x                              | IO              |
| [30]      | Hosting capacity        | ✓  | ✓  | ✓  | ✓  | P          | x                              | HHO             |
| [31]      | Energy cost             | ✓  | ✓  | ✓  | ✓  | D          | x                              | TLBO            |
| [32]      | Loss and voltage deviation | x  | ✓  | ✓  | ✓  | P          | x                              | MINLP           |
| [33]      | Loss                    | ✓  | ✓  | ✓  | ✓  | P          | x                              | MINLP           |
| [34]      | Loss                    | ✓  | ✓  | ✓  | ✓  | P          | x                              | MINLP           |
| [35]      | Loss, cost and voltage deviation | ✓  | ✓  | ✓  | ✓  | P          | x                              | MINLP           |
| [36]      | Energy loss             | ✓  | ✓  | ✓  | ✓  | P          | x                              | MINLP           |
| [37]      | Cost                    | ✓  | ✓  | ✓  | ✓  | P          | x                              | MINLP           |
| [38]      | Cost and emission       | ✓  | ✓  | ✓  | ✓  | P          | x                              | MINLP           |
| [39]      | Loss and voltage deviation | x  | ✓  | ✓  | ✓  | P          | x                              | GA              |
| [40]      | Loss, voltage deviation and voltage stability | ✓  | ✓  | ✓  | ✓  | P          | x                              | PSO             |
| This paper| Losses of energy, reliability and energy cost | ✓  | ✓  | ✓  | ✓  | P          | ✓                              | TFWO            |

Fig. 1. Update the position of particles and their rotation towards the center of the vortex under the influence of centripetal force and other vortices [45].

Fig. 2. Different forces of a whirlpool with centrifugal force [45].
the Monte Carlo simulation (MCS). The effect of production forecast errors on planning design is investigated in Ref. [30] considering photovoltaic energy uncertainty. In Ref. [31] an improved spotted hyena optimizer (ISHO) is used for deterministic and probabilistic allocation of wind units in the network with the objective of losses and voltage deviations minimization and voltage stability improvement. The improved spotted hyena optimizer (ISHO) is applied in Ref. [32] with the objective of losses reduction and security and voltage enhancement to allocate photovoltaic and wind units with power uncertainty. The placement of gas-wind units using interval optimization (IO) is evaluated with network performance enhancement in Ref. [33] considering wind capacity uncertainty. The harris hawks optimization (HHO) is applied for solving allocating the DGs in networks to maximize the hosting capacity of the network in Ref. [34] with load uncertainty. The sitting and the sizing of the wind and thermal units with load and power uncertainty is presented with objective of energy production cost minimization in Ref. [35] using estimation method via TLBO algorithm. Mixed-integer nonlinear programming (MINLP) is an area of optimization that is used to solve nonlinear problems with continuous and integer variables. The placement of wind resources is developed using the probabilistic approach in the networks in Ref. [36] using the mixed integer nonlinear programming (MINLP) method. In Ref. [37], the allocation of DGs in radial distribution networks is developed by presenting a MINLP model using the General Algebraic Modeling System (GAMS) environment. The obtained results cleared the reduction of energy losses based on the optimal size and location of the DGs. In Ref. [38], the optimal location and size of DGs in radial distribution networks is presented to minimize the power losses based on non-convex and non-linear optimization problem using the MINLP model. The results is showed that the power loss of the network is reduced using the optimal allocation of the DGs via the MINLP. In Ref. [39], a MINLP model has been presented for allocation of the DGs for minimizing the fuel cost of conventional and Wind turbine power plant. The results showed that the optimal determination of location and size of conventional and wind energy resources reduced the power loss, fuel cost and also improved the network voltage profile. In Ref. [40], probabilistic allocation of renewable DGs is performed in distribution networks considering the uncertainties of the wind power and the network load to minimize the energy losses and voltage deviations based on the MINLP formulation. In Ref. [41], planning of energy storage system is presented via stochastic MINLP-based bi-objective optimization method. The storage system is applied to alleviate output fluctuations of the renewable resources. The problem is formulated to minimize the fuel cost and the thermal resources pollutants with uncertainties of the wind power and the network demand. The results cleared that the planning of the storage system in the network reduced the cost of power generation and also the emission of the pollutants. In Ref. [42], a MINLP model is developed for allocation of combined cooling, heating, and power system integrated with renewable energy to investigate the economic and environmental aspects for several buildings. The results showed that the combined heating and power integrated with energy resources in heavy demand time is cost-effective. The optimal placement of distributed generation is presented in Ref. [43] with uncertainties of customers’ demand and DG power via GA with the goal of losses and voltage
deviations reduction. In Ref. [44], the Probabilistic allocation of wind energy resources is performed to minimize the losses and voltage deviation and also to enhance voltage stability using the MCS and the PSO. The literature review summary is presented in Table 1.

The literature review showed that most studies on the allocation of the RES have been carried out without considering changes in wind and photovoltaic energy resources and without considering their generation limitations. Also, the type of load model, percentage of load power consumption, and consumption pattern are not provided in detail. Due to the fact that in the network, load demand includes commercial, industrial, and residential customers and their consumption varies in terms of time and throughout the year, so each type of customer follows a specific pattern. Therefore, load consumption patterns can vary greatly in quarantine conditions and the COVID-19 pandemic conditions. Considering the network constant load can lead to incorrect results in the problem of allocating the RESs. In some studies, the load is considered to be multi-level, which will lead to contradictory and misleading results due to the fact that the peak consumption rate does not occur at the same time in residential, industrial and commercial customers. So, considering the multi-level load for all types of customers will not give the right results.

In this paper, allocation and planning of the RES resources are performed with the objective of reducing losses, improving the reliability, and minimizing the energy generation cost of the 33-bus network considering the effect of consumption pattern changes due to COVID-19 pandemic conditions. The problem is implemented based on two deterministic and probabilistic approaches with and without RES production uncertainty, respectively. The photovoltaic and wind resources in two cases are used as Distributed and Hybrid to investigate the impact of using each in the network performance enhancement and reducing losses and improving the reliability. Decision variables of the problem include optimal location, size, and power factor have been determined using the turbulent flow of water-based optimization (TFWO) to achieve the lowest power loss and higher reliability level. The TFWO is inspired by physics-based behavior and water vortex motion [45]. The main motivations for using this algorithm in problem solving are fast convergence, easy implementation, crossing local minima, low setting parameters, and fast exploration and search [45]. Also, in this study, the optimal and robust option in allocation and planning of the RESs is found during COVID-19 pandemic conditions subjected to the network operating point changes.

The highlights of this study are listed as follows:

- Allocation and planning of energy resources considering losses, cost and reliability
- Deterministic and probabilistic approaches to solve the problem
- Evaluating the effect of consumption pattern changes in COVID-19 pandemic conditions
- Identifying the COVID-19 conditions as a robust option in operating point changes
- Superiority of the turbulent flow of water optimization compared to other methods

In the continuation of the paper, the problem formulation is presented in section 2 with modeling of the wind and photovoltaic resources and also different types of loads modeling, as well as the objective function and constraints. In Section 3, the TFWO algorithm and its application for solving the problem are introduced. In Section 4, the studied system is presented along with the problem data and simulation results, and in Section 5, the main findings of the study are concluded.

