ISSN: 2251-9246
EISSN: 2345-6221

pp. 209:217

Transmission Congestion Management Using Crow Search Algorithm

Seyed Erfan Hosseini, Alimorad Khajehzadeh*, Mahdiyeh Eslami

Department of Electrical Engineering, Kerman branch, Islamic Azad University, Kerman, Iran
Erfan.Hosseini@engineer.com; khajehzadeh@iauk.ac.ir; m.eslami@iauk.ac.ir

Abstract

The generation rescheduling is one of the most important methods used in correctional congestion management, which has been the subject of many studies. In the deregulated environment, relieving congestion has a significant impact on the operation and security of the transmission system. Consequently, alleviation of transmission network congestion in all power systems is imperative. In addition, the cost is a top priority in all markets, both electrical and non-electrical. In this paper, the problem of managing congestion is solved using rescheduling (increasing or decreasing) of the active power output of the generators. However, the change in the active power generation imposes a cost depending on the prices offered by the generation companies. The objective is to reschedule the power generation of power plants in such a way as to minimize the congestion cost. The crow search optimization algorithm is employed to determine the optimal solution. Different constraints including those related to the network, transmission lines, and power plants are all modeled and considered in this study. Moreover, various contingencies related to line outage are taken into consideration to cause congestion and necessary measure are applied to relieve the congested lines with the least possible cost. In order to evaluate the accuracy and effectiveness of the proposed approach in finding the optimal solution, it is conducted on IEEE 30 and 57 bus test systems. The results obtained for the various cases studies indicate the superiority of the proposed method in comparison with other techniques presented in the literature.

Keywords: congestion management; transmission system; optimization; Crow search algorithm.
Article history: Received 17-Jul-2021; Revised 16-Aug-2021; Accepted 18-Aug-2021.

1. Introduction

The restructuring of the electric power industry has been proposed to raise the competition in production, resulting in lower prices, increased network efficiency and improved service in the power system. On one hand, in the deregulated environment, investment in the production sector and operating decisions are left to competitive mechanisms while, on the other hand, the transmission network remains a shared and non-competitive service. According to the definition, any violation of the thermal, security, and reliability limits of the transmission system, is called congestion. In other words, congestion is the use of a power grid outside the permitted range of operation. These limits can be related to the permitted range of busbar voltages, generators upper and lower bounds, transmission lines' constraints, and so on. From the transmission perspective, any overload on the network lines that occurs in the peak load or other emergency conditions, such as the outage of lines and generators, is referred to as congestion. The combination of the competitive generation sector and the public transmission system has made congestion management very arduous. This difficulty will increase as congestion swell due to the higher rate of increase in transactions of the electricity market in comparison with transmission system expansion. In the traditional structure, congestion was resolved using certain instructions, and since the transmission lines prone to congestion were known and their required amount of capacity at a given period depending on the load was almost constant, the main solution to alleviate congestion was increasing the installed capacity of transmission lines and/or generation rescheduling. However, under the restructuring era and with the open access scheme of the transmission network, the network congestion has become acuter and its occurrence from a fixed state in traditional systems has altered to an obscure, uncertain, with extra costs imposed to the network and sometimes in places not expected. Under these new conditions, the network operator has faced many limitations to relieve the congestion, and this has eventually resulted in new and different ways of congestion management.

Considering the importance and significance of congestion mitigation in the restructured power systems, several schemes have been proposed in the literature. These approaches include FACTS devices [1-3], distributed generations [4-6], congestion-driven transmission expansion planning [7-8], generation rescheduling [9-12] and so on.

Reference [9] suggests the power transfer distribution coefficients for congestion management; then, using these coefficients, a corrective method is proposed for congestion management. In [10], after identifying the sensitivity of the congestion to the power production of willing power plants to participate in congestion management scheme, attempts have been made to reduce the congestion by changing the power generation of these units; in this way, the goal is set to be minimization of variation in power production of generators. The linear programming technique has been used in [11] to manage network congestion via generation rescheduling. [12] has proposed congestion management considering transient and voltage stability; congestion has been relieved implementing variation in power production of generators as well as power consumption of some loads. In [13], management of congestion has been proposed by changing the power production of thermal units and changing the consumption of consumers according to the prices provided by them, as well as the load curtailment, if necessary.

