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Generation Scheduling with Large-Scale Wind Farms using Grey Wolf Optimization

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Abstract – Integration of wind generators with the conventional power plants will raise operational challenges to the electric power utilities due to the uncertainty of wind availability. Thus, the Generation Scheduling (GS) among the online generating units has become crucial. This process can be formulated mathematically as an optimization problem. The GS problem of wind integrated power system is inherently complex because the formulation involves non-linear operational characteristics of generating units, system and operational constraints. As the robust tool is viable to address the chosen problem, the modern bio-inspired algorithm namely, Grey Wolf Optimization (GWO) algorithm is chosen as the main optimization tool. The intended algorithm is implemented on the standard test systems and the attained numerical results are compared with the earlier reports. The comparison clearly indicates the intended tool is robust and a promising alternative for solving GS problems.

Keywords: Grey wolf optimization, Generation scheduling, Wind power

1. Introduction

In power system operation and control, Generation Scheduling (GS) is an imperative task that comprises of two main sub problems: Unit Commitment (UC) and Economic Dispatch (ED). UC may be defined as the determination of the units which needs to be committed in order to satisfy the load demand. ED is performed to determine the load sharing among the online generating units. As the load demands are time-varying, the GS problem involves the determination of the optimal operation strategy over the scheduling horizon subject to a variety of constraints.

Nowadays, integration of Renewable Energy Sources (RES) with the existing power system has become essential in order to meet the ever increasing load demand. Due to stringent environmental concerns and shortage of fossil fuels, RES has become the positive alternative from the last decades. Among RES, wind energy conversion system is expected to produce 10% of global electricity by the year 2020.

1.1 Wind integrated power system

Wind energy conversion system can potentially affect the power system negatively due to the fluctuation in wind power. It exhibits variability in its output power because of the stochastic nature of wind resources as a result of incessant changes in weather conditions. This intermittent and diffuse nature of the wind power introduces a new factor of uncertainty on the power system operation and control.

Wind power generation is often faced with difficulties with regards to reliability in terms of the generation, planning and scheduling of electrical power. There is always a lack of confidence by the utility operators in the system's capability to meet peak demands. The electric power is produced when wind speeds exceed a certain minimum and the wind generator output depends on these wind speeds. Wind speeds cannot be predicted with high accuracy over daily periods, and the wind often fluctuates from minute to minute and hour to hour. Consequently, electric utility system planners and operators are concerned that variations in the output of wind generators may increase the operating costs of the system. This concern arises because the system must maintain a balance between the aggregate demand for electric power and the total power generated by all power plants feeding the system.

1.2 Solution methods

The GS problem is a non-linear, large-scale, mixed integer combinatorial optimization problem. The exact solution of GS can be obtained by complete enumeration of all feasible combinations of generating units [1]. Since large economic benefits could be achieved from appropriate unit scheduling, a considerable attention has been taken to development of related solution methods. The solution approaches are categorized into analytical, meta-heuristic and hybrid methods. The solution methods include dynamic programming [2], neural networks [3], simulated annealing

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[4-6], evolutionary programming [7-9], constraint logic programming [10], genetic algorithm [11-12], Lagrangian relaxation [13-15], branch and bound [16], tabu search [17-18], particle swarm optimization [22-23], heuristics and Meta-heuristics [28-29] and have been reported to solve the GS problem.

The analytical approaches suffer from the drawback of trapping in local solutions and their applications are limited to small-scale GS problems. Withal, the meta-heuristic methods also have few drawbacks like algorithmic parameter settings, premature phenomena and trapping into infeasible solution. Hence, it is of great significance to improve the existing optimization techniques or exploring new optimization techniques to solve GS problem.

1.3 Research gap and highlights

The GS problem is complex in nature and it requires complete enumeration to determine the feasible solution. Inclusion of wind generation increases further the complexity in solution space and identifying the best feasible schedules has become tricky. This requires an efficient optimization tool to address the wind integrated GS problem.

Recently, inspiring the hunting mechanism of ant lions in nature, the so called Grey Wolf Optimization (GWO) algorithm, has been proposed [27, 31]. This algorithm has few parameters and easy to implement, which makes it superior than earlier ones. Moreover, the GWO has superior characteristics than other heuristic techniques in terms of improved exploration, local optima avoidance, better exploitation and superior convergence characteristics.