2. Problem formulation

In this study, the allocation and planning of the RESs in the network are performed with the objective of losses and energy cost reduction,
and reliability enhancement. In the following, the clean energy resources model and types of the network loads are presented along with the objective function and constraints.

2.1. Wind turbine modeling

The generation capacity of the wind turbines varies due to changes in wind speed. The power relationship of wind turbine is as follows [20, 31].

\[
P_{\text{wt}}(v) = \begin{cases} 
0 & v \leq v_{ci} \text{ or } v \geq v_{co} \\
P_{\text{rated-wt}} \frac{(v - v_{ci})}{(v_{r} - v_{ci})} & v_{ci} \leq v \leq v_{r} \\
P_{\text{rated-wt}} \frac{(v_{r} - v)}{(v_{r} - v_{co})} & v_{r} \leq v \leq v_{co}
\end{cases}
\]

where, \(v_{ci}\) is cut-in wind speed, \(v_{co}\) is cut-out wind speed, \(v_{r}\) is rated wind speed, \(P_{\text{rated-wt}}\) is the rated power.

2.2. Photovoltaic modeling

The output power of a photovoltaic array can be calculated with its nominal output power in standard test conditions and according to the
irradiance and ambient temperature as follows [20,31].

\[ P_{pv} = P_{STC} \frac{G_c}{G_{STC}} \left[ 1 + k(T_c - T_{STC}) \right] \]  

(2)

where, \( P_{pv} \) refers to the extracted power of the PV array, \( G_c \) is the irradiance, \( k \) indicates temperature coefficient of the power, \( T_{STC} \) is standard condition temperature, \( P_{STC} \) is the output power based on standard conditions, and \( T_c \) is the operating point temperature.

2.3. Load modeling

In each distribution substation, the type of load is different in terms of industrial, residential, and commercial, and the amount of power consumed will be a function of the voltage range of the substation. For this purpose, active and reactive load and power demand models can be mathematically defined as follows [46].

\[ P_i = P_{0i} \left| V_i \right|^\alpha \]  

(3)

\[ Q_i = Q_{0i} \left| V_i \right|^\beta \]  

(4)

where, \( P_i \) and \( Q_i \) are the active and reactive demand of the bus \( i \) and \( \alpha \) and \( \beta \) are exponents of the voltage-dependent loads (described in detailed in Ref. [47]). \( P_{0i} \) and \( Q_{0i} \) are active and reactive powers at nominal voltage and \( V \) refers to the ratio of terminal voltage magnitude to nominal value \([47]\).

2.4. Modeling of clean resources with uncertainty

Due to the random nature of wind and irradiance with long-term measurements at different time intervals, the probability distribution function (PDF) of wind speed and irradiance is used to calculate energy [31]. Weibull PDF is one of the continuous probabilistic distributions. In most cases, the Weibull statistical model has a very good correlation with the wind speed distribution. The Weibull PDF has been used to model wind speed uncertainty and describe its random behavior as follows [24,31].
Fig. 11. Convergence curve of different methods in deterministic solving the problem before COVID-19 pandemic conditions a) Distributed case b) Hybrid case.

Table 7
Numerical results of allocation and planning of the RESs before COVID-19 pandemic conditions in Distributed and Hybrid cases.

| Case   | Method | Optimal RESs | Objective Function | ENS (kWh/yr) | P\textsubscript{Loss} (kW) | Q\textsubscript{Loss} (kVAr) | Loss Cost ($) | RESs Cost ($) |
|--------|--------|--------------|--------------------|--------------|-----------------|------------------|--------------|--------------|
| No RESs| -      | 0            | Bus                | -            | 214033.76       | 1653.05          | 1100.48      | 99.18        | 0            |
| Distributed | PSO | 320.11      | 1                  | 1            | 157856.02       | 1177.36          | 786.43       | 70.64        | 7267         |
|         |        | 496.44      | pf                 | 0.800        | 1177.36         | 786.43           | 70.64        | 7267         |
|         | GWO    | 318.28      | 1                  | 1            | 158502.61       | 1209.87          | 797.86       | 72.59        | 7256         |
|         |        | 497.10      | pf                 | 0.893        | 1209.87         | 797.86           | 72.59        | 7256         |
|         | TFWO   | 314.09      | 1                  | 1            | 157101.89       | 1168.39          | 771.78       | 70.10        | 7189         |
|         |        | 493.70      | pf                 | 0.800        | 1168.39         | 771.78           | 70.10        | 7189         |
| Hybrid | PSO    | 210.59      | 1                  | 1            | 170322.16       | 1296.64          | 865.31       | 77.79        | 6296         |
|         |        | 496.88      | pf                 | 0.810        | 1296.64         | 865.31           | 77.79        | 6296         |
|         | GWO    | 184.66      | 1                  | 1            | 170338.94       | 1305.93          | 868.47       | 78.35        | 6002         |
|         |        | 489.73      | pf                 | 0.860        | 1305.93         | 868.47           | 78.35        | 6002         |
|         | TFWO   | 174.30      | 1                  | 1            | 170319.23       | 1295.03          | 863.84       | 77.70        | 5951         |
|         |        | 494.43      | pf                 | 0.800        | 1295.03         | 863.84           | 77.70        | 5951         |
α refers to the scale factor (m/s) and
\( f = \frac{k}{c} \left( -\frac{v}{c} \right)^{k-1} \ \exp \left( \frac{-v}{c} \right) \)
\( k = \frac{\sigma}{\mu} \)
\( c = \frac{\mu}{\sqrt{1 + k^{-1}}} \)
where, \( v \) is average wind speed (m/s), \( k \) is shape factor (dimensionless), \( c \) refers to the scale factor (m/s) and \( \mu \) and \( \sigma \) are mean and standard deviation values.

Irradiance is a random variable that depends on climatic conditions. The beta PDF for modeling the uncertainty and random behavior of irradiance is presented below
\( f(g) = \frac{T(a + \beta)}{T(a)} \ \Gamma(a + \beta) \ G^{a-1} (1 - G)^{\beta-1} \ a > 0, \beta > 0 \)
\( \beta = \left( 1 - \mu \right) \left( \frac{\mu(1 + \mu)}{\sigma^2} - 1 \right) \)
\( \alpha = \frac{\mu \beta}{1 - \mu} \)
where, \( G \) is the irradiance (W/m²) and \( \alpha \) and \( \beta \) are the function parameters. The parameters \( \alpha \) and \( \beta \) are calculated from the mean (\( \mu \)) and standard deviation (\( \sigma \)) of the irradiance values.

2.5. Objective function

In this section, modeling of each of the objective function sections is presented.

