AKADÉMIAI KIADÓ

Congestion management using grey wolf optimization in a deregulated power market

Madhu Mohan Gajjala* and Aijaz Ahmad

Department of Electrical Engineering, National Institute of Technology, Srinagar, 190006, India

Received: July 8, 2021 • Revised manuscript received: October 8, 2021 • Accepted: October 13, 2021
Published online: December 20, 2021

Pollack Periodica • An International Journal for Engineering and Information Sciences

17 (2022) 2, 14–19

DOI: 10.1556/606.2021.00472

ORIGINAL RESEARCH PAPER

ABSTRACT

Transmission congestion issues became more severe and difficult to control as the power sector became more deregulated. The grey wolf optimization algorithm is proposed to relieve congestion by rescheduling generation effectively, resulting in the least congestion cost. The selection of participating generators is based on sensitivity, and the proposed technique is used to determine the best-rescheduled output active power generation to minimize line overload. The IEEE-30 bus system is used to test the proposed optimization technique. It has been demonstrated that when compared to other algorithms like the real coded genetic algorithm, particle swarm optimization, and differential evolution algorithm, the proposed approach produces excellent results in terms of congestion cost.

KEYWORDS

deregulation, evolutionary algorithms, generator sensitivity factor, congestion

1. INTRODUCTION

1.1. General

Deregulation in the electrical sector has benefited from the popularity of deregulation in other industries, like airlines and telecommunications. Because of deregulation, the implementation of competition turns cost-based energy into a price-based market. Each independent generator can sell all of its generated power to consumers in a globally liberalized market due to competition. Consequently, they attempt to fit all of their generated power onto the transmission line, ignoring constraints like the voltage, thermal and stability limits, etc.

The transmission network is considered congested if it violates any of these constraints [1]. Since the power system would deviate from its ideal operation, congestion on the transmission line could cause overload lines, power system instability, and higher energy costs. As a result, transmission congestion must be reduced as soon as possible. The Independent System Operator (ISO) faces many challenges in the deregulated electricity sector, including determining the best auction approach to minimize market power and congestion while improving system stability and performance [2].

1.2. Literature review

A common Chaotic Map (CM) approach in Deregulated Power Market (DPM) is Generation Rescheduling (GR), one of the most frequently used CM approaches. As transmission grid bottlenecks arise, generated active power is rescheduled to alleviate the congestion. Using the multi-objective Particle Swarm Optimization (PSO) algorithm, part-optimal solutions were introduced by Hazara and Sinha [3] to minimize overloads and lower operating costs. Balaraman et al. [4] suggested using a Differential Evolution (DE) algorithm to manage congestion in a pooled electricity sector. The fuzzy adaptive bacterial foraging optimization algorithm for CM was demonstrated by Venkaiah et al. [5]. B. K. Panigrahi et al. [6] have proposed the Bacterial Foraging (BF) algorithm for CM. Batra and Ghosh [7] presented the

*Corresponding author.
E-mail: madhumohan@nitsri.net

AKJournals

new approach to congestion alleviation, an advanced Twin Extremity Chaotic Map adaptive Particle Swarm Optimization (TECM-PSO) algorithm for reducing the cost of rescheduling and power loss. Sarwar et al. [8] developed an efficient PSO optimizer to solve the nonlinear congestion cost problem. The Real Coded Genetic Algorithm (RCGA) has been used by Balaraman et al. [9] to find an efficient generation rescheduling strategy to minimize congestion. Boonyaritdachochai et al. [10] focused on an optimal CM method in a DPM by employing PSO with time-varying acceleration coefficients. Heuristic techniques, which are capable of dealing with complex, large-scale issues with a large number of factors, have been utilized to optimize the hydro-thermal coordination of hydroelectric and thermal power plants, among other applications. [11, 12].

2. PROBLEM FORMULATION

The following is an objective function for effective congestion management, emphasizing minimizing real power rescheduling costs:

$$\text{Minimize}\, F = \sum_{i=1}^{N_{pg}} \left(C_i^u.\Delta P_{gi}^u + C_i^d.\Delta P_{gi}^d \right) \frac{\$}{\text{hr}}, \tag{1}$$

where C_i^u and C_i^d are the generator's incremental and decremental bids, respectively. The active power adjustment of the generator is referred to as ΔP_{gi}. The number of participating generators is represented by N_{pg}.

