



# Solving energy management of renewable integrated microgrid systems using crow search algorithm

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## Abstract

This paper aims to percolate energy management of microgrid systems by minimizing the generation cost of the same. Energy management of microgrid refers to the optimal sizing and scheduling of the distributed energy resources to reduce the generation cost and pollutant emission. A recently developed crow search algorithm (CSA) is implemented to execute the optimization. The proposed CSA imitates the crows' memory and tactics of hiding and chasing their food. Six renewable integrated microgrid test systems and a total of eighteen different cases are considered for this study. Various practical complexities such as valve point loading effect, combined economic–emission dispatch using price penalty factor method, modeling of the renewable energy sources and energy storage systems are taken into consideration for energy management of the microgrid systems. Results obtained are then compared to a number of different soft computing techniques such as genetic algorithm and particle swarm optimization and the likes to justify the effectiveness of the proposed algorithm. A statistical analysis, viz. Wilcoxon signed-rank test, is performed to prove the superiority of the proposed approach over the various other optimization techniques used in the paper.

**Keywords** Combined economic–emission dispatch · Penalty factor · Microgrid · Grey wolf optimization · Teaching–learning-based optimization · Sine cosine algorithm · Crow search algorithm

## 1 Introduction

### 1.1 General overview

At a power generating station, the load demand is not sufficed by a single generating entity. Rather, a conglomerate of such entities fulfills the total demand. Moreover, to produce the same amount of power, each unit is incurred with its own cost function (price bid). Economic load dispatch (ELD) works on the fact that not all generating units incur the same amount of cost to suffice the same amount of load, rather some are relatively more costly than others for equal amount of production. So aptly allocating a certain share of the entire demand could actually lower the fuel cost. The total load demand is distributed among

various generators, which in turn affects the estimation, invoicing, unit commitment and numerous related functions (Sihna 2019). The total generation of power has to comply with the total current demand. To address this, the ELD could be further categorized into two variations depending upon the nature of load demand. The constant load, classical static economic load dispatch (SELD), ignores practical constraints because every load-consuming area does not have a constant all-day load demand characteristics, but its nature depends upon the prevalent climatic factors, location and attributes of job undertaken by the inhabitants (Yalcinoz and Short 1997; Dhillon et al. 1993). In opposition to this, a dynamic economic load dispatch (DELD) efficiently handles the practical constraint (Wang and Shahidehpour 1994). In DELD, we forecast the demand for the upcoming hours and accordingly distribute the load among different generation to optimize the production.

Energy management strategy (EMS) of microgrids falls in DELD category of cost minimization but is more complicated than SELD. To begin with, microgrid can be imagined as a collection of distributed energy resources

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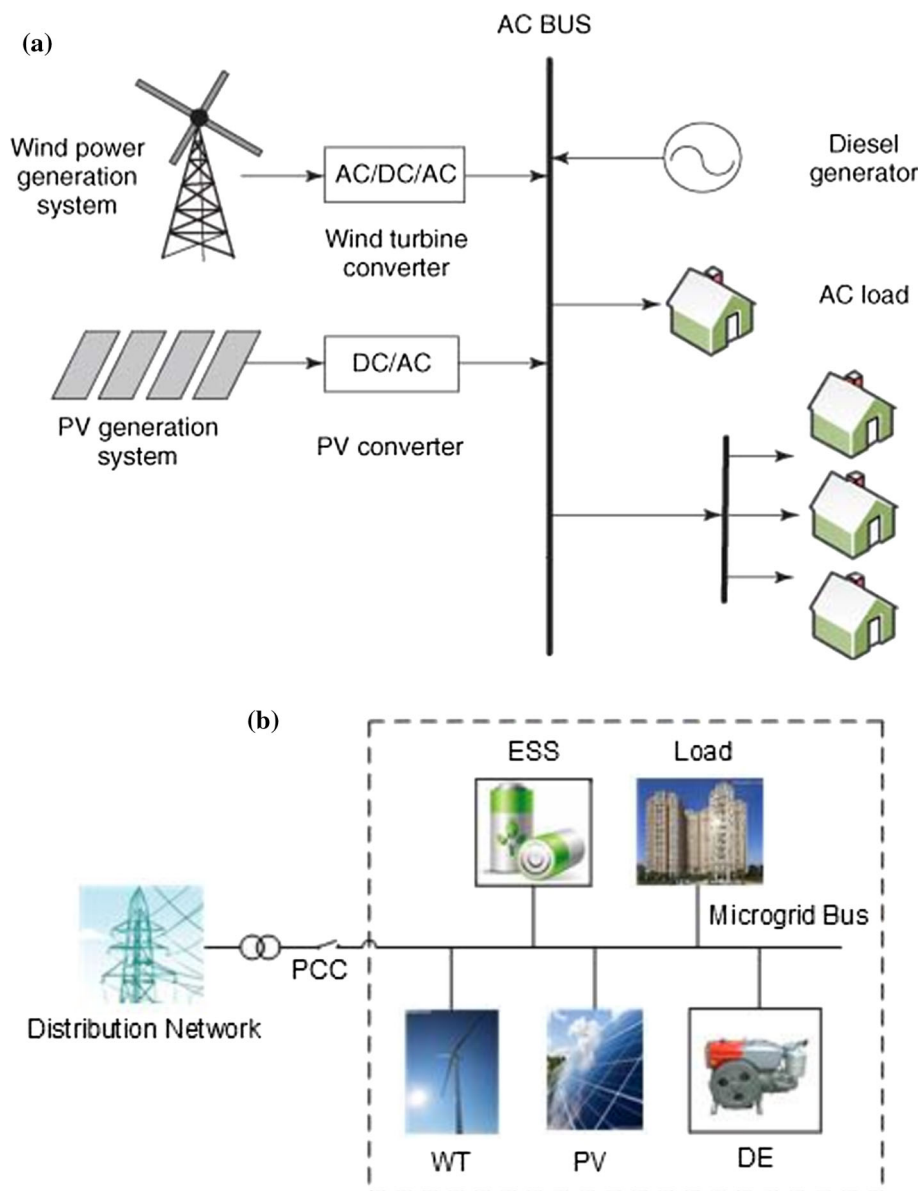
(DERs) and loads within a confined geographical area. DERs include fossil-fueled generators, various renewable energy sources (RES) depending upon the availability of the microgrid location, microturbines, fuel cells and energy storage systems (ESS) such as battery and flywheel (Hatzigiorgiou 2013). It is because of the individual modeling and constraints associated with these DERs that economic dispatch of microgrid becomes a complex and cumbersome process for power engineers. Microgrid basically operates in two modes: either islanded or utility connected (Luu 2014). Figure 1a, b depicts the two different working modes of a microgrid system. It is quite obvious that the utility-connected mode is more reliable and efficient as the microgrid can sell/buy power from the utility depending upon the surplus/deficit production of

power from its DERs. Also, utility-connected microgrid can rely on the grid in case one of its DER fails, thus preventing from an unwanted and major shutdown of the network.

### 1.2 Literature review

The last decade has witnessed a lot of research in the microgrid energy management area. Matrix real-coded GA (MRCGA) and imperialist competitive algorithm (ICA) were used by authors in Chen et al. (2011) and Kasaei (2018) to minimize the generation cost of a grid-connected microgrid, wherein various cases were studied to analyze the capability of algorithms in handling tight operating ranges of DERs, variable loads and fluctuating electricity

**Fig. 1** a Architecture of an islanded microgrid. b Architecture of grid-connected microgrid (Fan et al. 2018)



price. Cuckoo search algorithm (CuSA) yielded better results than PSO and DE when both SELD and DELD were performed by Basu and Chowdhury (2013). An islanded microgrid system was considered for DELD which consisted of two wind turbines (WTs) to be separately modeled based on wind speed. The authors performed pareto-optimal front-based economic–emission dispatch on a utility-connected microgrid system using adaptive modified PSO (AMPSO) in Moghaddam et al. (2011) and GAMS in Fan et al. (2018). Optimization results were reported giving maximum weightage to economic and emission dispatch separately, and thereafter a compromised solution emphasizing both the objectives with approximately equal weightage was studied where the proposed algorithms outperformed other optimized techniques studied. Trivedi et al. (2018) used interior search algorithm (ISA) to perform ELD and price-penalty-based combined economic–emission dispatch (CEED) on an islanded microgrid powered by three fossil-fueled generators, a PV and a wind system. These results were again outperformed by modified harmony search algorithm (MHSA) implemented by Elattar (2018) for the same microgrid system. But the major drawback in these two articles was that the formulation of different types of price penalty factors was not done. Neither any valid reason was mentioned about which type of price penalty factor was chosen to perform CEED. This demerit was attended by Dey et al. (2019) where the various price penalty factors were formulated and calculated and the least (min–max) penalty factor was chosen to perform CEED. Further, whale optimization algorithm (WOA) provided better-quality solutions than other optimization techniques used to evaluate CEED. The Lahon and Gupta (2018) proposed an energy management system for the coalition forming microgrids and utility. In the proposed framework, conditional value at risk, a measure to lessen the danger faced by the aggregator due to power transaction fluctuations was also considered. Lahon and Gupta (2018) proposed energy management framework that minimizes the operating cost of coalition microgrids incorporating worst-case net transaction mechanism. GA and improved GA (IGA) were used by authors in Yong and Tao (2007) and Ganjefar and Tofghi (2011) to minimize the dynamic cost of a 10-unit system with and without wind power, respectively. Sequential quadratic programming (SQP) was used by Wibowo et al. (2017) to minimize the generation cost of a grid-connected microgrid powered by a diesel generator, a battery, a microturbine and a PV system.

Optimal scheduling of the energy storage system was done in Bahmani-Firouzi and Azizpanah-Abarghoee (2014) by considering its lifetime, total per day cost, fixed

cost and maintenance cost, thereafter minimizing the generation cost of a grid-connected microgrid using improved bat algorithm (IBA). In recent years, authors have used quasi-oppositional swine influenza model-based optimization (QOSIMBO) in Sharma et al. (2018) and grey wolf optimization (GWO) in Sharma et al. (2016) for the same test system to yield better and superior results compared to IBA. 2 m point estimation method was used by authors in Sharma et al. (2018) for the uncertainty modeling of the RES and electricity market prices, and then WOA was implemented to minimize the microgrid cost. Mixed integer linear programming (MILP) was used by authors in Koltsaklis et al. (2018) to minimize the generation cost of a grid-connected microgrid system. The generation cost was influenced by the transaction price of the grid, annual investment cost of the DERs, capital recovery factor and penalized allowable limit of pollutants emission from fossil-fueled DERs. Artificial fish swarm algorithm (AFSA) was used in Kumar and Saravanan (2019) to minimize the generation cost of a microgrid system. Two scenarios were considered with different load demands and RES generation, and the generation cost was influenced by the penalized price of load shedding.

### 1.3 Motivation

Researchers are highly fascinated with soft computing techniques primarily because they are not restricted by complexity of system models, which has made them apply these techniques to power system optimization problems. Their vibrant results of techniques like genetic algorithm (GA), particle swarm optimization (PSO) and differential evolution (DE) over numerous benchmark functions have resulted in the application of these algorithms for solving energy management operations of microgrids such as minimization of generation and transmission costs and load scheduling. Nevertheless, GA, PSO and DE have their own list of disadvantages too. The crucial demerit of GA lies in its slow rate of convergence. This is precisely due to the uncontrolled mutation stage in GA where a random number is added to any parameter of a member from a whole lot or population. 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.