2.5.1. Power losses

Losses in the network are due to the current passing through the network lines based on the ohmic resistance (R) and reactance (X) of the line. The current of each line between bus b and b-1 in the network is defined as follows [20, 31].
\( P_{Loss,b} = I_b^2 R_b \)
(11)
where, \( R_b \) and \( I_b \) are refer to the ohmic resistance of the branch b.

The method of calculating active losses (\( P_{Loss,b} \)) and reactive losses (\( Q_{Loss,b} \)) in branch b of the network is as follows [20, 31]:
\( P_{Loss,b} = \frac{P_b^2 + Q_b^2}{|V|^2} \)
(12)
\( Q_{Loss,b} = \frac{P_b^2 + Q_b^2}{|V|^2} \)
(13)
where, \( P_b \) and \( Q_b \) are injected active and reactive power form branch b, \( X_b \) is reactance of branch b and \( V_i \) voltage at bus i.

The total active (\( P_{Loss} \)) and reactive (\( Q_{Loss} \)) losses in 24 h a day by calculating the losses per hour is defined as follows:
\( P_{Loss} = \sum_{n=1}^{N_{lBr}} P_{Loss,b} \)
(14)
\( Q_{Loss} = \sum_{n=1}^{N_{lBr}} Q_{Loss,b} \)
(15)
where, \( N_{lBr} \) is number of the network branches.

In this study, total energy losses of the network for 24 h as the first objective function is considered as follows.
\( F_1 = E_{Loss} = \sum_{n=1}^{N_{lBr}} \sum_{l=1}^{N_{lBr}} P_{Loss,b} \)
(16)

2.5.2. Reliability

The outage of the distribution network lines can cause a very large amount of power interruption for customers. Therefore, based on the concept of network line outage, the reliability index as energy not supplied (ENS) is defined as follows [20].
\( F_2 = \text{ENS} = \sum_{b=1}^{24} \sum_{i=1}^{N_{lBr}} \sum_{j=1}^{N_{lBr}} \text{ORL}_i \times \text{LNT}_i \times \text{ENS}_{cost} \times \text{TR}_i \times \text{INTL}_j \)
(17)
where, \( N_{lBr} \) refers to the number of network lines, \( N_{l} \) is number of loads that are cut off after the line i outage, \( \text{ORL}_i \) is outage rate of the line per km in a year, \( \text{LNT}_i \) indicates line length, \( \text{TR}_i \) refers to the time takes to repair the fault, \( \text{ENS}_{cost} \) is cost of ENS and \( \text{INTL}_j \) is the interrupted load due to line i outage.

2.5.3. Cost of RES

One of the important parameters in the allocation and planning of the RES resources in the networks is the cost of their application. In other words, the cost parameter is effective in finding the installation location and capacity of the RES resources. In this study, the cost (\( C_{RES} \)) of energy generation is defined as the sum of initial capital costs, operation and maintenance costs plus the cost of injected power to the network from the RES resources is formulated as follows [39, 46].
\( F_3 = C_{RES} = \left( (C_{\text{pv-cap}} + C_{\text{pv-o&m}}) + (C_{\text{wt-cap}} + C_{\text{wt-o&m}}) \right) + C_{\text{pv}} + \sum_{i=1}^{24} P_{\text{pv}}(t) + P_{\text{wt}}(t) \)
(18)
where, \( C_{pv\text{-cap}} \) and \( C_{pv\text{-O&M}} \) are initial capital and operation and maintenance costs. Also, \( C_{w} \) and \( C_{p} \) refer the cost of per kW injected power of wind and photovoltaic resources to the network.

2.6. Constraints

To solve the optimization problem, it is necessary to satisfy the constraints as follows [20, 31]:

2.6.1. Voltage

The buses voltage should not be more or less than the specified range \( (V_{i,\text{min}} \leq V_{i} \leq V_{i,\text{max}}) \).

Where, \( V_{i,\text{min}} \) and \( V_{i,\text{max}} \) refer to the lower and upper limit of the buses voltage.

2.6.2. Capacity and RESs penetration constraint

The capacity of RESs should not exceed a certain amount and the level of resource penetration should be limited to a certain amount as follows:

\[
\sum_{i=1}^{N_{RES}} P_{RES,i} \leq \lambda_{RES} \times \sum_{i=1}^{N_{Bus}} P_{load,i} \tag{19}
\]

where, \( \lambda_{RES} \) is level of penetration of RESs in the distribution network. Also, the selected capacity for each RES resource should be among the standard values and less than the suggested capacity.

\[
P_{min,RES,i} \leq P_{RES,i} \leq P_{max,RES,i} \quad i = 1, 2, ..., N_{RES} \tag{20}
\]

2.6.3. Power balance constraint

The power balance constraint resulting from the RESs generation, consumer, losses and network power are as follows.

\[
P_{sub} + P_{RES} = P_{loss} + \sum_{n=1}^{N_{Bus}} P_{load,n} \tag{21}
\]

where, \( P_{sub} \) is active power received from the network, \( P_{RES} \) is total power generation capacity by RESs and \( P_{load,n} \) is power consumption of per bus.

2.6.4. Allowable current constraint

The network lines have the allowable throughput capacity as follows:

\[
l_k \leq I_{k,\text{max}} \tag{22}
\]

where, \( I_{k,\text{max}} \) is maximum allowable current passing through the branch.
2.7. Multi-objective optimization

In this study, the weighted coefficient method has been applied to solve the multi-objective problem [48].

The normalization of each objective function is defined as follows:

\[
\xi^i = \frac{F_{i\text{min}}}{F_{i\text{max}}}
\]

where, \(F_{i\text{min}}\) and \(F_{i\text{max}}\) refer to minimum (after RES allocation) and maximum (before RES allocation) value of each objective function, respectively. In this study the maximum valuation of the cost objective function is refers to the maximum budget of the RESs allocation ($).

Finally, the total objective function based on the weighted coefficient method is defined as follows:

\[
\text{Objective Function} = w_1 \times \xi_1 + w_2 \times \xi_2 + w_3 \times \xi_3
\]

where, \(w_1\), \(w_2\) and \(w_3\) are weight coefficients of the functions \(\xi_1\) (power losses), \(\xi_2\) (reliability) and \(\xi_3\) (RES energy generation cost) that the sum of these coefficients is equal to 1. The defined objectives are opposite to each other and contradictory. Improving one of them may involve weakening the other. In this study, to determine the best weighted coefficient an analytical test is implemented which the results are given in sub-section 4.1.

3. Optimization method

In this study, the meta-heuristic TFWO is used to allocate and planning the RES resources in the distribution network, which is described in this section and its implementation in problem solving is presented.

3.1. Overview of the TFWO

The TFWO is inspired based on the vortex motion of water [45, 46]. A centripetal force related to a vortex that is stronger than the other vortex forces is defined as the best member of the group, the best member always trying to bring the position of the particles to the position of the center of the vortex and absorb it into the cavity [45, 46].

