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Optimal rescheduling of real power to mitigate congestion using gravitational search algorithm

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Abstract: The initiative to manage congestion has gained interest in the current deregulated scenario. The principle commitment of the work in this article is to extend the gravitational search algorithm (GSA) as an efficient metaheuristic optimizing algorithm to diminish the rescheduling cost and efficiently attenuate the overloading of the line with the minimal deviation in the active power generation. The congestion management drive is accomplished by prioritizing the generators based on their sensitivity values. Thereafter, the GSA is introduced to optimally minimize the rescheduling cost along with the minimization of the total amount of active power output and system losses. The potency of the proposed method is tested on the 39-bus New England System and the IEEE 30-bus system and 118-bus system, and the outcomes achieved with the GSA outperform the results reported with other algorithms.

Key words: Congestion management, generator rescheduling, gravitational search algorithm, generator sensitivity, optimization techniques, power flow

1. Introduction

The advent of restructuring in the power system industries has led to the functioning of vertically integrated utilities as separate independent entities. The independent system operator (ISO) coordinates the functioning of the generation, transmission, and distribution companies efficiently under one umbrella [1]. The transactions of the electricity are carried out in such a manner that all players taking part in the activity try to boost their own profits, resulting in the operation of the transmission network beyond the operational limits. The congestion in the power network results when any one of the transfer limits, such as thermal limits, voltage limits, and stability limits, in a transmission network is violated [2]. A sudden increase in the load, the outage of the transmission lines, sudden tripping of the generators, and the failure of other equipment are considered as integral reasons for the occurrence of congestion. The congestion results in the instability of the power system network leading to market inefficiency and also resulting in the abrupt hike in electricity prices. The ISO takes the obligation to deal with the congestion in the transmission lines so as to ensure proper reliability and stability to the power system network [3]. The scope of congestion management (CM) encompasses a set of rules to monitor and control the generators and load in order to preserve the adequate level of security and reliability of the power system. These sets of rules should provide long-term as well as short-term market efficiency and should ensure that no market player is able to exploit the loopholes existing in the electricity

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market. Rescheduling the generators' active power delivery, providing reactive power supply, and shedding the load are some of the active initiatives performed by the ISO to address the congestion. In [4], Hooshmand et al. optimally located the thyristor-controlled series capacitor (TCSC) to manage congestion based on the penalty emission cost of the generators. In [5], the determination of locational marginal pricing (LMP) was done based on the pool and bilateral transactions to mitigate the congestion in transmission lines. In [6] multiobjective CM was proposed based on the optimal location of flexible alternating current transmission system (FACTS) devices to maintain the voltage levels within limits. Rajamanickam et al. implemented distribution generation to manage congestion by reducing the losses and enhancing the voltage levels [7]. Reddy [8] managed congestion by adopting load shedding in association with rescheduling of generators. Their work dealt with the minimization of load shedding cost and operation cost. The rescheduling of the generators is adopted as the primary option by the ISO to manage congestion.

The fundamental philosophy underlining the proposed methodology is to outline an approach to overcome the congestion issue. A large number of conventional optimization techniques fail to function flawlessly due to issues relating to the nonlinearity and multidimensionality of the problem. In order to handle such complications, the present interest is to implement nature-influenced metaheuristic algorithms. The integral motivation of the research work is to adopt the GSA as an optimization approach to enable ISOs to relieve congestion from the power system network with the minimization of congestion cost, real power rescheduling, and system losses.

2. Literature survey

In recent times, several CM procedures have been embraced by analysts to address the CM issue. A detailed discussion and survey of several CM techniques concerning transmission congestion can be found in [9,10]. Esfahani and Yousefi proposed an algorithm to minimize the congestion clearing time for CM [11]. Hojjat et al. in 2016 considered power system uncertainties and proposed a chance-constrained programming method for CM [12]. In another study, Sarwar and Siddiqui mitigated congestion taking into account the locational marginal pricing differences for the placement of distributed generations (DGs) in the most congested zones [13]. Nesamalar et al. in 2016 proposed a cost-efficient model for the CM comprising renewable energy sources [14].