The highlights of this article are as follows:

i. Wind power generation has been integrated with the GS problem.
ii. Various operational issues including reserve requirement are considered.
iii. GWO algorithm has been applied for the first time to solve wind integrated GS problem.

1.4 Paper organization

The mathematical formulation of wind integrated GS problem has been detailed in section 2. The implementation of GWO for solving the chosen problem is presented in Section 3. The simulation studies and attained results are discussed in Section 4. Finally, the conclusion is presented in Section 5.

2. Mathematical Model

The main objective of the GS problem is the minimization of the total operating cost of the generating units subject to prevailing system and operational constraints over the scheduling horizon. The time horizon adopted this paper is one year with the monthly intervals.

2.1 Wind generator model

The power output from the wind plant is set by the power curve. The curve is usually plotted between output power and wind speed. The wind unit is designed to start generating once the speed reaches the cut-in speed (V_{ci}) and to shut down for safety reasons at the cut- out speed (V_{co}). The region between the rated speed and also the cut out speed is wherever the unit generates the constant rated power. The non-linear relationship between the power output and the wind speed when the wind speed lies within the cut-in speed and the rated speed.

The power generation (P_i) of the wind unit for various wind speeds (SW_i) is often expressed as follows:

$$P_i = \begin{cases} 0 & 0 < SW_i < V_{ci} \\ P_r \times (A + B \times SW_i + C \times SW_i^2) & V_{ci} \le SW_i < V_r \\ P_r & V_r \le SW_i < V_{co} \\ 0 & SW_i > V_{co} \end{cases} \quad (1)$$

where, A, B and C are the constants and are defined as follows [22]:

$$\text{A}= \frac{1}{(Vci - Vr)^2}\left\{V_{ci}\left(V_{ci}+V_r\right) - 4V_{ci}V_r\left[\frac{V_{ci}+V_r}{2V_r}\right]^3\right\}$$

$$\text{B}=[\frac{1}{(Vci - Vr)^2}\left\{4\left(V_{ci}+V_r\right)\left[\frac{V_{ci}+V_r}{2V_r}\right]^3 - 4\left(V_{ci}+V_r\right)\right\}$$

$$\text{C}= \frac{1}{(Vci - Vr)^2}\left\{2 - 4\left[\frac{V_{ci}+V_r}{2V_r}\right]^3\right\} \quad (2)$$

2.2 Operating cost model

The operating cost comprises of total generation cost, including fuel cost, the operation and maintenance costs. This can be mathematically expressed as:

$$\begin{aligned} \min J = &\sum_{t=1}^{T}\sum_{g=1}^{N_G}\{F(P_{GD}(g,t)).n(t))\}.U(g,t)\}+ \\ &\sum_{t=1}^{T}\sum_{g=1}^{N_G}\{(P_{GD}(g,t)+P_{GR}(g,t)).OMVCT(g).n(t)\}.U(g,t)+ \\ &\sum_{t=1}^{T}\sum_{g=1}^{N_G}\left\{\frac{P_{Gg,\max}(g).OMFCT(g).n(t)}{8760}\right\}+ \\ &\sum_{t=1}^{T}\sum_{w=1}^{N_W}\{(P_W(w,t)).OMVCW(w).n(t)\}.V(w,t)\}+ \\ &\sum_{t=1}^{T}\sum_{w=1}^{N_W}\left\{\frac{P_{W,\max}(w).OMFCW(w).n(t)}{8760}\right\} \end{aligned} \quad (3)$$

where,

$$F\left(P_{GD}(g,t)\right)=a_g+b_g.P_{GD}(g,t)+C_g.P_{GD}(g,t)^2 \quad (4)$$

2.3 System and operational constraints

i) Power balance constraint

$$\sum_{g=1}^{N_G} P_{GD}(g,t).U(g,t)+\sum_{w=1}^{N_W} P_W(w,t).V(w,t)=P_d(t) \quad (5)$$

ii) Reserve requirement

$$\sum_{g=1}^{N_G} P_{GR}(g,t).U(g,t)\geq P_R(t)+RESW\times\sum_{w=1}^{N_W} P_W(w,t).V(w,t) \quad (6)$$

iii) Wind power availability

The generating unit constraints should be satisfied so that the wind power availability can be described as shown below:

$$P_w(w,t)\leq W_{av}(w,t) \quad (7)$$

iv) Generation limits

$$\mathrm{P}_{\mathrm{Gg,min}}\leq P_{GD}(g,t)+P_{GR}(g,t)\leq \mathrm{P}_{\mathrm{Gg,max}} \quad (8)$$