3.1.1. Formation of vortices

The initial population (Np) of the TFWO algorithm is evenly divided among the NWh of the group and the most powerful member (Wh) is determined named the group center. Particles (X) are attracted to it based on their distance from the center of the vortex [46].

\[
x_i^0 = \text{rand} \cdot \left( x_{\text{max}} - x_{\text{min}} \right) + x_{\text{min}}
\]

3.1.2. Effect of vortices on particles and other vortices

The particles are attracted to the center of the vortex by each vortex (Wh) based on centripetal force. In the case of particle adsorption by a vortex, the position of the particle and the vortex are similar (\(X_i = Wh_j\)). Meanwhile, other vortices, based on their position and force, defined by the value of merit (\(f(Wh_j)\)), cause the particles to deviate from their path, which is equivalent to this deviation. The jth particle with position \(X_i\) rotates in a circular path due to the centripetal force of the Whj vortex and also changes direction as much as \(\Delta X_i\) due to the force of other vortices. The effect of vortices on particles is depicted in Fig. 1. It is cleared that the particle (X) rotates and approaches the center \(\delta\) of the vortex at an angle \(\delta\). The position of the particles is updated based on the following relation [39, 40].

\[
D_{t+1,NWh} = f(Wh_j) \cdot \left( |Wh_j - \text{sum}(X_i)| \right)^{0.5}
\]

\[
Wh_j = \text{Wh}_j \text{ if } \Delta_i = \Delta_{i\text{min}} \text{ & Wh}_j = \text{Wh}_j \text{ if } \Delta_i = \Delta_{i\text{max}}
\]
\[ \delta_{new}^i = \delta_i + \text{rand}_1 \times \text{rand}_2 \times \pi \]  

(28)

\[ \Delta X_i = \cos(\delta_{new}^i) \times (W_h_i - X_i) - \sin(\delta_{new}^i) \times (W_{hw} - X_i) \]  

(29)

\[ X_{new}^i = W_{h_i} - \Delta X_i \]  

(30)

3.1.3. Centrifugal force

In a situation where the centrifugal force (FE) is stronger than the centripetal force, then the particle is randomly directed to a new position. The centrifugal force and its effect are formulated according to Fig. 2, as follows [45, 46]:

\[ FE_i = \left( \left( \cos(\delta_{new}^i) \right)^2 \times \left( \sin(\delta_{new}^i) \right) \right)^2 \]  

(31)

Table 8

| Case       | Method | Optimal RESs | Objective Function | ENS (kWh/yr) | \( P_{loss} \) (kW) | \( Q_{loss} \) (kVAR) | Loss Cost ($) | RESs Cost ($) |
|------------|--------|--------------|--------------------|-------------|----------------|----------------|--------------|--------------|
| No RESs    | -      | 0            | -                  | 143412.52   | 616.60         | 414.26        | 36.99        | 0            |
| Distributed PSO | 300.11 | 0            | 33                 | 94478.61    | 345.40         | 243.74        | 20.72        | 7004         |
| GWO       | 486.96 | 0            | 16                 | 94523.85    | 353.95         | 247.43        | 21.23        | 7145         |
| TFWO      | 311.05 | 1            | 33                 | 94234.78    | 339.84         | 236.43        | 20.39        | 6560         |
| Hybrid PSO | 491.82 | 0.802        | 14                 | 496.55      | 0.800          | 16            | 0.60412      | 491.82       |
| GWO       | 311.05 | 1            | 33                 | 498.79      | 0.828          | 16            | 0.6995       | 498.79       |
| TFWO      | 491.82 | 1            | 16                 | 461.99      | 0.816          | 16            | 0.7123       | 461.99       |
| Hybrid TFWO | 496.96 | 0.801        | 16                 | 476.24      | 0.801          | 16            | 0.6991       | 476.24       |

3.1.4. The effect of vortices on each other

The vortex with more centripetal force moves the vortex around it and swallows it. The behavior of vortices moving towards each other is defined by [45, 46]:

\[
\begin{cases}
\text{if } \text{rand} < \text{FE}_i, \\
\quad p = \text{round}(1 + \text{rand} \times (D - 1)); \\
\quad x_{r_i} = x_{r_i}^* + x_{r_i}^\text{max} - x_{r_i}; \\
\quad f(X_i) = f(X_{new}^i);
\end{cases}
\]  

(32)

Fig. 16. Contribution of the RESs during COVID-19 pandemic conditions a) Distributed case b) Hybrid case.

Fig. 17. Active and reactive losses during COVID-19 conditions a) Distributed case b) Hybrid case.
Fig. 18. ENS variations during COVID-19 pandemic conditions a) Distributed case b) Hybrid case.

Fig. 19. Convergence curve of TFWO in solving the problem during COVID-19 pandemic conditions in Distributed case for 3 MW wind turbine.

Table 9
Numerical results of solving the problem during COVID-19 pandemic conditions in Distributed case for 3 MW wind turbine.

| Case         | Method | Optimal RESs | Objective Function | ENS (kWh/yr) | P_Loss (kW) | Q_Loss (kVAr) | Loss Cost ($) | Location (Bus) | Size (kW)/p.f. |
|--------------|--------|--------------|--------------------|--------------|-------------|---------------|---------------|----------------|----------------|
| No RESs      | -      | 0            | -                  | 143412.52    | 616.60      | 414.26        | 36.99         |                | 0              |
| 3 MW TFWO    | 954.81 | 0.837        | 30                 | 88862.55     | 334.06      | 236.94        | 20.04         | 1              | 493.70/0.80    |
| 0.5 MW TFWO  | 240.58 | 1            | 18                 | 94234.78     | 339.84      | 236.43        | 20.39         | 18             | 240.58/0.80    |

Table 10
Comparison of the results of the deterministic problem solving before and during COVID-19 pandemic conditions for Distributed case.

| Item/parameter | ENS (kWh/yr) | P_Loss (kW) | Q_Loss (kVAr) | Loss Cost ($) | Location (Bus) | Size (kW)/p.f. |
|----------------|--------------|-------------|---------------|---------------|----------------|----------------|
| Before COVID-19 | 157101.89    | 1168.39     | 771.78        | 70.10         | 18             | 314.09/1      |
| During COVID-19 | 94234.78     | 339.84      | 236.43        | 20.39         | 18             | 240.58/0.80   |

Table 11
Comparison of the results of the deterministic problem solving before and during COVID-19 pandemic conditions for Hybrid case.

| Item/parameter | ENS (kWh/yr) | P_Loss (kW) | Q_Loss (kVAr) | Loss Cost ($) | Location (Bus) | Size (kW)/p.f. |
|----------------|--------------|-------------|---------------|---------------|----------------|----------------|
| Before COVID-19 | 170319.23    | 1295.03     | 863.84        | 77.70         | 18             | 174.30/1      |
| During COVID-19 | 102872.50    | 419.88      | 283.64        | 25.20         | 18             | 136.22/0.80   |

Fig. 20. Contribution of the RESs during COVID-19 pandemic conditions in Distributed case for 3 MW wind turbine.
\[ \Delta t = 1: \text{Nwh} \{ j \} = f(\text{Wh}t) \times \| \text{Wh}t \| \text{sum} \text{Wh}j \| \text{Wh}f = \text{Wh} \text{ with minimum value of } \Delta_t \] (33)

\[ \delta_{\text{new}j} = \delta_j + \text{rand}_1 \times \text{rand}_2 \times \pi \] (34)

\[ \Delta \text{Wh}_j = \text{rand}(1, D) \times \| \cos(\text{rand}) + \sin(\text{rand}) \| \times (\text{Wh}_f - \text{Wh}_j) \] (35)

\[ \text{Wh}_{\text{new}}j = \text{Wh}_f - \Delta \text{Wh}_j \] (36)

The TFWO flowchart is shown in Fig. 3.