Prior to this, Yesuratnam and Thukaram proposed a CM technique involving generator rescheduling based on the relative electrical distance (RED) concept. The concept of RED is implemented to sort out the generator participating in the CM problem [15]. Dutta and Singh, in 2008, also selected the participating generators based on the generator sensitivity factor (GSF) for CM. The optimal real power output contributed by the generators is achieved with particle swarm optimization (PSO) [16]. In [17] Deb and Goswami mollified the congestion by adjusting the shift in the power delivered by the generators with the artificial bee colony (ABC) algorithm. In [18] Verma and Mukherjee introduced the firefly algorithm (FFA) to optimally carry out the real power adjustment for the generators engaged in the CM process. Talukder et al. performed CM considering the technique of generator rescheduling and load shedding. The selections of the generators were done based on the MF (design variables) values decided by the system operator [19].

Rashedi et al. [20] came forward with a metaheuristic algorithm in 2009 called the gravitational search algorithm, based on the law of gravitational forces stated by Newton. The implementation of this optimization algorithm has been popularly adopted in all sectors of research. Following this, Chen et al. concentrated their research by proposing an improved GSA technique for optimal reactive power problems [21]. In [22] Duman et al. achieved excellent values of control variables using the GSA for optimal power flow (OPF) problems. The fuel cost obtained with the GSA was optimally minimum when compared with biogeography-based optimization (BBO), differential evolution (DE), PSO, and an improved genetic algorithm (IGA). In another study, Chen et al. used the GSA to optimally reduce the active power losses and the results achieved with the GSA were superior to the outcomes obtained with DE, the self-adaptive real coded genetic algorithm (SARGA), and seeker optimization (SO) [23]. Bhattacharaya and Kumar in 2016 used the GSA to analyze the optimal operation of FACTS devices in combination with reactive power sources. The results achieved with the GSA seemed to be much more enhanced as compared to the GA and PSO [24]. Kumar et al. in their research found the performance of the GSA to be better than the ABC algorithm when the GSA was implemented to achieve the optimal location of a unified power flow controller (UPFC) taking into account the improvement in stability limits [25]. In [26] the GSA performed better than PSO and GA for the optimal strategic bidding method adopted by generating companies. A review on the application of the GSA in various fields of science and engineering can be found in [27]. Based on the previous work, the GSA bears the advantage of easy implementation, fast convergence, and low computational cost and has been used for optimization of parameters, cost, voltage control, and power dispatch. In view of the above discussion, it can be expected that the GSA will also yield better outcomes for the proposed CM problem in this paper. A comparison between the GSA and other heuristics algorithms is presented in the appendix.

3. Gravitational search algorithm

Inspired by the concept of the law governing planetary motions, Rashedi et al. formulated the GSA [20]. The execution of the algorithm deals with the mass and movement of the agents. The agents in this algorithm are treated as objects and a force of attraction is generated between each object. The overall attraction between the objects leads to the global drifting of all the objects towards the direction of the object with heavier mass. The objects with heavier masses are treated as better optimal solutions for the problem than the objects with lighter masses. Each of the objects bears four characteristics, i.e. the object has its position, active gravitational mass (M_{ai}), passive gravitational mass (M_{pi}), and inertial mass (M_{ii}). It can be interpreted that the position of each mass represents a solution and the exploration of the algorithm is done suitably by adapting the gravitational and inertial masses. From a group of N agents considered in the algorithm, the ith agent's position is given by:

$$X_i = (x_i^1, ..., x_i^d, ..., x_i^N) \qquad i = 1,\ 2,\ 3, ..., N \tag{1}$$

Here, the dimension for the problem is designated as d and x_i^d represents the ith agent's position in dimension d.

In the initial stage of the algorithm, the agents of the solution are defined in a random manner. A force of attraction, F_i^d(k), is exerted on mass j from mass i at the kth iteration, denoted as:

$$F_i^d(k) = G(k)\frac{M_i(k)M_j(k)}{R_{ij}(k)+\varepsilon}(x_j^d(k) - x_i^d(k)) \tag{2}$$

Here, G(k), ε, and R_{ij}(k) are the gravitational constant, constant with minimal value keeping the denominator from approaching zero, and Euclidian distance for the kth iteration, respectively. The Euclidian distance between the ith and jth agents is given by:

$$R_{ij}(k) = \left\| x_i^d(k), x_j^d(k) \right\|_2 \tag{3}$$

The aggregate amount of force exerted by other agents on agent i is represented as:

$$F_i^d(k) = \sum_{j \in k_{best}, j \neq i}^{N} Rand_j F_{ij}^d(k) \tag{4}$$

Here, Rand is a numeric value selected randomly between [0,1].