2.1. Equality constraints

a) Power equilibrium constraint

$$\sum_{i=1}^{Npg} \left(P_{gi}^{resh} \right) + \sum_{k,k \neq i}^{Ng} P_{gk} = \sum_{m}^{Nd} \left(P_{Dm}^0 + P_L \right), \tag{2}$$

where $P_{gi}^{resh} = P_{gi}^0 + \Delta P_{gi}$.

Here P_{gi}^0 and P_{gk} represents active power generation of initial scheduled value and not participated generator output power respectively. Rescheduled generation of a specific generator is denoted by P_{gi}^{resh}.

b) Real and reactive power balance equations

$$P_i - V_i \sum_{j=1}^{NB} V_j \left(G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij} \right) = 0, \quad i = 1, 2, \ldots, N_{B-1}, \tag{3}$$

$$Q_i - V_i \sum_{j=1}^{NB} V_j \left(G_{ij} \sin\theta_{ij} - B_{ij} \cos\theta_{ij} \right) = 0, \quad i = 1, 2, \ldots, N_{PQ}, \tag{4}$$

where P_i and Q_i represent the active and reactive power of the i^{th} bus, respectively, while G_{ij} and B_{ij} represent the conductance and susceptibility of the line connecting the i^{th} and j^{th} buses, respectively. N_{B-1} represents total number of buses except slack bus and N_{PQ} represents total number of load buses.

2.2. Inequality constraints

Inequality constraints can be summarized as follows:

2.2.1. Inequality constraints on state variables

a) The transmission line's apparent power flow limits are as follows:

$$S_{Li} \leq S_{Li}^{\max}, \quad Li \in N_{PQ}. \tag{5}$$

The maximum apparent power loading limit of the line is represented by $S_{Li}^{\max}$ and the apparent power loading of the i^{th} line is represented by S_{Li}.

b) Load bus voltage limit constraints

$$V_{Li,\min} \leq V_{Li} \leq V_{Li,\max}, \quad Li \in N_{PQ}. \tag{6}$$

The variables $V_{Li,\min}$ and $V_{Li,\max}$ represent the voltage limits of the load bus.

2.3. Participating generators selection

Generator Sensitivity (GS) factors are considered for the selection of participating generators for rescheduling process. The GS factor represents the variation in active power flow of a particular congested line due to the produced active power variation in the i^{th} generator. The GS factors of the i^{th} generator is calculated using Eq. (7), and the change in the power flow in congested line l, which connects buses p and q, is denoted by ΔP_{pq} and, ΔP_{gi} is the change in i^{th} generator active power generation on the congested line-l [10],

$$GS_i^{pq} = \frac{\Delta P_{pq}}{\Delta P_{gi}}. \tag{7}$$

3. GWO

3.1. Inspiration

Mirjalili et al. [13] suggested Grey Wolf Optimization (GWO) technique in 2014; it is a modern population-based metaheuristic optimization. GWO examines a pack of grey wolves' behavior as they hunt prey in a multi-dimensional search space. It is interesting to see how wolves have a really strict social governing hierarchy, as it can be seen in Fig. 1.

The alpha is primarily in charge of making decisions about hunting, sleeping, and waking times, among other things. The various positions of grey wolves are taken into account by the different position variables in the GWO algorithm. The objective function's fitness cost is determined by the distances between the grey wolves and the prey. The GWO saves the best solutions that occur during the iteration process.

Beta wolves are subordinate wolves, which assist the alpha wolf in decision-making and other pack activities, like

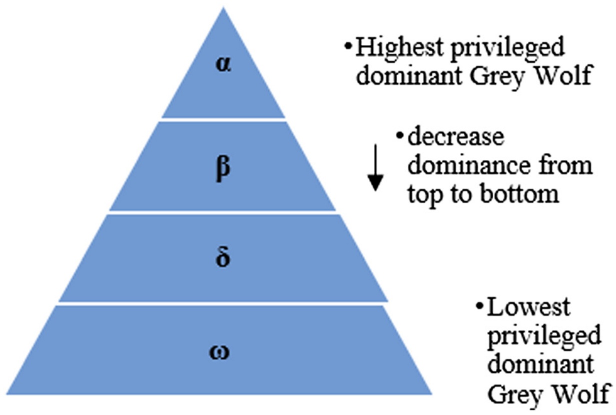

Fig. 1. Grey wolf social structure (dominance decreases from top-down)

hunting and trapping. The beta strengthens the alpha's commands and provides feedback to the leader in the pack. Omega is the grey wolf with the lowest rank. The omega serves as a scapegoat. They are the last wolves to have permission to feed. Delta wolves have many duties, including sentinels, scouts, elders, caretakers, and hunters.