3. Grey Wolf Optimization to RES Coordinated Power System

3.1 GWO in brief

The GWO algorithm resembles the leadership hierarchy and searching mechanism of grey wolves [27, 31]. In the societal hierarchy, grey wolves are categorized as alpha (α), beta (β), delta (δ) and omega (ω). The alphas are the dominant because the group follows his/her instructions and the betas; the secondary wolves assist the alphas in making decisions. Omega is the lowest ranking grey wolves. If a wolf is neither an alpha nor a beta, or an omega, he/she is called delta (sub-ordinate). Delta wolves come in the hierarchy next to the alphas and betas, but they lead the omega. In addition to the social hierarchy of wolves, group hunting is another appealing societal action of grey wolves.

The primary segments of GWO are encircling, hunting and attacking the prey. These steps are formulated mathematically to determine the best feasible solution for any optimization problem.

The mathematical modeling of encircling behavior is defined as,

$$\vec{D}=\left|\vec{C}.\vec{X}_p(t)-\vec{X}(t)\right| \quad (9)$$

$$\vec{X}(t+1)=\vec{X}_p(t)-\vec{A}.\vec{D} \quad (10)$$

where, t indicates the current iteration, $\vec{A}$ and $\vec{C}$ are coefficient vectors, X_p is the position vector of the preyand $\vec{X}$ indicates the position vector of a grey wolf.

The vectors $\vec{A}$ and $\vec{C}$ are calculated as follows:

$$\vec{A}=2\vec{a}.\vec{r_1}-\vec{a} \quad (11)$$

$$\vec{C}=2.\vec{r_2} \quad (12)$$

where components of $\vec{a}$ are linearly decreased from 2 to 0 over the course of iterations and r_1, r_2 are random vectors in [0, 1].

The first three best solutions obtained are saved and the other search agents (including the omegas) update their positions according to the position of the best search agent. The following formulas are proposed in this regard.

$$\overrightarrow{D_\alpha}=\left|\overrightarrow{C_1}.\overrightarrow{X_\alpha}-\vec{X}\right| \quad (13)$$

$$\overrightarrow{D_\beta}=\left|\overrightarrow{C_2}.\overrightarrow{X_\beta}-\vec{X}\right| \quad (14)$$

$$\overrightarrow{D_\delta}=\left|\overrightarrow{C_3}.\overrightarrow{X_\delta}-\vec{X}\right| \quad (15)$$

$$\overrightarrow{X_1}=\overrightarrow{X_\alpha}-\overrightarrow{A_1}.\left(\overrightarrow{D_\alpha}\right) \quad (16)$$

$$\overrightarrow{X_2}=\overrightarrow{X_\beta}-\overrightarrow{A_2}.\left(\overrightarrow{D_\beta}\right) \quad (17)$$

$$\overrightarrow{X_3}=\overrightarrow{X_\delta}-\overrightarrow{A_3}.\left(\overrightarrow{D_\delta}\right) \quad (18)$$

$$\vec{X}(t+1)=\frac{\overrightarrow{X_1}+\overrightarrow{X_2}+\overrightarrow{X_3}}{3} \quad (19)$$

The 'A' is an arbitrary value in the gap [-2a, 2a]. When $|A|<1$, the wolves are forced to attack the prey. Attacking the prey is the exploitation ability and searching for prey is the exploration ability. The random values of 'A' are utilized to force the search agent to move away from the prey. When $|A|>1$, the grey wolves are enforced to diverge from the prey. The computational flow of GWO for solving optimization problem is detailed in Fig. 1.

3.2 GWO implementation to GS problem

The algorithmic steps of GWO for solving GS problem are detailed below.

