Mitigating congestion by optimal rescheduling of generators applying hybrid PSO–GWO in deregulated environment

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Abstract

Deregulation in power system and increased power demand has introduced congestion in power system. With the depletion of fossil fuels, power sector has turned towards incorporation of the Renewable Energy Systems through private generators. This paper focuses on the non-cost-free method to mitigate congestion by rescheduling the generators for their active power output. The rescheduling is done in such a way that the cost of rescheduling is minimum. This paper presents a new method to merge two tested algorithms Particle Swarm Optimization (PSO) and Grey Wolf Optimization (GWO) to generate a new hybrid algorithm, HPSOGWO. The active power output is rescheduled to mitigate congestion with minimum cost of rescheduling. The priority of participating generators in rescheduling is set by generator sensitivity factor and its output is optimized by proposed HPSOGWO. The applied algorithm has reduced the rescheduled power to 16% less as done by GWO. HPSOGWO has moderated the congestion cost to 25% less as compared to GWO. The effectiveness of proposed HPSOGWO algorithm is validated on standard IEEE 30 bus system and results confirms the outperformance of proposed method over GWO and PSO in reducing congestion cost with reduction in power losses to mitigate congestion.

Keywords Deregulation · Congestion · HPSOGWO · Generator rescheduling · GSF · Power system

1 Introduction

With deregulation in power system and introduction of private energy players in power market, transmission lines are working under stressed conditions. With vertically integrated utilities in deregulation, the power system has changed from both generator and load end [1]. The deregulation has brought policies so that the private generators and distributors participating in the system may get attractive profits which in turn gives motivation for enhanced participation in power generation. These policies on one side has brought an uplift in generation but on the other hand has also created congestion in system. This congestion may be in the form of violation of voltage limits,

thermal limits and stability limits [2]. Congestion has to be mitigated for system stability and reliability. There are two methods for managing congestion cost free methods and non-cost-free methods. Cost free methods involves implementation of FACTS devices where the operational cost is considered to be constant. Non cost-free methods involve the operational costs in the form of generator operational costs [3].

A number of methods and algorithms has been proposed in literature which are more or less gives an efficient way to reduce congestion. But the main challenge lies with the cost of rescheduling of generator. When efficient rescheduling is done the cost increases and when cost is managed the problem of congestion is not solved

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efficiently. Taking care of both congestion mitigation and low congestion cost, this paper deals with the methodology to reschedule the generators in a congested system for re-dispatching active power so as to relieve the congested lines. Generator sensitivity factor (GSF) is implemented in paper for determining the generators which will participate in rescheduling process. After generators are selected, the power output for each generator is rescheduled with an objective of minimum congestion cost. A new methodology to merge PSO and GWO i.e., HPSOGWO is being applied here to optimally reschedule the selected generators. HPSOGWO has out-performed the parent methods i.e., GWO and PSO, which has been validated with the help of tables and figures.

This paper is arranged as: Sect. 2 presents the literature survey. The newly applied hybrid algorithm is presented in Sect. 3. The objective formulation is explained in Sect. 4. Section 5 discusses the results and the findings of the paper. Conclusion is outlined in Sect. 6.

2 Literature survey

Sensitivity based congestion management (CM) approach has been detailed where generator rescheduling and load shedding is based on the sensitivity index. The sensitivity index relates change in line current with respect to change in bus injections [4]. Congestion management has been a burning issue when system stability and electricity price control is concerned. Due to congestion in system there are power losses which ultimately results as burden on consumer's pocket. A number of methods has been explained and validated on different power systems [5]. The methods to mitigate transmission congestion due to insufficient infrastructure and high demand has been explained in detail [6]. Congestion management by applying particle swarm optimization with time-varying acceleration coefficients (PSO-TVAC) has been carried out to find out best generator to redispatch with minimal cost involved [7]. Different heuristics and metaheuristic methods like fuzzy evolutionary programming (FEP) and non-dominated sorting genetic algorithm has been suggested to manage congestion in system [8]. In order to assure availability of economic and reliable power to the consumers, adaptive bacterial foraging algorithm with Nelder–Mead (ABFNM) has been applied to optimize the generator output and minimizing the congestion cost [9]. Fuzzy adaptive bacterial foraging (FABF) based congestion management has been proposed for rescheduling generators. The generator selection is done on the basis of generator sensitivity to the congested line [10]. A real coded GA has been proposed to club transmission line losses with congestion cost index and congestion cost index with