The expression of acceleration a_i^d is given by:

$$a_i^d(k) = F_i^d(k)/M_i(k) \tag{5}$$

Velocity v_i^d and position x_i^d of the kth iteration are defined as:

$$v_i^d(k+1) = Rand(v_i^d(k) + a_i^d(k)) \tag{6}$$

$$x_i^d(k+1) = v_i^d(k+1) + x_i^d(k) \tag{7}$$

The gravitational constant, G(k), used in Eq. (2) decreases as the iteration number increases to maintain the search veracity. The gravitational constant G is a function of initial value G_0.

$$G(k) = G_0 e^{-\alpha k/k_{max}} \tag{8}$$

Here, α, k, and k_{max} are a constant specified by the user, iteration count, and the complete set of iterations, respectively.

The fitness evaluations are carried out to compute the masses of the agents. It is noted that the agents with heavier masses represent a better solution for the problem. The solutions for the masses are stated below:

$$M_i(k) = \frac{m_i(k)}{\sum_{j=1}^{N} m_j(k)} \tag{9}$$

$$m_i(k) = \frac{Fit_i(k) - F_{worst}(k)}{F_{best}(k) - F_{worst}(k)} \tag{10}$$

Fit_i(k) signifies the ith agent's fitness value at the kth iteration. The values corresponding to the best and the worst fitness are specified as F_{best}(k) and F_{worst}(k), which are represented as:

$$F_{best}(k) = \min_{i \in [1,\ldots,N]} Fit_i(k) \tag{11}$$

$$F_{worst}(k) = \max_{i \in [1,\ldots,N]} Fit_i(k) \tag{12}$$

In the proposed approach the value of G_0 is set to 100 and the value of α is set to 20. The pseudocode for the GSA is given below:

Step 1: Search space identification, k=0.

Step 2: Random initialization X_i(k) for k=1. . . . . . . .N.

Step 3: Fitness evaluation of objects.

Step 4: Update the parameters of G(k), best(k), worst(k), and M(k) for k=1………N.

Step 5: Calculation of the force on the object.

Step 6: Calculation of the velocity and acceleration of each object.

Step 7: Update the position of the agent by Eq. (7) to yield $X_i(k+1)$.

Step 8: Repeat steps 3 to 7 until the stop criterion is reached.

Step 9: End.

4. Problem formulation

The GSF can be expressed mathematically as the ratio of the variation in real power in the transmission line to a small shift in the real power output of the generator. In the case of a congested line k, the GSF is represented as:

$$GSF_g^k = \frac{\Delta P_{ij}}{\Delta P_{G_g}} \tag{13}$$

Here, ΔP_{ij} signifies the alteration in the amount of the power flowing through the congested line k. The gth generator's real power output is designated as ΔP_{G_g}.

The generators with high and nonuniform sensitivity values are sorted by the system operator to participate in the CM process as these generators exhibit greater responsiveness upon variation in the flow of power through the congested line. A detailed derivation for the GSF can be found in [16].

The aggregate rescheduling amount contributed by the generators participating in the CM problem based on their bids is achieved with the following optimization problem:

$$Minimize \sum_{g=1}^{N_g} C_g(\Delta P_{G_g}) * \Delta P_{G_g} \tag{14}$$

ΔP_{G_g} is the adjustment in the gth bus's real power, N_g is the number of participating generators, and C_g represents the price offers put forward by the associated generators. The rescheduling process is subjected to the following constraints:

GSF constraint:

$$\sum_{g=1}^{N_g} ((GSF_g) * \Delta P_{G_g}) + F_k^0 \leq F_k^{\max} \tag{15}$$

Ramp limit constraint:

$$P_{G_g} - P_{G_g}^{\min} = \Delta P_{G_g}^{\min} \leq \Delta P_{G_g} \leq \Delta P_{G_g}^{max} = P_{G_g}^{max} - P_{G_g} \tag{16}$$

Power balance constraint:

$$\sum_{g=1}^{N_g} \Delta P_{G_g} = 0 \tag{17}$$

$P_{G_g}^{\min}$ and $P_{G_g}^{max}$ correspond to the limits of generator g's minimum and maximum active power generation.