Step 1: Read the system data.

Step 2: Initialize the value of parameter such as population size (*pop*) maximum number of iteration (*iter_max*) and the vector variables (*a, A* and *C*).

Step 3: Initialization: In this process, a set of individual solutions is created in a random order. The positions of individual i in period t can be represented by a vector as,

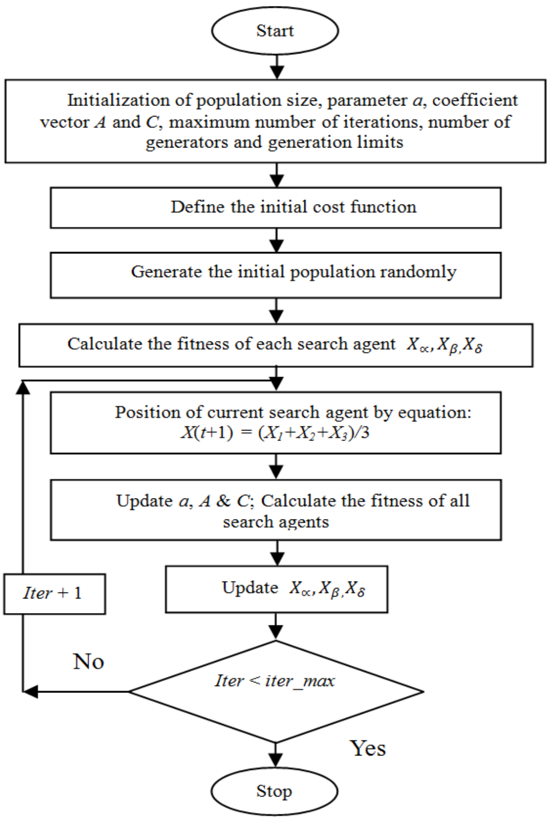


Fig. 1. Computational flow of GWO

$$X_i = (P_{GDi1,t}, P_{GDi2,t}, \ldots, P_{GDiG,t}, P_{GRi1,t}, P_{GRi2,t}, \ldots, P_{GRiG,t}, P_{Wi1,t}, P_{Wi2,t}, \ldots, P_{WiW,t}),$$

The initialization procedure is as follows:

3(a): The load contribution of thermal unit is obtained by,

$$P_{GDig,t} = [P_{Gg,\max} - P_{Gg,\min}] + P_{Gg,\min} \tag{20}$$

The load contribution of wind unit w,

$$P_{WiW,t} = W_{av}(w,t) \tag{21}$$

3(b): The value of the each unit is determined from the net system demand.

$$\text{Pure load} = P_d(t) - \sum_{w=1}^{w} P_{Wiw,t} \tag{22}$$

$$(P_{GDig,t})_{new} = P_d(t) - \sum_{w=1}^{w} P_{Wiw,t} \cdot \frac{(P_{GDig,t})_{old}}{\sum_{\forall g \notin \{\Psi\}} (P_{GDig,t})_{old}} \tag{23}$$

3(c): If $(P_{GDig,t})_{new} < P_{Gg,min}$, then,

$$(P_{GDig,t})_{new} = P_{Gg,min}$$

Elseif $(P_{GDig,t})_{new} > P_{Gg,max}$, then,

$$(P_{GDig,t})_{new} = P_{Gg,max}$$

3(d): If $\sum_{g=1}^{G} (P_{Gdig,t})_{new} + \sum_{W=1}^{W} P_{Wiw,t} = P_d(t)$ then go to next step, otherwise go to step3a.

3(e): Set the reserve power of each unit ($P_{GRig,t}$)for each section of i,

$$(P_{GRig,t}) = rand.(P_{Gg,\max} - (P_{GDig,t})_{new});$$
$$if \left(P_{GDig,t}\right)_{new} \neq 0$$

Otherwise, it is zero.

3(f): If $\sum_{g=1}^{G} P_{GRig,t} \geq P_R(t) + RESW \times \sum_{W=1}^{W} P_{Wiw,t}$ then go to next step, otherwise go step 3e.

3(g): Stop the initialization process.

