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Solving multi-objective economic emission dispatch of a renewable integrated microgrid using latest bio-inspired algorithms

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ABSTRACT

The concept of a microgrid system, when put in simple words, is a small scale generation and deployment of power to a small geographical area in order to avoid transmission losses and maintain an uninterrupted power supply. It has been a mandatory protocol to implement the available renewable energy sources (RES) in order to minimize the emission of harmful pollutants to the atmosphere from the combustion of the fossil fuels. Economic load dispatch (ELD) deals with the optimal sizing of the distributed energy resources (DERs) by minimizing the fuel costs. Emission dispatch does the optimal sizing of the DERs sources by minimizing the amount of pollutants released in the atmosphere. A multi-objective Combined Economic-Emission Dispatch (CEED) does the optimal DER sizing providing a compromised solution of minimizing both the fuel costs and pollutants emission. This paper performs all ELD, emission dispatch and CEED on an islanded and renewable-integrated microgrid separately using a recently developed novel Whale optimization Algorithm (WOA). Four various scenarios of load sharing among the DERs are studied. The results are then compared with other recently developed bio inspired algorithms to corroborate the effectiveness of the proposed technique. Further statistical analysis such as ANOVA test and Wilcoxon signed rank test are performed to prove the superiority of the proposed approach over the various other optimization techniques used.

1. Introduction

Microgrid can be defined as a recent small-scale form of the centralized power system. It typically consists of distributed generation (DG) units, energy storage resources and loads that are designed and sited close to the customers in small communities [1]. The DG units used in the microgrid can either be conventional generators (i.e. thermal and diesel generators) or renewable energy sources (i.e. wind power and solar power). However, recently renewable energy sources have been used widely in microgrids due to their cost and environmental benefits in comparison with the conventional generators [2]. Whereas, the energy storage resources used in the microgrid include batteries, flywheels and pumped storage. In addition, the microgrid connected different types of loads such as agriculture, industrial, commercial and residential.

Usually, the microgrids can either be operated in two different modes. The first one is the grid connected mode in which the microgrid is connected to the main grid. While the second mode is the islanded mode in which the microgrid is isolated from the main grid in the event of emergency and continue to deliver power to the local loads (Fig. 1) [1]. The microgrids' advantages contain the improvement of power quality and reliability and also the reduction of generation cost and carbon emission by using the renewable energy sources.

Economic load dispatch (ELD) is the key problem related to the operation of grid connected or islanded microgrids. The goal of the economic load dispatch problem is to share the output power of the running generation sources so as to provide the load demand satisfying the generator constraints at a minimized fuel cost [3]. Accordingly numerous optimization techniques are implemented to solve complex and convex ELD problems. Some of them include the participation factor methods, the gradient methods, the linear methods and Newtonian methods etc. [3–4]. These methods may be simple but they converge towards the solution very slowly.

The harm caused to the environment by the release of the toxic gases in the atmosphere has gained much attention in the last few decades by the utility companies. They are bound to maintain certain levels regarding the release of harmful gases like carbon-di-oxide (CO_2), carbon-monoxide (CO), Sulphur-di-oxide (SO_2) etc.

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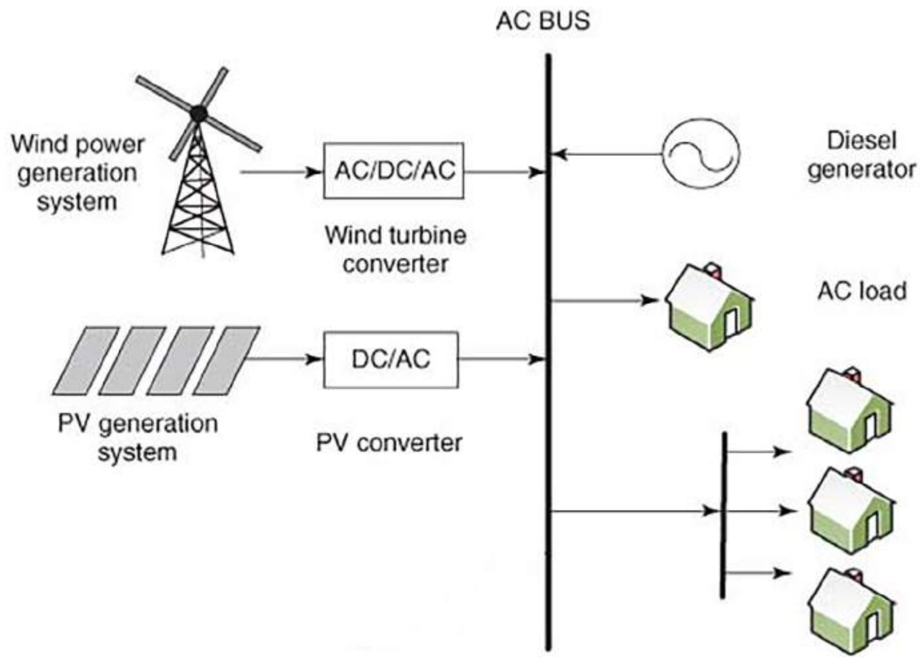

Fig. 1. Architecture of an islanded microgrid.

[5]. The emission of these harmful gases can be reduced by installing more efficient and clean generator that consumes less fuel, updating the control equipment and emission dispatch [6–8]. Emission dispatch was first performed [9] to minimize the emission of nitrous-oxide (NO_x) gases but the corresponding ELD proved to be costlier. The economic emission dispatch (EED) idea was brought to find a compromised solution between the cost and emission levels. A fuzzy interval optimization approach to solve the EED problem with uncertain parameters in the constraints and the objective functions is studied in [10]. Not only various algorithms were applied to solve emission problems subject to various constraints in [11–12], literature review also shows that the economic load dispatch was conducted by considering the emission dispatch as the constraint itself [13–14].

The ever increasing load demand along with the minimization of environmental pollution can be solved considering renewable energy sources (RES) as significant alternative DER. Microgrid comprises of a low voltage system along with DERs, storage devices and flexible loads. The DERs such as micro-turbines, fuel cells, wind turbines and photo voltaic (PV) system along with storage devices such as flywheel, battery, energy capacitor etc. all are used in a microgrid. A microgrid has two modes of operation viz. islanded and grid connected mode and hence it is of benefit to both the grid and customer. The primary microgrid control, also known as the coordinated control, is used to optimize the allocation of power among DER, cost of producing the energy and emission. The authors minimized the microgrid cost comprising of a micro-turbine fuel cell, PV, wind turbine and battery storage in [15] using particle swarm optimization. Authors used differential evolution technique to solve an economic and emission dispatch problem of a microgrid using combined heat and power in [16]. The forecasted value of PV and wind turbine and also the real time market prices were considered while minimizing the microgrid cost in [17] and both emission and microgrid cost in [18] implementing different variants of particle swarm optimization (PSO). Harmony search algorithm (HSA) was used to minimize the microgrid cost involving penetrable PV, micro-turbine and fuel cell in [19]. Ant lion optimizer was used in [20] for optimum allocation of RES in 33 and 69 bus radial distribution system to reduce the total power losses and hence maximizing the net saving. Multi-objective optimization techniques have also been developed to involve emission as a separate goal by choosing definite number of generating units and minimize the cost and emission level in [21–25]. Weighting factors was used to combine the fuel cost objective and emission objective into a single one in [26–28] and more recent techniques were also used in solving environmentally constrained ELD problems in [29–30]. A flower pollination algorithm (FPA) was used as the optimization tool by authors in [31] to perform ELD and CEED in various small and large test systems considering valve-point effect. FPA yielded better quality results is less computational time when compared to many optimization techniques from the literature. Authors in [32] used mine-blast algorithm (MBA) to perform ELD and CEED for 6-unit, 10-unit and 13-unit test systems considering valve-point effect and transmission loss. A normal boundary intersection method was used by authors in [33] to perform a multi-objective dynamic economic dispatch and minimize the generation costs, emissions and power loss in the system. Fuzzy decision making method was implemented to find the best compromised solution for the three different objectives. Individual residential loads were considered to perform dynamic ELD with demand side management on a fifteen generator test system in [34] which proved that shifting of flexible loads can decrease the generation loads. [35] used fuzzy based hybrid PSO-DE to perform multi-objective economic emission dispatch on 10, 40 and 160 unit systems consider power loss, ramp rate, prohibited operating zones and valve point effects. Authors in [36] implemented a number of PSO variants to perform Dynamic Economic Emission dispatch on different load models. Authors in [37] proposed a hybrid evolutionary algorithm based on shuffled frog leap algorithm and PSO (MSFLA-PSO) to perform multiple area ELD for 10-unit and 40-unit systems connected to multiple areas by tie-line. Authors in [38] implemented MSFLA-PSO to solve the multi-objective version of DFR problem on two different distribution systems considering power losses, Voltage Stability Index (VSI), and number of switching as fitness functions. An improved variant of both PSO and grey wolf optimizer was hybridized (IPSO-IGW) and implemented by authors in [39] to perform multi-objective dynamic distribution feeder reconfiguration on a 95-nodes test system to minimize the operating cost, power loss and energy not supplied. A multi-objective PSO (MOPSO) was proposed to perform multi-objective dynamic economic and emission dispatch with demand side management in [40].