3.2. Mathematical model of algorithm

Grey wolves were tracked, encircled, and attacked prey in GWO, created using a mathematical model of their hunting strategy and social hierarchy.

3.2.1. Social hierarchy. When it comes to model wolves' social hierarchy mathematically, authors believe the alpha solution is the best choice. So, the second and third-best solutions are known as beta and delta, respectively. Hunting is motivated by delta, beta, and alpha in the GWO optimization algorithm. Omega wolves are pursuing these three wolves.

3.2.2. Encircling prey. As previously stated, during the hunt, the grey wolves encircle the prey and kill it. The following equations have been proposed as a mathematical model for the behavior of encircling objects,

$$\mathbf{D} = \left|\mathbf{C}\cdot\mathbf{X}_p(t) - \mathbf{X}(t)\right|, \tag{8}$$

$$\mathbf{X}(t+1) = \mathbf{X}_p(t) - \mathbf{A}\cdot\mathbf{D}, \tag{9}$$

where t denotes the current iteration and $\mathbf{A}$ and $\mathbf{C}$ denote coefficient vectors, $\mathbf{X}_p(t)$ denotes the vector of the prey's location, and $\mathbf{X}(t)$ denotes the vector of the grey wolf's location.

The following is how the vectors $\mathbf{A}$ and $\mathbf{C}$ are determined:

$$\mathbf{A} = 2\mathbf{a}\cdot\mathbf{r}_1 - \mathbf{a}, \tag{10}$$

$$\mathbf{C} = 2\mathbf{r}_2, \tag{11}$$

where $\mathbf{r}_1$, $\mathbf{r}_2$ are the random vectors in the range [0,1] and components of vector $\mathbf{a}$ are linearly varies from 2 to 0 throughout iterations.

3.2.3. Hunting. To mathematically model grey wolves' hunting behavior, authors believe that the alpha, beta, and delta better understand the possible position of the prey. As a consequence, the first three best solutions discovered so far were saved. Following the location of the optimal search agent, the positions of all other search agents (including omegas) must be updated. The following formulas have been developed in this regard,

$$\mathbf{D}_\alpha = |\mathbf{C}_1\cdot\mathbf{X}_\alpha - \mathbf{X}|, \tag{12}$$

$$\mathbf{D}_\beta = \left|\mathbf{C}_1.\mathbf{X}_\beta - \mathbf{X}\right|, \tag{13}$$

$$\mathbf{D}_\delta = |\mathbf{C}_1\cdot\mathbf{X}_\delta - \mathbf{X}|. \tag{14}$$

Finally, the following changes are made to the positions of various wolf categories,

$$\mathbf{X}_1 = \mathbf{X}_\alpha - \mathbf{A}_1\cdot\mathbf{D}_\alpha, \tag{15}$$

$$\mathbf{X}_2 = \mathbf{X}_\beta - \mathbf{A}_2\cdot\mathbf{D}_\beta, \tag{16}$$

$$\mathbf{X}_2 = \mathbf{X}_\delta - \mathbf{A}_3\cdot\mathbf{D}_\delta, \tag{17}$$

$$\mathbf{X}(t+1) = \frac{\mathbf{X}_1 + \mathbf{X}_2 + \mathbf{X}_3}{3}. \tag{18}$$

3.2.4. Attacking prey (exploitation). When the prey ceases to move, the grey wolves abandon their search and attack it. This movement will depend on the value $\mathbf{a}$. $\mathbf{A}$ is a random vector with a range of $[-2\mathbf{a}, 2\mathbf{a}]$. The three wolves, delta, beta, and alpha wolves, listed in the hunting process and the prey attack cause search agents to change their positions in GWO.