### 3.2. Implementation of the TFWO in problem solving

In solving the problem with the probabilistic approach, the uncertainties of irradiance, temperature, and wind speed is considered in solving the allocation and planning of RESs in the 33-bus network. The Monte Carlo Simulation (MCS) has been used for modeling the uncertainty considering the PDFs. According to the MCS, number of 1000 scenarios are generated, and based on the scenario reduction method, unfavorable scenarios are eliminated and 500 scenarios are selected. Therefore, according to the number of selected scenarios, the problem is deterministically solved, and finally, each of the optimization variables is plotted in PDF. Also, the simulation results including active and reactive power losses and ENS index are demonstrated in the PDF form.

Finally, based on the PDFs of the results, the losses and the reliability index values are obtained. Flowchart of proposed methodology is demonstrated based on the TFWO in Fig. 4. Also, the TFWO implementation steps in problem-solving and determining the optimal variables are presented as follows:

**Step 1)** Initialize the TFWO parameters. The maximum number of iteration, population, and repetition based on user experience and trial and error are considered equal to 50, 50, and 30, respectively.

**Step 2)** Generation of the random data of irradiance, temperature, and wind speed are considered as PDF.

**Step 3)** Select the samples, randomly according to the number of scenarios \( N_{\text{Samp}} \) extracted from MCS.

**Step 4)** Determination of the decision variables (location, size, and power factor of the RESs), randomly according to the random samples selected in the previous step and for each population of the TFWO.

**Step 5)** Computing the objective function for the variables set and the best set with the lowest objective function is considered the best solution.

**Step 6)** Update the TFWO population and the new variables set are found for the updated population, randomly.

**Step 7)** Calculating the objective function value for the updated variables set and the best set with the lowest objective function is considered the best solution. If the best solution is lower compared with the obtained value in step 5, replace it.

**Step 8)** Go to step 9, when all scenarios are selected and the convergence criteria are established, otherwise go to step 3.

**Step 9)** Stop the TFWO and save the variables optimally as PDF.

### 4. Simulation results

#### 4.1. System under study

The results of the effect of consumption pattern changes caused by
COVID-19 pandemic conditions are shown in Figs. 9 and 10. The decision variables in different scenarios are considered as optimal size (between 0 and 0.1 MW), installation location (between 2 and 33) and power factor (between 0 and 1 for wind resources) of renewable energy resources which should be determined using the TFWO considering objective function and the constraints. Coefficients for modeling different types of loads are given in Table 2. In this study, the percentage of a load profile is measured through intelligent measurement systems in the distribution network, while in other study, the Loading profiles of residential, industrial, and commercial loads before and during COVID-19 pandemic conditions as a constant percentage of the load is shown in Figs. 9 and 10, respectively. Data about wind turbines and photovoltaic arrays for installation according to the capacity of each device is presented in Tables 3 and 4 [50–53].

Two simulation states are presented to perform the effect of changing the consumption pattern caused by the COVID-19 pandemic on the optimal allocation and planning of photovoltaic and wind clean energy sources in the distribution network as follows:

**State 1)** Deterministic allocation and planning of the RESs before COVID-19 pandemic conditions (in both Distributed and Hybrid cases)

**State 2)** Probabilistic allocation and planning of the RESs during COVID-19 pandemic conditions (in both Distributed and Hybrid cases)

Two scenarios are implemented before and during the Covid-19 pandemic condition. At first the data of the system includes irradiance, wind speed, temperature, load demand data (Figs. 6–10) and also the value of system components (Tables 2–4) are initiated. The Load demand in two scenarios is different for before and during Covid-19 condition. So, difference of scenarios is in pattern of load consumption due to pandemic condition of Covid-19 for different residential, commercial and industrial demand of the network. It should be noted that Distributed case means that each of the photovoltaic and wind sources is installed in a separate bus on the network, and the Hybrid case means that both photovoltaic and wind sources are installed as a hybrid system in one bus. In order to optimize the installation location of the wind turbine and photovoltaic array, this strategy is considered in the optimization program, which adds a penalty value of \(10^n\) to the objective function if both energy resources are installed in the same location (same bus). Considering that the goal of the program is to minimize the objective function, therefore the program does not want to add this penalty to the objective function, so according to this strategy, it removes infeasible solutions and looks for the best solution among feasible solutions. The decision variables are defined optimal installation location and size of photovoltaic and wind energy resources in the distribution network. The installation location refers to the bus of the distribution network. These variables are common in all scenarios. The defined scenarios are related to before and during the COVID-19 pandemic conditions and considering Distributed and Hybrid cases of energy resources application. So, at first state 1 is implemented as deterministic (without uncertainty) before and during the COVID-19 conditions. The irradiance, wind speed and temperature are initiated as probabilistic and with uncertainty during the COVID-19 conditions. The irradiance, wind speed and temperature are initiated as deterministic data according to Figs. 6–8. Then the decision variables are determined using the TFWO algorithm. Also, the state 2 is implemented as probabilistic and with uncertainty during the COVID-19 conditions. The irradiance and the wind speed are introduced as beta and weibull probability distribution function (PDF) to the program. The decision variables are determined as PDF using the TFWO algorithm.

To evaluate the superiority of the TFWO in deterministic problem solving, its performance is compared with powerful and well-known methods of PSO and GWO. These algorithms parameters are given in Table 5.

In many multi-objective optimization problems based on the weighted coefficients method, the coefficients are determined based on
the authors’ experience and the trial and error method. But this issue cannot guarantee the exact solution. In this study, the values of the weight coefficients according to Eq. (24), of the problem have been determined using an analytical test [54] considering the allocation and deterministic planning of RESs during the period of the pandemic conditions of COVID-19 for the distributed case. In Table 6, the effects of changes in the values of the weighted coefficients are presented on the objective function value and the losses and ENS reduction percentage. For the 25th to 36th runs for different configurations of the weighted coefficients, the effect of these coefficients is zero in improving losses and ENS, and thus they are ignored. Among 36 different runs resulting from different combinations of the weighted coefficients, the second run is determined more effective by achieving 44.88% loss reduction and 34.30% ENS reduction, and in this run, the weights of W1, W2, and W3 are determined to 0.7, 0.2 and 0.1 respectively.