Generation rescheduling for congestion management using evolutionary algorithms has been the subject of many researchers in the recent years. The differential evolution algorithm has been proposed in [14]; moreover, the effect of the presence of wind turbines is also considered in the optimization problem, and the optimal wind turbine location for managing the congestion has been determined. Firefly algorithm has been used in [15], for optimization of congestion management; the generation rescheduling approach has been utilized and the aim of optimization is to minimize its cost. In [16], a real-time intelligent method is proposed for the alleviation of congestion; various scenarios for evaluating the performance of the proposed method have been investigated and the Particle Swarm Optimization (PSO) has been used for optimization. In [17] Improved Particle Swarm Optimization (IPSO) is used for rescheduling-based congestion management schemes; obtained results demonstrate the superiority of the IPSO with distributed acceleration constants regarding the standard PSO. The symbiotic organic search algorithm is proposed in [18] to determine the optimal variation in power generation of generation units to alleviate congestion. The teaching-learning-based optimization algorithm is proposed in [19] for optimal rescheduling of the active power of generation units to lessen congestion; higher quality solutions were obtained compared with other techniques.

Engineering design is defined as a decision-making process for building products that meet specific needs. Most engineering design problems include sophisticated objective functions with a large number of decision variables. Available solutions are set of all designs with all possible values of design parameters (decision variables). An optimization technique strives to find an optimal solution, from all the available solutions.

Conventional search methods have long been used to solve engineering design problems. Although these methods are promising, they may fail in complex design problems. In real-life design issues, the number of decision variables can be very high, and their impact on the performance of the objective function can be very complicated. An objective function may include many local options, while the designer is interested in a global optimum. Such a problem cannot be solved by conventional methods that are only available locally. In these cases, effective optimization methods are required.

The meta-heuristic algorithms have shown promising performance in solving many real-world optimization problems that are highly non-linear and multifunctional. All evolutionary algorithms use a particular random-equation and local search. These algorithms can find suitable solutions of the optimization problems, but there is no guarantee of the optimum solution. All in all, these algorithms can be suitable for global optimization.

Recent decades have been the realm of evolutionary algorithms, and many approaches were introduced that have evolved the optimization process in many subjects, especially engineering problems. Many of these methods are used in practical cases. Crow Search Algorithm (CSA) is one the latest and sturdiest evolutionary algorithms, that has shown great supremacy when been employed to solve power system's optimization problems. Optimal rescheduling of real power generation for mitigating congestion via CSA is proposed in this paper.

The main contributions of this study are as follows:

- Employ CSA as a powerful optimizing means to reduce the rescheduling cost while taken into account various contingencies for the two case study, namely, IEEE 30-bus and IEEE 57-bus standard test system.
- Efficiently eliminate the overload in the transmission lines arisen by various studied contingencies with the least alteration in the generation schedule.
- Depreciate the total quantity of rescheduling and losses for different considered crises.
- Several security restrictions such as bus voltage and line loading are taken into consideration while modeling and solving this optimization problem.
- An effective penalty mechanism is deployed to penalize constraint violations and at the same time prevent from the elimination of good solutions that slightly infringe one or a few limits, so with a slight modification, they could become free of constraint contravention.
- Demonstrate the effectiveness of the proposed CSA-based approach over other techniques.

The rest of this paper is organized as follows: section 2 presents the problem modeling and formulation. CSA is briefly illustrated in section 3. Section 4 deals with the optimization procedure and the obtained results are provided and discussed in detail in section 5. Concluding remarks are drawn in section 6.

2. Problem Modeling and Formulation

In order to solve an optimization enigma, first, the problem should be described and modeled mathematically, and it is then that optimization mechanisms could be applied to determine the solution. Accordingly, this section provides the problem formulation of congestion management. In this regard, primarily, the objective function is mathematically delineated and next equality and inequality constraints are given.