3.2.5. Searching for prey (exploration). The grey wolves separate from one another in search of prey. Use $\mathbf{A}$ with random values to compel the search agent to distinguish itself from the goal. The $\mathbf{C}$ vector provides random weights to the search field, which is why $\mathbf{A}$ and $\mathbf{C}$ exploration allows this algorithm to search the entire region. The effect of obstacles posed by the prey is also included in the $\mathbf{C}$ vector.

4. CONGESTION MANAGEMENT USING GWO

Step1: For a congested line, determine the GS factors for selecting participating generators. The adjusted active power of those generators is taken GWO control variables (ΔP_{Gi}).
Step2: Set the GWO parameters ($\mathbf{a}$, $\mathbf{A}$, and $\mathbf{C}$) and the maximum number of iterations. As it is shown below Eq. (19), the position matrix is generated based on the initial search agents (control variables).
Step3: Evaluate the fitness of each existing population solution using constraint Eqs (2)–(6). Each fitness value reflects the individual wolf's distance from the prey,

$$\mathbf{P} = \begin{bmatrix} \Delta P_{g1}^{1}, & \Delta P_{g2}^{1}, \dots & \Delta P_{gn}^{1} \\ \Delta P_{g1}^{2} & \Delta P_{g2}^{2}, \dots & \Delta P_{gn}^{2} \\ \Delta P_{g1}^{np} & \Delta P_{g2}^{np}, \dots & \Delta P_{gn}^{np} \end{bmatrix}. \tag{19}$$

Step4: Sort the positions or population into groups, start with the best, and work your way down to the worst.
Step5: Using the concepts of encircling prey, looking for a target, hunting, and attacking the target, adjust the position of each search agent. Each search agent's function represents a potential solution to the CM problem of real power generation rescheduling in congested areas.
Step6: It is tested whether or not it meets any of the inequality constraints. Infeasible options are replaced with the best feasible alternatives.
Step7: Return to Step 2 before all of the termination conditions have been met. When the maximum number of iterations (generations) has been reached or no discernible change in the solution has been achieved, the GWO is terminated.

5. RESULTS AND DISCUSSION

The IEEE 30 bus system [14] is used in this paper to test it. First, an N-1 contingency study is conducted, and the results of this analysis report are used to categorize severe outages. The different contingency test cases are listed in Table 1. Table 2 shows the GENerator COmpanieS (GENCOS) price bids for CM in terms of dollars.

Newton-Raphson (N-R) power flow is performed in each case, and the overloaded lines are detected. For each test case, an overall number of power violations and the GS values are shown in Table 3.

The simulation was conducted out on a Windows 10 PC with 20 GB of RAM and Matlab 2016 installed software 58.06 MW power is overloaded on lines 2–6,4–6,5–7 and 6–7 in Case 1. This is due to the unavailability of line 2–5 and a 50% rise in the load on buses 2, 3, 4, and 5. As it is shown in Table 3, the value of generator sensitivities is calculated for the congested line 2–5 using Eq. (7) to identify the generators that genuinely contributed to CM. Because the GS values of generators G2 and G3 are higher, the adjustment in the generation of these two generators is considered a control variable (apart from the first generator) for rescheduling. Initial populations are produced at random within the bounds of the limit. They are expressed as $Ui = \{\Delta P_{iG2}, \Delta P_{iG3}, i = 1, 2, \ldots, 20\}$. With given parameters and a maximum of 300 iterations, the best solution was obtained with the following values: {+4.017, +32.5}. The solution suggests that the active power output of generators 2 and 3 has increased (except slack generator in bus 1). Finally, by executing the N-R power flow, it is possible to compute slack bus generation. In this case, it is determined that the slack generator should increase the generation by 14.559. The GWO approach yields the lowest possible congestion cost of 1769.6 $/MWhr, the lowest possible cost compared to the RCGA, PSO, and DE methods.

Adjustment of generator active power for all test cases using GWO for CM is shown in Table 4, which is intended to reduce overloads. 1-2 line has been overloaded in test case 2, causing a power violation of 25.66 MW, and generators G2 has been used as a control element for rescheduling. The GWO method was used to determine the lowest possible congestion cost of 663.89 $/MWhr. The minimal congestion cost calculated from the GWO approach is 1417.44 $/MWhr in test case 3, where one line has overloaded, and 70.241 MW power has been violated. In contrast, Table 5 illustrates the CM analysis for all test cases. Figure 2 depicts a comparison of adjustment active power and rescheduling cost for all remaining methods.

