

MGWOSCACSA: A Novel Hybrid Algorithm for Energy Management of Microgrid Systems



Bishwajit Dey, Sourav Basak, and Biplab Bhattacharyya

Abstract Optimal scheduling of distributed energy resources (DER) in a microgrid system is a crucial step to accord an economic check in the planning and operation of the system. Among the many DERs, involvement of renewable energy sources (RES) also plays an important role in diminishing the release of harmful pollutants to the atmosphere from fossil-fuelled generators. This paper involves a novel hybrid method of recently developed three strong optimization methods viz. grey wolf optimizer (GWO), sine cosine algorithm (SCA) and crow search algorithm (CSA) to minimize the overall cost of a grid-connected microgrid system. The results were then compared to that of GWO, MGWO and those mentioned in literature. Numerical and pictorial results assert that proposed MGWOSCACSA outperformed all the optimization techniques in yielding consistent and superior quality results.

Keywords Microgrid · Energy management · Grey wolf optimizer · Sine cosine algorithm · Crow search algorithm

1 Introduction

At a power generating station, the load demand is not sufficed by a single generating entity. Rather a conglomerate of such entities fulfil 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 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 [1]. The total generation of power has to comply with the total current demand. To

B. Dey (✉) · S. Basak · B. Bhattacharyya
Indian Institute of Technology (Indian School of Mines), Dhanbad, India

B. Bhattacharyya
e-mail: bhattacharyya.b.ee@ismdhanbad.ac.in

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 [2, 3]. In opposition to this, a dynamic economic load dispatch (DELD) efficiently handles the practical constraint [4]. In DELD, we forecast the demand for the upcoming hours and accordingly distribute the load among different generations 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 (DERs) and loads within a confined geographical area. DERs include fossil-fuelled generators, various renewable energy sources (RES) depending upon the availability of the microgrid location, micro-turbines, fuel cells, energy storage systems (ESS) such as battery and flywheel, etc. [5] It is because of the individual modelling 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 [6]. 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 system.

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 [7, 8] to minimize the generation cost of a grid-connected microgrid, wherein various cases were studied to analyse the capability of algorithms in handling tight operating ranges of DERs, variable loads and fluctuating electricity price. Cuckoo search algorithm (CuSA) yielded better results than PSO and DE when both SELD and DELD were performed by author in [9]. An islanded microgrid system was considered for DELD which consisted of two wind turbines (WT) to be separately modelled based on wind speed. Authors performed pareto-optimal front-based economic-emission dispatch on a utility-connected microgrid system using adaptive modified PSO (AMPSO) in [10] and GAMS in [11].

2 Objective Function Formulation

The objective function consists of generation cost function and emission cost function for a microgrid mathematically stated as follows [12]:

$$\text{Min} F(P_i^t) = \sum_{i=1}^{ng} F_g(P_i^t) + \sum_{g=1}^n F_e(P_i^t) \quad (1)$$

where $F(P_i)$ is operating cost of microgrid with ng number of DG units. Generation cost is $F_g(P_i)$, and $F_e(P_i)$ is emission cost of the DGs, respectively. P_i is the output power from the i^{th} DG. t is the hour which varies from 1 to 24.

Again generation cost is summation of fuel costs, operation and maintenance cost and depreciation cost [12], i.e.

$$F(P_i^t) = F_{f_{c,i}}(P_i^t) + F_{o\&m,i}(P_i^t) + F_{d_{c,i}}(P_i^t) + c_{GRID}^t * P_{GRID}^t \tag{2}$$

where fuel cost is $F_{f_{c,i}}(P_i^t)$, operation and maintenance cost is $F_{o\&m,i}(P_i^t)$, and $F_{d_{c,i}}(P_i^t)$ is the depreciation cost of i th DG source represented as a function of their respective power outputs P_i . c_{GRID}^t is market price of electricity bought/sold by the grid at t^{th} hour.

The objective function mentioned in (1) are bound to some constraints such as:

$$\sum_{i=1}^n P_i^t + P_{GRID}^t = P_{load}^t \tag{3}$$

$$P_{i,min}^t \leq P_i^t \leq P_{i,max}^t \tag{4}$$

$$-P_{i,GRID,min}^t \leq P_{GRID}^t \leq P_{i,GRID,max}^t \tag{5}$$

3 Hybrid Grey Wolf Optimizers

This paper implements GWO and hybrid MGWO-SCA-CSA for performing EMS on microgrid systems. The mathematical modelling of these algorithms is detailed below.