4.2. Deterministic allocation and planning results

4.2.1. Before COVID-19 pandemic conditions

The results of optimal allocation and planning of photovoltaic and wind clean energy sources in the distribution network are presented deterministically with the certain parameters of radiation, wind speed, and temperature before COVID-19 pandemic conditions for two Distributed and Hybrid cases. The convergence curves of different optimization algorithms in deterministic problem solving for Distributed and Hybrid cases are depicted in Fig. 11. As can be seen in the Distributed case, the objective function value is obtained less than in the Hybrid case, which indicates the better network performance in the Distributed case and a better effect on the power losses and network reliability. In addition, it is observed that the TFWO achieves convergence with less objective function value (better value), fast convergence rate in less iteration than the PSO and GWO methods.

Numerical results of allocation and planning of photovoltaic and wind energy sources before COVID-19 conditions using various optimization methods for Distributed and Hybrid cases are presented in
Table 7. The values of active and reactive losses and ENS in the basic network state are 1653.05 kW, 1100.48 kVAr, and 214033.76 kWh, respectively. The results show that the amount of these parameters has been significantly reduced by allocating and planning renewable resources. For Distributed case, the photovoltaic capacity is installed 314.09 kW at bus 18 and the wind capacity is found 493.70 kW with a power factor of 0.8 at bus 16 and for Hybrid case the capacity of photovoltaic is obtained 174.30 kW and this value is achieved 494.43 kW for wind sources with a power factor of 0.8 using the TFWO. For the Hybrid case, the active loss is obtained 1295.03 kW, 1305.93 kW, and 1296.64 kW, the reactive loss is calculated 863.84 kVar, 868.47 kVar and 865.31 kVar and the ENS is achieved 170319.23 kWh, 170338.94 kWh and 170322.16 kWh using the TFWO, PSO, and GWO, respectively. Also, For the Distributed case, the active loss is obtained 1168.39 kW, 1209.87 kW, and 1177.36 kW, the reactive loss is calculated 771.78 kVar, 797.86 kVar, and 786.43 kVar and the ENS is achieved 157101.89 kWh, 158502.61 kWh and 157856.02 kWh using the TFWO, PSO, and GWO, respectively. As it is clear, the TFWO has a lower active and reactive loss and also minimum ENS in comparison with the PSO and GWO methods in Distributed and Hybrid cases which confirm the better performance of the proposed method. In addition, it is clear that the allocation and planning of the RESs based on the Distributed case has achieved better results of network performance compared to the Hybrid case.

4.2.2. During COVID-19 pandemic conditions

The results of deterministic allocation and planning of RESs in the distribution network during COVID-19 pandemic conditions are presented for the Distributed and Hybrid cases in this section. The convergence curves of the TFWO, PSO, and GWO optimization algorithms in problem-solving are shown in Fig. 15. It is clear that in the

Table 14
Comparison of deterministic and probabilistic results for Distributed case and without and during COVID-19 pandemic conditions.

| Item/parameter | ENS (kWh/yr) | P_Loss (kW) | Q_Loss (kVAr) | Location (Bus) | Size (kW)/p.f. |
|----------------|--------------|-------------|---------------|----------------|----------------|
| Deterministic (Before Covid-19) | 157101.89 | 1168.39 | 771.78 | 18 | 314.09/1.00 |
| Deterministic (During Covid-19) | 94234.78 | 339.84 | 236.43 | 18 | 493.70/0.80 |
| Probabilistic (Before Covid-19) | 167,800 | 1194.65 | 806.33 | 18 | 201.84/1.00 |
| Probabilistic (During Covid-19) | 103,906 | 355.72 | 250.19 | 18 | 300.15/0.85 |

Fig. 24. The PDF of a) active losses b) reactive power losses and c) ENS.

Table 7. The values of active and reactive losses and ENS in the basic network state are 1653.05 kW, 1100.48 kVAr, and 214033.76 kWh, respectively. The results show that the amount of these parameters has been significantly reduced by allocating and planning renewable resources. For Distributed case, the photovoltaic capacity is installed 314.09 kW at bus 18 and the wind capacity is found 493.70 kW with a power factor of 0.8 at bus 16 and for Hybrid case the capacity of photovoltaic is obtained 174.30 kW and this value is achieved 494.43 kW for wind sources with a power factor of 0.8 at bus 18 using the TFWO. For the Hybrid case, the active loss is obtained 1295.03 kW, 1305.93 kW, and 1296.64 kW, the reactive loss is calculated 863.84 kVar, 868.47 kVar and 865.31 kVar and the ENS is achieved 170319.23 kWh, 170338.94 kWh and 170322.16 kWh using the TFWO, PSO, and GWO, respectively. Also, For the Distributed case, the active loss is obtained 1168.39 kW, 1209.87 kW, and 1177.36 kW, the reactive loss is calculated 771.78 kVar, 797.86 kVar, and 786.43 kVar and the ENS is achieved 157101.89 kWh, 158502.61 kWh and 157856.02 kWh using the TFWO, PSO, and GWO, respectively. As it is clear, the TFWO has a lower active and reactive loss and also minimum ENS in comparison with the PSO and GWO methods in Distributed and Hybrid cases which confirm the better performance of the proposed method. In addition, it is clear that the allocation and planning of the RESs based on the Distributed case has achieved better results of network performance compared to the Hybrid case.

The contribution of generated power using each of the wind and photovoltaic sources for the 24-h period for Distributed and Hybrid cases is depicted in Fig. 12. It can be said that with the optimal injection of the clean energy resources power based on the considered loading, the loss of the network is declined, and also the reliability is improved. The losses, as well as the ENS values for the 24-h period, are Distributed and Hybrid cases are given in Figs. 13 and 14, respectively. It can be seen that the losses value is significantly decreased in comparison with the base network with the allocation and planning of RESs units in the 33-bus network according to Fig. 13. In addition, the results showed that in the Distributed case, the reduction of power loss and ENS is higher than in the Hybrid case.