Table 1. Contingency test cases

Cases	Contingency
Case1	Disconnect line 2-5, and the load on buses 2, 3, 4, and 5 increased by 35%
Case2	The load on bus 19 increased by 130% when line 1-3 disconnected
Case3	Line 3-4 disconnected, and the load at bus 2 increased by 250%

Table 2. Generator price bids

Gen no	Gen Bus no	Generator Price Bids ($/MWhr)		P_g^{min} (MW)	P_g^{max} (MW)
		C_k^u	C_k^d		
1	1	22	18	0	360.2
2	2	21	19	20	140
3	5	42	38	15	100
4	8	43	37	10	100
5	11	43	35	10	100
6	13	41	39	12	100

Table 3. Line flow results and GS values of all test cases

Cases	Congested Lines	Line limit (MW)	Magnitude of power violation (MW)	GS Factors					
				G1	G2	G3	G4	G5	G6
1	2–6	65	16.27	0	−0.55	−0.53	−0.44	−0.43	−0.41
	4–6	90	2.76						
	5–7	70	32.61						
	6–7	130	6.39						
2	1–2	130	25.66	0	−0.66	−0.71	−0.68	−0.65	−0.55
3	1–2	130	66.32	0	−0.68	−0.72	−0.77	−0.65	−0.71

Table 4. Control variable setting for corrective actions

Test cases	Generator adjustment power for congestion management (MW)						Net Power adjustment
	ΔP_{G1}	ΔP_{G2}	ΔP_{G3}	ΔP_{G4}	ΔP_{G5}	ΔP_{G6}	
Case1	14.559	4.017	32.5	0	0	0	51.0768
Case2	−8.507	24.322	0	0	0	0	32.8294
Case3	−7.330	61.159	0	0.027	0	0	68.5161

Table 5. CM analysis

Case	Congested Lines	Before CM (MW)	Line Limit (MW)	power violation (MW)	After CM (MW)	Congestion Cost ($/MWhr)			
						RCGA	PSO	DE	GWO
1	2–6	81.27	65	16.27	64	1837.800	1914.50	1818.70	1769.60
	4–6	92.76	90	2.76	69				
	5–7	102.60	70	32.61	68				
	6–7	136.39	130	6.39	96				
2	1–2	155.66	130	25.66	129.95	671.614	773.73	668.41	663.89
3	1–2	196.32	130	66.32	128.59	1721.900	2150.50	1424.40	1417.44