Evolvement of soft computing tools, which are not restricted by complexity of system models, inspired the research workers to apply them in the field of power system optimization. The versatile properties and attractive performance of Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Differential Evolution (DE) over wide range of benchmark functions have inspired the many researchers to implement these algorithms for solving energy management issues of microgrids involving optimal costs and load scheduling. Nevertheless GA, PSO and DE have their own list of disadvantages too. The very basic disadvantage of GA is its unguided mutation. The mutation operator in GA functions like adding a randomly generated number to a parameter of an individual of the population. This is the only reason of a very slow convergence of genetic algorithm**.** DE suffers from unstable convergence and easily drops down to regional optimum. Likewise PSO also drops down to regional optimum and has untimely convergence. In addition to that multiplicity of population is not enough in PSO. Also some time is consumed in tuning the control parameters present in all of the aforementioned optimization techniques.

However, there exists a few recently developed *meta*-heuristic swarm evolutionary algorithms viz. Symbiotic Organisms Search (SOS) (2014), Grey wolf optimizer (GWO) (2013) and Whale Optimization Algorithm (WOA) (2016) which are free from the various demerits of the aforementioned optimization tools. The crucial merit of SOS, GWO and WOA is that they have no tuning parameters and thus the tedious and numerous combinations of tuning various factors doesn't exist. By increasing or decreasing the population size better quality results can be obtained in these algorithms.

The fitness function is evaluated four times per iteration throughout the various stages of SOS and the best of them is stored. This process is repeated until the termination criteria is attained. Both GWO and WOA are iteration dependent optimization techniques. This means that the exploration and exploitation in these two optimization techniques happens throughout the iterations. The adaptive values of some crucial parameters in GWO and WOA allow smooth transition between exploration and exploitation. The initial iterations perform the exploration and the rest of the iteration exploits the solution in the search space to obtain a superior quality result. Literature shows SOS [41–42], GWO [43–44] and WOA [45–46] have found to be beneficial in various power system problems in the recent times. Not much emphasis was given in solving multi objective CEED problems on microgrids with these algorithms.

This motivated the author to study all of PSO, DE, SOS and GWO along with the proposed WOA as the optimization tools to minimize the combined economic and emission dispatch of a renewable incorporated microgrid system, abiding the various equality and inequality constraints. Furthermore a comparative analysis is performed to prove the efficacy and superiority of WOA among these five algorithms in providing a better and profound solution.

This paper considers a renewable integrated islanded microgrid and all of ELD, emission dispatch and CEED are performed by using five swarm and population based evolutionary techniques. Section 2 of this paper forms the objective function. The superior optimization technique, WOA is discussed in detail in Section 3. Various combinations are studied and the results are discussed in Section 4. The paper concludes in Section 5.

2. Objective function formulation

Economic Load Dispatch: The Economic Load Dispatch (ELD) problem speculates the objective of sharing the load of a power system among the various generation units in such a way as to minimize the fuel costs of the conventional generators satisfying the various constraints and fulfilling the load demand of the system. The fuel costs of the conventional generators which is a convex polynomial can be mathematically expressed as [47]:

$$F(P)=\sum_{t=1}^{24}\sum_{i=1}^{g}\{u_iP_i^2(t)+v_iP_i(t)+w_i\} \tag{1}$$

where 'g' is the number of conventional generators in the system, P_i is the output power of the generation unit i and u_i,v_i and w_i are the cost coefficients of the i^{th} generator. $F(P)$ is in \$/hr.

Emission Dispatch: The combustion of fossil fuels by the conventional generators releases some harmful toxic gases such as CO_2, SO_x etc. in the atmosphere which should also be taken care of. The emission dispatch minimizes the release of these harmful gases in the atmosphere. The emission dispatch function is also a convex polynomial like the ELD and can be written as

$$E(P)=\sum_{t=1}^{24}\sum_{i=1}^{g}\{x_iP_i^2(t)+y_iP_i(t)+z_i\} \tag{2}$$

where x_i, y_i and z_i are the emission coefficients of the i^{th} generation unit. The unit of $E(P)$ is kg/hr.

Combined Economic-Emission Dispatch: As discussed above it can be seen that the economic load dispatch and emission dispatch are complete two different objectives. The former deals with the minimization of the fuel costs of the conventional generators and the latter minimizes the emission of harmful and toxic pollutants in the atmosphere. Hence it is necessary to arrive at a compromised solution which can attain both minimized fuel cost emitting least amount of pollutants in the atmosphere. This is done by creating a multi-objective problem combining (1) and (2) with the help of a parameter called "*Penalty factor*". The penalty factor acts as an intermediate to reform the emission criteria into an equivalent fuel cost for the emission. Mathematically, the price penalty factor or simply penalty factor is a multiplication factor associated with each of the emission coefficients which transforms two differently aimed single objective function to a CEED problem. Needless to say, lower the value of the penalty factor, lesser the value of the CEED problem. The various types of penalty factors are formulated and calculated in later section of this paper.

The multi-objective economic-emission dispatch problem can thus be mathematically stated as:

$$C(P)=\sum_{t=1}^{24}\sum_{i=1}^{g}\left[\{u_iP_i^2(t)+v_iP_i(t)+w_i\}+h_i\times\{x_iP_i^2(t)+y_iP_i(t)+z_i\}\right] \tag{3}$$

where h_i is the penalty factor of the i^{th} generating unit. The units of $C(P)$ is *\$/hr* and h_i is *\$/kg*.

Renewable Energy Integration: Furthermore both the fuel costs and the pollutants emission can be reduced by the inclusion of available renewable resources for the generation of power. The renewable energy resources are clean sources of energy which neither incurs any fuel cost nor does it emits harmful toxic gases in the atmosphere. Although these renewable energy sources do include some installation or maintenance cost whose cost function can be calculated as below [47]:

$$F(P_{RES})=P_{RES}\left(AC.I^P+G^E\right) \tag{4}$$

where P_{RES} is the output power of the renewable energy resources, AC is the annuitization coefficient, I^P is the ratio of investment cost to established power in \$/kW and G^E is the operational and maintenance cost in \$/kW. Annuitization coefficient can be calculated with the formula

$$AC = \frac{r}{1-(1+r)^{-N}} \tag{5}$$

where r is the interest scale and N is the investment duration in years.

This work on an islanded microgrid uses wind farms and photo voltaic (PV) system as the available RES for the minimization of fuel and emission costs and also to increase the efficiency and maintain an uninterrupted power supply. The operational and maintenance cost for the wind farm and PV system is 0.016\$/kW invested at 9% interest scale for 20 years. The ratio of investment cost to establish power is 5000\$/kW for PV system and 1400\$/kW for wind farm. So the cost function of PV becomes $F_{PV} = 547.7483 * P_{PV}$ and the cost function of wind is $F_{WIND} = 153.3810 * P_{WIND}$. [47]

Hence with the inclusion of RES the economic load dispatch function becomes [47]:

$$ELD(P) = \sum_{i=1}^{g}\left(a_iP_i^2 + b_iP_i + c_i\right) + 547.7483 * P_{PV} + 153.3810 * P_{WIND} \tag{6}$$

And the inclusion of RES in the combined economic emission dispatch function, turns it into

$$EED(P) = \sum_{i=1}^{g}\left[\left(a_iP_i^2 + b_iP_i + c_i\right) + h_i\left(l_iP_i^2 + m_iP_i + n_i\right)\right] + 547.7483 * P_{PV} + 153.3810 * P_{WIND} \tag{7}$$

The above objective functions (6) and (7) are subject to constraints such as:

i Generation constraints: The power generated by the conventional generators as well as the RES must lie between a maximum and minimum limit. Mathematically,

$$\begin{aligned} P_{i,\min} \leqslant P_i \leqslant P_{i,\max} \\ P_{RES,\min} \leqslant P_{RES} \leqslant P_{RES,\max} \end{aligned} \tag{8}$$

ii. Power supply-demand balance constraint: the power generated at any instant of time by all the conventional generators and the RES should satisfy the total desired load of the system. This can be mathematically stated as:

$$P_{LOAD} = P_i + P_{RES}, i = 1,2,3,\ldots g \tag{9}$$

This work focuses on minimizing (6) and (7) separately using various optimization techniques and a comparative study among the techniques as well as the minimized costs of ELD and EED.