Crow search algorithm (CSA) is a recently developed optimization technique which imitates the memory-based sly nature of the crows to hide their food from other crows

and also steal food from others. Few of the noticeable advantages of CSA are explained below:

1. *Minimum number of pivotal equations-*

Unlike GA, DE, GWO, WOA, symbiotic organisms search (SOS) which have many stages and equations to go through the entire optimization process, CSA has only one such equation which makes the algorithm not only easy to be coded and executed but also consumes less computational time to attain the stopping criteria yielding a prominent and better-quality solution.

Algorithms like sine cosine algorithm (SCA), JAYA and PSO also have very less number of pivotal equations like CSA, but these algorithms have their own demerits. JAYA has no dedicated control over the search space, whereas SCA is less consistent, yielding a different value for the fitness function every time due to higher number of random numbers. This reduces the robustness of SCA. PSO suffers from getting trapped in local minima. All of these three algorithms are prone to premature convergence.

We are only left with ‘*fl*’ to tune with, the value of which conducts the search for optimal values globally or locally.

3. *Capacity to handle large-dimensional problems in less amount of computational time*

A microgrid consists of many DERs whose prime concern is to satisfy the load demand through a given period of time. Now, these DERs have their own set of constraints to be abided by while sizing them to obtain the optimum value of the fitness function.

Let us suppose a microgrid has *D* DERs and a 24-h period is studied. A particle of the population will contain *D times 24* elements and is represented as:

$$P_i = [P_{i,DER1}^1, P_{i,DER1}^2, \dots, P_{i,DER1}^{24}, P_{i,DER2}^1, P_{i,DER2}^2, \dots, P_{i,DER2}^{24}, \dots, P_{i,DERD}^1, P_{i,DERD}^2, \dots, P_{i,DERD}^{24}]; \tag{1}$$

$i = 1, 2, \dots, Pop\_Size$

And if *D* = 10 (as in microgrid test system 4 discussed in Sect. 4) the population size (*Pop\_Size*) is say 80, then the population matrix becomes

$$P = \begin{bmatrix} P_{1,DER1}^1, P_{1,DER1}^2, \dots, P_{1,DER1}^{24}, P_{1,DER2}^1, P_{1,DER2}^2, \dots, P_{1,DER2}^{24}, \dots, P_{1,DER10}^1, P_{1,DER10}^2, \dots, P_{1,DER10}^{24} \\ P_{2,DER1}^1, P_{2,DER1}^2, \dots, P_{2,DER1}^{24}, P_{2,DER2}^1, P_{2,DER2}^2, \dots, P_{2,DER2}^{24}, \dots, P_{2,DER10}^1, P_{2,DER10}^2, \dots, P_{2,DER10}^{24} \\ P_{3,DER1}^1, P_{3,DER1}^2, \dots, P_{3,DER1}^{24}, P_{3,DER2}^1, P_{3,DER2}^2, \dots, P_{3,DER2}^{24}, \dots, P_{3,DER10}^1, P_{3,DER10}^2, \dots, P_{3,DER10}^{24} \\ \dots \dots \dots \\ P_{80,DER1}^1, P_{80,DER1}^2, \dots, P_{80,DER1}^{24}, P_{80,DER2}^1, P_{80,DER2}^2, \dots, P_{80,DER2}^{24}, \dots, P_{80,DER10}^1, P_{80,DER10}^2, \dots, P_{80,DER10}^{24} \end{bmatrix} \tag{2}$$

2. *Minimum number of tuning parameters and random numbers*

GA, DE and PSO have many parameters to be tuned and checked to obtain a better result. GWO, WOA, SOS, TLBO and DE have many stages, and every stage employs some random numbers to be multiplied with the string of decision (control) variables (or a particle of the population as we may say it). The presence of these tuning parameters and random numbers makes the optimization process cumbersome, reduces the consistency-cum-robustness of the algorithms and indulges in consuming a huge amount of computational time to attain the best value of fitness function, satisfying all the pre-assigned limits and constraints of every element of the particle. CSA on the other hand has only two tuning parameters: flight length (*fl*) and awareness probability (*AP*). *AP* can be formulated to gradually decrease its value (linearly/exponentially) from 1 to 0 throughout the iterations to maintain a smooth transition between intensification and diversification.

i.e., (10\*24\*80 = 19,200) elements to be optimally sized together to obtain a best value of the fitness function in every iteration. It is also to be noted that each of this DERs has its own set of constraints, such as operating limits, on/off time, charging/discharging limits and state of charge (if the DER is a battery) to be maintained at the end of every iteration.

So, if an algorithm has multiple stages and equations (as discussed in the previous point), it is very much time-consuming process for a particle of the population to pass through all those stages, thereafter satisfying their own assigned constraints. This significant and critical disadvantage is avoided by CSA.

4 *Memory-based algorithm*

CSA is a memory-based optimization technique like PSO. This means after every iteration, CSA compares the solution obtained in the current iteration with that of the

previous iteration and memorizes the best solution between them. Further, the algorithm updates its particles with the best position found for itself and the best position ever found of the population. Thereafter, these best positions are used to proceed with successive iterations. This crucial nature of CSA enables the algorithm to attain a superior and prominent quality solution compared to many algorithms mentioned above.

### 1.4 Contribution

This paper employs the proposed CSA to perform EMS on six different microgrid test systems (total of 18 different cases) as mentioned in Table 2. Also, nine more algorithms are studied on the same test systems and a comparative analysis among the results obtained using all of these algorithms is presented. Furthermore, a statistical analysis is also carried out to prove the significance of the proposed approach.

### 1.5 Organization of the paper

Section 2 of this paper formulates the objective function. The superior optimization technique, CSA, is discussed in detail, and the rest of the optimization techniques which are studied to provide a comparative analysis are concisely mentioned in Sect. 3. Various combinations of the microgrid test systems are studied, and the results are reported in Sect. 4. The paper concludes in Sect. 5.

## 2 Objective function formulation

### 2.1 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 standard ELD equation for a grid-connected microgrid powered with FFG numbers of fossil-fueled generators, RES numbers of renewable energy sources and ESS numbers of energy storage devices can be expressed as:

$$F(P_{DER}) = \sum_{t=1}^{24} \sum_{b=1}^{ESS} \sum_{r=1}^{RES} \sum_{g=1}^{FFG} \left\{ \underbrace{u_g * (P_g^t)^2 + v_g * (P_g^t) + w_g}_{\text{Cost function of conventional FFG}} \right\} + c_{RES} * (P_{RES}^t) + c_{ESS} * (P_{ESS}^t) + c_{grid} * (P_{grid}^t) \tag{3}$$

where  $P$  is the power output of the DER.  $u_g, v_g$  and  $w_g$  are the cost coefficients of the  $g$ th fossil-fueled generator.  $c_{RES}, c_{ESS}$  and  $c_{grid}$  are the cost coefficients of RES, ESS and electricity market price, respectively.  $F(P_{DER})$  is in \$/h.

### 2.2 Valve point loading effect

Valve point loading effect (VPE) is a natural attribute of a thermal turbine. The turbine of a generator has several governing valves to control the flow rate of steam into the turbine. The fuel cost curve of the generator is shown in Fig. 2. With the inclusion of VPE, fuel cost curve becomes nonlinear (non-smooth and non-convex) and non-differentiable and contains multiple minima. In this paper, for practical operation of generators, the VPE is considered as a result of which the objective function is the superposition of quadratic and sinusoidal functions. Incorporating VPE in the fuel cost function of the generating units, the cost function of the conventional generators in Eq. (3) will be replaced with the expression  $\sum_{t=1}^{24} \sum_{g=1}^{FFG} \{u_g * (P_g^t)^2 + v_g * (P_g^t) + w_g + |\delta_g \sin \theta_g (P_{g,min}^t - P_g^t)|\}$ . The rest of Eq. (3) remains unaltered.  $\delta$  and  $\theta$  are the VPE parameters of the  $g$ th generating unit.

### 2.3 Emission dispatch

The combustion of fossil fuels by the conventional generators releases some harmful toxic gases such as CO<sub>2</sub> and SO<sub>x</sub> 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

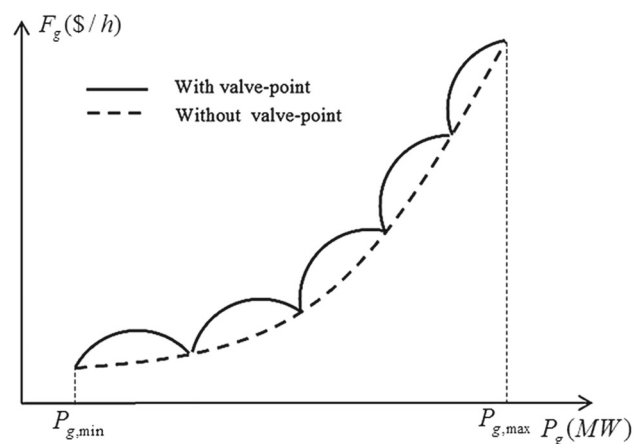


Fig. 2 Fuel cost curve of a generator with and without VPE

function is also a convex polynomial like the ELD and can be written as

$$E(P_{FFG}) = \sum_{t=1}^{24} \sum_{g=1}^{FFG} \left\{ x_g * (P_g^t)^2 + y_g * (P_g^t) + z_g \right\} \tag{4}$$

where  $x_g, y_g$  and  $z_g$  are the emission coefficients of the  $g$ th generation unit. The unit of  $E(P)$  is kg/h.

### 2.4 Combined economic–emission dispatch

As discussed above, it can be seen that the economic load dispatch and emission dispatch are 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 formulating a combined economic–emission dispatch (CEED) problem by combining Eqs. (3) and (4) with the help of a parameter called ‘Price Penalty factor.’ 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, the lower the value of the penalty factor, the lesser the value of the CEED problem. The various types of penalty factors are formulated in Table 1 (Dey et al. 2019).

The combined economic–emission dispatch problem can thus be mathematically formed by including the expression

$$\sum_{t=1}^{24} \sum_{g=1}^{FFG} \left[ \{ u_g * (P_g^t)^2 + v_g * (P_g^t) + w_g \} +$$

**Table 1** Penalty factor calculation (Dey et al. 2019)

Penalty factor types	Penalty factor formula
Max–min ( $h_{i,max-min}$ )	$\frac{u_i P_{i,max}^2 + v_i P_{i,max} + w_i}{x_i P_{i,min}^2 + y_i P_{i,min} + z_i}$
Max–max ( $h_{i,max-max}$ )	$\frac{u_i P_{i,max}^2 + v_i P_{i,max} + w_i}{x_i P_{i,max}^2 + y_i P_{i,max} + z_i}$
Min–min ( $h_{i,min-min}$ )	$\frac{u_i P_{i,min}^2 + v_i P_{i,min} + w_i}{x_i P_{i,min}^2 + y_i P_{i,min} + z_i}$
Min–Max ( $h_{i,min-max}$ )	$\frac{u_i P_{i,min}^2 + v_i P_{i,min} + w_i}{x_i P_{i,max}^2 + y_i P_{i,max} + z_i}$
Average ( $h_{i,avg}$ )	$\frac{h_{i,max-min} + h_{i,max-max} + h_{i,min-min} + h_{i,min-max}}{4}$
Common ( $h_{i,com}$ )	$\frac{h_{i,avg}}{\text{number of generators}}$

$h_g * \{ x_g * (P_g^t)^2 + y_g * (P_g^t) + z_g \}$  in Eq. (3) in place of the cost function of the conventional fossil-fueled generators.

where  $h_g$  is the penalty factor of the  $g$ th generating unit. The unit of  $h_g$  is \$/kg. The cost functions of the remaining DERs of Eq. (1) remain unchanged.