DG installation cost. This helped the operator to select the solution depending on the severity of congestion and priority of the situation [11]. Multi-Objective Genetic Algorithm has been proposed to solve the Voltage Stability Constrained Optimal Power Flow (VSCOPF). SVC and TCSC are sized and optimally placed together with rescheduling of generators for voltage stability and reduced cost of FACTS devices [12]. In an event of congestion, the seller and buyers both try to level the supply and demand. In trying to maintain it the system security and reliability is adversely affected. To get rid of this security concern, generators are rescheduled with the help of Genetic Algorithm (GA) with a concern to minimize the cost of rescheduling [13]. Particle swarm optimization technique merged with improved time-varying acceleration coefficients (PSO-ITVAC) has been detailed for minimizing cost of rescheduling of active power output of the participating generator [14]. Firefly Algorithm has been proposed for reducing transmission line congestion in a pool-based market with voltage stability and line loading as constraint to obtain minimal cost generator active power rescheduling [15]. A fuzzy inference system (FIS)-based algorithm has been applied to indicate the overloaded transmission line. The overload factors and transmission congestion distribution factors (TCDF) are used here as input to get the congested line [16]. Ant Lion Optimization (ALO) algorithm-based congestion management technique has been proposed to reschedule the real power of participating generators selected on the basis of the sensitivity [17]. GA based rescheduling has been reported in [18] by using Locational Marginal Price (LMP) for transmission congestion alleviation. Strength Pareto Evolutionary Algorithm, implementing voltage-dependent load models for generator rescheduling and load shedding has been suggested [19]. A multi-objective function has been used to mitigate the congestion problem.

3 Hybrid PSO–GWO algorithm

3.1 Grey wolf optimizer

This algorithm is based on hunting behavior of a pack of Grey wolves. Hunting in Grey wolf is a very important aspect of social hierarchies of the pack. The strongest wolf which leads the pack for hunting a prey is alpha (α), the wolves supporting and assisting alpha wolf in hunting are beta (β) wolves. Gamma (γ) wolves are the next hierarchies of the pack also assisting the alpha and beta wolves in maintaining a discipline in pack. Remaining wolves are called delta (δ) wolves which generally follow other wolves and help in encircling the prey. This behavior of grey wolves can be represented mathematically as encircling, hunting

and attacking the prey [20]. The encircling of prey can be represented by Eq. (1):

$$\vec{D} = \left| C * \vec{X}_{-prey}(t) - \vec{X}_{GW}(t) \right| \quad (1)$$

$$\vec{X}_{GW}(t+1) = \vec{X}_{-prey}(t) - \vec{A} * \vec{D} \quad (2)$$

$$\left. \begin{aligned} \vec{A} &= 2\vec{a} * \vec{r}_1 - \vec{a} \\ \vec{C} &= 2 * \vec{r}_2 \\ \vec{a} &= 2 * iter_count * \left(\frac{2}{\max_iter} \right) \end{aligned} \right\} \quad (3)$$

where $\vec{D}$ final position of prey, t current position of grey wolf, $\vec{X}_{-prey}$ position vector of the prey, $\vec{X}_{GW}$ position vector of the grey wolf, $\vec{A}$ and $\vec{C}$ coefficient vectors, $\vec{a}$ error introduced to avoid premature convergence. a is reduced from 2 to 0 through the span of emphases and $\vec{r}_1, \vec{r}_2$ are random values between 0 and 1.

After initialization of wolf population, all wolves are randomly distributed in the search space by Eqs. (2) and (3), then sorted using Eq. (4) for getting three best positions. This can be mathematically represented as:

$$\left. \begin{aligned} \vec{X}_1 &= \vec{X}_{-a}(t) - \vec{A}_1 * \vec{D}_{-a} \\ \vec{X}_2 &= \vec{X}_{-b}(t) - \vec{A}_1 * \vec{D}_{-b} \\ \vec{X}_3 &= \vec{X}_{-g}(t) - \vec{A}_1 * \vec{D}_{-g} \end{aligned} \right\} \quad (4)$$

Also the values of $\vec{D}_{-a}, \vec{D}_{-b}$ and $\vec{D}_{-g}$ can be calculated as:

$$\left. \begin{aligned} \vec{D}_{-a} &= \left| C * \vec{X}_{-a}(t) - \vec{X}_{GW}(t) \right| \\ \vec{D}_{-b} &= \left| C * \vec{X}_{-b}(t) - \vec{X}_{GW}(t) \right| \\ \vec{D}_{-g} &= \left| C * \vec{X}_{-g}(t) - \vec{X}_{GW}(t) \right| \end{aligned} \right\} \quad (5)$$