3. The whale optimization algorithm

This algorithm is motivated by Humpback whale for capturing prey and bubble-net hunting strategy and was first proposed by Mirjalili and Lewis [48] in 2016. The key features and methodology of WOA are described in the following subsection.

(a) Features

Whales are the biggest mammals in the world and are considered as highly intelligent animal with emotion. The most interesting fact of this mammal is that they never sleep because they have to breathe from surface of the oceans. They have twice the number of spindle cells than an adult human and that is the main reason of their smartness. It has been proved that whales can think, learn, judge, communicate and exhibit emotion. One of the biggest baleen whale is Humpback whale (*Megaptera movaeangliae*) and they have a unique hunting method known as bubble-net feeding method.

(b) Methodology

The whales have a specific encircling prey pattern. They use bubble-net strategy while searching and attacking their prey. The mathematical models of these behaviours are discussed below:

(i) Search for the prey (Exploration phase)

In the exploration phase, the position of a search agent is updated according to a randomly chosen search agent instead of best search agent obtained. This behaviour can be represented as follows:

$$\vec{D} = \left|\vec{C}.\vec{X}_{rand} - \vec{X}\right| \tag{10}$$

$$\vec{X}(iter+1) = \vec{X}_{rand} - \vec{A}.\vec{D} \tag{11}$$

where, $\vec{X}_{rand}$=Random position vector of whale chosen from current population.

(ii) Encircling prey

The whales have the ability to recognize the location of prey and encircle them. This encircling behaviour is represented by the following equations:

$$\vec{D} = \left|\vec{C} \times \vec{X}_P(iter) - \vec{X}(iter)\right| \tag{12}$$

$$\vec{X}(iter+1) = \vec{X}_P(iter) - \vec{A} \times \vec{D} \tag{13}$$

where *iter* indicates current iteration, A and C are coefficient vectors.

X_P specifies position vector of the prey and X specifies position vector of Whale.

The vector A and C are calculated as follows:

$$\begin{aligned} \vec{A} &= 2.\vec{a}.\vec{r}_1 - \vec{a} \\ \vec{C} &= 2.\vec{r}_2 \end{aligned} \tag{14}$$

where component of $\vec{a}$ are linearly decreased from 2 to 0 over the course of iteration (in both exploration and exploitation phases) and r_1 and r_2 are random vectors in range [0,1].

(iii) Bubble-net attacking method (Exploitation phase)

There are two approaches for bubble-net behaviour of the whales which are described below:

- *Shrinking encircling mechanism*

This ability is achieved by decreasing the value of 'a' in the equation (28). Hence fluctuation range of $\vec{A}$ is also decreased by $\vec{a}.\vec{A}$ is the random value in the interval $[-a,a]$ where a is decreased from 2 to 0 over the course of iterations.

- *Spiral updating positions*

This behaviour is achieved by calculating the distance between the whale and the location of its prey. A spiral equation has been created to mimic the helix-shaped movement of humpback whales which is as follows:

$$\overrightarrow{X}(iter+1) = \overrightarrow{D}.e^{bl}.Cos(2\pi l) + \overrightarrow{X}(iter) \tag{15}$$

where, $\overrightarrow{D} = \left|\overrightarrow{X}_p(iter) - \overrightarrow{X}(iter)\right|$ signifies the distance between i^{th} whale to its prey (best solution).where, b = Constant for defining the shape of logarithmic spiral.

l = Random number in [−1, 1].
= Element-by-element multiplication.

In fact, the whales swim around its prey within a shrinking circular as well as a spiral-shaped path simultaneously. Due to this behaviour, we assume that there is a probability of 50% in choosing either the shrinking encircling mechanism or the spiral model to update the position of whales during optimization. Mathematical model for this behaviour is as follows:

$$\overrightarrow{X}(iter+1) = \begin{cases} \overrightarrow{X}_P(iter) - \overrightarrow{A}.\overrightarrow{D} & if \quad p < 0.5 \\ \overrightarrow{D}.e^{bl}.Cos(2\pi l) + \overrightarrow{X}_P(iter) & if \quad p \geqslant 0.5 \end{cases} \tag{16}$$

where, p = Random number in [0,1].

At the starting of WOA, initial search space is created randomly where each search agent represents position of a whale. After every iteration, search agents update their positions with respect to either a randomly selected search agent or the best solution obtained till then. The parameter 'a' is decreased in order to provide exploration and exploitation. This is exactly what happens in GWO, as the iteration proceeds to attain the stopping criteria. Apart from this, there exists these 'shrinking encircling mechanism' and 'spiral updating position' methods of attacking prey in WOA, that provides a rigorous exploitation mechanism between the whale and its prey, thus allowing the optimization tool to attain a solution of superior quality than many other optimization techniques including GWO.

Nevertheless this rigorous and multiple method of exploration and exploitation capability of WOA may consume more amount of time during every iteration if complex and non-linear equality and inequality constraints are involved. This shall give rise in overall computational time of WOA which may be considered as a disadvantage of the algorithm.

Finally WOA comes to end by satisfying all the termination conditions which was given initially. Algorithmic procedure for the complete execution of the proposed work using WOA is given below:

Set the number of search agents and the maximum number of iterations.
Define the boundary limits of control variables i.e. the 3 conventional generators say G_1, G_2 and G_3 and the load demands of 24 h for all the four cases
Initialize the population matrix for 'n' number of search agents (population size) abiding by the various equality and inequality constraints mentioned in (8) and (9)

$$\begin{bmatrix} G_{1,1,1}, G_{1,1,2}, G_{1,1,3} \ldots G_{1,1,24}, G_{1,2,1}, G_{1,2,2}, G_{1,2,3} \ldots G_{1,2,24}, G_{1,3,1}, G_{1,3,2}, G_{1,3,3} \ldots G_{1,3,24} \\ \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \\ G_{n,1,1}, G_{n,1,2}, G_{n,1,3} \ldots G_{n,1,24}, G_{n,2,1}, G_{n,2,2}, G_{n,2,3} \ldots G_{n,2,24}, G_{n,3,1}, G_{n,3,2}, G_{n,3,3} \ldots G_{n,3,24} \end{bmatrix}$$

The suffixes of G are in the order search agent number, generator number and hour. For instance $G_{n,3,24}$ means the 24th hour output of the 3rd generator from the n^{th} search agent.

Initialize *a, A* and *C* using (14).
Evaluate and compare the fitness solution value with all the search agent solution. Store the minimum value of fitness function and the corresponding position of search agent.
Set the iteration number equal to 1.
The new prey is searched (exploration phase) by using (10).
After new prey is searched then encircling of prey is done using (12).
Update the position of search agents for attacking the prey with bubble-net strategy using (14).
Update the value of *a, A* and *C* using (14) with new position of search agent.
Check all the equality and the inequality constraints mentioned in (8) and (9) with the new position of each search agent.
Repeat Step 5.
Increase the iteration number by 1, i.e., *iter = iter + 1*.
If the maximum number of iteration has reached then terminate the iterative process and store the fitness value as the best solution of optimization problem otherwise repeat the steps-(7) to steps-(13).

The stepwise performance of the WOA algorithm is shown in a flowchart in Fig. 2.

4. Results and discussions

4.1. Description of the system

The test system is an islanded microgrid consisting of 3 conventional generators, one 30 MW wind farm and one 40 MW PV system. The operating ranges, cost and emission coefficients of the conventional generators are listed in Table 1. Four different combinations of distributed generation sources have been studied in this work viz. all sources included, without PV, without wind and without both PV and wind. The 24 h output of wind and PV are calculated for various wind speed and solar radiation at a location east coast of USA [47] and are listed in Table 2 along with the hourly load demand of the microgrid. Five meta-heuristic swarm evolutionary based soft computing techniques viz. particle swarm optimization (PSO), differential evolution (DE), Symbiotic Organism Search (SOS), Grey Wolf Optimization (GWO) and Whale Optimization Algorithm (WOA) were applied to solve ELD, emission dispatch and CEED for all the four combinations in MATLAB R2010a platform installed in a personal computer with 2.53 GHz core i3 processor and 2 GB RAM. The program is run with 30 population and 1000 iterations for 20 repeated trials and this was same for all the optimization techniques used. While performing PSO, the acceleration factors c_1 and c_2 were set at 2 and the inertia weights w_{max} and w_{min} were 0.9 and 0.4 respectively. The scaling factor F and the cross over ratio CR were maintained at 0.7 and 0.2 respectively when DE was performed. The Benefit Factors for SOS were set at 2.