F_k^0 corresponds to the flow of the power in the kth transmission line due to all the contacts requesting the transmission service.

$F_k^{\max}$ corresponds to the MVA flow limit of the transmission line joining buses i and j.

Eq. (17) states the power balance without considering the losses. The losses are addressed at the end of the optimization process by allocation of generation at the slack bus. Eq. (17) also comprises the variation in the active power in the slack bus [16].

The fitness function for the CM problem discussed in this article is designed by converting the constraints into the penalty function, represented as follows:

$$\sum_{g=1}^{N_g} C_g(\Delta P_{G_g}) * \Delta P_{G_g} + penalty\, multiplier * [(\sum_{g=1}^{N_g} ((GSF_g) * \Delta P_{G_g}) + F_k^0 - F_k^{\max}) + (P_g - P_g^{\min}) + (\sum_{g=1}^{N_g} \Delta P_{G_g})] \tag{18}$$

The penalty function is used to restrict the search space so that the masses do not fly away to unacceptable regions. The multiplier thus used must be chosen carefully so that there is a proper limitation. If the multiplier is too large, it will not be able to search several regions effectively and will converge prematurely, whereas with too small a value it might escape the search area and converge to an undesired point. The penalty multiplier is taken as 1000 throughout the simulation process [18].

5. System studies

The proposed GSA approach for the CM problem has been implemented using MATLAB version 2013a software. The computer used for the execution of the simulation bears a core i5 processor with 2.4 GHz clock speed accompanied with 4 GB RAM. Simulations are executed on the 39-bus New England framework and IEEE 30-bus system and 118-bus framework to evaluate the potency of the projected CM problem with GSA in this article. The outcomes achieved with the GSA are put in comparison with the outcomes reported in [15], [16], and [17] for the 39-bus New England framework. References [16], [18], and [19] are considered to compare the results achieved in the case of the IEEE 30-bus system and references [16] and [19] are considered to compare results in the case of the 118-bus system.

5.1. Modified 39-bus New England system

The framework of the 39-bus New England system has 29 load buses and 10 generator buses. The line loaded to 262.3 MVA is subjected to an outage, connected between buses 14 and 34 emanating in the overloading of the line connected between buses 15 and 16 whose flow is 628.6 MVA (flow limit: 500 MVA). The congested case power flow detail is presented in Table 1. The alleviation of the congestion for the overloaded line is accomplished with a small shift in the generators' active power output. Table 2 represents the GSF values computed for the congested line. The generators taking part in the CM process are sorted out based upon their sensitivity indices towards the congested line. From Table 2, it is noticed that generators 2, 3, 8, 9, and 10 have nonuniform GSF values towards the congested line. These generators with nonuniform GSFs are selected to take part in the CM problem. Generator 1 is the slack bus generator and is rescheduled to take care of the losses.

The outcomes obtained with the implementation of the GSA are tabulated in Table 3. For comparative analysis, the outcomes gained with RED, PSO, and ABC reported in the literature in [15], [16], and [17], respectively, are also included in Table 3. The total amount of active power rescheduling and the total amount of rescheduling cost achieved with the GSA for the CM problem are 511.05 MW and 8033 $/day, respectively.

Table 1. Power flow details (line 15-16).

Congested line	Power flow (MW)	Line limit (MW)
15-16	628.6	500

Table 2. Generator sensitivity factors for 39-bus New England system.

Gen no.	1	2	3	4	5	6	7	8	9	10
GSF	0.00	–0.47	–0.04	–0.35	–0.35	–0.35	–0.35	–0.49	–0.44	–0.51

From Table 3 it is noted that the total amount of real power rescheduling and the aggregate cost of rescheduling achieved with the proposed method to manage congestion is best and optimally minimum when compared with the results reported in [15], [16], and [17]. The power flow status achieved after CM with the GSA is 499.10 MW. A comparative pictorial representation for the amounts of active power rescheduled is portrayed in Figure 1. The real power loss is reduced to 57.02 MW from 59.35 MW. The convergence profile with the GSA is shown in Figure 2.