Step 4: Evaluate the objective function given and compute the fitness subject to variety of constraints. An individual having minimum fitness is mimicked as alpha (α), second minimum as beta (β) and third minimum as delta (δ).

Step 5: Update the position of the wolves using [27] considering constraints. The position updating process considering constraints is as follows:

5(a): $P_{GDig,t}$, $P_{GRig,t}$, $P_{Wiw,t}$ are calculated by the following equation.

$$X_{id}^{j+1} = X_{id}^{j} + v_{id}^{j+1} \tag{24}$$

5(b): If $P_{Wiw,t}^{j+1} < 0$ then $P_{Wiw,t}^{j+1} <= 0$

If $P_{Wiw,t}^{j+1} > W_{av}(w,t)$, then $P_{Wiw,t}^{j+1} = W_{av}(w,t)$

If $P_{Gdig,t}^{j+1} < P_{Gg\min}$, then $P_{Gdig,t}^{j+1} = P_{Gg\min}$

If $P_{Gdig,t}^{j+1} > P_{Gg\max}$, then $P_{Gdig,t}^{j+1} = P_{Gg\max}$ and $P_{GRig,t}^{j+1} = 0$

If $P_{GDig,t}^{j+1} = 0$ or $P_{GRig,t}^{j+1} \leq 0$ and set $P_{GRig,t}^{j+1} = 0$

If $P_{GRig,t}^{j+1} \geq P_{Gg,\max} - P_{GDig,t}^{j+1}$ then set $P_{GRig,t}^{j+1} = P_{Gg,\max} - P_{GDig,t}^{j+1}$

5(c): The value of the each unit is determined by the following equation.

$$(P_{GDig,t}^{j+1})_{new} = P_d(t) - \sum_{w=1}^{w} P_{Wiw,t} \cdot \frac{(P_{GDig,t}^{j+1})_{old}}{\sum_{\forall g \notin \{\Psi\}} (P_{GDig,t}^{j+1})_{old}} \quad \forall g \notin \{\Phi\} \tag{25}$$

5(d): If the $(P_{GDig,t}^{j+1})_{new}$ is in the range of its operating region of unit g then go to next step otherwise go step 5c.

5(e): If $\sum_{g=1}^{G}(P_{Gdig,t}^{j+1})_{new} + \sum_{W=1}^{W} P_{Wiw,t}^{j+1} = P_d(t)$ then go to next step otherwise go to step 5h.

5(f): The load contribution of thermal unit is obtained by the following equation

$$P_{GDig,t}^{j+1} = [P_{Gg,\max} - P_{GDig,t}^{j+1})_{new}] \;\; If\,(P_{GDig,t}^{j+1})_{new} \neq 0 \tag{26}$$

5(g): If $\sum_{g=1}^{G} P_{GRig,t}^{j+1} \geq P_R(t) + RESW \times \sum_{W=1}^{W} P_{Wiw,t}^{j+1}$ then go to step 5h, otherwise go step 5f.

5(h): Above procedure must be repeated for all time periods and then stop the updating process.

Step 6: Update the vector values (*a, A, C*).

Step 7: Compute the fitness subject to constraints and find the new values of alpha (α), beta (β) and delta (δ).

Step 8: Termination criterion: Repeat the procedure from (5) – (7) until *iter_max* is reached.

4. Case Studies and Discussions

The intended GWO algorithm is developed in Matlab platform and is executed on a personal computer with the hardware configurations of Intel i3 2.30 GHZ processor and 4GB RAM. The algorithm is implemented on the standard test systems. In all test cases, 2 wind farms are considered and each wind farm possesses 40 wind turbine units with 2 MW capacities [22]. In this work, the RESW is assumed to 10% of total wind power availability of each wind farm [22].

Parameter selection is the vital important for the implementation of GWO in the generation scheduling. Parameter sensitivity analysis is performed and based on the analysis the desirable parameters are identified as *pop* = 50 and *iter_max* =100.

4.1 Test cases

The test system 1 contains 12 generating units with 10 conventional units and 2 wind farms (units 11 and 12) (10C+ 2W). The input data, load percentage in each time interval, wind speed and wind power availability of the two wind farms for the test system 1 are obtained from [22].The annual peak load is specified as 1500 MW.