Now best position of grey wolf is calculated by getting the updated position of omega wolves with respect to the previous position of alpha, beta and gamma wolves and can be represented as the average of the positions of these wolves.

$$\vec{X}_{GW}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (6)$$

Algorithm for GWO

Initialize population of grey wolf ($n=100$) && a, A and C

Set iteration counter, $t=0$

Evaluate fitness value of all wolves and sort for three best values

if $iter == itr(max)$

$\vec{X}_{GW}(t+1)$ is final solution

else decrease the value of 'a' to calculate new values of A and C by

$$a(iter) = 2 * iter_count \left(\frac{2}{\max_iter} \right)$$

Get updated values of D_a, D_b and D_g

Update position of each solution

if $\vec{X}_{GW}(t) == \vec{X}_{GW}(t+1)$

stop iteration

else increase iteration counter $t=t+1$

end

end

3.2 Particle swarm optimizer

The basic criteria to develop particle swarm optimization lies with the social behavior of fish schooling or bird flocking. This is a population based stochastic optimization technique [21]. This optimization technique mimics the food searching behavior of a flock of birds. For getting the food, bird with least distance from food (solution) is followed by all other birds. The 'birds' in PSO are actually the solutions of the problem in the search space. These 'solutions' here are called 'particles.' The fitness value of each particle is evaluated by a fitness function and the direction of flying is decided by their velocity. The particle nearest to the solution is optimal position and its velocity is considered as optimal velocity for all other particles.

Initialization in PSO is done by considering random number of particles and optimal position is calculated by updating of generations. With successive iterations each

particle is updated succeeding the two best positions. First best position is the current best position of the particle obtained after sorting and other best position in that obtained by other neighboring particles also called global best position (g_{best}). When a particle takes the topological position of its neighborhood particle it is called its local best position (l_{best}).

The updated particle velocity and its position is given by:

$$\left. \begin{aligned} v_t &= V_t + 2 * rnd * [p_b(t) - t] + 2 * rnd * [g_b(t) - t] \\ t &= t + V_t \end{aligned} \right\} \quad (7)$$

where v_t is the previous velocity, p_b is the best position particle have seen, g_b is the global best position particle has seen.

Algorithm for PSO

```

for each particle, initialize particle
  Initialize the population, n
for all particles
  Calculate  $f(p_b)$  and  $f(g_b)$ 
  Update the velocity,  $v_t$ 
  Update the position  $t-t+v_t$ 
Do apply the limits
  if  $v_t \geq v_{tmax}$ 
    put  $v_t = 0$ 
  if  $t \geq t_{max}$ 
    put  $t = t$ 
  else calculate  $f = fun(t)$ 
for  $f < func(p_b)$ 
  Set  $p_b = g_b$ 
end
end
```

3.3 Merged PSO-GWO

Pseudo code for Hybrid PSO-GWO

```

Create population randomly
Set a small probability rate : p
Fix maximum iterations and initiate iteration count itr=0
Run PSO for fitness evaluation of all particle
Sort and index fitness of each particle
if itr = itrmax
    stop
else update particle velocity and position
end if
for current particle
    if rand(0,1) < p , then set the values a, A & C (for avoiding local minima)
        else run PSO for fitness evaluation of all particle
    end if
    Evaluate the fitness of all wolves
    Update Xa, Xb and Xg
    if itr < itrmax
        Calculate X(t+1)
        Substitute this position to PSO particles
        Run PSO
        else update the position of wolf
    end if
end for

```

4 Problem formulation

The generators that have to participate in rescheduling are determined by Generator Sensitivity Factor (GSF) which represent the sensitivity of a particular generator for a congested line. GSF can be explained as the ratio of change in active power flow in a transmission line due to an incremental shift in real power output of the generator [22]. For getting an expression for GSF, AC load flow-based approach is used.