3.1 Grey Wolf Optimizer (GWO)

GWO [13] mimics the hunting behaviour of the wolves while devouring its prey. A pack of 10–12 wolves maintains a hierarchy among themselves. The leader wolf is said to be alpha (α). It guides the pack but might not be the strongest in the pack. Next in rank is beta (β) whose prime duty is maintaining discipline in the pack and assisting alpha to reach the prey. Delta (δ) comes third in rank and may be considered as a scapegoat. Rest all the wolves fall in the omega (Ω) category and comes last in the pack. In the GWO algorithm, the best three solutions are α , β and δ . Rest of the solutions are Ω . The hunting procedure of the wolves can be mathematically represented as:

$$\left. \begin{aligned} \vec{D}_\alpha &= \left| \vec{C}_1 \cdot \vec{X}_\alpha - \vec{X} \right| \\ \vec{D}_\beta &= \left| \vec{C}_2 \cdot \vec{X}_\beta - \vec{X} \right| \\ \vec{D}_\delta &= \left| \vec{C}_3 \cdot \vec{X}_\delta - \vec{X} \right| \end{aligned} \right\} \tag{6}$$

And the position updating procedure of the wolves is given as:

$$\left. \begin{aligned} \vec{X}_1 &= \vec{X}_\alpha - \vec{A}_1 \cdot (\vec{D}_\alpha) \\ \vec{X}_2 &= \vec{X}_\beta - \vec{A}_2 \cdot (\vec{D}_\beta) \\ \vec{X}_3 &= \vec{X}_\delta - \vec{A}_3 \cdot (\vec{D}_\delta) \end{aligned} \right\} \tag{7}$$

$$\vec{X}_{(iter+1)} = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{8}$$

The value of vectors A and C can be calculated as:

$$\begin{aligned} \vec{A} &= 2 \cdot \vec{a} \cdot \vec{r}_1 - \vec{a} \\ \vec{C} &= 2 \cdot \vec{r}_2 \end{aligned} \tag{9}$$

Wolves move away from the current prey if absolute value of vector A is more than 1 and is forcefully pulled towards the prey when absolute value of vector A is more than 1. ‘ a ’ decreases linearly from 2 to 0 iteration-wise using the formula

$$a = 2 * \left(1 - \frac{\text{iter}}{\text{Max_iter}} \right) \tag{10}$$

3.2 Modified GWO

To eliminate the possibility of the solution getting trapped within the position of the Ω wolves, authors in [14] proposed that a few number of Ω wolves also take part in the hunting procedure along with the δ wolves. The hunting equation will therefore differ from earlier GWO algorithm by:

$$\left. \begin{aligned} \vec{D}_\alpha &= \left| \vec{C}_1 \cdot \vec{X}_\alpha - \vec{X} \right| \\ \vec{D}_\beta &= \left| \vec{C}_2 \cdot \vec{X}_\beta - \vec{X} \right| \\ \vec{D}_\delta &= \left| \vec{C}_3 \cdot \vec{X}_\delta - \vec{X} \right| \\ \vec{D}_\Omega &= \left| \vec{C}_4 \cdot \vec{X}_\Omega - \vec{X} \right| \end{aligned} \right\} \tag{11}$$

The position updating procedure will be performed including the δ in the family of wolves as:

$$\left. \begin{aligned} \vec{X}_1 &= \vec{X}_\alpha - \vec{A}_1 \cdot (\vec{D}_\alpha) \\ \vec{X}_2 &= \vec{X}_\beta - \vec{A}_2 \cdot (\vec{D}_\beta) \\ \vec{X}_3 &= \vec{X}_\delta - \vec{A}_3 \cdot (\vec{D}_\delta) \\ \vec{X}_4 &= \vec{X}_\Omega - \vec{A}_4 \cdot (\vec{D}_\Omega) \end{aligned} \right\} \tag{12}$$

$$\left. \begin{aligned} \vec{X}_3'' &= \frac{\vec{X}_3 + \vec{X}_4}{2} \\ \vec{X}_{(iter+1)} &= \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3''}{3} \end{aligned} \right\} \tag{13}$$

Hereafter, the hybridization will be done with GWO and not GWO as the results of MGWO were obviously found better and promising than GWO.