4.2.2. During COVID-19 pandemic conditions

The results of deterministic allocation and planning of RESs in the distribution network during COVID-19 pandemic conditions are presented for the Distributed and Hybrid cases in this section. The convergence curves of the TFWO, PSO, and GWO optimization algorithms in problem-solving are shown in Fig. 15. It is clear that in the
Distributed case the TFWO has obtained the optimal solution with a lower value of the objective function than the Hybrid case. Also, the TFWO has reached a better objective function value with less convergence tolerance and higher convergence speed compared to the PSO and GWO methods. Numerical results are given in Table 8. The active loss, reactive loss, and ENS in the basic network are obtained 616.60 kW, 414.26 kW, and 143412.52 kWh, respectively. For Distributed case, 240.58 kW of photovoltaic power is installed in bus 18 and 496.55 kW wind power is placed with a power factor of 0.8 in bus 33 and for Hybrid case 136.22 kW photovoltaic power and 476.24 kW wind power with a power factor of 0.801 is installed in bus 16 using the TFWO. For the Hybrid case, active, reactive, and ENS are calculated 419.88 kW, 283.64 kVAr, and 105476.11 kWh via the GWO, and using the PSO the active loss, reactive loss, and ENS are determined 433 kW, 285.18 kVAr, and 102920.31 kWh, respectively. For Distributed case, the active loss, reactive loss, and ENS are obtained 339.84 kW, 236.43 kVAr, and 94234.78 kWh, respectively using the TFWO, 353.95 kW, 247.43 kVAr, and 95423.85 kWh via the GWO and 345 kW, 243.74 kVAr, and 94478.61 kWh by the PSO. The results clearly that the TFWO has the lowest objective function, active and reactive power losses, and ENS than the PSO and GWO methods for Distributed and Hybrid cases, which confirm the superiority of the proposed method. Moreover, the Distributed case also is achieved lower losses and more reliability compared to the Hybrid case.

Using the proposed method the cost of energy resources using the TFWO are found 6560 $ whereas this cost is zero in base case (without energy resources). But the two other objectives such as power loss and ENS are obtained lower than the base case, considerably. So, the total objective function is better than the total objective function in base case. Therefore, it is observed that the cost of renewable energy resources (6560 $) is insignificant compared to the savings due to reliability improvement (59899.49 $).

The power contribution of wind and photovoltaic sources for Distributed and Hybrid cases is also shown in Fig. 16 during a 24-h period. It can be argued that by optimally injecting the RESs power, the losses are declined and the network reliability is enhanced. The active and reactive losses of the lines, as well as the ENS variations during a 24-h period for Distributed and Hybrid cases, are depicted in Figs. 17 and 18, respectively. The results demonstrate that with the allocation and planning of the RESs in the 33-bus distribution network according to Fig. 17, the active and reactive losses value compared to the base network is significantly reduced. In addition, the results show that in the Distributed case, the reduction of losses and improvement of the ENS is higher than the Hybrid case. Here, the effect of considering wind turbines with higher capacity (3 MW) on solving the problem is evaluated. The obtained results of deterministic allocation and planning of RESs in the distribution network during COVID-19 pandemic conditions are presented for the Distributed with 3 MW wind turbine. The convergence curve of the TFWO optimization algorithm in problem-solving is depicted in Fig. 19. According to the results in Table 9, for the higher capacity of the wind turbine (3 MW) in 33-bus distribution network, it can be seen that results showed that the photovoltaic power capacity optimization program considered zero and determined the value of 954.81 kW of wind power in bus 30 with a power factor of 0.837. The results cleared that the amount of power losses and ENS have decreased by 1% and 3.7%, respectively compared by considering the capacity of 0.5 MW. Contribution of the RESs during COVID-19 pandemic conditions in Distributed case for 3 MW wind turbine is demonstrated in Fig. 20. It should be mentioned that these reductions have been obtained by increasing the turbine capacity by 6 times in the basic state and spending 29888$ more than the basic state, which is due to the consideration of cost minimization as one of the important parts of the objective function, level of the network demand in different buses for the placement of the turbine with a high capacity to satisfy the operating constraints and supply a part of the network load based on the RESs, the use of a turbine with a capacity of 0.5 MW is desired in this study.

4.2.3. Comparison the results before and during COVID-19 pandemic conditions

The results of deterministic allocation and planning of the RESs are compared before and during COVID-19 conditions for Distributed and Hybrid cases. The comparison of the results is presented in Tables 10 and 11. For Distributed case, before COVID-19 conditions, the photovoltaic array is located in bus 18 with size of 314.09 and the wind resources is located in bus 16 with size of 493.70 kW and power factor equal to 0.80 and during COVID-19 conditions, the photovoltaic array is located in bus 18 with size of 240.57 and the wind resources is located in bus 33 with size of 496.55 kW and power factor equal to 0.80. For Hybrid case, before COVID-19 conditions, the photovoltaic array is located in bus 18 with size of 174.30 and the wind resources is located in bus 18 with size of 494.43 kW and power factor equal to 0.80 and during COVID-19 conditions, the photovoltaic array is located in bus 18 with size of 136.22 and the wind resources is located in bus 16 with size of 476.24 kW and power factor equal to 0.801. The results cleared that during COVID-19 pandemic conditions, active and reactive loss, cost of losses as well as the amount of ENS has decreased, significantly due to the change in network load. The active loss in the Distributed case has decreased from 1168.39 kW to 339.84 kW and the ENS has reduced from 157101.89 kWh to 94234.78 kWh. In addition, the active loss in the Hybrid case has been declined from 1295.03 kW to 419.88 kW and the ENS is declined from 170319.23 kWh to 102872.50 kWh.

4.2.4. Robust operation in the deterministic approach

In this section, in solving the deterministic problem, we seek to find the optimal location and capacity of the clean energy resources that can respond to various changes of the network operational point, including changes in consumption pattern in COVID-19 pandemic condition. According to the optimal results, to change the load, whether reducing or increasing the load, the generation capacity of the photovoltaic and wind resources should also change. Since the location and amount of generation of these resources are unchangeable, so we should look for an approach based on which the network operating point is as close as possible to the optimal conditions to obtain the effectiveness of using these resources in the distribution network. Therefore, in this study, in robust operation, in COVID-19 pandemic conditions, the optimal location and capacity of photovoltaic and wind clean energy sources (optimal design) have been determined in such a way that the least power losses and ENS can be achieved both in quarantine conditions and with the same optimal design. For loading before COVID-19 conditions, the values of power losses and ENS are obtained with the least difference. To understand the robust operation, two concepts are considered as follows:

First Concept) The optimal variables obtained using the TFWO method including location, size, and power factor (for wind resources) of clean sources for the Distributed case and before COVID-19 conditions (DCBC) are applied for loading during COVID-19 conditions (DCAC) and then the numerical results including active and reactive losses, loss cost and ENS are calculated. According to Table 12, the values of active and reactive losses, losses cost, and ENS values for DCBC are obtained 1168.39 kW, 771.78 kW, $ 70.16, and 157101.89 kW, respectively, which by applying the optimal variables (optimal design) in this state for loading during COVID-19 conditions these values decreased to 393.71 kW, 266.80 kW, $ 23.62 and 93086.27 kWh. Therefore, by applying the optimal variables obtained in DCBC to the quarantine conditions caused by COVID-19, there is a large difference between the results.