### 2.5 Formulation of the cost component of RES

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 incur any fuel cost nor do emit harmful toxic gases in the atmosphere. Although these renewable energy sources do include some installation cost, depreciation cost, lifetime degradation cost and operation and maintenance cost, the cost component of RES can be calculated as below (Trivedi et al. 2018):

$$c_{RES} = c_{DC} + G^E \tag{5}$$

where  $G^E$  is the operation and maintenance cost of the RES used. The depreciation cost of the DGs which is a function of the depreciation cost per kilowatt hour (DC), the maximum power output of the DG ( $P_{max}$ ), the hourly output of the DG and its capacity factor  $cf$  can be accounted as:

$$c_{DC} = \frac{DC}{P_r^{max} \times 8760 \times cf} \times P_r \tag{6}$$

$DC$  is further dependent on the installation cost (IC), rate of interest ‘ $k$ ’ and the life span ‘ $l$ ’ of the DG sources as shown in (6):

$$DC = IC \times \frac{k(1+k)^l}{(1+k)^l - 1} \tag{7}$$

### 2.6 Modeling of RES

- Wind Turbine** The power output of wind generator depends on the available wind speed  $v_{i,t}$  and the parameters of the WT wind power conversion curve, as shown in Fig. 3. The speed at which the turbine starts to rotate and generate power is called the cut-in wind speed  $v_{cut-in}$ . As the wind speed rises above  $v_{cut-in}$ , the electrical power output rises rapidly and at rated wind speed  $v_{rated}$ , the power output reaches the limit that the generator is capable of. Beyond  $v_{rated}$ , forces on the turbine structure continue to rise and at some extreme wind speed, called the cutout wind speed  $v_{cutout}$ , there is a risk of damage to the rotor. Consequently, a braking system is employed to bring the rotor to standstill. We

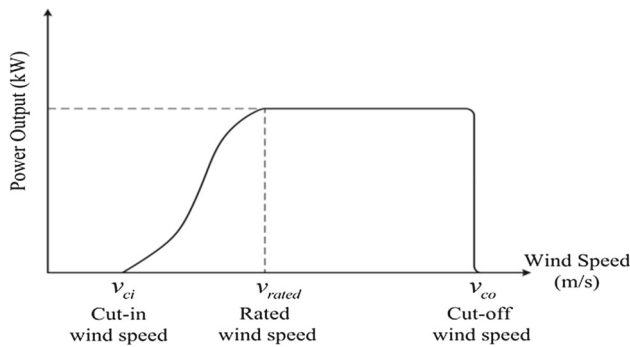


Fig. 3 Flow of wind

therefore employ the piecewise linear approximation of the wind power curve as follows (Chen et al. 2011)

$$P_{wt,i}^t = \left\{ P_{wt,i}^{\max} * \begin{pmatrix} 0 & v < v_{\text{cut-in}} \\ \frac{v - v_{\text{cut-in}}}{v_r - v_{\text{cut-in}}} & v_{\text{cut-in}} \leq v < v_r \\ P_{wt,i}^{\max} & v_r \leq v < v_{\text{cut-out}} \\ 0 & v \geq v_{\text{cut-out}} \end{pmatrix} \right\} \tag{8}$$

- **PV System** The output power of each PV module depends on the amount of solar irradiance, the ambient temperature and the characteristics of the module itself. The available PV power output at actual cell temperature  $T_t$  C and insolation  $G_C$  can be modeled as (Chen et al. 2011)

$$P_{i,t}^{\text{PV}} = P^{\text{STC}} \frac{G_C}{G^{\text{STC}}} [1 - 0.0045(T_t^C - T^{\text{STC}})] \tag{9}$$

where  $P^{\text{STC}}$  denotes the output at standard test conditions of 298 K ( $T^{\text{STC}}$ ) and insolation 1000 W/m<sup>2</sup> ( $G^{\text{STC}}$ ).

### 2.7 Equality and inequality constraints

The above objective function is subject to constraints such as:

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

$$\begin{aligned} P_{g,\min} &\leq P_g^t \leq P_{g,\max}; & \forall g \in \text{FFG} \\ P_{r,\min} &\leq P_r^t \leq P_{r,\max}; & \forall r \in \text{RES} \\ P_{b,\min} &\leq P_b^t \leq P_{b,\max}; & \forall b \in \text{ESS} \\ P_{\text{grid},\min} &\leq P_{\text{grid}}^t \leq P_{\text{grid},\max} \end{aligned} \tag{10}$$

- Energy storage system constraints**

$$E_b^t = E_b^{t-1} - P_b^t * \eta \tag{11}$$

$$E_{b,\min} \leq E_b^t \leq E_{b,\max} \tag{12}$$

where  $E_b$  denotes the energy stored in the  $b$ th battery and  $\eta$  is the efficiency of the battery.

- Power supply–demand balance constraint** The power generated at any instant of time by all the conventional generators, the RES and transaction with the grid (if available) should satisfy the total desired load of the system. This can be mathematically stated as:

$$P_{\text{Load Demand}}^t = P_{\text{FFG}}^t + P_{\text{ESS}}^t + P_{\text{RES}}^t + P_{\text{grid}}^t \tag{13}$$

## 3 Optimization techniques used

### 3.1 Crow search algorithm

The family of crow (corvids) are the most intelligent and clever species in the avian kingdom. Evidence of slyness of crows is manifold. Owing to these characteristics of the bird, *Askarzadeh* developed an optimization algorithm in 2016 and named it as crow search algorithm (CSA) (Askarzadeh 2016). Crows possess the habit of observing and follow other birds in order to determine their food storage locations and take their food in their absence. Moreover, if the crow does steal food from another bird, it becomes extra cautious and keeps shifting its own hiding place to avoid becoming a victim of robbery in the future. Not only this, it also uses its own knowledge to prevent its food from the robbers. The CSA is based on these behaviors of a crow.

Let us suppose that there is a  $d$ -dimensional environment including  $N$  number of crows. The position of  $i$ th crow during iteration ‘ $iter$ ’ is denoted by a vector  $X^{i,iter}$  ( $i \in 1, 2, \dots, N$ ;  $iter \in 1, 2, \dots, iter_{\max}$ ) where  $X^{i,iter} =$

$[X_1^{i,iter}, X_2^{i,iter}, \dots, X_d^{i,iter}]$  and  $iter_{\max}$  is the maximum number of iterations. Now, every crow memorizes its hiding place. For iteration ‘ $iter$ ,’ the hiding place of crow  $i$  is denoted by  $m^{i,iter}$  and is the current best position of crow  $i$ .

Supposedly at iteration ‘ $iter$ ’ crow ‘ $j$ ’ wants to visit its hiding place  $m^{j,iter}$ . And in the same iteration, say crow ‘ $i$ ’ plans to follow crow ‘ $j$ ’. At this instant, two cases may happen:

*Case 1:* Crow ‘ $j$ ’ is totally unaware of the fact that it is followed by crow ‘ $i$ ’ and as a result crow ‘ $i$ ’ will know the hiding place of crow ‘ $j$ ’.

Case 2: Crow ‘j’ knows that it is being followed by crow ‘i’ and hence fools crow ‘i’ by diverting it to a different random location within the search space.

These two cases can be mathematically represented with a set of equations as:

$$X^{i,iter+1} = \begin{cases} X^{i,iter} + rand_i \times fl^i \times (m^{j,iter} - X^{i,iter}) & rand_j \geq AP^j \\ \text{a random position} & \text{otherwise} \end{cases} \tag{14}$$

where  $rand_i$  and  $rand_j$  are random numbers with uniform distribution between 0 and 1 and  $fl^i$  is the flight length of the  $i$ th crow. If ‘Case 1’ occurs, the updating of the memory of crow ‘i’ will occur based on the formula below:

$$m^{i,iter+1} = \begin{cases} X^{i,iter+1} & \text{if } f(X^{i,iter+1}) \text{ is better than } f(m^{i,iter}) \\ m^{i,iter} & \text{otherwise} \end{cases} \tag{15}$$

$f(\bullet)$  denotes the value of the fitness function.

The value of ‘ $fl$ ’ decides the vicinity of search space. Small values of ‘ $fl$ ’ indicate local search, i.e., near and around  $x^{i,iter}$ . Larger values of ‘ $fl$ ’ lead to global search far away from  $x^{i,iter}$ .  $AP$  means the awareness probability of crow ‘j’. Since it is a probability, its value lies between 0 and 1, both inclusive.  $AP$  maintains the exploration and exploitation of the crow search algorithm. Lower value of  $AP$  means CSA searches near and around the local best position where the current best solution is obtained. This increases the exploitation capability of the algorithm. On the other hand, larger values of  $AP$  make CSA expand the vicinity of the search space to a global scale, thus increasing the exploration capability of CSA. Proper selection of  $AP$  and  $fl$  helps to maintain an appreciable balance between exploration and exploitation, which is a must quality of a metaheuristic algorithm. Figure 4 depicts the flowchart of the proposed CSA.

### 3.2 Particle swarm optimization (PSO)

Particle swarm optimization or PSO as we all know is one of the most popular and widely used metaheuristic soft computing techniques in the field of optimization. Since it was developed by Kennedy and Eberhart (2010), PSO has been widely used by engineers and mathematicians for optimization of both single- and multi-objective problems. The PSO algorithm works on the social behavior of particles in the swarm. Therefore, it finds the global best solution by simply adjusting the trajectory of each individual toward its own best location and toward the best particle of the entire swarm at each time step (generation). The PSO method is becoming very popular due to its simplicity of implementation and ability to quickly converge to a reasonably good solution. Mathematically, PSO is summed up using two governing equations, viz. the

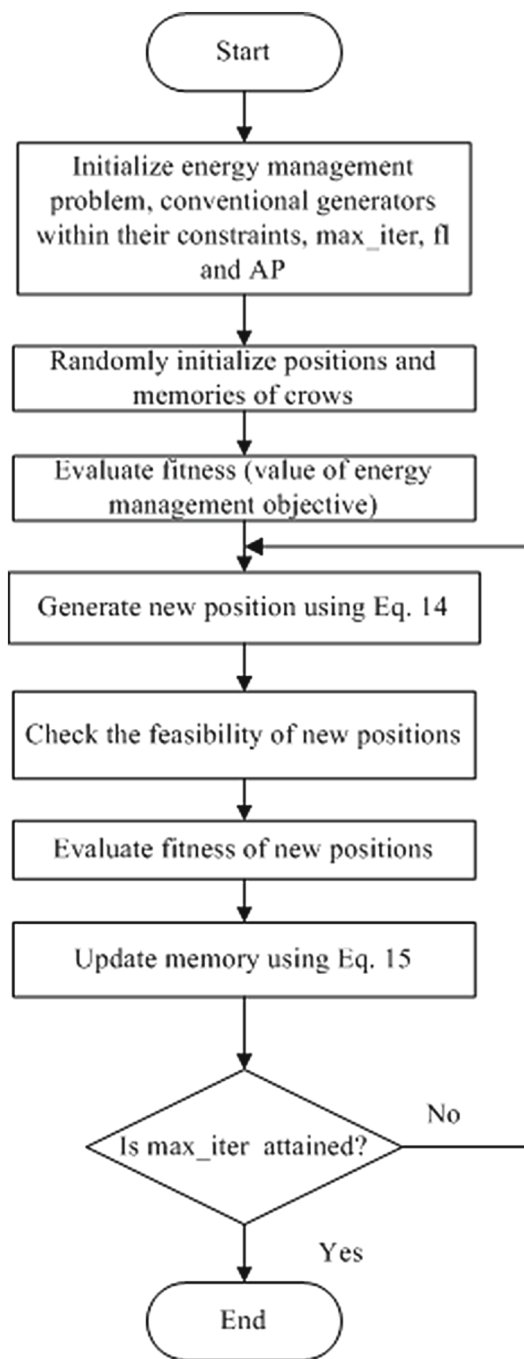


Fig. 4 Flowchart of crow search algorithm

velocity update equation and the position update equation, which are represented in (10) and (11), respectively.