3. Objective Function

The primary purpose of congestion management is to minimize costs while meeting network and units constraints. In this paper, the generation rescheduling is used to mitigate congestion caused by contingencies such as transmission line outage. However, the Generation Companies (GenCos) change their output active power at a cost, which is provided in their offers. Therefore, the objective function is to minimize congestion costs [15].

$$C_c = \sum_{j \in N_g} (C_k \Delta P_{Gj}^{+} + D_k \Delta P_{Gj}^{-}) \$/h \tag{1}$$

Where, is the total congestion cost imposed to the power system. ΔP_{Gj}^{+} and ΔP_{Gj}^{-} (MW) are the active power increment and decrement of generator j amongst N_g generators, respectively. While C_k and D_k (\$/MWh) denote incremental and decremental price offers provided by GENCOs. This optimization problem is subjected to several equality and inequality constraints presented in the following section.

4. Constraints

The following equations provide the equality constraints of the optimization problem under study. Eqs. (2) and (3) represent the active and reactive power balance constraint at each bus while Eqs. (4) and (5) illustrate the final generated and consumed power secured from the market mechanisms [15].

$$P_{Gk} - P_{Dk} = \sum_j |V_j||V_k||Y_{kj}| \cos(\delta_k - \delta_j - \theta_{kj}); \quad j = 1,2,...,N_b \tag{2}$$

$$Q_{Gk} - Q_{Dk} = \sum_j |V_j||V_k||Y_{kj}| \sin(\delta_k - \delta_j - \theta_{kj}); \quad j = 1,2,...,N_b \tag{3}$$

$$P_{Gk} = P_{Gk}^{C} + \Delta P_{Gk}^{+} - \Delta P_{Gk}^{-}; \quad k = 1,2,...,N_g \tag{4}$$

$$P_{Dj} = P_{Dj}^{C}; \quad j = 1,2,...,N_d \tag{5}$$

In the above Eqs. P_{Gk}, Q_{Gk}, P_{Dk} and Q_{Dk} are the generated active and reactive power and the active and reactive load at bus k, respectively. Indices V and δ denote voltage magnitude and angle, while θ is the admittance angle of line with admittance *Y* connected between two nodes under enquiry. P_G^C and P_D^C denote active generated and consumed power at the related bus at the time of congestion occurrence. Besides N_d, N_b are number of loads and buses, respectively.

The inequality constraints are those related to operating and physical limitations of the transmission facilities, and generators as provided in Eqs. (6) to (10) [20]. These constraints include bus voltage constraint, transmission lines upper boundary, and active and reactive power limits of generating units.

$$V_n^{\min} \le V_n \le V_n^{\max}, \quad \forall n \in N_b \tag{6}$$

$$P_l \le P_l^{\max}, \quad \forall l \in N_l \tag{7}$$

$$P_{Gk}^{\min} \le P_{Gk} \le P_{Gk}^{\max}, \quad \forall k \in N_g \tag{8}$$

$$Q_{Gk}^{\min} \le Q_{Gk} \le Q_{Gk}^{\max}, \quad \forall k \in N_g \tag{9}$$

$$(P_{Gk}^{C} - P_{Gk}^{\min}) = \Delta \mathrm{P}_{\mathrm{Gk}}^{\min} \le \Delta \mathrm{P}_{\mathrm{Gk}} \le \Delta \mathrm{P}_{\mathrm{Gk}}^{\max} = (P_{Gk}^{\max} - P_{Gk}^{C}) \tag{10}$$

Where, P_l shows the power transferred over the transmission line connecting two buses of the network, while N_l indicates the lines number. It should be noted that superscripts *min* and *max* express the minimum and maximum values of the associated variables.

5. Crow Search Algorithm

Crows are considered the most intelligent birds. They have the largest brain size compared to their body size. Considering the ratio of brain to the body, their brain is slightly smaller than the human brain. There is plenty of evidence about the crows' intelligence. They have shown self-awareness in mirror experiments and the ability to make tools. Crows can remember faces and warn when they face an unfriendly approach. In addition, they can use tools, communicate in complex ways, and recall their hidden food locations a few months later [34]. The CSA follows the following steps to determine the optimal solution:

A) Initialize problem and optimization parameters

The optimization problem, decision variables and constraints are established. Then, the CSA parameters including flock size (N), the maximum number of iterations, flight length (fl) and the probability of awareness (AP) are set.