Consider a line m , between bus k and bus l . The active power transfer between the buses can be represented as:

$$P_{kl} = Y_{kl} [V_k V_l \cos(\theta_{kl} + \theta_k - \theta_l) - Y_{kl} \cos \theta_{kl}] \quad (8)$$

from Eq. (8) it can be seen that the active power flow between buses k and l is a function of magnitude of voltages at the buses i.e., V_k, V_l and their corresponding angles i.e., θ_k, θ_l . Thus, active power flow can be represented as:

$$P_{kl} = f(V_k, V_l, \theta_k, \theta_l) \quad (9)$$

Table 1 Equality and inequality constraints

S No	Constraints	Constraints equations
1	GSF	$\sum_{n=1}^N ((GSF_n) \times \Delta PG_n) + P_i^0 \leq P_i^{\max}$
2	Change in gen active power	$\Delta PG_n^{\min} \leq \Delta PG_n \leq \Delta PG_n^{\max}$
3	Active power	$P_{gn} - P_{dn} - P_n(V_n, \theta_n) = 0$
4	Generated active power	$P_{gn}^{\min} \leq P_{gn} \leq P_{gn}^{\max}$
5	Bus voltage	$V_{n\min} \leq V_n \leq V_{n\max}$

Fig. 1 IEEE 30 bus system [23]

Fig. 2 Congested lines with outage between bus 5–7

Table 2 The GSF values for generator number 2

Line number	Line flow base case (MW)	Line flow with outage (MW)	Line flow with change in gen o/p (MW)	GSF for generator
5	58.69	75.93	75.04	− 0.89
18	21.74	21.89	21.43	− 0.45
19	10.67	10.78	10.42	− 0.36
21	7.06	7.17	6.82	− 0.35
30	7.98	8.11	7.72	− 0.38
40	2.52	2.64	2.55	− 0.09

Table 3 The GSF values for generator number 5

Line number	Line flow base case (MW)	Line flow with outage (MW)	Line flow with change in gen o/p (MW)	GSF for generator
5	58.69	75.93	73.98	− 1.96
18	21.74	21.89	21.43	− 0.45
19	10.67	10.78	10.42	− 0.36
21	7.06	7.17	6.82	− 0.35
30	7.98	8.11	7.72	− 0.38
40	2.52	2.64	2.55	− 0.09

Table 4 The GSF values for generator number 8

Line number	Line flow base case (MW)	Line flow with outage (MW)	Line flow with change in gen o/p (MW)	GSF for generator
5	58.69	75.93	75.04	− 0.89
18	21.74	21.89	21.41	− 0.48
19	10.67	10.78	10.4	− 0.38
21	7.06	7.17	6.8	− 0.37
30	7.98	8.11	7.7	− 0.4
40	2.52	2.64	2.69	0.05

Table 5 The GSF values for generator number 11

Line number	Line flow base case (MW)	Line flow with outage (MW)	Line flow with change in gen o/p (MW)	GSF for generator
5	58.69	75.93	75.04	− 0.89
18	21.74	21.89	21.35	− 0.54
19	10.67	10.78	10.35	− 0.43
21	7.06	7.17	7.55	0.38
30	7.98	8.11	6.84	− 1.27
40	2.52	2.64	2.69	0.05

With an introduction of disturbance in power system, there will be a change in active power flow in line m , represented in Eq. (10):

$$\Delta P_{kl} = f\{(V_k^0 + \Delta V_k), (V_l^0 + \Delta V_l)(\theta_k^0 + \Delta \theta_k)(\theta_l^0 + \Delta \theta_l)\} - P_{kl}^0 \quad (10)$$

where P_{kl}^0 is the initial active power flow before the disturbance with corresponding voltage and angle as

V_k^0, V_l^0, θ_k^0 and θ_l^0 . Also, the new active power can be written as:

$$P_{kl} = P_{kl}^0 + \Delta P_{kl} \quad (11)$$

Equation (10) can be re-written as:

$$\Delta P_{kl} = p_{kl}\Delta \theta_k + q_{kl}\Delta \theta_l \quad (12)$$

Table 6 The GSF values for generator number 13

Line number	Line flow base case (MW)	Line flow with outage (MW)	Line flow with change in gen o/p (MW)	GSF for generator
1	79.83	80.28	83.05	2.77
5	58.69	75.93	75.04	− 0.89
18	21.74	21.89	21.62	− 0.27
19	10.67	10.78	10.57	− 0.21
21	7.06	7.17	6.97	− 0.2
30	7.98	8.11	7.88	− 0.23
40	2.52	2.64	2.54	− 0.1

Table 7 Selected GSF values of all generators by simulation

Generator	1	2	5	8	11	13
GSF	0	− 0.89	− 1.96	− 0.89	− 1.27	− 0.89

Table 8 Consolidate results for scheduled generations before and after CM

Generations	During congestion (MW)	After congestion being mitigated (MW)		
		PSO [24]	GWO	HPSOGWO
PG_2	62.96	68.3	49.74	47.59
PG_5	20.76	22.88	37.27	37.75
PG_8	27.80	34.42	23.76	25.91
PG_{11}	19.52	19.93	20.45	18.87
PG_{13}	39.7	22.05	39.51	35.53

Fig. 3 Convergence characteristics for GWO

where p_{kl} and q_{kl} are the coefficients that can be evaluated as partial derivative of Eq. (8) with respect to θ_k and θ_l respectively. The effect of change in voltages is neglected

Fig. 4 Convergence characteristics for PSO

as there is no significant effect of voltage change on active power flow in a line.