$$vel_i^{iter+1} = \omega * vel_i^{iter} + c_1 * rand() * (pbest_i^{iter} - x_i^{iter}) + c_2 * rand() * (gbest^{iter} - x_i^{iter}) \tag{16}$$

$$x_i^{iter+1} = x_i^{iter} + vel_i^{iter+1} \tag{17}$$

$$\omega = \omega_{max} - (\omega_{max} - \omega_{min}) * \frac{iter}{max\_iter} \tag{18}$$



where  $vel$  denotes the velocity of the particle ' $i$ '.  $\omega$  is the inertia weight.  $c_1$  and  $c_2$  are the social and cognitive factors.  $x$  denotes the position of the particle  $i$ .  $pbest$  and  $gbest$  are the position best of the  $i$ th particle and global best of the population, respectively.

### 3.3 Genetic algorithm (GA)

Here, GA is used to determine the optimum magnitude of DERs which are the control variables and appear within a solution string in GA as shown in Eq. (1). Initially, a set of solution strings are created randomly in such a manner so that all the control variables have to be within their maximum and minimum limits as defined. Hence, in the initialization process of GA (Goldberg and Holland 1988), a population vector consisting of several control variables is generated. Then, the objective function is computed for every individual of the population. A biased roulette wheel is created from the values obtained after computing the objective function for all the individuals of the current population. Thereafter, the usual genetic operation such as reproduction, crossover and mutation takes place. Two individuals are randomly selected from the current population for reproduction. Then, crossover takes place with a probability close to one (here 0.8). Finally, mutation with a specific probability (very low) completes one genetic cycle and individuals of same population with improved characters are created in the next generation. The objective function is then again calculated for all the individuals of the new generation and all the genetic operations are again performed and the second generation of same population size is produced. This procedure is repeated till the final goal is achieved.

### 3.4 Differential evolution (DE)

Like GA, initialization is also done in the case of DE (Storn 1997) to prepare a population matrix of the control variables. Each population vector is nothing but the control variables represented by a string such a way that all the parameter values should lie within their maximum and minimum value and abide by their self-assigned constraints. Here, each vector in a population becomes a target vector. Each target vector is combined with a donor vector and a random vector differential in order to produce the DERs. These population vectors are created in a trial vector. If the cost of the trial vector is less than the target vector, the trial vector replaces the target in the next generation. The donor vector is selected in such a way so that its cost is either less than or equal to the target vector.

Mutation in GA is generally performed by generating random value utilizing a predefined probability density

function. In DE, the differential vector, where the contributors are the target vectors, donor vector and two other randomly selected vectors perform the mutation operation. The objective function is calculated for all the individuals of the new generation and all the operations are again performed. This procedure is repeated till the final goal is achieved.

### 3.5 JAYA algorithm

JAYA is a Sanskrit word meaning victory or success. The algorithm has only one governing equation. In every iteration, the algorithm tends to shift away from the worst solution (or failure), hence getting close to the best solution (or success/victory) as the termination criteria are attained. The simple governing equation of the JAYA algorithm is (Venkata Rao 2016):

$$X_{p,q,r}^{\text{updated}} = X_{p,q,r} + c' * (X_{p,best,r} - |X_{p,q,r}|) - c'' * (X_{p,worst,r} - |X_{p,q,r}|) \quad (19)$$

where  $p$ ,  $q$  and  $r$  are whole numbers denoting number of variables, particle of the population and current iteration, respectively.  $c'$  and  $c''$  are random numbers lying between 0 and 1, both inclusive. The positive term in the equation defines the tendency of shifting the solution toward the best solution (success), and the negative term in the equation depicts the tendency to shift the solution away from the worst solution (failure).

### 3.6 Sine cosine algorithm (SCA)

The entire process of a stochastic population-based optimization algorithm can be divided into two phases. The first phase is the exploration phase where the random solutions of the fitness function involve very high rate of randomness to broaden the search space and locate the promising region of a superior solution. On the other hand in the second phase, also called the exploitation phase, the degree of randomness decreases and slow and gradual changes are implemented in the solutions to proceed toward a better-quality solution.

The sine cosine algorithm (SCA) employs these two stages in its governing equation which is (Mirjalili 2016):

$$X_d^{\text{iter}+1} = \begin{cases} X_d^{\text{iter}} + r_1 * \sin(r_2) * |r_3 * P_d^{\text{iter}} - X_d^{\text{iter}}|, & r_4 < 0.5 \\ X_d^{\text{iter}} + r_1 * \cos(r_2) * |r_3 * P_d^{\text{iter}} - X_d^{\text{iter}}|, & r_4 \geq 0.5 \end{cases} \quad (20)$$

where  $d$  is the dimension,  $X$  is the solution and  $P$  is the position of solution from the destination point. The random numbers  $r_1$ ,  $r_2$ ,  $r_3$  and  $r_4$  have their own significance. The

direction of the next position, whether it lies in between solution and destination or away from both, is governed by  $r_1$ , whereas  $r_2$  implies how lengthy should be the displacement and should it be away from or toward the destination. While  $r_3$  acts as a weightage factor for the destination, the random number  $r_4$  switches between the sine and cosine function.

### 3.7 Grey wolf optimizer (GWO) and modified GWO

Grey wolves' hunt in packs. There exists a hierarchical leadership among the wolves of the pack. The leader wolf is called alpha. It may not be the strongest in the pack but maintains dominance and is followed by all the other members of the pack. The second ranked wolf is called beta. Beta acts as an advisor to alpha in decision making, maintains discipline in the pack and is most likely the successor to take the position of alpha when alpha becomes old or passes away. Omega is the third ranked wolf in the hierarchy and is very submissive in nature. It often acts as a scapegoat or babysitter for the pack. The rest of the wolves are collectively termed as delta.

In mathematical modeling of GWO, three best solutions are considered. The best solution is termed as alpha. Beta and omega are the second and third best solutions. The rest of the solutions are termed as delta. The mathematical equations to express the hunting behavior of the wolves and the position updating procedure are mentioned in Mirjalili et al. (2014).

Considering the fact that the best solution (prey) may be trapped among the delta wolves too, modified GWO (MGWO) involves the participation of the delta wolves in hunting procedure. A new family is generated by finding the mean position of omega and delta wolves, and their position is considered as the fourth best solution. Thereafter, the position updating procedure is formulated as explained in Khandelwal et al. (2018).

### 3.8 Whale optimization algorithm (WOA)

Whales hunt in a three-dimensional space, and hence their hunting mechanism (exploitation phase) is a bit more rigorous and sophisticated compared to GWO. The foraging behavior of whale is also called bubble-net feeding method. Whale approaches its prey in two ways: the shrinking circle path and the spiral-shaped path. It is to be noted that a whale hunts its prey simultaneously in both the ways. To model this simultaneous behavior, we assume that there is a probability of 50% to choose between *the shrinking encircling mechanism* and *the spiral model* to update the position of whales during optimization as mentioned in

Mirjalili and Lewis (2016). The search for prey (exploration phase) by the whales is mathematically similar to that of GWO.

### 3.9 Teaching-learning-based optimization (TLBO)

In a real-time classroom, the teacher tries to imbibe the student with his knowledge. He does not focus on one pupil only but tries to teach every student equally. However, despite the best efforts of teacher, not all students learn the same amount. Some excel more than others. This happens because of personal merit of a student and the ability to grasp quickly. The main difference between getting taught from a teacher in a classroom than from a fellow student is the interaction the students have with one another. Here also, the personal grasping power of a student plays an important role, but the probability of learning from a better student is more than from a less sophisticated student. Teaching-learning-based optimization (TLBO) algorithm (Rao et al. 2011) also portrays this environment and could be understood as follows:

The intelligence level of a student is ascertained by his fitness value obtained from the fitness function. During the first phase, it is assumed that the best student (with best fitness value) will inherit the entire knowledge of the teacher and will be at the same intelligence level as the teacher himself (Teacher). Now, the job of the Teacher is to impart knowledge to students in such a way so as to increase the overall mean of all subjects in the class and to increase the overall mean to a new level (Desired). Their difference helps to modify the current level of each student. Thereafter, two random students are chosen and their fitness functions are compared. Depending upon this comparison in terms of fitness values and their difference, a change in the current level of student is proposed again. Hence, we come across a two-level modification to ensure achievement of optimal result.

### 3.10 Symbiotic organisms search (SOS)

There exist three types of relationships between any two organisms in an ecosystem as stated by Cheng and Prayogo (2014). They are mutualism, commensalism and parasitism. The relation between a flower and a bee can be termed as mutualism where both bees and flower are benefitted from each other. Bees suck nectar from the flower and in turn help the flower with pollination. Commensalism is a relation between two organisms where one of them is benefitted without providing any positive or negative impact on the other one. Remora fish sticks itself with the shark feeding on shark's excreta which is an

example of commensalism. Parasitism is that relation between two organisms where one is benefitted harming the other. The organism that is harmed is called the host, whereas the organism that is benefitted in parasitism is called the parasite. Deer ticks stick themselves to the body of the deer sucking their blood and make the host prone to harmful and fatal diseases.

In SOS, initially an ecosystem (population matrix) is formed with a defined value of organisms (particles). All the organisms maintain their self-assigned constraints, and their fitness functions are evaluated. Thereafter, each of the organisms pass through the aforementioned three relations represented mathematically until the algorithm yields the best value of the fitness function.