4.2. Comparative Analysis

Table 3 enlists the various costs when ELD was performed on the microgrid test system for various cases using PSO, DE, SOS, GWO and WOA. It can be seen that for all the four different cases of varying loads, WOA incurred superior and better results than all of PSO, DE, SOS and GWO. The various costs attained by WOA were \$299895.7531, \$203987.5104, \$272031.0549 and \$176166.5662 for the cases 'all sources', 'without PV', 'without wind' and 'without RES' respectively. These values are the minimum among the costs obtained using rest of the optimization techniques for the aforementioned cases.

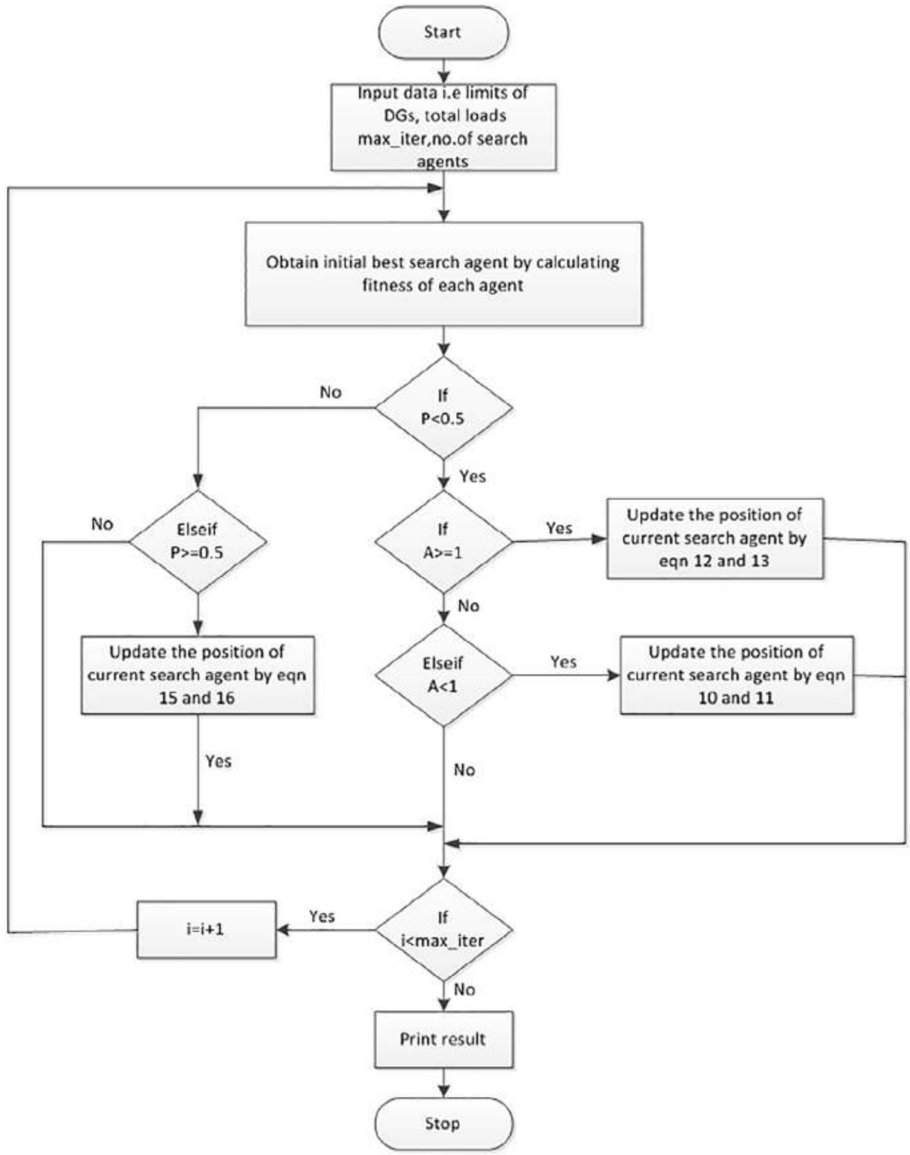

Fig. 2. Flow chart of Whale Optimization Algorithm.

Table 1
Generator power limits, fuel cost coefficients and emission coefficients [47].

DG sources	Min Power (MW)	Max Power (MW)	u (\$/MW^{2}h)	v (\$/MWh)	w (\$/h)	x (kg/MW^{2}h)	y (kg/MWh)	z (kg/h)
G1	37	150	0.0024	21	1530	0.0105	-1.355	60
G2	40	160	0.0029	20.16	992	0.008	-0.6	45
G3	50	190	0.021	20.4	600	0.012	-0.555	90

Emission dispatch was performed in the microgrid test system using PSO, DE, SOS, GWO and WOA and the pollutants emitted (in kg) are shown in Table 4**.** The pollutants emitted using WOA when all sources were used was 2183.9629 kg, without using PV was 2264.9788 kg, without using wind was 2254.2557 kg. and without using both the RES was 2379.4554 kg. It can be realized from the table that these values are pretty less when compared to the rest of the optimization techniques used. It is also to be noted that the maximum pollutants are emitted when no RES were used. This is obviously because the entire load demand was to be fulfilled by the conventional generators, thus consuming more fuel and releasing harmful pollutants.

Authors in [49] and [50] discussed about the various types of penalty factors for amalgamating an economic dispatch problem and an emission dispatch problem formulating a multi-objective CEED problem. All those various types of penalty factor were formulated, calculated and listed in Table 5. It can be realized that Min-Max penalty factor is the least and the best type. Therefore this penalty factor was chosen to formulate the CEED problem.

Multi-objective CEED was performed using various optimization techniques mentioned earlier and the results were highlighted in Table 6**.** Similar to the other two cases and by virtue of its swift and broad exploration and exploitation capability, WOA outperformed all the rest of the optimization techniques in giving a better

Table 2
Day ahead forecasted hourly output of PV and wind and hourly load demand.

Time (hours)	Load (MW)	PV (MW)	WT (MW)
1	140	0	1.7
2	150	0	8.5
3	155	0	9.27
4	160	0	16.66
5	165	0	7.22
6	170	0.03	4.91
7	175	6.27	14.66
8	180	16.18	25.56
9	210	24.05	20.58
10	230	39.37	17.85
11	240	7.41	12.80
12	250	3.65	18.65
13	240	31.94	14.35
14	220	26.81	10.35
15	200	10.08	8.26
16	180	5.30	13.71
17	170	9.57	3.44
18	185	2.31	1.87
19	200	0	0.75
20	240	0	0.17
21	225	0	0.15
22	190	0	0.31
23	160	0	1.07
24	145	0	0.58

and profound result. The microgrid cost was found to be \$325364.621 when all the sources were used to share the load, \$230019.0483 when PV system was not considered, \$297907.5634 when wind turbine was unused and \$202881.7751 without considering RES. It can be realized from Table 6 that these results are better and less than those obtained by the rest of the optimization techniques.

Tables 7–10 lists the hourly output of the conventional generators for various cases when CEED was evaluated using WOA. All the values can be seen to be satisfying their equality and inequality constraints. This constraint handling capability of any algorithm is also an appreciable feature. During the first and last few hours when load demand is less, the generators out flow the minimum power required to satisfy their demand. But during the peak hours when the demand is high, the generators can be seen to deliver maximum power than rest of the time intervals. These values are much higher when RES are not considered and the generators satisfy the load demands among themselves.

Figs. 3(a) to 3(d) shows the convergence curve characteristics when ELD was performed using PSO, DE, SOS, GWO and WOA for the four different cases respectively. Figs. 4(a) to 4(d) portrays the convergence curve characteristics when CEED was evaluated using all the five algorithms for the four cases respectively. It can be realized for maximum of the cases WOA converges in earlier iterations than the other optimization algorithms. Fig. 5 shows the hourly distribution of costs when CEED was evaluated using WOA. It can be seen that the rise in the cost curve is during the peak demand of load i.e. from 8th to 18th hour. Also due to the high cost coefficient of PV system, the cost curve maintains a low profile throughout the day in the two cases when PV was not considered i.e. 'without PV and 'without RES'. Fig. 6 is a bar diagram representing the total time taken by the algorithms to evaluate CEED for the various cases. It can be seen for all the cases WOA consumed the minimum amount of time (20 to 25 s) to deliver

Table 3
Microgrid cost (in \$) for ELD using optimization techniques.

	All Sources	Without Solar	Without Wind	Without RES
PSO	299919.4357	204025.1856	272045.2086	176177.9174
DE	299916.0487	204006.9307	272036.3530	176169.0719
SOS	299906.3846	204001.6485	272034.5209	176168.04244
GWO	299896.6562	203988.3084	272033.5531	176167.8827
WOA	299895.7531	203987.5104	272031.0549	176166.5662

Table 4
Microgrid emission dispatch (in kg) using optimization techniques.