The simulation is conducted and the attained costs are detailed in Table 1. The reserve requirement of the third

Table 1. Fixed and variable costs for test system1

Month	1	2	3	4	5	6	7	8	9	10	11	12
P_d (MW)	1317	1320	1125	1255.5	1350	1344	1320	1200	1170	1321.5	1410	1500
% of Peak load	87.8	88	75	83.7	90	89.6	88	80	78	88.1	94	100
Fuel Cost*$10^8$$	2.47	2.48	2.37	2.45	2.50	2.48	2.47	2.43	2.42	2.47	2.50	2.61
Variable OMT *10^3 $	1.78	1.79	1.58	1.71	1.81	1.81	1.79	1.65	1.63	1.79	1.87	1.95
Fixed OMT($)	7.29E+03	7.32E+03	5.97E+03	10684	7.44E+03	10684	10684	10684	10684	10684	10684	10684
Variable OMW($)	24.16	65.84	5.66	24.16	94.92	24.16	24.16	5.66	5.66	24.16	39.04	24.16
Fixed OMW($)	0	0	0	0	0	0	0	0	0	0	0	0
Cost (M$)	247.14	247.29	240.52	245.06	247.76	247.85	247.29	242.91	241.87	247.24	249.54	260.95

Table 2. Feasible dispatches for test system 1

Month	1	2	3	4	5	6	7	8	9	10	11	12
P_d (MW)	1317	1320	1125	1255.5	1350	1344	1320	1200	1170	1321.5	1410	1500
% of Peak load	87.8	88	75	83.7	90	89.6	88	80	78	88.1	94	100
1	455	455	455	455	455	455	455	455	455	455	455	455
2	244.8	250.1446	259.953	170.644	266.809	270.297	250.144	150	150	248.439	330.3	390.844
3	20	20	20	20	20	20	20	22.7041	20	20	20	37.9888
4	130	130	130	130	130	130	130	130	130	130	130	130
5	162	162	25	162	162	162	162	162	162	162	162	162
6	80	80	20	80	80	80	80	44.0959	28.2528	80	80	80
7	85	85	78.0603	85	85	85	85	85	85	85	85	85
8	55	55	55	55	55	55	55	55	55	55	55	53.2577
9	10	10	10	10	10	10	10	10	10	10	10	10
10	55	55	43.0225	55	55	55	55	47.8896	47.0742	55	55	55
11	3.576	2.23	3.717	9.817	14.604	11.905	2.23	9.122	12.097	4.937	6.007	8.973
12	16.607	15.675	25.718	23.076	16.607	9.798	15.675	29.202	15.529	16.119	21.715	32.676
Total MW	1317	1320.04	1125	1255.53	1350.02	1344.00	1320.04	1200.0	1170	1321.5	1410	1500
Cost (M$)	247.14	247.29	240.52	245.06	247.76	247.85	247.29	242.91	241.87	247.24	249.54	260.95

period 59.1935 MW is the summation of the two parts; the first part is 56.25 MW (5% of the total load) and the (power availability). The cost split up for each interval is evaluated separately for both the conventional units and the wind units are evaluated and presented in Table 1. The cost split up consists of the fuel cost, fixed and variable costs for thermal and wind units. From Table 1, it is found that the wind units do not posses any fixed costs. The best feasible generation schedules and the associated costs attained using GWO are detailed in Table 2. The total operating costs attained by GWO is compared with earlier reports and the comparison is presented in Table 3. The comparison clearly indicates that the GWO settles with the least cost schedules.

Further, the GWO algorithm is implemented on the three different sizes of test systems. Test systems 2, 3 and 4 comprises of 15, 26 and 40 generating units respectively. The peak load demands are taken as 2630 MW, 2700 MW and 9500 MW for test systems 2, 3 and 4 respectively. The load demand for each interval is computed as detailed in test system 1.

4.2 Total operating costs comparison

The GWO algorithm is implemented on four different test systems and the attained total operating costs are compared with the earlier reports. The comparison is presented in Table 3. The minimum and average of generation costs attained by GWO is compared with Global variant based Passive Congregation PSO – Constriction Factor Approach (GPAC+CFA) [22] and PSO-Inertia Weights Approach (PSO+IWA) [22] methods.