B) Initialize flock and memory of crows

Flock is randomly positioned as a $N \times d$ matrix in which, N is the number of crows and d is the number of decision variables. Each crow, in turn, indicates a solution of the problem under study.

$$Crows = \begin{bmatrix} x_1^1 & x_2^1 & \dots & x_d^1 \\ x_1^2 & x_2^2 & \dots & x_d^2 \\ . & . & \dots & . \\ . & . & \dots & . \\ . & . & \dots & . \\ x_1^N & x_2^N & \dots & x_d^N \end{bmatrix} \tag{11}$$

Then the memory of every crow is initialized. Considering that the crows have no experiences at the first iteration, it is presumed that they have wrapped their foods at their first positions.

$$Memory = \begin{bmatrix} m_1^1 & m_2^1 & \dots & m_d^1 \\ m_1^2 & m_2^2 & \dots & m_d^2 \\ . & . & \dots & . \\ . & . & \dots & . \\ . & . & \dots & . \\ m_1^N & m_2^N & \dots & m_d^N \end{bmatrix} \tag{12}$$

C) Generate a new position

Each crow creates a new position in the search space as follows: assume crow *i* wants to get a new position. For this purpose, this crow randomly chooses one of the flock crows (for instance crow *j*) and follows it to find the position of the foods stored by this crow (m^j). The new position of crow *i* is determined using Eq. (13). This manner is reproduced for all the crows.

$$x^{i,iter+1} = \begin{cases} x^{i,iter} + r_i \times fl^{i,iter} \times (\mathrm{m}^{j,iter} - x^{i,iter}) & \mathrm{r}_j \ge AP^{j,iter} \\ a\ random\ position & otherwise \end{cases} \tag{13}$$

Where, r_j is a random value with uniform distribution between 0 and 1 and $AP^{j,iter}$ symbolizes the awareness probability of crow *j* at *iter*th iteration.

D) Check the feasibility of new positions

The practicability of the new position of any crow is reviewed. The crow renews its position provided that the new position is feasible, otherwise, tarries in its current position and does not migrate to the new position.

E) Evaluate fitness of the new positions

The value of the objective function for the new position of each crow is measured.

F) Update memory

The following equation is used to update the memory of crows.

$$m^{i,iter+1} = \begin{cases} x^{i,iter+1} & f\ (x^{i,iter+1})\ \text{is better than}\ f\ (\mathrm{m}^{i,iter}) \\ m^{i,iter} & otherwise \end{cases} \tag{14}$$

In which, *f()* represents the objective function value.

The crow refreshes its memory provided that the value of fitness function of its new position is greater than the value of its memorized position, by the new position.

G) Check termination criterion

Steps D to G are revolved until $iter_{\max}$ is reached. When the termination criterion is satisfied, the best position of the memory from the objective function value point of view is identified as the best solution of the optimization problem.

6. CSA for congestion management problem

One of the main motivations of this paper is to create a user-friendly evolutionary technique with a simple concept and easy implementation that can achieve satisfactory results while solving the optimization problem. In this regard CSA is employed to solve the congestion management problem. In this work, each population has N number of design variables where N is the number of generators taking part in the CM problem. The objective function is considered as the minimization of costs, therefore, lower costs means better fitness.

In optimization problems, there could be a solution that has great fitness but slightly violates a constraint. In a crisp perspective, this solution will be discarded, however, with a small modification a good solution may result. Therefore, in this study, a penalty approach is borrowed from [21], which builds a single objective taking into account the constraints.