	All Sources	Without Solar	Without Wind	Without RES
PSO	2189.6784	2269.4351	2260.4334	2385.7962
DE	2187.4739	2266.6284	2259.5973	2383.2908
SOS	2185.2421	2266.3662	2257.9951	2381.9505
GWO	2184.7448	2265.6551	2256.9551	2380.519
WOA	2183.9629	2264.9788	2254.2557	2379.4554

Table 5
Calculation of various price penalty factor for G1, G2 and G3.

Penalty Factor types	Penalty Factor Formula	h_1 (\$/kg)	h_2 (\$/kg)	h_3 (\$/kg)
Max-Min ($h_{i,\max-\min}$)	$\frac{u_iP_{i,\max}^2 + v_iP_{i,\max} + w_i}{x_iP_{i,\min}^2 + y_iP_{i,\min} + z_i}$	215.3509	146.7455	162.2976
Max-Max ($h_{i,\max-\max}$)	$\frac{u_iP_{i,\max}^2 + v_iP_{i,\max} + w_i}{x_iP_{i,\max}^2 + y_iP_{i,\max} + z_i}$	56.1290	32.2496	14.6306
Min-Min ($h_{i,\min-\min}$)	$\frac{u_iP_{i,\min}^2 + v_iP_{i,\min} + w_i}{x_iP_{i,\min}^2 + y_iP_{i,\min} + z_i}$	96.530	54.5798	5.5334
Min-Max ($h_{i,\min-\max}$)	$\frac{u_iP_{i,\min}^2 + v_iP_{i,\min} + w_i}{x_iP_{i,\max}^2 + y_iP_{i,\max} + z_i}$	**25.1597**	**11.9948**	**4.6750**
Average ($h_{i,avg}$)	$\frac{h_{i,\max-\min} + h_{i,\max-\max} + h_{i,\min-\min} + h_{i,\min-\max}}{4}$	98.2924	61.3924	46.7841
Common ($h_{i,com}$)	$\frac{h_{i,avg}}{number\ of\ generators}$	32.76	20.46	15.59

Table 6
Microgrid cost (in $) for CEED using optimization techniques.

	All Sources	Without Solar	Without Wind	Without RES
PSO	325377.3173	230029.0775	297912.8001	202886.6496
DE	325371.3072	230024.3813	297911.5005	202884.8852
SOS	325369.7976	230023.7559	297910.2332	202882.0837
GWO	325368.4448	230020.3064	297908.2971	202882.6042
WOA	325364.4919	230019.0483	297907.5634	202881.7751

Table 7
Hourly outputs (in MW) of conventional generators for CEED using WOA (All sources).

Time (hours)	G1 (MW)	G2 (MW)	G3 (MW)
1	48.2994	40.0006	50.0000
2	51.4987	40.0004	50.0009
3	55.7286	40.0003	50.0011
4	53.3387	40.0006	50.0007
5	64.0879	43.6867	50.0054
6	66.3493	48.6901	50.0206
7	62.9977	41.0701	50.0021
8	47.2587	40.0005	50.0008
9	66.3881	48.9600	50.0219
10	67.7507	52.108	52.9212
11	74.4747	67.4736	77.8417
12	75.5121	70.0425	82.1454
13	71.5053	60.6438	66.691
14	68.4943	53.5823	55.6334
15	69.0334	55.0468	57.5798
16	65.1250	45.8616	50.0034
17	63.9238	43.0645	50.0016
18	68.9211	54.5960	57.3029
19	71.4439	60.7420	67.0641
20	77.3194	74.1609	88.3497
21	75.0815	69.1129	80.6556
22	70.1958	57.5931	61.9011
23	64.5596	44.3606	50.0098
24	54.4178	40.0013	50.0009

Table 8
Hourly outputs (in MW) of conventional generators for CEED using WOA (without PV).

Time (hours)	G1 (MW)	G2 (MW)	G3 (MW)
1	48.2866	40.0006	50.0128
2	51.4538	40.0258	50.0204
3	55.7008	40.0120	50.0171
4	53.3381	40.0006	50.0014
5	63.2853	44.1454	50.3493
6	65.9342	48.8788	50.2770
7	65.8464	44.3622	50.1314
8	61.9369	41.4910	50.0121
9	69.8893	58.2664	61.2643
10	73.7800	65.4173	72.9528
11	75.0000	69.6254	82.5746
12	75.0000	71.6199	84.7301
13	75.0000	69.6379	81.0121
14	72.8146	65.0150	71.8204
15	70.1807	58.2778	63.2815
16	65.7650	50.3204	50.2046
17	66.4587	49.6219	50.4793
18	69.1471	56.0426	57.9404
19	72.8175	60.8880	65.5444
20	75.0000	74.6353	90.1947
21	75.0000	69.2765	80.5735
22	70.4006	57.0814	62.2080
23	63.9844	44.8716	50.0740
24	54.3541	40.0480	50.0179

Table 9
Hourly outputs (in MW) of conventional generators for CEED using WOA (without wind).

Time (hours)	G1 (MW)	G2 (MW)	G3 (MW)
1	49.9639	40.0000	50.0361
2	59.9731	40.0000	50.0269
3	64.2244	40.6730	50.1027
4	64.0309	45.9308	50.0383
5	65.8119	48.5359	50.6522
6	67.4012	51.1905	51.3783
7	67.4248	50.2121	51.0931
8	67.4268	46.2874	50.1058
9	69.6540	57.3296	58.9664
10	70.4058	58.3716	61.8526
11	74.9236	72.7051	84.9613
12	75.0000	77.5698	93.7802
13	73.1866	64.9654	75.0380
14	70.0538	57.0356	60.9706
15	70.1991	57.2878	62.4331
16	68.0370	51.9447	54.7183
17	65.4648	44.9197	50.0455
18	69.1727	55.8040	57.7132
19	71.6440	60.0821	68.2739
20	74.9468	75.4474	89.6058
21	75.0000	69.1320	80.8680
22	70.5373	57.4949	61.9678
23	64.1677	45.7400	50.0924
24	54.9815	40.0000	50.0185

Table 10
Hourly outputs (in MW) of conventional generators for CEED using WOA (without RES).

Time (hours)	G1 (MW)	G2 (MW)	G3 (MW)
1	49.9999	40.0001	50.0000
2	59.9907	40.0092	50.0000
3	63.1746	41.8252	50.0002
4	65.3077	44.6904	50.0019
5	66.3383	48.6612	50.0005
6	67.4001	51.1628	51.4371
7	68.1186	52.7819	54.0994
8	68.7783	54.4583	56.7635
9	72.9873	64.2170	72.7957
10	74.9999	71.1608	83.8393
11	74.9997	74.9274	90.0729
12	75.0000	78.7473	96.2527
13	74.9997	74.9316	90.0687
14	74.4516	67.5371	78.0113
15	71.6682	61.0287	67.3031
16	68.7930	54.3192	56.8879
17	67.4580	51.1158	51.4262
18	69.4959	56.0071	59.4970
19	71.6479	60.9877	67.3643
20	74.9999	74.9222	90.0780
21	74.9996	69.2318	80.7687
22	70.2168	57.6447	62.1385
23	64.7099	45.2893	50.0009
24	54.9994	40.0003	50.0002

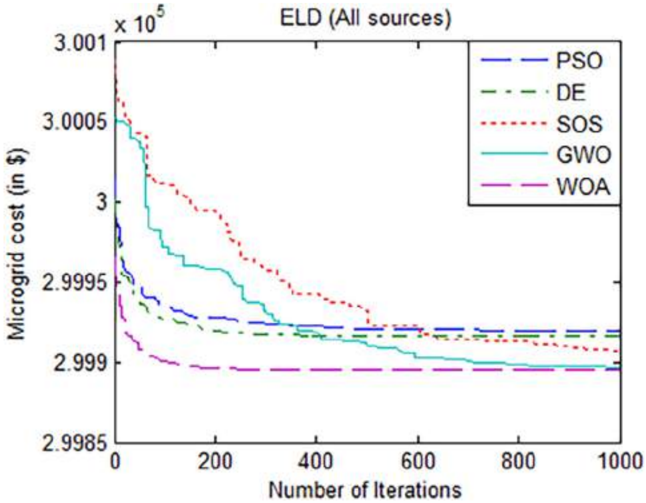

Fig. 3a. Economic Load Dispatch when all sources are included.

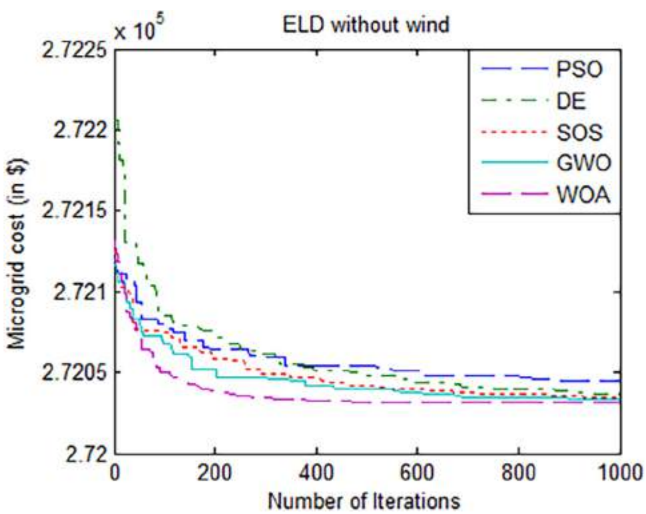

Fig. 3b. Economic Load Dispatch when wind farms are excluded.