For test system 1, the average cost of generation with GPAC+CFA and PSO+IWA are 256.6246M$ and 256.41 M$ respectively. The cost of generation attained by the GWO is to be 240.4485M$ which is cheaper than both methods. For test system 2 (15C+2W) has the cost of generation with GWO as 260.9033M$ which is lesser than the other methods of 263.2219 M$ and 264.2486 M$. The cost of generation achieved by the intended method for the test system 3 (26C+2W) is also comparatively cheaper than other methods. Similarly for the test system 4 (40C+2W)

Table 3. Comparison of total operating costs

Test Systems	Methods	Minimum (M$)	Average (M$)
Case1 (10C+2W)	GPAC+CFA[22]	251.3254	256.6246
	PSO+IWA[22]	252.4464	256.41
	GWO	**238.18**	**240.4485**
Case2 (15C+2W)	GPAC+CFA[22]	260.735	263.2219
	PSO+IWA[22]	260.712	264.2486
	GWO	**259.03**	**260.9033**
Case3 (26C+2W)	GPAC+CFA[22]	298.9714	304.8163
	PSO+IWA[22]	293.6009	297.9482
	GWO	**292.04**	**295.3116**
Case4(40C+2W)	GPAC+CFA[22]	898.3872	918.0216
	PSO+IWA[22]	883.8288	910.6416
	GWO	**881.204**	**886.327**

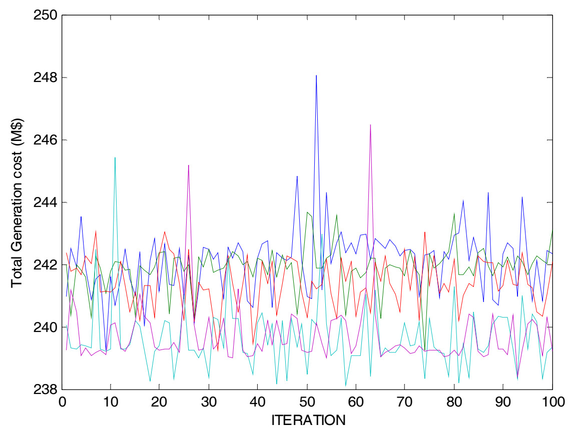
the cost of generation of proposed method 887.4475 M$ is found to be cheaper than the GPAC and PSO, the cost for which are 918.0216 and 910.6416 M$. From the Table 3, it is confirmed that the GWO provides the least cost schedules for all test systems. It also confirms that the intended tool works well even for large scale systems.

4.3 Convergence and robustness behaviors

In population based algorithms, the number of individuals in a population is an important parameter that decides the search capability of the algorithm in the solution space. As GWO is a population based swarm intelligence algorithm, change in population sizes affects its performance. The desirable population size is found to be related to the problem dimension and complexity. Moreover, when the number of population size increases, the execution time also increases. The selection for number of wolves to be produced in each generation is a compromise between a wider exploration of the search space and increased computational burden. Due to the stochastic nature of the GWO algorithm many trials are required to find out the optimum results.

First, the GWO algorithm is implemented on test system 1 for different population sizes such as 10, 20, 30, 40 and 50. The algorithm is executed for different trails and the attained robustness characteristics of the GWO algorithm are presented in Fig. 2. Further, the minimum and average values of the attained total operational costs are also presented in Table 4.

From Fig. 2 and Table 4, it is clear that the population size 50 is desirable parameter for the chosen GS problem as it resulted in achieving global solutions more consistently. Increasing the population sizes beyond this value did not produce any great significant improvement; rather, it increases the execution time. Hence, the population size of 50 is chosen to achieve the optimal results.