The inequality limits, including load bus voltage and line power flow, are turned into the penalty functions which in turn are added to the objective function. In this paper, the equality limits, as well as reactive power inequality constraints, are dealt with efficiently during Newton–Raphson power flow [22]. The objective function of the congestion management problem is, therefore, as presented in Eq. (15) [21]:

$$Min\ F = PF_T \times PF_V \times C_C \tag{15}$$

Where, F is the objective function and, PF_T and PF_V are the proposed penalty functions line limit and bus voltage constraints, respectively and are calculated as follows:

$$PF_T = \prod_{l=1}^{N_l} F_{T,l} \tag{16}$$

$$PF_V = \prod_{n=1}^{N_b} F_{V,\mathrm{n}} \tag{17}$$

In which, $F_{T,i}$ and $F_{V,n}$ are the penalty functions for each line and each bus as shown in Figs. 1 and 2, respectively. Now that the objective function incorporating the constraints is determined, the proposed optimization algorithm based on CSA could be applied. This procedure is explained hereinafter in ten steps.

Step 1. Read the load, line and bus data, along with the price bids and GenCos information.

Step 2. Design a contingency by line outage and/or load increase.

Step 3. Perform the load flow and determine the overloaded lines and bus voltage violation, if any.

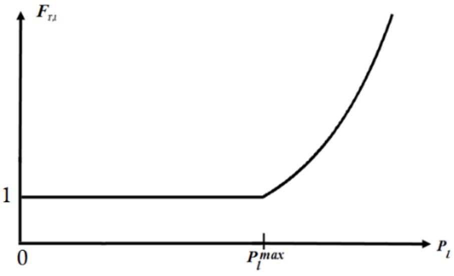

Fig. 1. Proposed penalty function for transmission lines limit

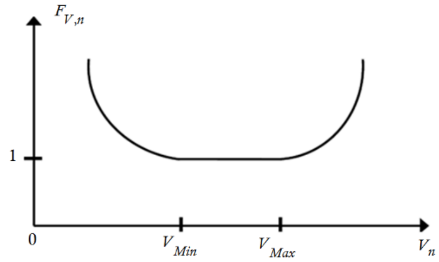

Fig. 2. Proposed bus voltage penalty function

Step 4. Determine the permissible range of rescheduling of each generators using Eq. (10).

Step 5. Initialize the first population of CSA and memory of crows, which is randomly resolved within the limits determined in the above step.

Step 6. Load flow is executed for each member of the population and, equality and inequality constraints are checked.

Step 7. Using the data obtained from the load flow execution, penalty functions are determined using Eq. (16) and (17). Consequently, the objective function is appraised by Eq. (15).

Step 8. A new population of crows is created using the related equations and terms.

Step 9. The objective function is evaluated for the new population, and the memory of crows is updated, provided that the new position of a crow has better fitness (lower objective function) compared with the current memory of the same crow.

Step 10. The optimization procedure is stopped if the maximum number of iteration is reached; otherwise, it returns to Step 8.

7. Simulation results and discussion

In order to verify the effectiveness of the CSA in solving congestion management problem, the proposed approach is carried out on modified IEEE 30-bus and 57-bus test systems. The data of these test systems is extracted from [15]. For each test systems, two different cases are considered to thoroughly examine the performance of the proposed CSA approach to optimally reschedule the active power generation of GenCos to mitigate congestion. Moreover, the results obtained are compared with those reported in [15] and [23]. For the sake of simulation, and to highlight the congestion problem the capacity of lines is decreased as to the associated standard boundaries. Furthermore, line overloads are created by considering generator or line outage as well as load increase. The best solution is reported out of 20 independent execution of the proposed approach. It should be noted that the parameters fl and AP are chosen to be 0.19 and 0.1, respectively. Besides, the maximum number of iteration is 100 for all cases.

A) Modified IEEE 30 bus test system

This test system has 41 transmission lines, 24 load buses, and 6 generators. The cumulative active and reactive load of this system is 283.4MW and 126.2 MVAR, respectively. The bids submitted by the GENCOs for these test systems are presented in Table 1. The primary market clearing values are considered to be the same as the generation and load values reported in [15]. It is assumed that congestion is created due to the unexpected line failure and/or a rise in load. For comparison compatibility, two different cases of congestion occurrence are taken into account for this test system.