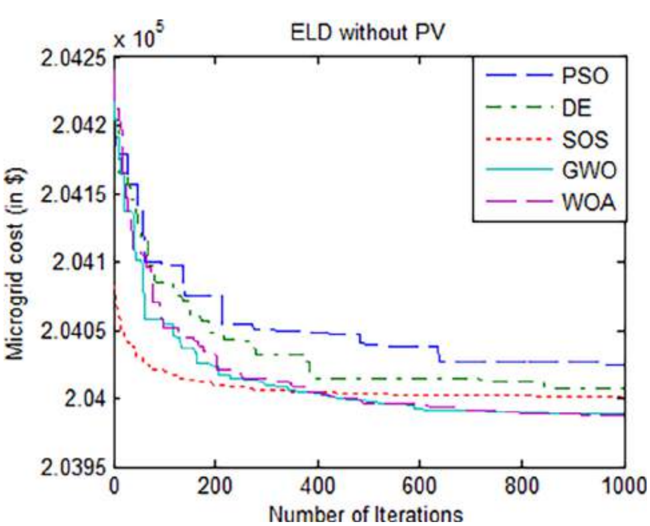

Fig. 3c. Economic Load Dispatch when PV system is excluded.

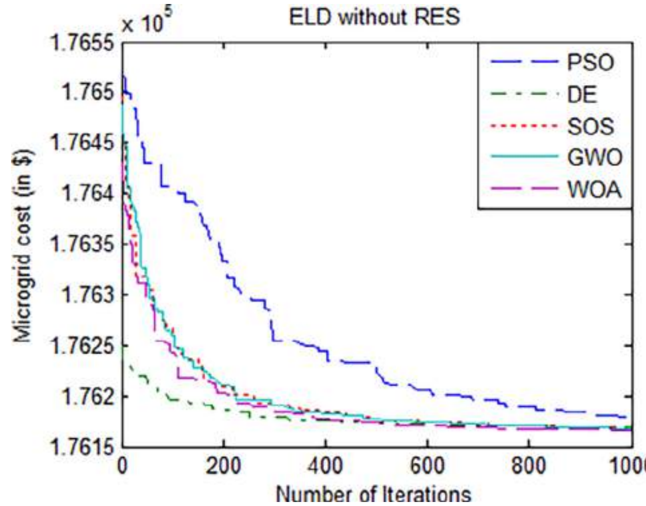

Fig. 3d. Economic Load Dispatch when both PV system and wind farms are excluded.

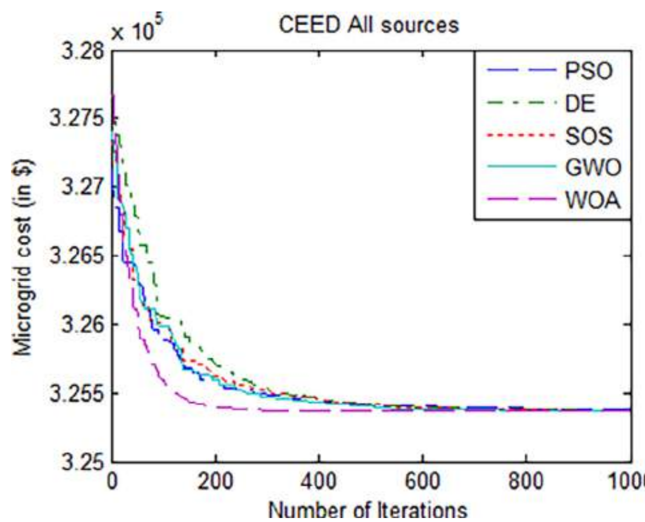

Fig. 4a. Combined Economic Emission Dispatch when all sources are included.

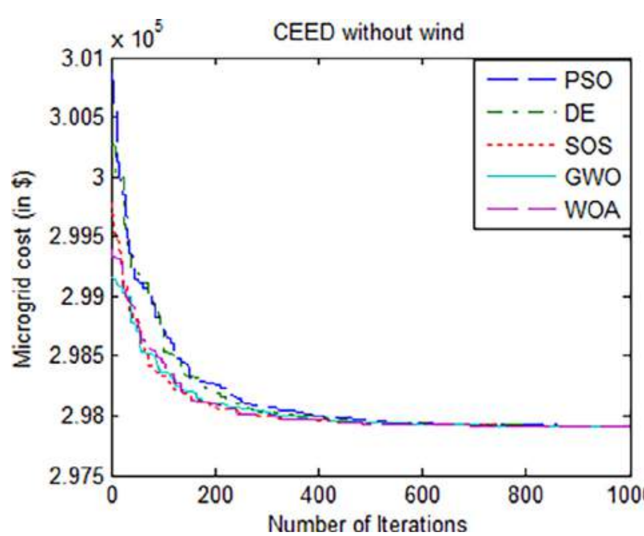

Fig. 4b. Combined Economic Emission Dispatch when wind farms are excluded.

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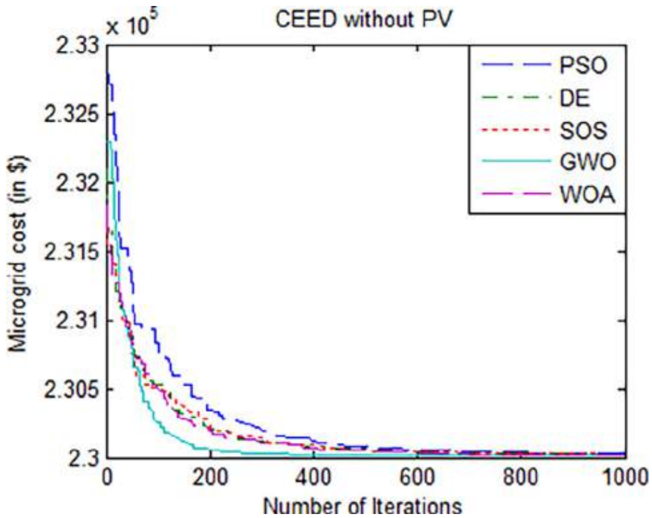

Fig. 4c. Combined Economic Emission Dispatch when PV system is excluded.

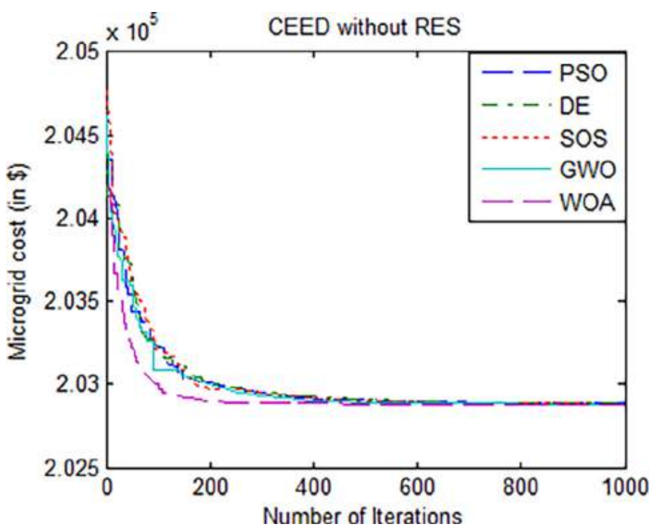

Fig. 4d. Combined Economic Emission Dispatch when both PV system and wind farms are excluded.

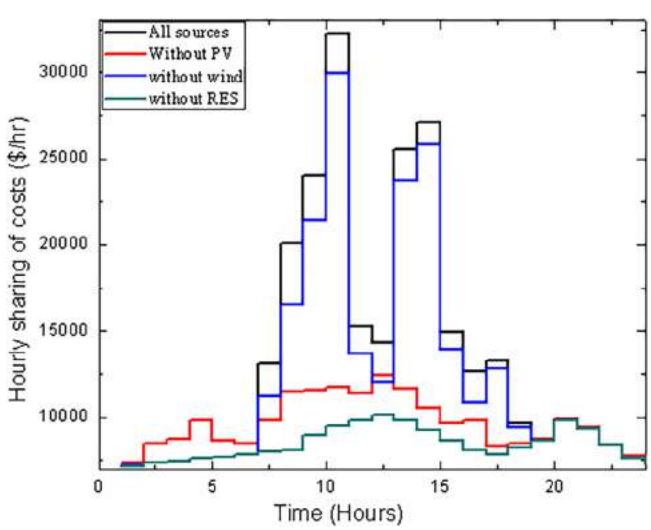

Fig. 5. Hourly sharing of costs (in $/hr.) for all the cases for CEED using WOA.