3.3 Modified GWO-SCA-CSA

Hybrid MGWO-SCA-CSA is the amalgamation of MGWO, SCA and CSA in which the mathematical implications of SCA [15] is done in the hunting method of grey wolves as follows:

$$\left. \begin{aligned} \vec{D}_\alpha &= rand * \sin(rand) * \left| \vec{C}_\alpha \cdot \vec{X}_\alpha - \vec{X} \right| \text{ if } rand > 0.5 \\ \vec{D}_\alpha &= rand * \cos(rand) * \left| \vec{C}_\alpha \cdot \vec{X}_\alpha - \vec{X} \right| \text{ otherwise} \end{aligned} \right\} \tag{14}$$

Similarly, we calculate the hunting vectors D_β , D_δ and D_Ω . Crow search algorithm (CSA) [16] 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. The flight length (fl) of the crow broadens or concise the search space, while the awareness probability (AP) helps in the transition from exploration to exploitation stage. The iteration updating step of MGWO, i.e. (13) is changed to:

$$\left. \begin{aligned} \vec{X}_{(iter+1)} &= \vec{X} + fl * rand * \left\{ (\vec{X}_1 - \vec{X}) + (\vec{X}_2 - \vec{X}) + (\vec{X}_3'' - \vec{X}) \right\} / 3 \text{ if } AP > rand \\ \vec{X}_{(iter+1)} &= \vec{X} + fl * rand * (\vec{X}_1 - \vec{X}) \text{ otherwise} \end{aligned} \right\} \tag{15}$$

AP decides whether to consider all the alpha, beta, delta and omega wolves for updation process or to rely on the alpha (leader) wolf only. To reduce the cumbersome task of tuning a parameter, AP which is a probabilistic value changes in every using the formula:

$$AP = 1 - \left(\frac{1.01 * \text{iter}^3}{\text{Max_iter}^3} \right) \quad (16)$$

The pseudo code of MGWOSCACSA is mentioned below:

<p>Hybrid MGWO-SCA-CSA</p> <p>Initialize the grey wolves population $X_i(i=1,2,3,\dots,N)$</p> <p>Initialize a, A and C</p> <p>Define Max_{iter} = maximum number of iterations</p> <p>Calculate hunting positions D_α, D_β, D_δ, D_Ω using Eq. (14)</p> <p>Evaluate objective function for each search agent</p> <p>X_α = best search agent</p> <p>X_β = second best search agent</p> <p>X_δ = third best search agent</p> <p>X_ω = remaining search agent</p> <p>while $t < Max_{iter}$ do</p> <p> for each search agent do</p> <p> Perform position updation of the existing search agent by Eq. (15)</p> <p> end for</p> <p> Update a, A and C</p> <p> Evaluate objective function for all search agents</p> <p> Update X_α, X_β, X_δ, and X_ω</p> <p> $t = t+1$</p> <p>end while</p> <p>return X_α</p>

4 Results and Analysis

System Description. GWO, MGWO and proposed MGWOSCACSA, coded in MATLAB2013a environment installed in a desktop with core i3 processor and 4 GB RAM, were used as optimization tools to minimize the overall generation cost of a grid-connected microgrid system. The system parameters and constants of the subject microgrid system, which consisted of three fossil-fuelled generators and one each of microturbine (MT), fuel cell (FC), photo voltaic system (PV) and wind turbine (WT), were gathered from [12]. The codes were executed with 50 population size and 1000 iterations to maintain an unbiased comparative analysis with the algorithms mentioned in literature.

Analysis of Results. Four cases were evaluated viz. grid-connected mode, without RES, islanded mode and fixed base load mode of microgrid operation, and the generation costs obtained are listed in Table 1. Among the four cases evaluated, it was obvious that the grid-connected mode (Case 1) which is the most efficient mode of microgrid operation, turned out to be the cheapest one with \$882.5. The second case did not consider the RES, and hence, the generation cost rose up to \$1701 due to the increase in contribution of emission cost of the fossil-fuelled DERs. The generation

Table 1 Comparative analysis (in \$)

Optimization tool	Grid connected	Without RES	Islanded	Fixed base load
	Case 1	Case 2	Case 3	Case 4
PSO [12]	889	1709	1158	978
DE [12]	886	1704	1113	964
DEGL [12]	883	1703	1112	963
GWO [S]	1086	1803	1217	1123
MGWO [S]	1049	1746.5	1167.6	1063.5
MGWOSCACSA [P]	882.5	1701.5	1111.34	962.28

S studied; *P* proposed

cost of the system in islanded mode of operation turned out to be \$1111 as yielded by the proposed MGWOSCACSA. Case 4 is fixed base load scenario where the most efficient and least pollutant emission DER (in this case FC) is fixed to generate the base load (25 kW), and the generation cost is evaluated. This turned out to be the second cheapest case with generation cost \$962. Figures 1 and 2 show the hourly load sharing of Case 1 and Case 2, respectively. The increase in the participation of grid and the fossil-fuelled generators in Case 2 increased the emission cost, and hence, the generation cost of the system is maximum in Case 2.