## 4 Results and discussion

### 4.1 Overview of the test systems

For the purpose of energy management evaluation, six microgrid test systems are considered in this paper. An overall description of all the test systems is displayed in Table 2. The operating ranges, cost, emission and valve point coefficients of the conventional generators of microgrid test systems 1 and 2 are listed in Tables 3 and 4, and the necessary parameters to model the RES for these two systems are listed in Tables 5 and 6, respectively. Figures 5, 6 and 7 show the load demand, wind speed and

PV outputs of microgrid test systems 1 and 2, respectively. Table 7 contains the DG parameters of microgrid test system 3. Figure 8 shows the RES output, load demands and market price of electricity of microgrid test system 3. The DG parameters of test system 4 and 5 are gathered from Yong and Tao (2007), Ganjefar and Tofghi (2011) and Wibowo et al. (2017). Microgrid test systems 3 and 5 are both grid-connected microgrid systems; the difference being microgrid test system 3 does not include an ESS, and the real-time electricity price varies with time, whereas microgrid test system 5 is backed up by an ESS and the electricity price is fixed throughout the day. Lastly, the necessary data for performing ELD and CEED on microgrid test system 6 were collected from Trivedi et al. (2018). The proposed crow search algorithm (CSA) was applied to solve energy management problem for the microgrid test systems along with nine other optimization algorithms discussed in Sect. 3. The algorithms were coded in MATLAB R2013a environment installed in a personal computer having specifications of core i3 as processor with a clock frequency of 2.53 GHz and a RAM of capacity 2 Gigabyte. For all optimization techniques, the population size was varied altered in the range 60–80 with 500 iterations for 20 repeated trials. For PSO, the values of  $w_{\max}$ ,  $w_{\min}$ ,  $c_1$  and  $c_2$  are 0.9, 0.7, 2 and 2, respectively. The mutation factor and crossover probability for DE were considered as 0.7 and 0.25, respectively.

**Table 2** Description of the microgrid test systems considered for energy management

Microgrid test system	Mode of operation	Number of PV units	Number of WT units	Number of fossil-fueled generators	Valve point loading effect	ED/CEED	Cases studied
1	Islanded	0	1	5	No	Both	4
2	Islanded	1	1	5	Yes	ED	4
3	Grid	1	1	1	No	ED	3
4	Islanded	0	1	10	Yes	ED	2
5	Grid	37	0	1	No	ED	1
6	Islanded	1	1	3	No	Both	4

**Table 3** DG parameters of microgrid test system 1

	$u$ (\$/kW <sup>2</sup> )	$v$ (\$/kW)	$w$ (\$)	$P_{\min}$ (kW)	$P_{\max}$ (kW)	$x$ (kg/kW <sup>2</sup> )	$y$ (kg/kW)	$z$ (kg)
$G_1$	0.005	3.51	44.4	100	400	0.01378	1.2489	173.37
$G_2$	0.006	3.89	40.6	50	200	0.00767	0.8051	363.705
$G_3$	0.004	2.78	66.9	50	300	0.0905	0.756	198.5
$G_4$	0.0026	2.86	87.67	75	500	0.0127	1.1677	11.67
$G_5$	0.003	2.45	105	150	600	0.01265	1.3552	22.983

**Table 4** DG parameters of microgrid test system 2

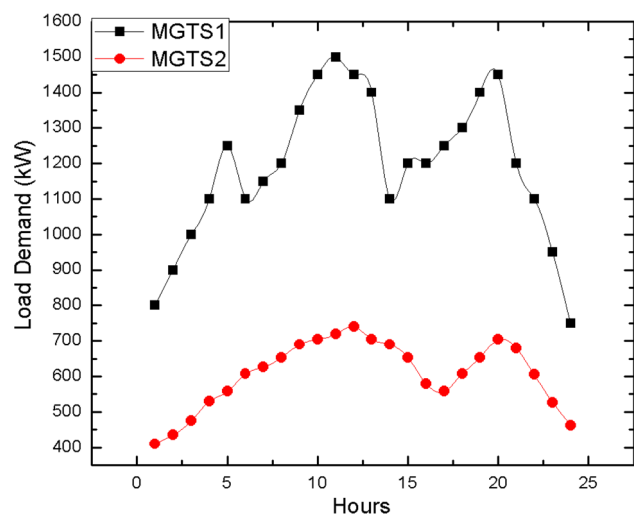
	$u$ (\$/kW <sup>2</sup> )	$v$ (\$/kW)	$w$ (\$)	$P_{min}$ (kW)	$P_{max}$ (kW)	$\delta$ (\$/h)	$\theta$ (rad kW <sup>-1</sup> )
$G_1$	0.008	2	25	10	75	100	0.042
$G_2$	0.003	1.8	60	20	125	140	0.040
$G_3$	0.0012	2.1	100	30	175	160	0.038
$G_4$	0.001	2	120	40	250	180	0.037
$G_5$	0.0015	1.8	40	50	300	200	0.035

**Table 5** Renewable energy sources' parameters for microgrid test system 2 (Lahon and Gupta 2018)

	PV	WT <sub>2</sub>
Acquisition cost (\$/kW)	3500	1670
Interest rate (%)	20	20
Project lifetime (years)	20	20
Maintenance cost (\$/kW)	1.40	0.0028
Capacity factor	0.272	0.347

**Table 6** Wind energy parameters for microgrid test systems 1 and 2

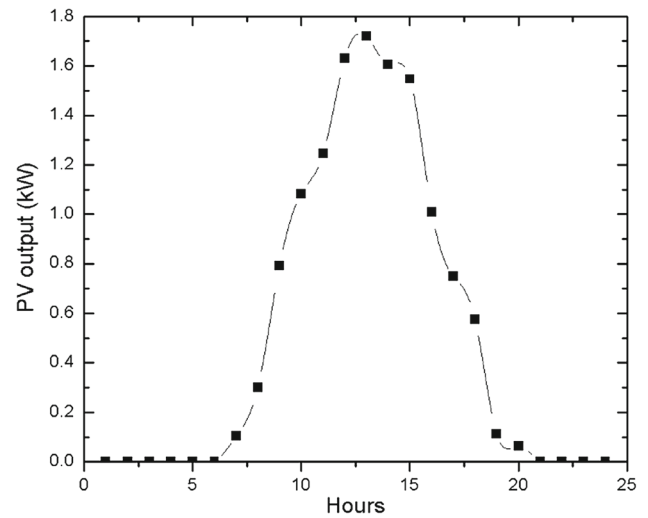
Parameters	WT <sub>1</sub>	WT <sub>2</sub>
$v_{cut-in}$ (m/s)	5	3
$v_{cut-out}$ (m/s)	15	25
$v_r$ (m/s)	10	14
$P_{rated}$ (kW)	300	300



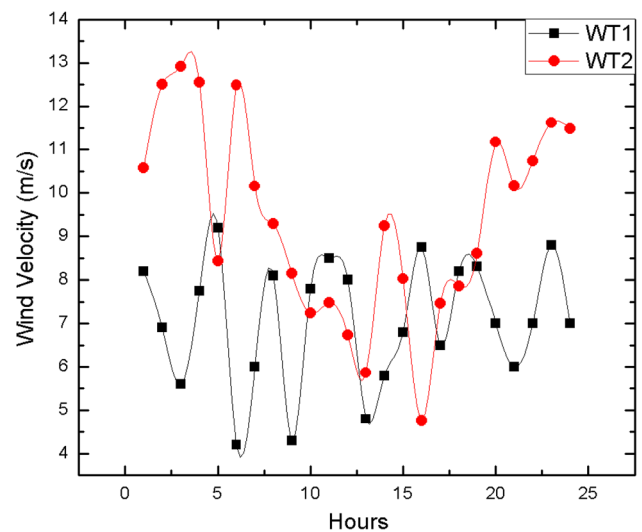
**Fig. 5** Load demand of microgrid test systems 1 and 2

**4.2 Comparative analysis**

Various penalty factors were calculated as listed in Table 1, and their values are displayed in Table 8. It can be realized that *min-max penalty factor* is the least among all. Furthermore, CEED was evaluated with and without RES



**Fig. 6** PV output of microgrid test system 2

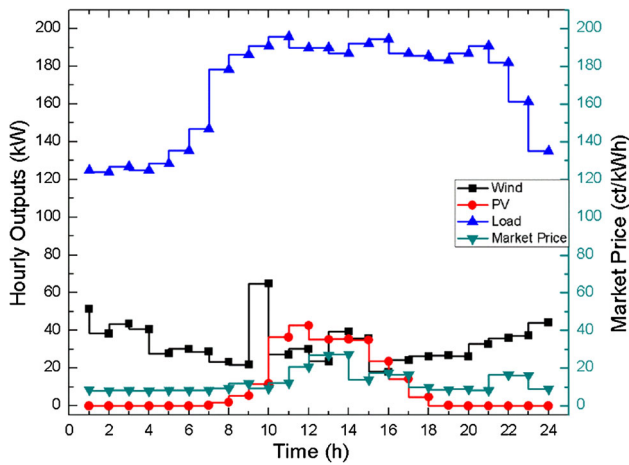


**Fig. 7** Wind speed for microgrid test systems 1 and 2

using the min-max penalty factor for microgrid test system 1. Table 9 enlists the generation cost when ELD and CEED were performed using the ten optimization techniques with and without RES. The effect of RES can be realized with the decrease in the value of ELD and CEED. A 12% drop in the values of ELD and CEED can be observed after the

**Table 7** DG parameters for microgrid test system 3

	$u$ (\$/kW <sup>2</sup> )	$v$ (\$/kW)	$w$ (\$)	$P_{min}$ (kW)	$P_{max}$ (kW)
DE	0.00104	0.0304	1.30	20	60
MT	0.00051	0.0397	0.40	10	30
FC	0.00024	0.0267	0.38	10	30
GRID	–	–	–	– 80	80



**Fig. 8** Load demands, hourly outputs of RES and utility price for microgrid test system 3

**Table 8** Penalty factors (\$/kg) calculated for microgrid test system 1

Types	$h_1$	$h_2$	$h_3$	$h_4$	$h_5$
Max–max	0.4925	0.7813	1.2730	0.1471	0.5748
Max–min	5.1968	5.1561	2.5018	2.7259	12.6998
Min–max	0.1001	0.1547	0.3007	0.0251	0.0840
Min–min	1.0569	1.0214	0.5910	0.4667	1.8560
Average	1.7116	1.7784	1.1666	0.8412	3.8036
Common	0.3423	0.3556	0.2333	0.1682	0.7607

**Table 9** Generation cost for microgrid test system 1 (\$)

Algorithms	ELD without RES	ELD with RES	CEED without RES	CEED with RES
GA	11,7624.7444	103,625.2777	137,164.3491	120,305.9871
PSO	117,437.3618	103,474.3922	137,081.6066	120,218.7259
DE	117,604.5094	103,600.8322	137,162.3173	120,293.9634
SCA	117,445.1701	103,477.1104	137,068.6468	120,224.3862
TLBO	117,449.9535	103,478.8230	137,090.4104	120,254.9188
GWO	117,437.4440	103,486.5133	137,065.0906	120,225.3156
MGWO	117,437.0158	103,482.1640	137,063.0927	120,221.5939
WOA	117,797.3479	103,732.5368	137,583.3914	120,600.9558
MWOA	117,667.9840	103,662.4691	137,386.8488	120,464.7106
CSA	117,436.5559	103,469.3322	137,062.8987	120,219.0719

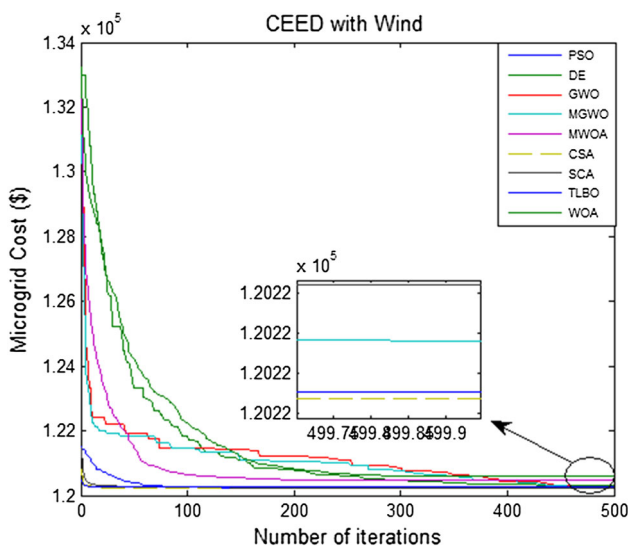
inclusion of the RES in the system. The generation cost (ELD) was found to be **\$117,436.5559** without RES which dropped down to **\$103,469.3322** upon the inclusion of RES. Similarly, the value of CEED was **\$137,062.8987** before wind turbine was incorporated to share which later reduced to **\$120,219.0719** after the inclusion of wind turbine. The proposed CSA yielded the least and profound result for all the four cases studied for microgrid test system 1 when compared to all the other optimization techniques used. Table 10 highlights the hourly outputs of various generators and the wind turbine when CEED was evaluated including RES to achieve a minimum and best cost of **\$120,219.0719**. Figure 9 shows the convergence characteristic curve for all the optimization techniques used when CEED was evaluated including RES. It can be seen that CSA converges pretty early with the minimum possible cost compared to all the other algorithms.