Case 1:

In this case, it is assumed that the line number 1 of the network that connects the buses number one and two of the systems experience an outage. Due to the interruption of service of this line, congestion occurs and an overload in lines number 2 (between buses 1 and 7) and number 4 (between buses 7 and 8). Right after the outage of line 1, the flows of these lines are equivalent to 147.43MW and 136.29MW, respectively, which violate the line limit of 130MW for both lines. Therefore, optimal generation rescheduling should be employed to mitigate congestion. The optimal rescheduling obtained by the proposed method to solve the congestion management problem, in this case, are illustrated in Table 2. In order to provide comparability, the results of other approaches including FFA [15], and DSM, SA and PSO [23] are also included in Table 2. The Crow Search algorithm offers the best solution at a cost of 490.04$/h. The total system loss before the congestion management was 16.32MW; while this number is reduced to 12.21MW after the proposed congestion, management strategy is applied. With comparing the results given in Table 2, it can be concluded that the proposed algorithm provides the best solution, by giving the minimum cost of generation rescheduling of GenCos compared to other methods reported in previous studies. The results demonstrate that the proposed method has been able to minimize the objective function and, by optimizing the generation rescheduling, in addition to reducing the cost of congestion of the system, minimizes the system losses. Figure 3 illustrates the graph of power generation changes based on the proposed method compared to the FFA algorithm proposed in reference [15] and the DSM, SA and PSO algorithms reported in reference [23]. As shown in this figure, the proposed algorithm based on the Crow Search algorithm has been subjected to less variation than the FFA and PSO algorithms in the generating output of the GenCos, thereby yielding lower cost for managing the congestion. The DSM, SA algorithms, although having the slightest variations in comparison to other methods, but perform inadequately in the optimization of the objective function, and while the optimal solution yields the objective function of less than 500$/h, the solutions of these two algorithms account for more than 700$/h, which is very high. Additionally, the convergence characteristic of the proposed approach is depicted in Fig. 3.

Table.1.
Price bids provided by GENCOs for modified IEEE 30-bus test system [15].

Bus Number	***Increment ($/MWh)***	***Decrement ($/MWh)***
1	22	18
2	21	19
3	42	38
4	43	37
5	43	35
6	41	39

Table.2.
Comparison of results retrieved from various algorithms for Case 1 of the modified IEEE 30-bus test system

Parameter	***CSA***	***FFA [15]***	***PSO [23]***	***RSM [23]***	***SA [23]***
Total Congestion Cost ($/h)	490.1414	511.8737	538.95	716.25	719.861
Power flow (MW) on previously congested line 1–7	129.957	129.812	129.97	129.78	129.51
Power flow (MW) on previously congested line 7–8	120.77	120.617	120.78	120.60	120.35
ΔP_{G1}(MW)	-8.6341	-8.7783	-8.6123	-8.8086	-9.0763
ΔP_{G2}(MW)	+7.3731	+15.0008	+10.4059	+2.6437	+3.1332
ΔP_{G3}(MW)	+1.7189	+0.1068	+3.0344	+2.9537	+3.2345
ΔP_{G4}(MW)	+2.6065	+0.0653	+0.0170	+3.0632	+2.9681
ΔP_{G5}(MW)	+1.2878	+0.1734	+0.8547	+2.9136	+2.9540
ΔP_{G6}(MW)	+1.4246	-0.6180	-0.0122	+2.9522	+2.4437
Total generation rescheduled	23.0452	24.7425	22.936	23.339	23.809

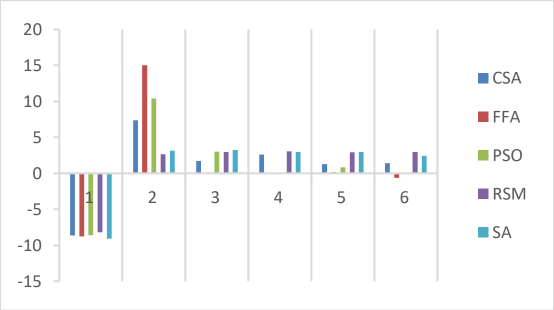

Fig. 3. Generating power changes in the proposed method compared with references [15] and [23]