Now generator active power output is changed by ΔPG_n and same process is applied to again calculate the change in active power flow in line m .

Mathematically for incremental active power change, ΔPG_n , in n th generator and corresponding change in active power flow in line m between bus k and l , GSF can be given as:

$$GSF_n^m = \frac{\Delta P_{kl}}{\Delta PG_n} \quad (13)$$

Fig. 5 Convergence characteristics for HPSOGWO

Table 9 Results for cost, active power rescheduled and iteration count for IEEE 30 bus system

Outputs	PSO	GWO	HPSOGWO
Congestion cost (\$/MW-Day)	8664.3	10,774.33	8036.2
Active power rescheduled	32.92	38.7	32.3
Number of iterations	75	62	22

GSF_n^m represents the active power flow sensitivity of line m in between the bus k and bus l with respect to bus active power injection by generator n .

The GSF for each generator is calculated for all congested lines. The generators with highest and non-uniform values of GSF will be having greater impact on change in

active power flow through the congested line. This makes a base for the generators to participating in rescheduling process for congestion mitigation.

The change in magnitude of active power output of a generator participating in rescheduling process is governed by their respective bids and CM problem can be formulated as the cost incurred in the rescheduling. This is termed as congestion cost (CC). Thus, optimization problem can be formulated as objective function as below:

$$f(CC) = \text{minimize} \left(\sum_{n=1}^N C_{bn} (\Delta PG_n) \times \Delta PG_n \right) \quad (14)$$

In Eq. (14) ΔPG_n is the change in n th generator active power output when that generator offers a congestion costing bid (CCB) of C_{bn} . N represents number of generators participating in rescheduling. CCB can be explained as the maximum amount of power a generator can willingly increase and the price charging for it to mitigate congestion. The GWO, PSO and HPSOGWO optimization algorithms now optimize the congestion cost function in Eq. (14) by selecting best rescheduled value of the active power output of the generators as per the algorithm explained in Sect. 3 (A, B and C).

The optimization problem has to be solved applying constraints as shown in Table 1. Both equality and inequality constraints for line flows, voltage limits for buses, voltage limits for generators, generator active power limit and GSF limits are to be considered. The predefined limits are to be followed as if constraint moves out of limit the system may become unstable.

Fig. 6 Comparison of change in generation when PSO, GWO and HPSOGWO is applied

Table 10 Consolidated results for power flow in congested line before and after CM

Line no	<i>P</i> (normal) (MW)	<i>P</i> (5–7 line outage) (MW)	<i>P</i> (after CM)		
			GWO (MW)	PSO (MW)	HPSOGWO (MW)
1	79.83	80.28	78.9	80.03	78.77
5	58.69	75.93	58.4	59.06	58.79
18	21.74	21.89	21.7	21.63	21.66
19	10.67	10.78	10.6	10.56	10.6
21	7.06	7.17	7.07	6.93	7
30	7.98	8.11	7.99	7.9	7.91
40	2.52	2.64	2.51	2.47	2.52

5 Results and analysis

The proposed methodology is validated on IEEE 30 bus system [23] as shown in Fig. 1 using MATLAB 2016a. The simulation results are obtained for GWO, PSO and HPSOGWO and compared. The comparison shows the effectiveness of HPSOGWO over GWO and PSO. The system is studied for single line outage.

In this case there is a line outage between bus 5–7. Figure 2 shows the congested lines when compared to the base case.

From Fig. 2 we can see that line number 1, 5, 18, 19, 21, 30 and 40 are congested due to outage of line between bus 5 and 7. This congestion in the lines has to be mitigated by rescheduling of generators. The generators which will participate in rescheduling process are obtained by using GSF. For this, OPF with NR is carried out on congested system with output of one generator increased by 1 MW and all other generators are at their scheduled active power output. The GSF value for each generator is calculated by Eq. (8). Table 2, elaborate the GSF values obtained for generator 2. Further the same process is applied to generator number 5, 8, 11 and 13 to get the GSF values.