Table 11 displays the generation cost of the microgrid test system 2 which was effected by valve point loading considering RES like PV and wind. Various cases were studied for this test system, namely without wind, without PV and without RES. For all the cases, it can be seen from Table 11 that CSA provided better results with the minimum possible cost even though the cost function was a non-smooth one. 9% savings in the cost function was attained by CSA when the fitness function was evaluated using both the RES as the generation cost dropped down to **\$37,704.0429** from **\$41,650.8604**. Table 12 highlights the hourly outputs when the generation cost was calculated for microgrid test system 2 with RES. Figures 10 and 11 show the convergence characteristics when generation cost of microgrid test system 2 was evaluated using ten optimization techniques without and with RES, respectively. The proposed crow search algorithm shows quick convergence with better and superior quality results when compared with the rest of the optimization techniques used.

Table 13 displays the minimum generation cost, for grid-connected microgrid test system 3, obtained using

**Table 10** Hourly outputs for microgrid test system 1 using CSA (CEED with RES) (kW/h)

H	G <sub>1</sub>	G <sub>2</sub>	G <sub>3</sub>	G <sub>4</sub>	G <sub>5</sub>	WT <sub>1</sub>
1	100.0000	50.0000	50.0000	214.0785	193.9215	192.0000
2	100.0000	50.6265	50.0000	317.282	268.0915	114.0000
3	120.8212	80.64993	50.0001	391.2002	321.3285	36.0000
4	115.6481	76.49311	50.0002	379.9726	312.8858	165.0000
5	126.7501	86.11833	50.0000	404.3498	330.7817	252.0000
6	144.5901	100.9769	50.0000	445.0157	359.4174	0.0000
7	400.0000	200.0000	168.4434	156.9742	164.5823	60.0000
8	130.0706	88.38241	50.0000	411.7781	333.7688	186.0000
9	228.6337	115.7447	50.0000	500.0000	455.6216	0.0000
10	246.2203	200.0000	259.1157	372.8108	203.8531	168.0000
11	400.0000	200.0000	218.9104	301.9348	169.1548	210.0000
12	400.0000	200.0000	300.0000	182.7065	187.2935	180.0000
13	357.6167	200.0000	189.836	500.0000	152.5473	0.0000
14	185.1167	177.0331	164.6676	174.716	350.4667	48.0000
15	178.3831	200.0000	193.8445	237.0617	282.7107	108.0000
16	122.5598	82.25551	50.0002	395.7092	324.4752	225.0000
17	132.0527	50.0000	50.0000	500.0000	427.9473	90.0000
18	144.5756	78.7051	50.0000	500.0000	334.7193	192.0000
19	175.4323	200.0000	300.0000	250.5812	275.9864	198.0000
20	161.9437	200.0000	300.0000	347.6994	320.3569	120.0000
21	149.2949	110.3747	52.4489	459.1237	368.7582	60.0000
22	205.6009	200.0000	166.0421	209.9409	198.4162	120.0000
23	100.0000	50.0000	50.0000	280.408	241.592	228.0000
24	100.0000	50.0000	50.0000	226.8795	203.1205	120.0000



**Fig. 9** Convergence characteristics of microgrid test system 1 using wind

eight different soft computing techniques. Three different cases, viz. normal loading, without PV and 5% overloading, were studied for this test system. CSA minimized the microgrid generation cost to a great extent for all the three

cases when compared with other optimization techniques used. 21% to 25% savings in the generation cost was realized when the proposed CSA minimized the value of the fitness function to **\$225.7871** during normal conditions, **\$272.9262** without the support of PV and **\$251.0270** when the system was 5% overloaded. The dashed line in Fig. 12 represents the convergence curve of CSA to minimize the fitness function in the normal condition. It is clearly evident that CSA converges early with much superior quality result than most of the optimization tools used. Figures 13 and 14 depict the hourly scheduling of the DERs when the generation cost was minimized using CSA for normal and 5% overloading condition, respectively. The active participation of grid to buy and sell power to and from the microgrid system is distinct from the figures. Also, the fuel cell with the lowest cost coefficients is scheduled to its maximum output for maximum hours. The rest of the load is shared between DE and MT along with the grid based on peak demand and high electricity price.

The proposed CSA outperformed PSO, TLBO, SCA and other hybrid optimization tools found in the literature when the non-smooth fuel cost function of microgrid test system 4 was evaluated with and without the support of wind power. Table 14 lists the generation cost of the microgrid system minimized with the aforementioned soft computing

**Table 11** Generation cost for microgrid test system 2 (\$)

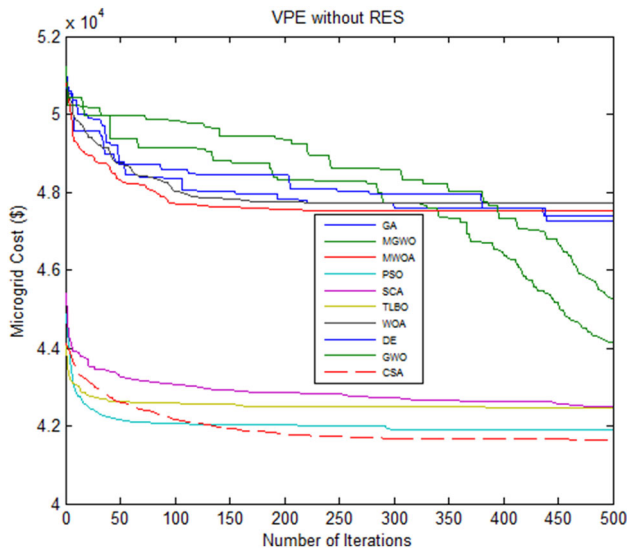
Algorithms	VPE without RES	VPE with PV	VPE with WT <sub>2</sub>	VPE with RES
GA	47,399.7164	47,783.5964	41,872.4346	41,705.7366
PSO	41,886.7300	42,133.9850	38,012.7069	38,087.6086
DE	47,248.2778	47,740.3770	41,689.4719	41,628.0833
SCA	42,508.1297	42,449.3850	38,011.7289	37,980.8981
TLBO	42,468.0241	42,685.3736	38,484.1919	38,369.9556
GWO	45,259.7774	44,874.5632	39,927.3332	40,543.7842
MGWO	44,133.8004	44,536.4826	39,905.9341	39,984.3456
WOA	47,731.1971	48,871.8012	43,389.8151	43,359.9863
MWOA	47,516.0669	47,602.1864	42,448.5524	42,239.2616
CSA	41,650.8604	41,646.8605	37,732.3824	37,704.0429

**Table 12** Hourly outputs for microgrid test system 2 using CSA (VPE with RES) (kW/h)

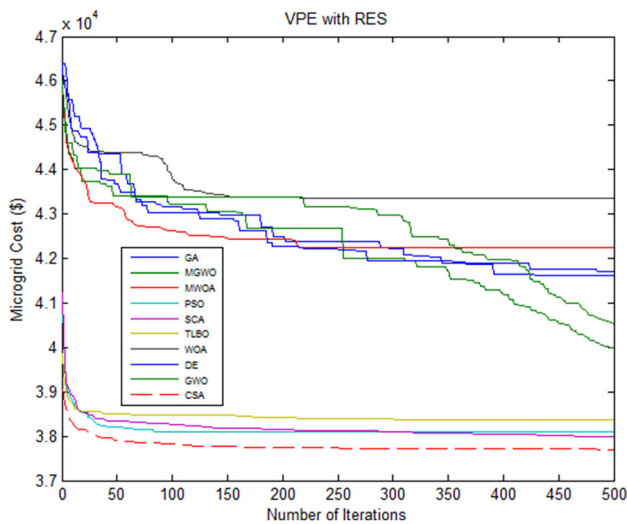
H	G <sub>1</sub>	G <sub>2</sub>	G <sub>3</sub>	G <sub>4</sub>	G <sub>5</sub>	PV	WT <sub>2</sub>
1	63.2729	20.0000	30.0000	40.0000	50.0000	0	206.7271
2	35.8351	20.0000	30.0000	40.0000	50.0000	0	259.1649
3	64.7373	20.0000	30.0000	40.0000	50.0000	0	270.2627
4	40.0000	20.0000	30.0000	40.0000	139.7598	0	260.2402
5	10.1223	20.0000	30.0718	209.8147	139.7596	0	148.2315
6	29.9302	20.0000	30.0000	40.0000	229.5196	0	258.5502
7	32.5976	98.5398	30.0000	40.0000	229.5196	0.1051	195.2379
8	10.0000	94.9271	112.6732	124.9078	139.7599	0.3012	171.4308
9	73.1393	99.0953	113.1819	124.7277	138.7869	0.7923	140.2766
10	73.5559	124.3121	171.2293	105.9042	112.3609	1.0821	115.5554
11	35.3262	103.4763	30.0000	195.9673	231.9339	1.2457	122.0506
12	74.8314	98.7255	112.7415	209.9911	140.1700	1.6317	101.9089
13	63.3838	98.5401	112.6744	209.8173	139.7590	1.7214	78.1041
14	28.9416	20.0000	30.0000	209.9422	229.4530	1.6046	170.0586
15	25.8705	20.0000	30.0000	210.2951	229.2319	1.5470	137.0555
16	41.6343	20.0000	30.0000	209.8154	229.5199	1.0099	48.0205
17	37.5958	98.5398	30.0000	40.0000	229.5196	0.7501	121.5947
18	75.0000	125.0000	30.0000	40.0000	204.7222	0.5762	132.7016
19	11.5640	20.0000	30.0000	210.0324	229.3114	0.1130	152.9791
20	10.0000	93.7191	112.6734	124.9079	139.7598	0.0635	222.8763
21	10.0000	97.2606	112.6728	124.9080	139.7595	0	195.3991
22	10.0000	89.2444	30.0000	124.9079	139.7598	0	211.0879
23	62.1909	20.0000	30.0000	40.0000	139.7598	0	235.0493
24	13.0119	98.5398	30.0000	40.0000	50.0000	0	231.4483

techniques and those available in the literature. CSA brought down the generation cost to **\$1,014,996.2345** without wind and **\$979,585.5032** with wind, thus saving 1.5–2% than the predetermined cost. Figure 15 shows the convergence curves when fitness function of test system 4 was minimized using PSO, TLBO, SCA and CSA. CSA

converged as early as 170–180 iterations with the best and minimized generation cost compared to the rest of the three optimization techniques. The hourly load sharing among the 10 generators and wind turbine when the least cost was obtained using CSA is shown in Fig. 16. Figure 17 shows the cost comparative analysis when the generation cost of