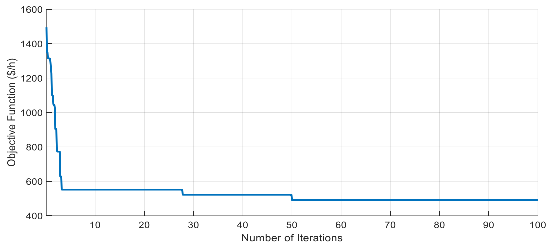

Fig. 4. The convergence characteristic of the proposed approach for case 1 of modified IEEE 30-bus test system

Case 2:

In this case, it is assumed that line 2 of the network, which connects buses number 1 and 7 of the systems, encounters an outage. Also, in order to exert more pressure on the network, an increase in the network load by 50% is also taken into consideration. For this purpose, it is assumed that the load of all buses is 1.5 times the base state and the load of each bus is proportional to its base load. This increase is considered for both active power and reactive power. After the outage of line 2, overload is observed in lines number 1 (connecting buses 1 and 2), number 3 (connecting buses 2 and 8), and number 6 (connecting buses 2 and 9). The optimal power flow [20] results show that the power flow over these lines is equal to 310. 917MW, 97.353MW, and 103.524MW, respectively, while the transmission power flow constraint of these lines is 130MW, 65MW, and 65MW, respectively.

Therefore, the proposed approach is employed to alleviate congestion. The obtained results using the proposed method for this case are presented in Table 3. Moreover, the results for the FFA reported in [15] and DSM, SA and PSO algorithms reported in [23] are also incorporated in this table. The CSA based approach yields the best solution at $ 5303.0240 per hour. The total system loss before the congestion management is 37.8MW, while the number was reduced to 15.8235MW after the implementation of the proposed strategy, which is very significant. Comparison of the results of different algorithms provided in Table 3, it could be concluded that the proposed algorithm deliver the best solution among compared approaches. Figure 5 clarifies the generation rescheduling based on the proposed method compared to the FFA proposed in [15]. Furthermore, the convergence diagram of the CSA is shown in Fig. 6.

B) Modified IEEE 57 bus test system;

This test system has 7 generators, 50 load buses, and 80 transmission lines. Total active and reactive loads are 1250.8MW, and 336MVAR, respectively. Similar to the previous test system, two different cases are considered for this test system.

Table.3.
Comparison of results retrieved from various algorithms for Case 2 of the modified IEEE 30-bus test system

Parameter	***CSA***	***FFA [15]***	***PSO [23]***	***RSM [23]***	***SA [23]***
Total Congestion Cost ($/h)	5303.0240	5304.40	5335.5	5988.05	6068.7
Power flow (MW) on previously congested line 1–2	129.8981	130	129. 7	129.91	129.78
Power flow (MW) on previously congested line 2–8	62.7324	62.713	61.1	52.36	51.47
Power flow (MW) on previously congested line 2–9	64.8371	64.979	64.67	55.43	54.04
ΔP_{G1}(MW)	-8.6919	-8.5798	NR*	NR	NR
ΔP_{G2}(MW)	+72.0424	+75.9954	NR	NR	NR
ΔP_{G3}(MW)	+6.9032	+0.0575	NR	NR	NR
ΔP_{G4}(MW)	+43.6675	+42.9944	NR	NR	NR
ΔP_{G5}(MW)	+20.4562	+23.8325	NR	NR	NR
ΔP_{G6}(MW)	+15.9538	+16.5144	NR	NR	NR
Total generation rescheduled (MW)	167.7572	167.974	168.03	164.55	164.53

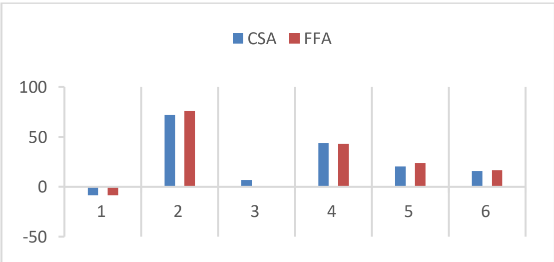

Fig. 5. Generation rescheduling in the proposed CSA compared with FFA [15]