Table 3. Comparison of results with GSA for 39-bus New England system.

	GSA [proposed]	RED [15]	PSO [16]	ABC [17]
Approx. cost of rescheduling ($/day)	8033	8639.17	8872.9	8456
Run time (s)	9.39	—	—	—
Power flow after CM, line 15-16 (MW)	499.10	510	490.00	499.50
ΔP_1 (MW)	–130.82	–99.59	–149.1	–131.0
ΔP_2 (MW)	46.43	98.75	65.6	63.2
ΔP_3 (MW)	–124.69	–159.64	–129	-132.0
ΔP_4 (MW)	Not involved	12.34	Not involved	Not involved
ΔP_5 (MW)	Not involved	24.69	Not involved	Not involved
ΔP_6 (MW)	Not involved	24.69	Not involved	Not involved
ΔP_7 (MW)	Not involved	12.34	Not involved	Not involved
ΔP_8 (MW)	88.90	24.69	75.4	72.2
ΔP_9 (MW)	47.95	12.34	52.1	49.1
ΔP_{10} (MW)	72.26	49.38	83	78.8
Total amount (MW)	511.05	518.45	554.2	526.3

5.2. Modified IEEE 30-bus system

There are 6 buses that are designated as generator buses along with 24 buses designated as load buses in the case of the IEEE 30-bus system. The slack bus is marked as bus number 1, followed by the generator buses and then the load buses. To analyze the potency of the proposed approach the line existing between buses 1 and 3 is subjected to an outage. The outage results in the overloading of the lines placed between buses 2-1 and 9-2. Lines 2-1 and 9-2 are subjected to power flows of 170 MW and 66 MW, which are beyond their normal flow limits. The power flow details are represented in Table 4. Table 5 represents the GSF values for

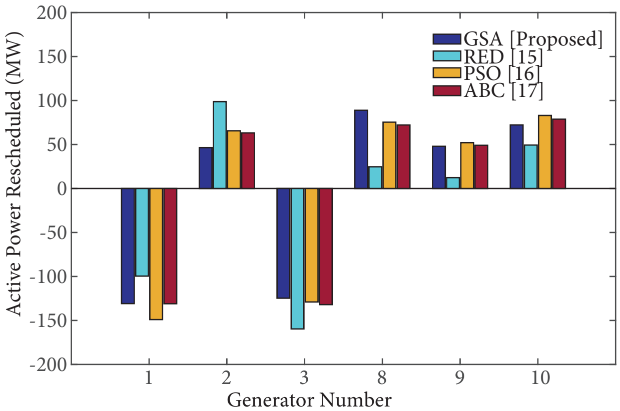

Figure 1. Comparison of active power rescheduling for 39-bus New England system.

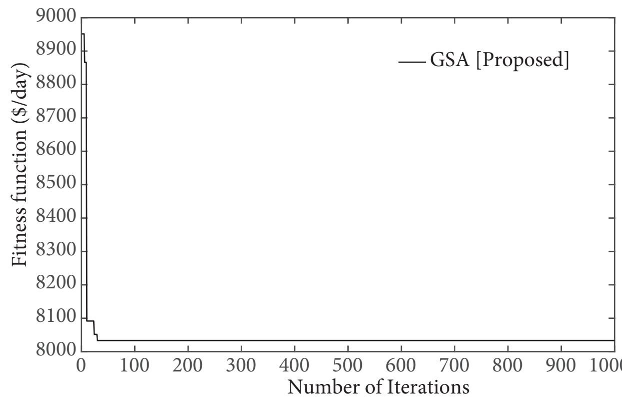

Figure 2. GSA-based convergence characteristics for 39-bus New England system.

the congested lines. It is observed from Table 5 that the GSF values achieved do not deviate significantly from each other. As the system is compact and firmly electrically connected, all the generators exhibit high impact towards the variation in the congested line power flow. Thus, all the generators are selected to participate in the CM problem. Table 6 represents the bidding cost submitted by the generators.

Table 4. Power flow details (lines 2-1 and 9-2).