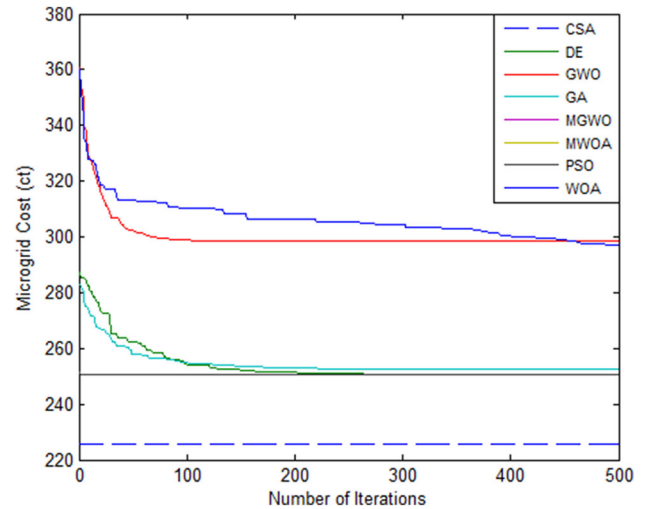
**Fig. 10** Convergence characteristics of microgrid test system 2 without RES



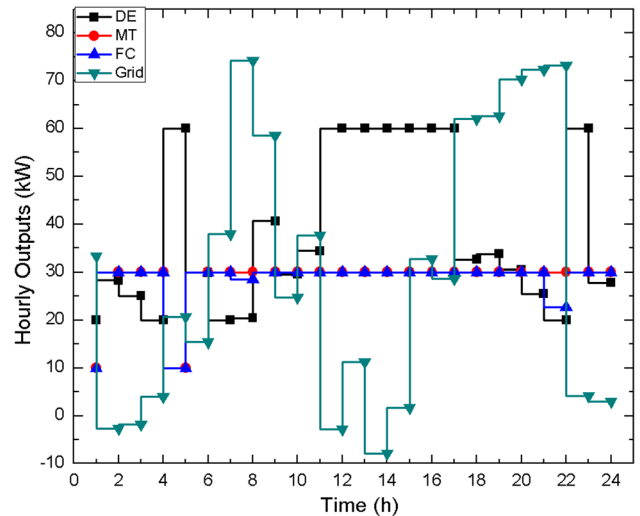
**Fig. 11** Convergence characteristics of microgrid test system 2 using wind and PV

**Table 13** Generation cost for microgrid test system 3 (\$)

Algorithms	Normal	Without PV	5% Overload
GA	252.3062	296.6136	277.8332
PSO	250.4731	296.5358	276.6178
DE	250.5026	296.5608	276.6178
GWO	298.5187	345.327	326.6882
MGWO	296.8825	343.7400	325.4600
WOA	296.6812	343.9049	326.8285
MWOA	295.9887	343.1282	325.5492
CSA	225.7871	272.9262	251.0270



**Fig. 12** Convergence characteristics of microgrid test system 3 under normal loading condition



**Fig. 13** Hourly output of microgrid test system 3 under normal loading condition using CSA

microgrid test system 4 was calculated with and without wind support. It can be realized from the figure that 3.14% savings in the generation cost was attained when the subject microgrid test system was incorporated with wind power. Also, CSA diminished the generation costs to 0.4% and 1.19% than the costs reported in Ganjefar and Tofighi (2011) and Yong and Tao (2007) when microgrid test system 4 was functioning without and with wind power, respectively.

Figure 18 depicts the load sharing of the DERs included in microgrid test system 5. The ESS charges itself during the off-peak hours and maintains its state of charge. PV, with the highest cost coefficient maintains a low profile,



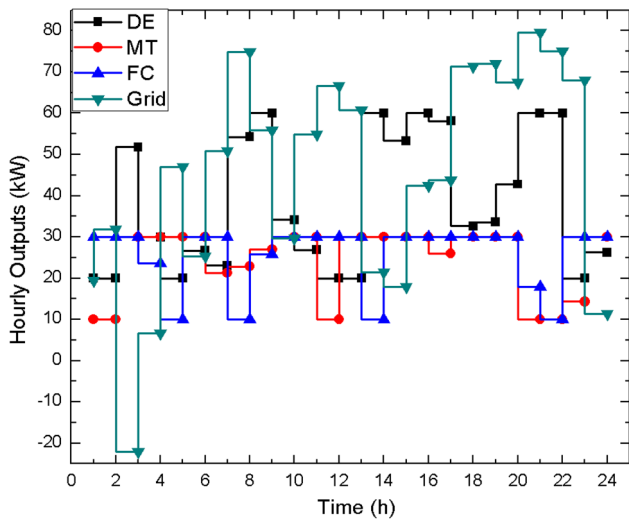


Fig. 14 Hourly output of microgrid test system 3 with 5% overloading condition using CSA

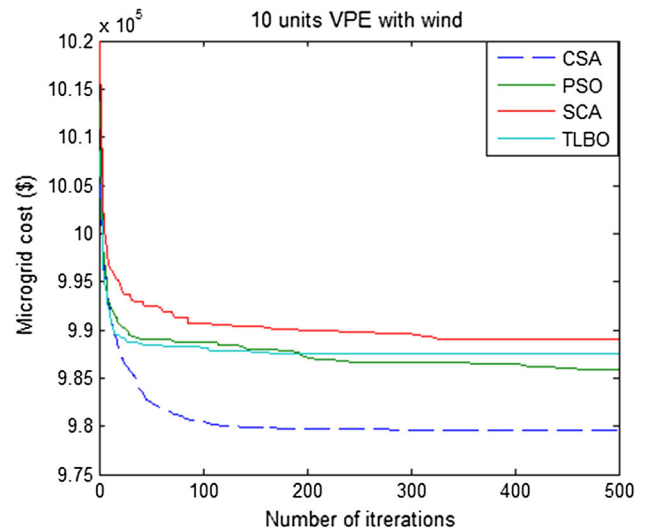


Fig. 15 Convergence characteristics of microgrid test system 4 with wind

Table 14 Generation cost for microgrid test system 4 (\$)

Algorithms	VPE	VPE with Wind
Hybrid EP-SQP (Ganjefar and Tofighi 2011)	1031746	—
Hybrid PSO-SQP (Ganjefar and Tofighi 2011)	1027334	—
MDE (Ganjefar and Tofighi 2011)	1031614	—
IPSO (Ganjefar and Tofighi 2011)	1023807	—
IGA-NSPF (Ganjefar and Tofighi 2011)	1019145	—
GA(Yong and Tao 2007)	—	997528
PSO	1,025,665.9723	985,875.3797
TLBO	1,024,624.6866	987,461.5342
SCA	1,023,303.5957	988,955.6750
CSA	1,014,996.2345	979,585.5032

whereas grid with the lowest cost coefficient delivers the remaining load after DE and MT have contributed its share, thus maintaining the supply–demand equation. A massive 33% savings in the generation cost was realized when CSA was implemented to minimize the generation cost of microgrid test system 5 by reducing the cost to **\$574.350** compared to that of \$866.758 by SQP. The generation costs achieved by PSO and proposed CSA for microgrid test system 5 are listed in Table 15, and the percentage of savings is shown in Fig. 19.

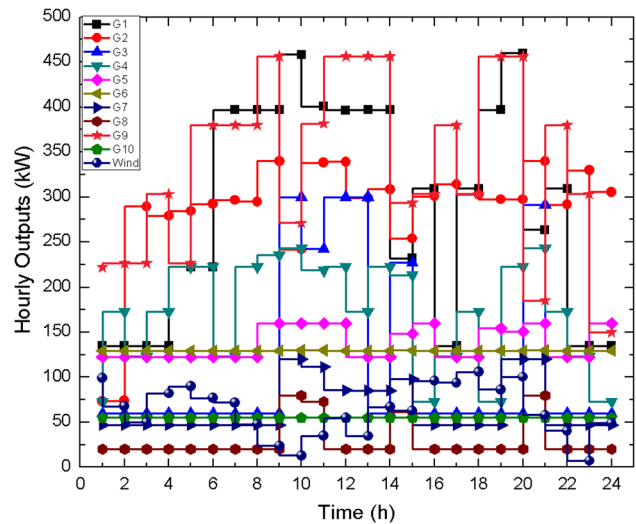
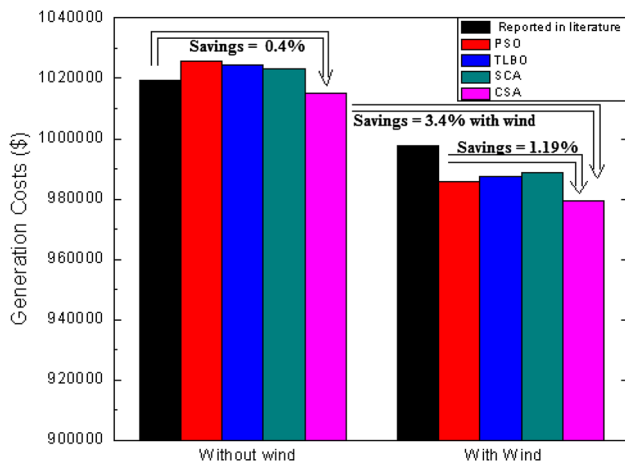
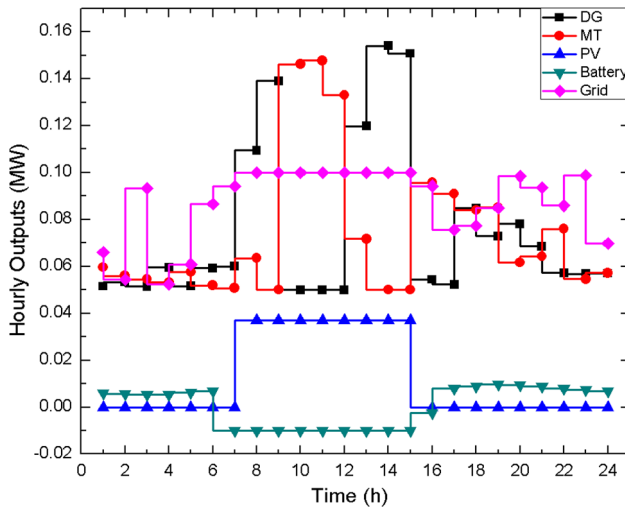


Fig. 16 Hourly output of microgrid test system 4 with wind

Table 16 highlights the generation costs when ELD was performed on microgrid test system 6 using DE, SOS, JAYA and proposed CSA. It can be seen that the proposed CSA outperformed various algorithms in providing a better and minimized cost in all the four scenarios studied for the aforementioned test system. CSA brought down the generation cost to **\$166,792.8781** which saves 9% economy compared to that of reported in the literature. Table 17 lists the various price penalty factors evaluated for the test system 6 as per Eq. (1). Min–Max penalty factor is the