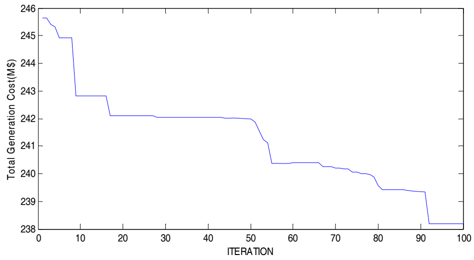


pop10 Red, pop20 Green, pop30 Purple, pop40 Mint, pop50 Blue

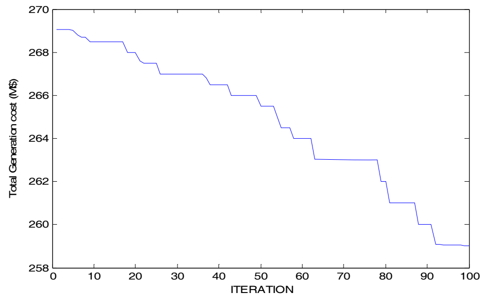
Fig. 2 Robustness characteristics for proposed GWO in test system 1

Table 4. Total operational costs attained by GWO for various population sizes (Test system 1)

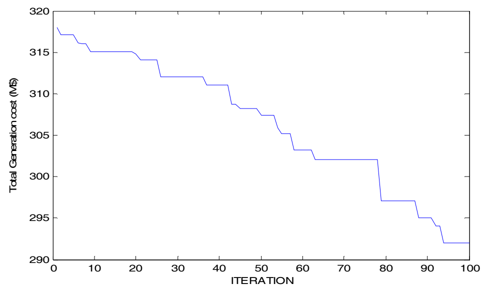
Population size	Minimum cost (M$)	Average cost (M$)
10	239.29	243.944
20	239.32	242.355
30	239.34	241.628
40	238.29	242.9689
50	238.18	240.4485



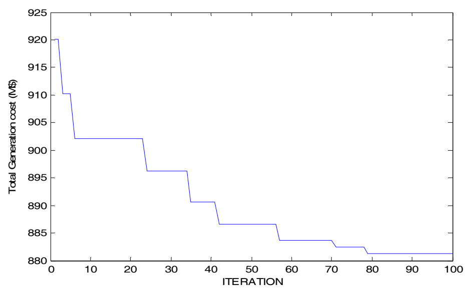
(a) Test System 1 (10C+2W)



(b) Test System 2 (15C+2W)



(c) Test System 3 (26C+2W)



(d) Test System 4 (40C+2W)

Fig. 3 Convergence characteristics with 100 iterations of GWO

5. Conclusion

This paper presents the application of modern bio-inspired algorithm GWO for solving the GS problem in power systems. The GS problem has been formulated for the wind integrated power system with the main objective of minimizing the total operational cost subject to variety of constraints. The GWO algorithm has been implemented on different scale of test systems. The system and operational constraints are handled effectively. The attained numerical results are compared with the recent reports in order to validate the solution quality. The concluding remarks of the article are:

- The GWO is applied for the first time to solve wind integrated GS problem.
- The least cost schedules are presented for four different test systems.
- As the intended tool provides the best feasible solution for 40C+2W test case, the algorithm is highly suitable for large scale systems.

The photovoltaic cells can be integrated with the existing GS problem in order to meet out the upcoming power demands.

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Nomenclature

a_g, b_g,c_g	coefficients of generating unit g
$n(t)$	number of hours in time t
N_G	number of thermal generators
N_W	number of wind units
$OMFCT(g)$	operation and maintenance fixed cost of thermal unit g

$OMFCW(w)$	operation and maintenance fixed cost of wind unit w
$OMVCT(g)$	operation and maintenance variable cost of thermal unit g
$OMVCW(w)$	operation and maintenance variable cost of wind unit w
$P_R(t)$	a fraction of total system load for system reserve
$P_W(w,t)$	generation of wind unit w at time t (MW)
$P_{W,max}$	maximum generation of wind unit w
$P_d(t)$	system demand at time t
$P_{GD}(g,t)$	load contribution of thermal unit g at time t (MW)
$P_{Gg,max}$	upper limit of thermal unit g
$P_{Gg,min}$	lower limit of thermal unit g
$P_{GR}(g,t)$	reserve contribution of thermal unit g at time t (MW)
$RESW$	a fraction of total wind power employed to compensate wind power prediction error
T	number of periods under study
$U(g,t)$	commitment state of thermal unit g at time t (on=1; off=0)
$V(w,t)$	commitment state of wind unit w at time t (on=1; off=0)
w	index for wind unit
$W_{av}(w,t)$	maximum available wind power of wind unit w at time t

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