Second Concept) Optimal variables obtained using the TFWO for the Distributed case and during COVID-19 conditions (DCAC) are applied for loading before COVID-19 conditions (DCBC) and then numerical results including active and reactive losses, losses cost, and ENS are calculated. According to Table 13, the values of active and reactive
losses, losses cost, and ENS values for DCAC mode are achieved 339.84 kW, 236.43 kW, $20.39, and 94234.78 kWh per year, respectively which by applying the optimal variables in this state for loading before COVID-19 conditions, these values have been reduced to 370.57 kW, 256.45 kW, $22.23 and 103153.94 kWh. It is observed that applying the optimal variables obtained in DCAC conditions to pre-quantarize conditions, there is a slight difference between the loss and ENS results. This analysis shows that the optimal design of renewable resources (optimal installation location and size of renewable resources) for the worst case, ie during COVID-19 pandemic conditions, can be extended to conditions before COVID-19, so that the difference between the losses and ENS due to loading changes in these conditions have been low. In other words, the optimal design in terms of COVID-19 conditions can be considered as a suitable and robust option for changing the operational point of the network, and on the other hand, it is observed that there is a little difference between the results obtained. The results showed that COVID-19 pandemic conditions as a robust option in network operating point changes. Moreover, the numerical results of the first concept proved that the optimal design in normal conditions and before COVID-19 pandemic conditions is not a good option in changing the network operating point and the difference between the losses and ENS is very large in comparison with changes in operating point of the network. The proposed method can be implemented and applied based on meteorological data of each city and region.

4.2.5. Results of probabilistic approach during COVID-19 conditions

In this section, the results of probabilistic allocation and planning of photovoltaic and wind clean energy sources are presented during COVID-19 pandemic conditions for the Distributed case using the TFWO. The Beta and Weibull PDFs have been used to consider the irradiance and wind speed uncertainties, respectively. Also, the normal PDF has also been applied to model the temperature uncertainty. The PDF of the output power of the photovoltaic array and wind turbine is considered to be such that the maximum power is 500 kW and the power range is close to 500 kW. The MCS is used to model the uncertainty. The number of 1000 scenarios has been considered and based on the scenario reduction algorithm by removing undesirable scenarios, 500 scenarios have been selected. The curves of irradiance, wind speed, and temperature for a number of 500 scenarios are depicted during 24 h in Fig. 21. Also, the PDFs of the wind speed, irradiance, and temperature for 12:00 are depicted as an example in Fig. 22. The PDF of the photovoltaic array with two parameters 50 and 3 and the PDF of the wind speed with two-scale and shape parameters equal to 10 and 1.75 are modeled.

The PDF of irradiance, wind speed, and temperature has been applied to the program of allocating and planning the photovoltaic and wind resources in the distribution network. For each of the scenarios, allocation, and planning problem is implemented deterministically. After implementing all the scenarios, the PDF of each variable including installation location, size, and power factor (for wind sources) is extracted as Fig. 23. In solving the probabilistic problem based on the extracted PDFs (in Figs. 23), 175.63 kW of photovoltaic power is installed in bus 18 (with more frequency) and 309.81 kW of wind power is installed in bus 11 (with more frequency) with a power factor of 0.831. It should be noted that the numerical value related to PDFs of the sizes of clean resources and also the power factor is obtained from the sum of the product of each scenario value in its probability.

By determining the PDFs of each decision variable, the simulation results including the PDF of active and reactive power losses and also ENS are achieved as shown in Fig. 24. According to Fig. 24, it is clear that the amount of active and reactive losses with uncertainty are obtained 242.19 kW and 351.72 kVAR, respectively, and also the ENS value is achieved 103,906 kWh. Therefore, based on the obtained probabilistic results the active and reactive losses have increased by 4.67% and 5.82%, respectively, and the ENS is increased by 10.26% compared to the deterministic approach results. The deterministic and probabilistic results for the Distributed case after the COVID-19 condition are compared in Table 14. The optimal and feasible locations for Distributed case in deterministic approach are bus 18 (314.09 kW, photovoltaic) and bus 16 (493.70 kW, wind turbine). Also, optimal and feasible locations for Distributed case in probabilistic approach are bus 18 (240.58 kW, photovoltaic) and bus 33 (496.55 kW, wind turbine).

The results proved that, considering the uncertainties (probabilistic) of the network demand and also the renewable energy resources power, the power losses and ENS are increased in comparison with the deterministic approach. Moreover, the power losses and ENS is reduced considerably during Covid-19 condition compared with the before Covid-19 condition. Therefore, due to the inherent existence of the uncertainties in photovoltaic and wind energy generation, the probabilistic approach is a real and logical approach for an accurate understanding of the losses and reliability. Also, network operators are able to make the right decisions in uncertain conditions while this important is not possible in a deterministic approach.

5. Conclusion

In this paper, the allocation and planning of photovoltaic and wind energy resources are studied in the radial distribution network considering the effect of load consumption pattern changes due to the COVID-19 pandemic condition for a 24 h study period in deterministic and probabilistic approaches. The objective function is defined to minimize the losses and enhance the network reliability as the ENS minimization. The optimal location and size of energy resources have been determined using the TFWO method. The proposed method is performed on the IEEE 33-bus distribution network in form of Distributed and Hybrid cases of energy resources to find the best network operation. The results of the deterministic approach before COVID-19 pandemic conditions using the TFWO show the lowest active and reactive losses and better reliability in comparison with the Hybrid case. In comparison to the cases, the results show that in the Distributed case the active loss is reduced from 1168.39 kW to 339.84 kW and the ENS is declined from 157101.89 kWh to 94234.78 kWh compared to the Hybrid case before COVID-19 pandemic conditions. The results also cleared that the TFWO achieved lower losses and better reliability in comparison with the PSO and GWO in solving the deterministic approach. Moreover, the results confirmed that allocation and planning of the clean resources in the face of changing consumption patterns due to the effects of COVID-19 conditions can be an appropriate and robust option in changes of the network operating point. Therefore, considering the worst conditions in problem-solving improves the operating conditions of the network. The findings cleared that the power losses and ENS is reduced considerably during Covid-19 condition compared with the before Covid-19 condition. Moreover, the results of the probabilistic approach in comparison with deterministic results demonstrated that the active and reactive losses and also the ENS are increased by 4.67%, 5.82%, and 10.26%, respectively. The optimal and feasible locations for Distributed case in deterministic approach are bus 18 (314.09 kW, photovoltaic) and bus 16 (493.70 kW, wind turbine). Also, optimal and feasible locations for Distributed case in probabilistic approach are bus 18 (240.58 kW, photovoltaic) and bus 33 (496.55 kW, wind turbine). Therefore, the probabilistic approach can lead to rational decisions as well as desirable planning by the operator, while in deterministic problem solving, the occurrence of the worst probabilities is hidden from the operator, and creating detailed planning with the right decisions will not be possible.

Credit author statement

Li Feng: Supervision, Resources, Project management, Jiajun Liu: Writing original manuscript, Writing review, Data curation. Haitao Lu: Software, Conceptualism, Writing review. Bingzhi Liu: Data curation, Writing review, Investigation, Yuning Chen: Software, Conceptualism, Writing review. Shenyu Wu: Investigation, writing original draft,
Writing Review.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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