**Fig. 17** Cost comparative analysis of microgrid test system 4 with and without wind support

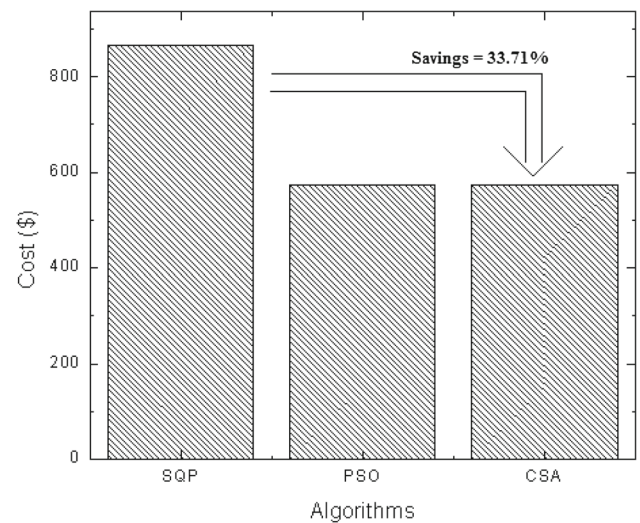


**Fig. 18** Hourly output of microgrid test system 5

**Table 15** Generation cost for microgrid test system 5 (\$)

Algorithms	Minimum cost
SQP (Wibowo et al. 2017)	866.758
PSO	574.6761
CSA	574.350

least among all and is used for further evaluation of CEED. A 17% savings was realized when CEED was performed using CSA in test system 6 considering both PV and wind together. CSA minimized the generation cost to



**Fig. 19** Cost comparative analysis of microgrid test system 5 using the proposed CSA

**\$192,169.3625** which outperformed \$232,053 obtained by reduced gradient method (RGM) as reported in the literature, and this is shown in Table 18. Similarly, in all the subsequent scenarios for this test system, CSA consistently provided a superior result outperforming all the other soft computing techniques reported. Tables 19 and 20 list the various hourly outputs and hourly costs when CSA was used to minimize the generation cost, while CEED was evaluated with and without RES, respectively. Figure 20 shows the cost comparative analysis for various cases studied of microgrid test system 6. It is clear from the figure that the generation cost of the system was reduced (up to 5.23%) when RES was incorporated compared to the case without RES. One more benefit of involving RES is that it reduces stress on the FFGs by sharing their loads, thus improving their durability and longevity.

### 4.3 Wilcoxon signed-rank test

Wilcoxon signed-rank test (Wilcoxon 1945) was used to test one sample data set, received as the outcome of the mentioned algorithm. It is a pairwise test done to find substantial variances in the behavior of two diverse algorithms. 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. The  $p$  value (probability value) which comes out to be less than 0.05 achieved by employing this test gives clear proof against the proposed null hypothesis. The  $p$  values received from this test for all the cases with their minimum,

**Table 16** Generation cost (ELD) for microgrid test system 6 (\$)

Algorithms	All sources	with PV only	With Wind only	Without RES
RGM (Trivedi et al. 2018)	183,520	175,966	–	177,291
ACO (Trivedi et al. 2018)	173343	174879	–	176212
CSA* (Trivedi et al. 2018)	167,044	172,038	171,314	176,370
ISA (Trivedi et al. 2018)	167,012	172,008	171,274	176,320
DE	166,815.8024	171,853.1639	171,142.4342	176,226.8178
SOS	166,793.2985	171,809.8544	171,104.2563	176,166.5832
JAYA	166,794.9367	171,814.9342	171,107.1593	176,166.0276
CSA**	166,792.8781	171,809.5355	171,104.0247	176,165.7890

CSA\* cuckoo search algorithm; CSA\*\* crow search algorithm; – results not reported

**Table 17** Penalty factors (\$/kg) calculated for microgrid test system 6

Types	$h_1$	$h_2$	$h_3$
Max–max	56.1290	32.2496	14.6306
Max–min	215.3509	146.7455	162.2976
Min–max	25.1597	11.9948	4.6750
Min–min	96.530	54.5798	5.5334
Average	98.2924	61.3924	46.7841
Common	32.76	20.46	15.59

maximum, average values and standard deviation are listed in Table 21. From this table, 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.

**Table 18** Generation cost (CEED) for microgrid test system 6 (\$)

Algorithms	All sources	With PV only	With wind only	Without RES
RGM (Trivedi et al. 2018)	232,053	234,198	–	240,780
ACO (Trivedi et al. 2018)	217,655	223,784	–	229,887
CSA* (Trivedi et al. 2018)	192,309	197,668	197,132	202,867
ISA (Trivedi et al. 2018)	192,250	197,601	197,093	202,799
DE	192,438.3157	197,895.5124	197,429.9647	203,244.7612
SOS	192,543.2341	197,832.4901	197,294.4772	202,868.7606
JAYA	192,254.6732	197,676.0104	197,131.9934	202,871.3677
CSA**	192,169.3625	197,590.3024	197,045.4757	202,782.7539

CSA\* cuckoo search algorithm; CSA\*\* crow search algorithm; – results not reported

#### 4.4 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. CSA was evaluated for 20 trial runs for all cases. The number of times it hit the minimum solution is shown in Table 21. It can be seen that the lowest number of times it hit the minimum solution was 17, whereas the highest number was 19. The average success rate came out to be 90% which is highly appreciable.

#### 5 Conclusion

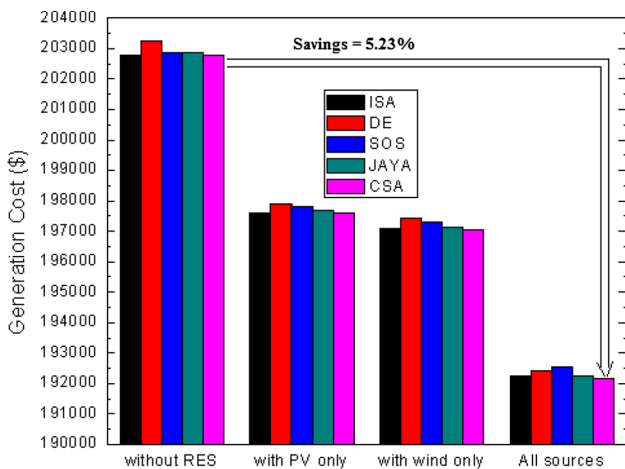
Renewable integrated microgrid systems, operating in both islanded and grid-connected modes, were considered in this paper for solving energy management problems. Modeling of the RES which are based on the day-ahead evaluation of solar irradiance, wind speed, etc., was done to calculate the

**Table 19** Hourly outputs (kW) and hourly costs (\$/h) for CEED using CSA (all sources)

Hours	G <sub>1</sub>	G <sub>2</sub>	G <sub>3</sub>	Hourly costs
1	48.3	40	50	7149.373
2	51.5	40	50	7199.6696
3	55.73	40	50	7275.1599
4	53.34	40	50	7231.2471
5	64.1312	43.64,877	50	7540.9343
6	66.3426	48.71,735	50	7719.3362
7	63.0043	41.06,575	50	7453.5663
8	47.26	40	50	7134.2899
9	66.4368	48.93318	50	7727.1378
10	67.7756	52.00178	53.00257	7917.1217
11	74.4699	67.34495	77.97518	9227.6826
12	77.1448	95.24162	55.31357	9465.9234
13	71.4866	60.50727	66.84614	8621.3576
14	68.7655	52.98217	55.96234	8046.0983
15	69.0402	54.90004	57.7198	8150.8676
16	65.1063	45.88368	50	7618.4608
17	63.8913	43.09875	50	7522.1295
18	68.9205	54.62588	57.27357	8128.4809
19	71.5447	60.64142	67.0639	8632.88
20	97.5558	67.57365	74.70051	9841.1835
21	75.1904	68.99644	80.66315	9379.4961
22	70.1836	57.52088	61.98548	8367.7789
23	64.4806	44.44944	50	7568.5024
24	54.42	40	50	7250.6852
Total cost				192169.3625

**Table 20** Hourly outputs (kW) and hourly costs (\$/h) for CEED using CSA (without RES)

Hours	G <sub>1</sub>	G <sub>2</sub>	G <sub>3</sub>	Hourly costs
1	49.2238	40	50.7762	7175.4381
2	52.2611	46.0151	51.7238	7361.7887
3	60.0096	40.8314	54.159	7475.268
4	55.025	51.687	53.288	7594.3826
5	62.1435	48.9904	53.8661	7717.8614
6	67.7054	50.9927	51.3019	7845.2671
7	66.9946	52.9247	55.0807	7974.955
8	65.2163	52.6479	62.1357	8106.683
9	72.425	51.5306	86.0445	8939.8877
10	61.8617	102.975	65.1632	9536.1556
11	65.9105	78.9483	95.1412	9846.5282
12	82.8675	57.5189	109.614	10,165.064
13	72.1964	97.642	70.1617	9846.5295
14	74.4256	73.8016	71.7728	9233.9433
15	58.2191	86.4539	55.327	8653.9938
16	54.2504	73.9653	51.7843	8106.683
17	54.7886	58.0668	57.1446	7845.2673
18	67.7765	66.5262	50.6973	8240.451
19	52.4165	83.6626	63.9208	8653.9941
20	76.0781	66.8355	97.0864	9846.5285
21	82.9845	62.6923	79.3232	9384.0293
22	59.8675	57.1514	72.9811	8376.2583
23	64.7903	45.1992	50.0105	7594.3725
24	53.8174	40.4927	50.6898	7261.4235
Total cost				202,782.7539



**Fig. 20** Cost comparative analysis of microgrid test system 6 for various scenarios

hourly support provided by them to share the loads with the conventional generators. Incorporation of RES in micro-grid systems does not only reduce the emission of harmful pollutants released in atmosphere by the fossil-fueled generators but also provides less stress on the generators by reducing their load, thereafter increasing their durability and longevity. Classical optimization techniques like sequential quadratic programming, state-of-the-art evolutionary algorithms like GA, DE, PSO and many recently developed metaheuristic soft computing algorithms were involved in this study. The proposed CSA outperformed all the soft computing techniques in providing a least generation cost for 18 different scenarios of all the six test systems which included both smooth and non-smooth and non-convex cost functions. Statistical parameters such as standard deviation and Wilcoxon signed-rank test prove the superiority of the proposed CSA over the others in handling complex-constrained smooth and non-smooth fuel cost functions.

**Table 21** Wilcoxon signed-rank test for various results obtained using CSA

Cases studied	Best value	Worst value	Mean	Number of hits to the best value	Standard deviation	p value
CEED without RES	137,062.8987	137,062.0184	137,062.8546	19	0.1968	1.1933e−5
CEED with RES	120,219.0719	120,218.5814	120,218.9983	17	0.1796	2.2956e−5
VPE without RES	41,650.8604	41,650.0074	41,650.7751	18	0.2625	1.7074e−5
VPE with RES	37,704.0429	37,703.7521	37,704.0138	18	0.0895	1.7074e−5
Normal	225.7871	225.4843	225.7582	19	0.0910	1.0212e−5
VPE with wind	979,585.5032	979,584.8917	979,585.4388	17	0.1928	2.8557e−5

## Compliance with ethical standards

**Conflict of interest** The authors declare that they have no conflicts of interest.

**Human and animal rights** This article does not contain any studies with human participants or animals performed by any of the authors.

**Informed consent** Informed consent was obtained from all individual participants included in the study.

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