Comparative analysis of Optimization tools. All of GWO, MGWO and MGWOSCACSA were executed for 30 individual trials, and their best results are reported in Table 1. Figures 3 and 4 depict the cost convergence curve of all the three optimization techniques used to minimize the generation cost of the microgrid

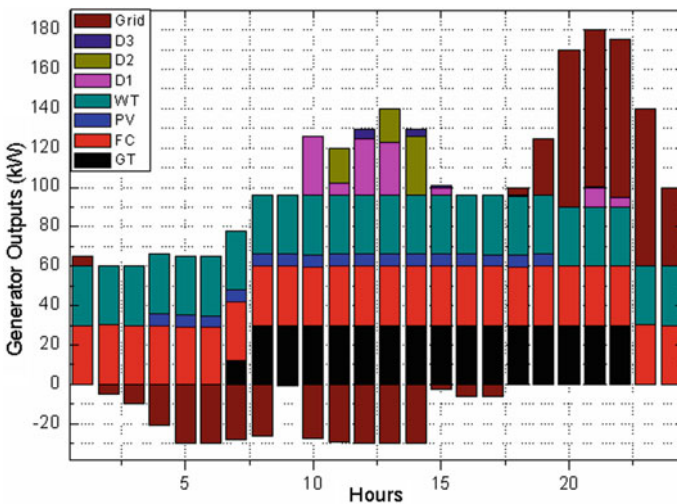


Fig. 1 Hourly output of DERs for Case 1 using MGWOSCACSA

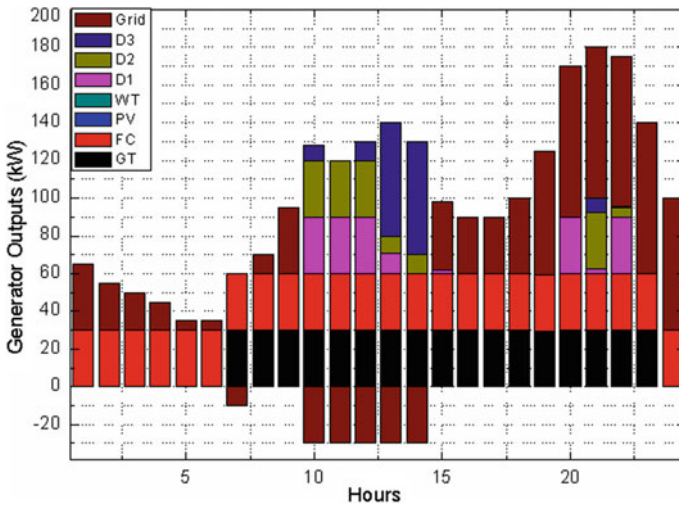


Fig. 2 Hourly output of DERs for Case 2 using MGWOSCACSA

Fig. 3 Cost convergence graph of case 1

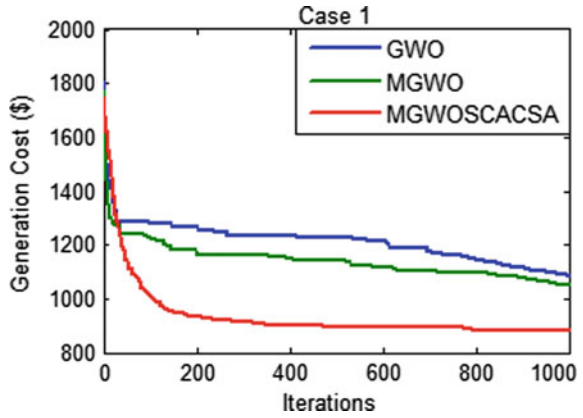


Fig. 4 Cost convergence graph of case 2

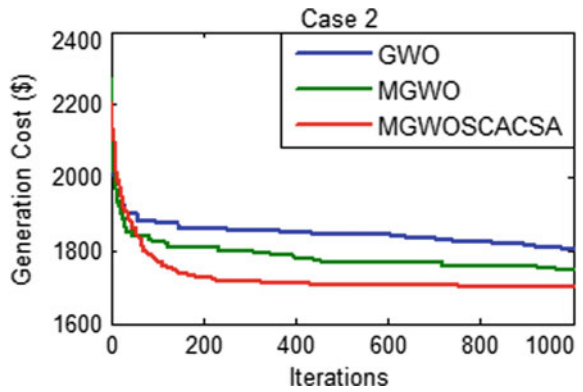


Table 2 Statistical analysis of MGWOSCACSA

Cases	Min. cost (\$)	Max. cost (\$)	Avg. cost (\$)	Hits	STD	p-value (e-07)
1	882.5	884	882.60	28	0.38	1.01
2	1701.5	1709	1701.75	29	1.37	0.68
3	1111.34	1112	1111.36	29	0.12	0.68
4	962.28	964	962.39	28	0.44	1.01