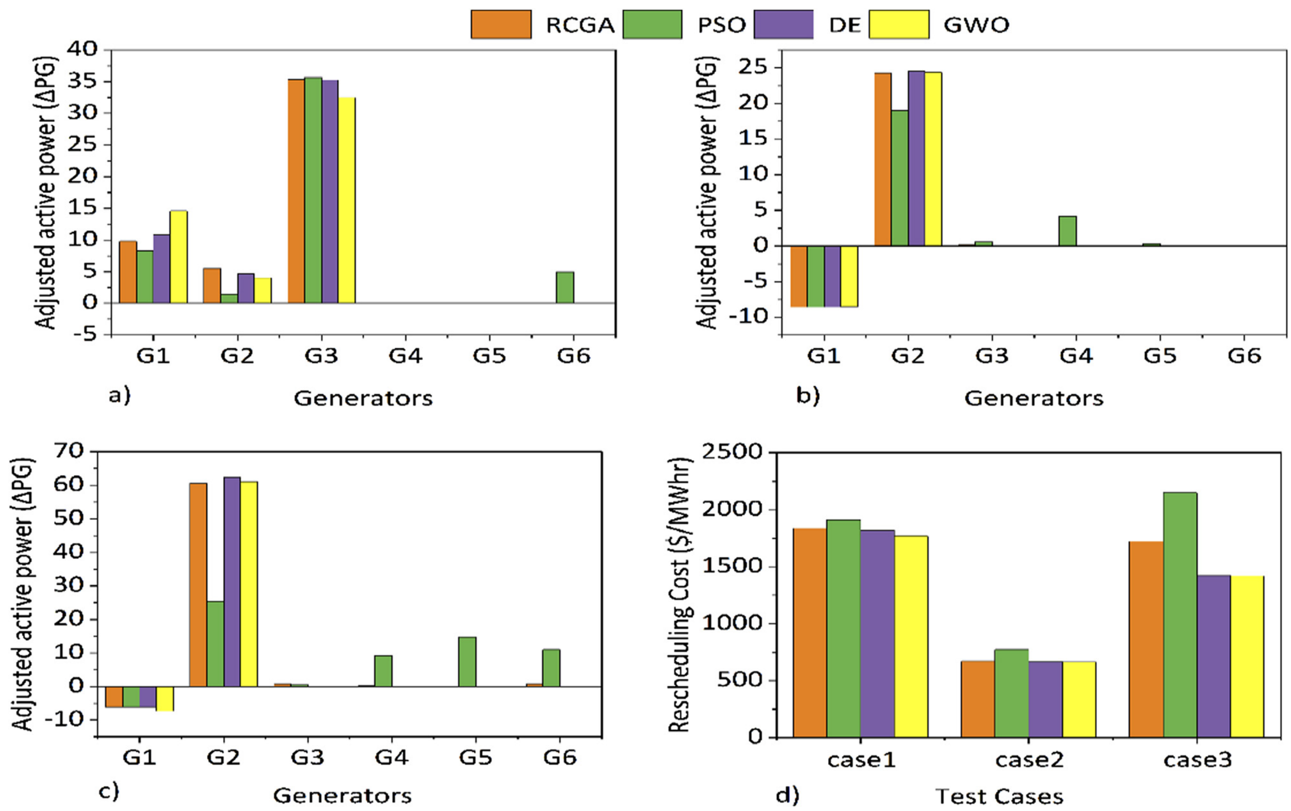

Fig. 2. a, b, c) Amount of active power generation adjustment, d) Rescheduling cost

Comparison of convergence characteristics for line outage case 1 using several different evolutionary algorithms is shown in Fig. 3. Figure 4 shows the power flow condition of congested lines in all cases before and after congestion.

The overall cost of CM is represented in Table 5. It is evident from this table that the GWO algorithm is efficient and provides cost-effective solutions as compared to the RCGA, PSO, and DE algorithms, as it has advantages in terms of accuracy and speed of convergence.