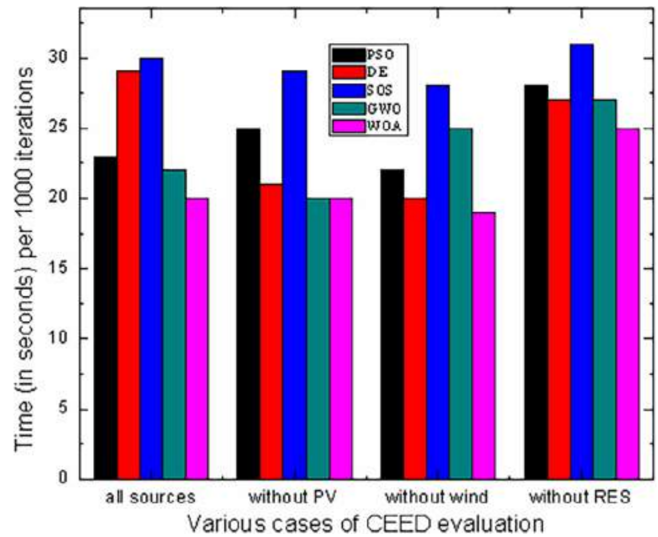

Fig. 6. Time (seconds per 1000 iterations) for various cases of CEED evaluation using PSO, DE, SOS, GWO and WOA.

the minimum cost. SOS due to its property of multiple evaluation of fitness function consumed as high as 30 s in almost all the cases.

4.3. Statistical analysis of the proposed approach

Two statistical evaluations were considered to test the feasibility and the robustness of the proposed algorithm compared to the other optimization techniques used to minimize the CEED problem. The statistical tests are reported with their results obtained as under:

a. *Analysis of Variance (ANOVA) test:* ANOVA test result is taken considering all the optimization methods. This test is conducted to get idea of variance of the mean of the system operating cost with different optimization methods. Various statistical entities like mean, standard deviation, variance etc. are involved in performing the ANOVA test [51]. The ANOVA test result is shown in the Table 11. Here ANOVA test is performed by the coding method. In the proposed work, ANOVA test is performed between five optimization techniques namely PSO, DE, SOS, GWO and WOA (i.e., k = 5) and each optimization algorithm was executed for 20 times (i.e., t = 20). The Table 11 also shows that the calculated value of F for both the systems are less than the tabulated value of F at 5% level of significance with degrees of freedom being 4 and 15 found in [52]. These analysis contradicts the null hypothesis advocating no differences in minimize cost by the techniques. We may therefore conclude that the difference in the minimized cost by the techniques is significant and is not just a matter of chance. Hence the ANOVA test by the virtue of its nature supports the fact that one among the five techniques used gives better result.
b. *Wilcoxon signed rank test:* Wilcoxon signed rank test was used to test one sample data set, obtained from the results of the proposed algorithm. It is a pairwise test done to find substantial variances in the behavior of two diverse algorithms. J. Derrac et al., elaborated the use of this test using examples in [53]. Any given algorithm maybe considered robust if is able to prove its statistical worth. For this purpose, it has to provide sufficient evidence against the null hypothesis. A *p*-value (probability value) below 0.05 achieved using this test is measured as ample evidence

Table 11
ANOVA test for various cases while minimizing the CEED problem.

Source of variation	Sum of square	Degrees of Freedom	Mean square	F-ratio	5% F-limit [37]
All sources					
Between techniques	1843.5096	(k-1)=4	460.8774	90.7005	3.0556
Within techniques	76.2196	(t-k)=15	5.0813		
Without PV					
Between techniques	1409.6144	(k-1)=4	352.4036	69.7528	3.0556
Within techniques	75.7827	(t-k)=15	5.0522		
Without wind					
Between techniques	374.4765	(k-1)=4	93.6191	15.8883	3.0556
Within techniques	88.3848	(t-k)=15	5.8923		
Without RES					
Between techniques	378.3388	(k-1)=4	94.5847	190.3147	3.0556
Within techniques	7.4549	(t-k)=15	0.4970		

Table 12
Statistical analysis of WOA for the 4 cases using Wilcoxon signed rank test for 20 trials.

Cases	Best solution	Average solution	Worst solution	No. of hits to optimum soln.	Standard deviation	p-value
All sources	325364.6210	325364.6281	325364.7634	19	0.0318	1.1933e-05
Without PV	230019.0483	230019.1423	230019.9891	18	0.2896	1.7075e-05
Without wind	297907.5634	297907.6723	297908.6532	18	0.3354	1.7075e-05
Without RES	202881.7751	202881.7790	202881.8542	19	0.0177	1.1933e-05

against the null hypothesis. The *p*-values obtained using this test for all cases with their minimum, maximum, average values and standard deviation are listed in Table 12. From the Table 12, it was observed that the *p*-value in every case was much lower than the desired value of 0.05 thereby establishing statistical significance of results.

c. *Robustness:* Initialization of evolutionary algorithms is always done randomly which is why multiple trial runs are needed to arrive at a decision regarding robustness of the same. WOA was evaluated for 20 trial runs for all cases. The number of times it hit the minimum solution is shown in Table 12. It can be seen that the lowest number of times it hit the minimum solution was 18 whereas the highest number was 19. The average success rate came out to be 92% which is highly appreciable.

5. Conclusion

A renewable integrated islanded microgrid with conventional generators is considered in this paper for solving both single objective and multi-objective optimization problems. Major findings of this paper are listed below:

i. Two single objective formulated problems viz. economic dispatch and emission dispatch is combined to form a combined economic emission dispatch (CEED) problem and is minimized using five evolutionary algorithms.
ii. Various types of price penalty factor were calculated and the least and best price penalty factor was used to convert two single objective problems to a multi objective one.
iii. Four different cases were studied for the CEED problem.
iv. Proposed WOA gave better quality results for all the cases when compared to other optimization techniques used to minimize the CEED problem.
v. Two different types of statistical analysis viz. ANOVA test and Wilcoxon signed rank test were performed to prove the superiority of the proposed algorithm over the others.

Solving CEED for a grid-connected microgrid can be considered as a scope of future work. Also to make the problem more viable, some practically occurring issues such as prohibited operating zone, valve-point effect and ramp rates of the conventional generators may be considered to increase the complexity of the test system and hence testing the robustness and capability of the proposed algorithm to handle complex constraints. Also weighted sum approach with pareto fronts may be proposed in future work to solve multi-objective problems with dedicated multi-objective optimization techniques.

Conflicts of interest

The author states that they have no conflicts of interest

References

[1] N.I. Nwulu, X. Xia, Optimal dispatch for a microgrid incorporating renewables and demand response, Renew. Energy 101 (2017) 16–28.
[2] R. Velik, P. Nicolay, Grid-price-dependent energy management in microgrids using a modified simulated annealing triple-optimizer, Appl. Energy 130 (2014) 384–395.
[3] J. Zhu, Optimization of Power System Operation, Wiley, New Jersey, 2009.
[4] S.A.H. Soliman, A.A.H. Mantawy, Modern Optimization Techniques with Applications in Electric Power Systems, Springer, 2012.
[5] A.A. El-keib, H. Ma, J.L. Hart, Environmentally constrained economic dispatch using a Lagrangian relaxation method, IEEE Trans. Power Syst. 9 (4) (1994) 1723–1729.
[6] S.F. Brodesky, R.W. Hahn, Assessing the influence of power pools on emission constrained economic dispatch, IEEE Trans. Power Syst. 1 (1) (1986) 57–62.
[7] J.S. Heslin, B.F. Hobbs, A multi-objective production costing model for analyzing emissions dispatching and fuel switching, IEEE Trans. Power Syst. 4 (3) (1989) 836–842.
[8] R. Ramanathan, Short-term energy and emission trading analysis, IEEE Trans. Power Syst. 10 (2) (1995) 1118–1124.
[9] M.R. Gent, J.W. Lamont, Minimum-emission dispatch, IEEE Trans. PAS 90 (1971) 2650–2660.
[10] A. Derghal, N. Golea, N. Essounbouli, A fuzzy interval optimization-based approach to optimal generation scheduling in uncertainty environment, J. Renew. Sustain. Energy 8 (65501) (2016).
[11] J.H. Talaq, F. El-Hawary, M.E. El-Hawary, A summary of environmental/economic dispatch algorithms, IEEE Trans. Power Syst. 9 (3) (1994) 1508–1516.
[12] J.W. Lamont, E.V. Obessis, Emission dispatch models and algorithms for the 1990's, IEEE Trans. Power Syst. 10 (2) (1995) 941–947.
[13] G.P. Granelli, M. Montagna, G.L. Pasini, P. Marannino, Emission constrained dynamic dispatch, Electr. Power Syst. Res. 24 (1992) 55–64.
[14] E.-A.A. Keib, H. Ma, J.L. Harr, Economic dispatch in view of clean air act of 1990, IEEE Trans. Power Syst. 9 (4) (1994) 972–978.