system for Cases 1 and 2, respectively. It can be seen from Figs. 3 and 4 that for all the scenarios proposed MGWOSCACSA yielded the minimum cost among all the optimization tools reported in literature and studied. The maximum time taken by MGWOSCASCA taken to attain the minimum generation cost was 48 s which is much less than the results reported in [12]. It can be seen that MGWOSCACSA converged pretty early yielding best solution for both the cases. Statistical analysis viz. Wilcoxon’s signed rank test was also performed for the proposed algorithm. Let H_0 be the hypothesis that there is no significance difference between the methods used to evaluate the generation cost, and all the results discussed so far are obtained using one technique. And let H_1 be the reverse hypothesis that contradicts H_0 . As per Wilcoxon’s signed rank test if p-value of the superior algorithm is less than 0.05, the hypothesis H_0 stands obsolete. It can be seen from Table 2 that the p-value for all the cases and scenarios studied is much less than 0.05. This means that there are at least two methods involved to minimize the generation costs out of which proposed MGWOSCACSA is the superior one. Minimum value of standard deviation and maximum hits (93–96%) to the best solution also claim the consistency and robustness of the proposed approach.

5 Conclusion

Four different modes of operation were evaluated to minimize the overall generation cost of a grid-connected microgrid system. It was seen that grid-connected mode was the cheapest and also can be considered to be the most reliable mode of operation, whereas excluding RES increases both the generation cost and pollutants emission in atmosphere. Proposed MGWOSCACSA proved to be the superior algorithm in terms of efficiency, consistency, robustness and less computational time when compared to the algorithms reported in the literature as wells as GWO and MGWO. Owing to these capabilities, MGWOSCACSA may be implemented to solve much complex constrained engineering problems.

References

1. Sihna N, Some studies on application of intelligent techniques to economic operation of power systems. Jadavpur University, Calcutta
2. Yalcinoz T, Short MJ (1997) Neural networks approach for solving economic dispatch problem with transmission capacity constraints. *IEEE Power Eng Rev* 17(10):40
3. Dhillon JS, Parti SC, Kothari DP (1993) Stochastic economic emission load dispatch. *Electr Power Syst Res* 26(3):179–186
4. Wang C, Shahidehpour SM (1994) Ramp-rate limits in unit commitment and economic dispatch incorporating rotor fatigue effect. *IEEE Trans Power Syst* 9(3):1539–1545
5. Hatziargyriou N (2013) Microgrids: architectures and control
6. NA Luu (2014) Control and management strategies for a microgrid acknowledgments
7. Chen C, Duan S, Cai T, Liu B, Hu G (2011) Smart energy management system for optimal microgrid economic operation. *IET Renew Power Gener* 5(3):258
8. Kasaei MJ (2018) Energy and operational management of virtual power plant using imperialist competitive algorithm. *Int Trans Electr Energy Syst* 28(11):1–13
9. Basu M, Chowdhury A (2013) Cuckoo search algorithm for economic dispatch. *Energy* 60:99–108
10. Moghaddam AA, Seifi A, Niknam T, Alizadeh Pahlavani MR (2011) Multi-objective operation management of a renewable MG (micro-grid) with back-up micro-turbine/fuel cell/battery hybrid power source. *Energy* 36(11):6490–6507
11. Fan QY, Cheng H (2018) Multi-objective stochastic optimal operation of a grid-connected microgrid considering an energy storage system. *Appl Sci* 8(12)
12. Dey B, Bhattacharyya B (2019) Dynamic cost analysis of a grid connected microgrid using neighborhood based differential evolution technique. *Int Trans Electr Energy Syst* 29(1):1–14
13. Mirjalili S, Mirjalili SM, Lewis A (2014) Grey wolf optimizer. *Adv Eng Softw* 69:46–61
14. Khandelwal A, Bhargava A, Sharma A, Sharma H (2018) Modified grey wolf optimization algorithm for transmission network expansion planning problem. *Arab J Sci Eng* 43(6):2899–2908
15. Mirjalili S (2016) SCA: a sine cosine algorithm for solving optimization problems. *Knowl-Based Syst* 96:120–133
16. Askarzadeh A (2016) A novel metaheuristic method for solving constrained engineering optimization problems: crow search algorithm. *Comput Struct* 169:1–12