Congested line	Power flow (MW)	Line limit (MW)
2-1	170	130
9-2	66	65

Table 5. Generator sensitivity factor (IEEE 30-bus system).

Gen no.	1	2	3	4	5	6
GSF	0.00	–0.85	–0.78	–0.68	–0.66	–0.64

Table 6. Generators' price bids ($/MW day) (IEEE 30-bus system).

Gen no.	1	2	3	4	5	6	7	8	9	10
Bids	15	20	17	16	12	17	13	11	14	19

In this case, the rescheduling of the generators is performed optimally using the GSA and the details of the results achieved are tabulated in Table 7. The effectiveness of the results achieved is contrasted with the outcomes detailed in [16], [18], and [19]. The cost of the congestion yielded from the generator rescheduling process is 1433.48 $/day, which is minimum when weighted against the outcomes achieved in the literature in [16], [18], and [19]. The total amount of the real power rescheduling achieved in this case is 104.53 MW, which is also lower than the total amount achieved with other methods presented in [16], [18], and [19]. From Table 7, it is also observed that the power flow on the congested lines after CM is 129.8 MW and 60 MW. After CM, the system loss is minimized to 14.96 MW from 21 MW. A pictorial comparative analysis of the generators' active power outputs is shown in Figure 3. The convergence characteristic achieved with the implementation of the GSA is projected in Figure 4.

Table 7. Comparison of results with GSA for IEEE 30-bus system.

	GSA [proposed]	PSO [16]	FFA [18]	MF = 0.6 [19]	MF = 0.8 [19]
Approx. cost of rescheduling ($/day)	1433.48	1542.8	1560.00	2769.54	1521
Run time (s)	9.06	—	—	—	—
Power flow after CM, line 2-1 (MW)	129.8	129	129.7	130	130
Power flow after CM, line 9-2 (MW)	60	60	64.97	60	62
ΔP_1 (MW)	–51.89	–59	–8.579	–58	–56
ΔP_2 (MW)	20.03	19.9	75.99	20.5	23.4
ΔP_3 (MW)	14.18	13	0.0575	14.5	17
ΔP_4 (MW)	4.00	6	42.99	8	10.3
ΔP_5 (MW)	6.67	6.5	23.83	9.2	Not involved
ΔP_6 (MW)	7.76	7	16.51	Not involved	Not involved
Total amount (MW)	104.53	111.4	167.97	110.2	106.7

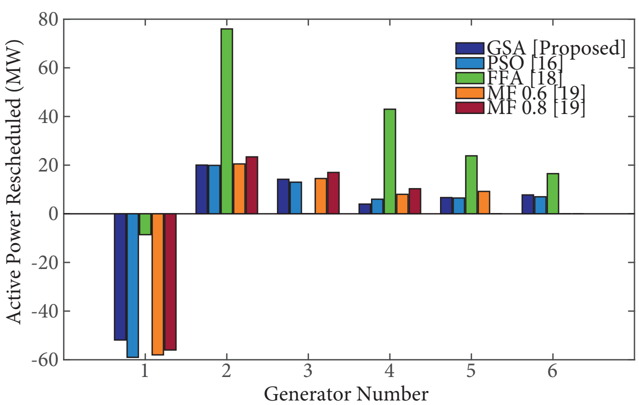

Figure 3. Comparison of the active power rescheduling for 30-bus system.

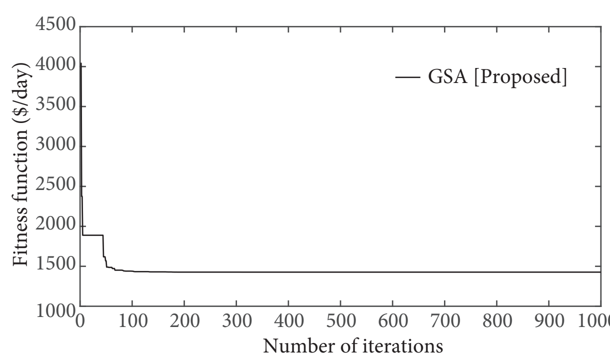

Figure 4. GSA-based convergence characteristics for IEEE 30-bus system.