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[15] J. Radosavljević, M. Jevtić, D. Klimenta, Energy and operation management of a microgrid using particle swarm optimization, Eng. Optim. 273 (May) (2015) 1–20.
[16] A.K. Basu, A. Bhattacharya, S. Chowdhury, Planned Scheduling for Economic Power Sharing in a CHP-Based Micro-Grid, IEEE Trans. Power Syst. 27 (1) (2012) 30–38.
[17] T. Niknam, F. Golestaneh, A. Malekpour, Probabilistic energy and operation management of a microgrid containing wind/photovoltaic/fuel cell generation and energy storage devices based on point estimate method and self-adaptive gravitational search algorithm, Energy 43 (1) (2012) 427–437.
[18] A.A. Moghaddam, A. Seifi, T. Niknam, M.R. Alizadeh Pahlavani, Multi-objective operation management of a renewable MG (micro-grid) with back-up micro-turbine/fuel cell/battery hybrid power source, Energy 36 (11) (2011) 6490–6507.
[19] A.G. Anastasiadis, S.A. Konstantinopoulos, G.P. Kondylis, G.A. Vokas, P. Papageorgas, Effect of fuel cell units in economic and environmental dispatch of a Microgrid with penetration of photovoltaic and micro turbine units, Int. J. Hydrogen Energy 1 (2016) 6–13.
[20] E.S. Ali, S.A. Elazim, A.Y. Abdelaziz, Ant lion optimization algorithm for renewable distributed generations, Energy 116 (2016) 445–458.
[21] H. Sayyaadi, M. Babaie, M.R. Farmani, Implementing of the multi-objective particle swarm optimizer and fuzzy decision-maker in exergetic, exergoeconomic and environmental optimization of a benchmark cogeneration system, Energy 36 (8) (2011) 4777–4789.
[22] A.J. Wood, B.F. Wollenberg, Power generation, operation and control, Wiley, New York, 1984.
[23] J.H. Talaq, F. El-Hawary, M.E. El-Hawary, A summary of environmental/economic dispatch algorithms, IEEE Trans. Power Syst. 9 (1994) 1508–1516.
[24] M.R. Gent, J.W. Lamont, Minimum emission dispatch, IEEE Trans. Power Apparatus Syst. 90 (1971) 2650–2660.
[25] C.A.C. Coello, A comprehensive survey of evolutionary-based multi objective optimization techniques, Knowl. Inf. Syst. 1 (3) (1999) 269–308.
[26] J.S. Dhillon, S.C. Parti, D.P. Kothari, Stochastic economic emission load dispatch, Electr. Power Syst. Res. 26 (1993) 179–186.
[27] C. Palanichamy, N.S. Babu, Analytical solution for combined economic and emissions dispatch, Electr. Power Syst. Res. 78 (2008) 1129–1137.
[28] R. Balamurugan, S.A. Subramanian, Simplified recursive approach to combined economic emission dispatch, Electr. Power Compon. Syst. 36 (1) (2007) 17–27.
[29] G. Razeghi, B. Brouwer, S. Samuelsen, A spatially and temporally resolved model of the electricity grid–economic vs environmental dispatch, Appl. Energy 178 (2016) 540–556.
[30] A.Y. Abdelaziz, E.S. Ali, S.M. Abd Elazim, Combined economic and emission dispatch solution using flower pollination algorithm, Int. J. Electr. Power Energy Syst. 80 (2016) 264–274.
[31] A.Y. Abdelaziz, E.S. Ali, S.A. Elazim, Implementation of flower pollination algorithm for solving economic load dispatch and combined economic emission dispatch problems in power systems, Energy 101 (2016) 506–518.
[32] E.S. Ali, S.A. Elazim, Mine blast algorithm for environmental economic load dispatch with valve loading effect, Neural Comput. Appl. 30 (1) (2018) 261–270.
[33] M.R. Narimani, J.Y. Joo, M. Crow, Multi-objective dynamic economic dispatch with demand side management of residential loads and electric vehicles, Energies 10 (5) (2017) 624.
[34] M.R. Narimani, J.Y. Joo, M.L. Crow, Dynamic economic dispatch with demand side management of individual residential loads, in: North American Power Symposium (NAPS), pp. 1–6. IEEE. (2015, October).
[35] E. Naderi, A. Azizivahed, H. Narimani, M. Fathi, M.R. Narimani, A comprehensive study of practical economic dispatch problems by a new hybrid evolutionary algorithm, Appl. Soft Comput. 61 (2017) 1186–1206.
[36] K. Mason, J. Duggan, E. Howley, Multi-objective dynamic economic emission dispatch using particle swarm optimisation variants, Neurocomputing 270 (2017) 188–197.
[37] H. Narimani, S.E. Razavi, A. Azizivahed, E. Naderi, M. Fathi, M.H. Ataei, M.R. Narimani, A multi-objective framework for multi-area economic emission dispatch, Energy 154 (2018) 126–142.
[38] A. Azizivahed, H. Narimani, E. Naderi, M. Fathi, M.R. Narimani, A hybrid evolutionary algorithm for secure multi-objective distribution feeder reconfiguration, Energy 138 (2017) 355–373.
[39] A. Azizivahed, H. Narimani, M. Fathi, E. Naderi, H.R. Safarpour, M.R. Narimani, Multi-objective dynamic distribution feeder reconfiguration in automated distribution systems, Energy 147 (2018) 896–914.
[40] B. Lokeshgupta, S. Sivasubramani, Multi-objective dynamic economic and emission dispatch with demand side management, Int. J. Electr. Power Energy Syst. 97 (2018) 334–343.
[41] D. Saha, A. Datta, P. Das, Optimal coordination of directional overcurrent relays in power systems using symbiotic organism search optimisation technique, IET Gener. Transm. Distrib. 10 (11) (2016) 2681–2688.
[42] S. Das, A. Bhattacharya, Symbiotic organisms search algorithm for short-term hydrothermal scheduling, Ain Shams Eng. J. (2016).
[43] S. Sharma, S. Bhattacharjee, A. Bhattacharya, Grey wolf optimisation for optimal sizing of battery energy storage device to minimise operation cost of microgrid, IET Gener. Transm. Distrib. 10 (3) (2016) 625–637.
[44] T. Jayabarathi, T. Raghunathan, B.R. Adarsh, P.N. Suganthan, Economic dispatch using hybrid grey wolf optimizer, Energy 111 (2016) 630–641.
[45] S. Raj, B. Bhattacharyya, Optimal placement of TCSC and SVC for reactive power planning using Whale optimization algorithm, Swarm Evol. Comput. 40 (2018) 131–143.
[46] P.V.C. Dinakara Prasasd Reddy, T. Reddy, Optimal renewable resources placement in distribution, Electr. Power Energy Syst. 28 (2017) 669–678.
[47] N. Augustine, S. Suresh, P. Moghe, K. Sheikh, Economic dispatch for a microgrid considering renewable energy cost functions, IEEE PES innovative smart grid technologies (ISGT), Washington, DC, 2012, pp. 1–7.
[48] S. Mirjalili, L. Andrew, The whale optimization algorithm, Adv. Eng. Softw. 95 (2016) 51–67.
[49] R.H. Bhesdadiya, M.H. Pandya, I.N. Trivedi, N. Jangir, P. Jangir, A. Kumar, Price penalty factors based approach for combined economic emission dispatch problem solution using Dragonfly Algorithm, in: Energy Efficient Technologies for Sustainability (ICEETS), 2016 International Conference on, pp. 436–441. IEEE. (2016, April).
[50] S. Krishnamurthy, R. Tzoneva, Impact of price penalty factors on the solution of the combined economic emission dispatch problem using cubic criterion functions, in: Power and Energy Society General Meeting, 2012 IEEE, pp. 1–9. IEEE. (2012, July).
[51] C.R. Kothari, Research methodology: Methods and techniques, New Age International, 2004.
[52] F-Distribution table for ANOVA test http://www.socr.ucla.edu/applets.dir/f_table.html
[53] J. Derrac, S. García, D. Molina, F. Herrera, A practical tutorial on the use of nonparametric statistical tests as a methodology for comparing evolutionary and swarm intelligence algorithms, Swarm Evol. Comput. 1 (1) (2011) 3–18.