The generator with maximum negative value of GSF will be the most suitable generator to participate in the process of rescheduling as these generators have maximum effect on reducing the incremented power flow through the congested lines.

Tables 2, 3, 4, 5 and 6 shows the GSF values of generators number 2, 5, 8, 11 and 13 obtained after simulation. From these GSF values the most negative values are chosen. These values are tabulated in Table 7. The generator with large negative values of GSF shows that the active power flow through the congested line is being reduced by a significant value when there is a change in active power output of generator. Here all the generators have significantly large values of GSF, which indicate that all generators will participate in the rescheduling, in such a manner so that the congestion cost is minimized.

Table 8 shows the values of scheduled power generations before and after CM. The rescheduled active power of

generators is calculated and a comparison is made among PSO [24], GWO and HPSOGWO.

Figures 3, 4 and 5 indicate the convergence characteristics obtained for GWO, PSO and HPSOGWO respectively. These graphs show that the GWO require approximately 62 iteration to converge, PSO require 75 iteration and HPSOGWO require 22 iterations to converge.

The results obtained by simulating the test system and by applying PSO, GWO and HPSOGWO algorithms are elaborated in Table 9. It can be depicted that the congestion cost obtained with hybrid algorithm is 8036.2 \$/MW-Day which is significantly lower than GWO (10,744.33 \$/MW-Day) and that obtained by PSO (8664.3 \$/MW-Day). Also, the magnitude of active power rescheduled is lowest in case of HPSOGWO (32.3 MW), as compared to GWO (38.7 MW) and PSO (32.92 MW) which is one of the prime objectives of the work presented here. The method applied to merge the two algorithms is quite efficient as the number of iterations required to converge HPSOGWO is 22, that required for GWO is 62 and for PSO it is 75.

Figure 6 represents the change in generator output when rescheduled with PSO, GWO and HPSOGWO. Generator 2 changes the active power output by 13.2 MW with PSO, 18.47 MW with GWO and 13.36 MW with HPSOGWO. Similarly, generator 5 reschedule its power output by 16.15 MW, 15.9 MW and 16 MW when rescheduled by PSO, GWO and HPSOGWO respectively. 0.94 MW, 0.91 MW and 1 MW are the active power rescheduling for generator 8. Generator 11 shows a significant difference in change of active power output with three methods. The changes are 0.33 MW, 3.19 MW and 0.30 MW with PSO, GWO and HPSOGWO.

When generator 13 is rescheduled the change in output power obtained is 1.46 MW, 0.29 MW and 1.47 MW. The total change in active power when summed up is lowest in case of rescheduling done with HPSOGWO (32.3 MW) as given in Table 9.

Table 10 elaborates the effectiveness of HPSOGWO over traditional GWO and PSO. It can be seen that the active power flow through congested lines has been changed to relieve the congestion after the generation being

rescheduled with HPSOGWO, GWO and PSO. The active power flow with HPSOGWO rescheduling is much close to the active power flow during normal conditions, hence relieving congestion.

6 Conclusion

The proposed methodology to merge PSO and GWO is successfully validated on standard IEEE 30 bus system. This paper mitigates the CM problem with the optimal rescheduling of real power generation using PSO, GWO and Hybrid PSO–GWO algorithms. Here the generators are rescheduled in such a way to keep the congestion cost at its minimum value together with least rescheduled value of active power output of each generator. The rescheduling is successfully done with all the constraints satisfied. Suitable generators have been selected in accordance with their GSF values for congested lines. The simulation results validate that with the application of HPSOGWO, the congestion cost is reduced by approximately 25% less as obtained by GWO and 7.24% less as obtained from PSO. In the test system has been mitigated at minimum cost of rescheduling (CC) and in minimum number of iterations. The comparison of results obtained from three methods proves that HPSOGWO outperform PSO and GWO. PSO has a very efficient initialization while GWO is very efficient with convergence. Thus, here the hybrid algorithm initializes with PSO and converges with GWO. PSO has a shortcoming of premature convergence while GWO gets complicated with increased complexity of system. In future more complex systems with penetration of renewable energy generators including wind generators together with traditional generators can be rescheduled for active power output to mitigate congestion.

Compliance with ethical standards

Conflict of interest All the authors declare that we have no conflicts of interest to declare. All co-authors have seen and agree with the contents of the manuscript and there is no financial interest to report. We certify that the submission is original work and is not under review at any other publication.

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