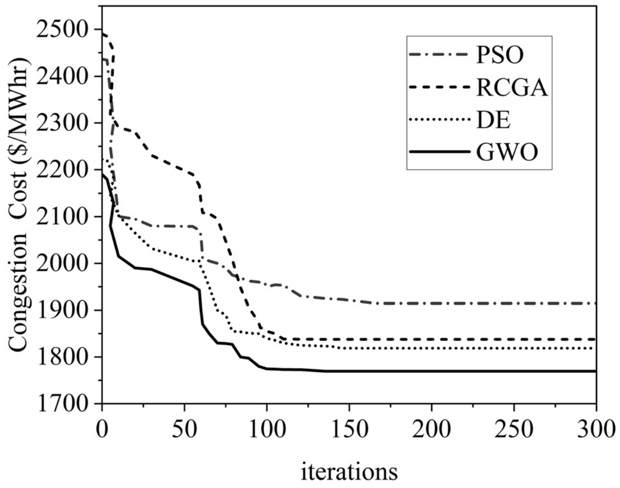

Fig. 3. Comparison of characteristics of different evolutionary algorithms

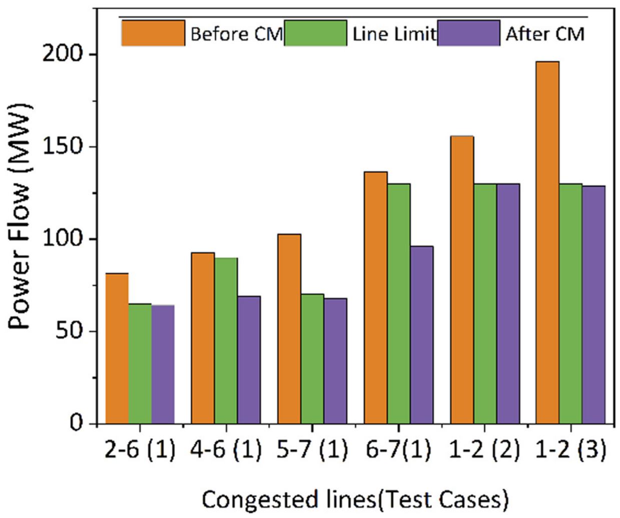

Fig. 4. Power flow condition of congested lines in all cases

6. CONCLUSION

This paper employed the GWO algorithm to demonstrate an efficient CM through generation rescheduling in case of power system restructuring, which was tested using an IEEE 30 bus test system. The GWO algorithm could help to reduce transmission line overloads in a deregulated power market. It effectively decreases congestion costs while keeping the system in a stable operating condition. The adaptive value of A is responsible for these enhanced capabilities. In GWO, half of the iterations are devoted to exploration ($|A|>1$) and the other half to exploitation ($|A|<1$). This method enables GWO to provide excellent exploration, local minima avoidance, and exploitation all at the same time. For the rescheduling operation, generators with the highest and most non-uniform flow of GS values are chosen. Furthermore, the GWO algorithm is used to determine generators' optimum adjustment active powers to reduce rescheduling costs. In comparison to the RCGA, PSO, and DE methods, the proposed method is more effective.

REFERENCES

[1] L. L. Lai, *Power System Restructuring and Deregulation Trading, Performance and Information Technology*. Wiley, 2001.

[2] A. Pillay, S. P. Karthikeyan, and D. P. Kothari, "Congestion management in power system: A review," *Int. J. Electr. Power Energy Syst.*, vol. 70, pp. 83–90, 2015.

[3] J. Hazra and A. K. Sinha, "Congestion management using multi-objective particle swarm optimization," *IEEE Trans. Power Syst.*, vol. 22, no. 4, pp. 1726–1734, 2007.

[4] S. Balaraman and N. Kamaraj, "Application of differential evolution for congestion management in power system," *Mod. Appl. Sci.*, vol. 4, no. 8, pp. 33–42, 2010.

[5] C. Venkaiah and D. M. V. Kumar, "Fuzzy adaptive bacterial foraging congestion management using sensitivity based optimal active power re-scheduling of generators," *Appl. Soft Comput. J.*, vol. 11, no. 8, pp. 4921–4930, 2011.

[6] B. K. Panigrahi and V. R. Pandi, "Congestion management using adaptive bacterial foraging algorithm," *Energy Covers. Manag.*, vol. 50, no. 5, pp. 1202–1209, 2009.

[7] I. Batra and S. Ghosh, "An improved tent map-adaptive chaotic particle swarm optimization (ITM-CPSO) - based novel approach toward security constraint optimal gongestion management," *Iran. J. Sci. Technol. Trans. Electr. Eng.*, vol. 42, pp. 261–289, 2018.

[8] M. Sarwar and A. S. Siddiqui, "An efficient particle swarm optimizer for congestion management in deregulated electricity market," *J. Electr. Syst. Inf. Technol.*, vol. 2, no. 3, pp. 269–282, 2015.

[9] J. R. Chintamand and M. Daniel, "Real-power rescheduling of generators for congestion management using a novel satin bowerbird optimization algorithm," *Energies*, vol. 11, no. 1, pp. 1–16. 2018.

[10] P. Boonyaritdachochai, C. Boonchuay, and W. Ongsakul, "Optimal congestion management in electricity market using particle swarm optimization with time varying acceleration coefficients," *Comput. Math. Appl.*, vol. 60, no. 4, pp. 1068–1077, 2010.

[11] P. Šulek and T. Kinczer, "Impact of differential evolution parameters on optimization of hydrothermal coordination," *Pollack Period.*, vol.14, no. 3, pp. 121–130, 2019.

[12] T. Kinczer and P. Šulek, "The impact of genetic algorithm parameters on the optimization of hydro-thermal coordination," *Pollack Period.*, vol. 11, no. 2, pp. 113–123, 2016.

[13] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey wolf optimizer," *Adv. Eng. Softw.*, vol. 69, pp. 46–61, 2014.

[14] M. Shahidehpour and Y. Wang, "Appendix C: IEEE30 Bus System Data," in *Communication and Control in Electric Power Systems.* John Wiley & Sons, Inc., 2003, pp. 493–495.