5.3. Modified IEEE 118-bus system

The configuration of the 118-bus system has 54 generator buses and 64 load buses. The numbering sequence for the 118 buses is done with the slack bus as 1, which is followed by the generator buses and then the load buses. The congested line is connected between buses 13 and 16. The details of the congested line are given in Table 8. The congestion leads to the power violation of 62 MW in the line connected between buses 13 and 16. The GSF values are represented in Figure 5. From Figure 5, it is seen that the GSF values corresponding to generator numbers 13–18 represent nonuniform GSF values. Generators 13–18 are considered to take part in the CM problem. The rescheduling of the slack bus generator at bus 1 is done to check the system losses. There are 54 generators present in the 118-bus framework, but according to the GSF values, only 7 generators will participate in rescheduling purposes to relieve the overloading of the congested line. It can be observed that the number of generators is drastically reduced from 54 to 7. The power outputs of these 7 generators are required to be rescheduled for the CM problem. Table 9 represents the financial bids given by the generators.

Table 8. Power flow details (line 13-16).

Congested line	Power flow (MW)	Line limit (MW)
13-16	262	200

Table 9. Generators' price bids ($/MW day) (118-bus system).

Gen no.	Bids	Gen no.	Bids	Gen no.	Bids
1	60	19	14	37	18
2	25	20	10	38	17
3	19	21	20	39	16
4	16	22	21	40	15
5	21	23	13	41	11
6	12	24	18	42	9
7	13	25	16	43	10
8	14	26	15	44	21
9	17	27	17	45	30
10	19	28	19	46	15
11	70	29	25	47	14
12	15	30	27	48	11
13	17	31	15	49	20
14	19	32	14	50	21
15	20	33	17	51	22
16	15	34	9	52	23
17	10	35	6	53	19
18	18	36	20	54	25

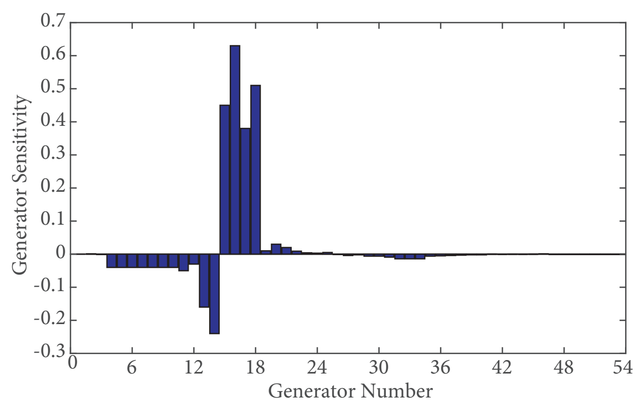

Figure 5. Generator sensitivity values for 118-bus system.

The optimal rescheduling of the generators is done using the GSA to relieve the overloading of 62 MW absolutely. The detailed results obtained in this CM technique are listed in Table 10. A comparative analysis is established with the results in [16] and [19]. From Table 10, it is observed that the total amount of active power rescheduling achieved with the GSA is 180.38 MW and this is less in amount than the total amounts of active power rescheduling obtained in the other cases in [16] and [19]. A comparison with the amount of the active power rescheduling obtained with the GSA and other methods is represented in Figure 6. Table 10 represents that the rescheduling cost to manage congestion with the GSA approach is 3206.56 $/day, which is also minimum when compared to the other methods. From Table 10 it is also noted that the power flow achieved after CM with the GSA is 198.38 MW. The system loss at the time of congestion was 140 MW, which was reduced to 135 MW after CM. The convergence profile for the selected case is portrayed in Figure 7.

Table 10. Comparison of results with GSA for 118-bus system.

	GSA	PSO [16]	MF = 0.6 [19]	MF = 0.8 [19]
Approx. cost of rescheduling ($/day)	3206.56	3479.7	3789.6	8241
Run time (s)	10.70	—	—	—
Power flow after CM in line 13-16 (MW)	198.38	199	200	201
ΔP_1 (MW)	–3.00	–3.79	–5.52	–8.65
ΔP_{11} (MW)	Not involved	Not involved	14	90.9
ΔP_{13}(MW)	72.35	81.9	74.7	Not involved
ΔP_{14} (MW)	18.56	16.4	Not involved	Not involved
ΔP_{15} (MW)	–1.46	–17	Not involved	Not involved
ΔP_{16} (MW)	–32.31	–55	–64.3	–90
ΔP_{17} (MW)	–2.31	–9	–24.4	–0.9
ΔP_{18} (MW)	–50.39	–16.3	Not involved	Not involved
Total amount (MW)	180.38	199.4	183	190.5

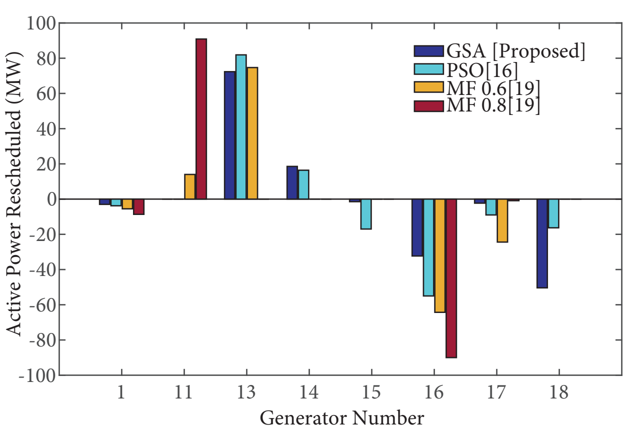

Figure 6. Comparison of the active power rescheduling for 118-bus system.

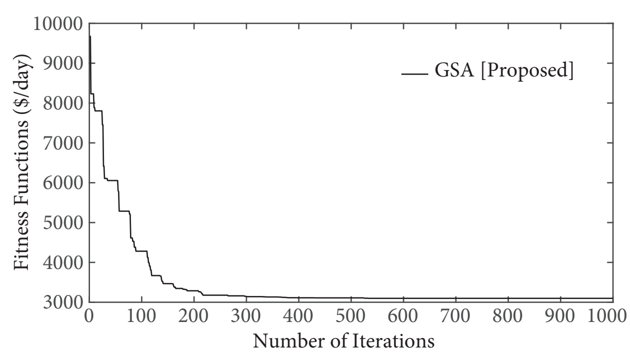

Figure 7. GSA-based convergence characteristics for 118-bus system.

6. Conclusion

This article presents a proficient CM approach considering the rescheduling of the generators. The selection of the generators for the CM problem is achieved based on the values of GSF. The contingencies are created by performing the tripping of the lines. The 39-bus New England and IEEE 30- and 118-bus test cases have been considered to validate the CM approach. The GSA is implemented to achieve the optimal state for the proposed CM strategy. It is noticed that the proposed GSA approach for CM efficiently attenuates the overburdening of the lines and the cost of rescheduling is less than that of other approaches. The achieved results with the GSA outperform the results with other algorithms like PSO, RED, ABC, FFA, and MF. The congestion cost achieved with the GSA is minimum among the other techniques discussed in this article. The reduction in the total system losses has been noticed with the implementation of the GSA. The simulation results indicate that the GSA can be used to address the solution of nonlinear and multimodal problems. The GSA implanted in this CM problem has many advantages; it is simple and easily understandable. It is also much more efficient than PSO and other algorithms discussed in this article as this method does not require memory to store the intermediate result as in the case of PSO (to compute P_{Best}). It may be concluded that the proposed CM technique with the GSA serves as a potent and competent approach to solve such CM optimization problems, maintaining the security and reliability of the system.

This proposed work can be extended by developing different dispatch and curtailment strategies. The recent trend revolves around the application of renewable energy and distributed generation. The influence of renewable energy and distributed generation on the rescheduling of power delivery can also be analyzed. This philosophy can be extended to consider the optimal setting of the parameters like reactive power loss and voltage stability index in addition to the generation cost as prospective future works.

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Appendix. Comparative analysis of GSA with other heuristic algorithms.

	GSA	PSO	GA	FFA	ABC
Memory requirements	Memory-less [20]	Requires memory [16]	Memory-less [20]	Memory-less [18]	Requires memory [17]
Execution time	Low [26]	High [26]	High [26]	—	—
Convergence profile	Better [20–27]	Good [16]	Good [20]	Good [18]	Good [17]