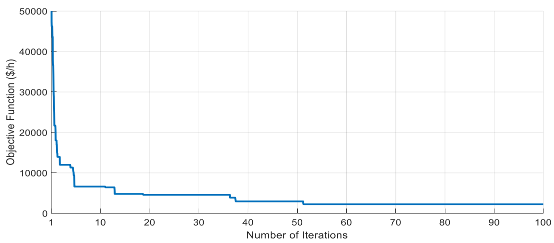

Fig. 6. The convergence diagram of the CSA for case 2 of modified IEEE 30-bus test system

Case 1:

In this case, the line limits are set as 175MW for line number 8 (5-6) instead of 200MW and 35MW for line number 10 (6-12), instead of 50MW of the main case, respectively, to create congestion. Due to these changes overload is observed in lines 5-6 and 6-12 that are transferring 195.97MW and 49.35MW, respectively. Therefore, CSA is employed to eliminate the overloads in the network. As a result, congestion is entirely managed and the overloads are lifted. Details of the results are presented in Table 4 and are compared with those obtained by FFA [15]. PSO [23], RSM [23] and SA [23]. From Table 4, it can be remarked that the proposed CSA renders the least total cost of congestion management (5378.23$/h) among compared algorithms,. However, in this case, the total losses of the system before generation rescheduling was 21.458MW, and after congestion management, it increases to 27.4292MW. But since the proposed approach imposes lower changes to active power generation of GenCos, the lesser cost is achieved. Figure 7 exhibits the convergence sketch of the objective function.

Case 2:

In this case, to create congestion, capacity limit of line number 2 (connecting buses 2–3) is set to be 20MW (initial value 85MW). In base condition, 37.048MW electric power is flowing over this line, consequently, there will be an overload in this line after diminishing its limit. In order to relieve the congestion, active power rescheduling of GenCos are carried out by applying the proposed CSA approach.

The results of the proposed method are tabulated in Table 5 along with the results of other methods published in the literature, namely, FFA [15], PSO [23], RSM [23] and SA [23]. Interpreting this table demonstrates that the proposed CSA technique incur the lowest cost (2596.1$/h) among different approaches. The total losses of the system are marginally increased to 29.437MW following congestion remission, which was originally 21.458MW. Fig. 8 portrays the convergence graph of the objective function, as obtained via the proposed CSA.

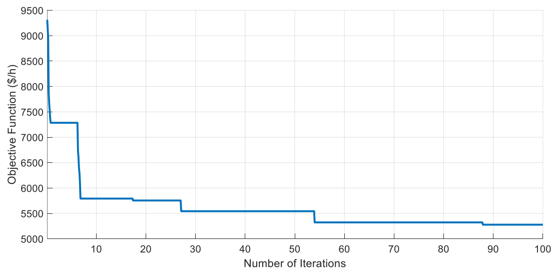

Fig. 7. The convergence sketch of the CSA for case 1 of modified IEEE 57-bus test system

Table.4.
Comparison of results of different algorithms for Case 1 of the modified IEEE 57-bus test system

Parameter	***CSA***	***FFA [15]***	***PSO [23]***	***RSM [23]***	***SA [23]***
Total Congestion Cost ($/h)	5378.2304	6050.1	6951.9	7967.1	7114.3
Power flow (MW) on previously congested line 5–6	174.6858	174.318	141	148.4	146.60
Power flow (MW) on previously congested line 6–12	34.9801	34.993	34.67	35	34.84
ΔP_{G1}(MW)	+29.3525	+5.6351	+23.135	+59.268	+74.499
ΔP_{G2}(MW)	+18.7677	+2.5230	+12.447	0	0
ΔP_{G3}(MW)	+13.1412	+0.5098	+7.493	+37.452	-1.515
ΔP_{G4}(MW)	-2.9703	+0.1070	-5.385	-47.391	+9.952
ΔP_{G5}(MW)	-42.5276	-39.1514	-81.216	-52.125	-85.920
ΔP_{G6}(MW)	-6.7956	-35.1122	0	0	0
ΔP_{G7}(MW)	-2.1332	+62.1938	+39.03	0	0
Total generation rescheduled (MW)	115.6884	145.227	168.70	196.23	171.87

Table.5.
Comparison of results of different algorithms for Case 2 of the modified IEEE 57-bus test system

Parameter	***CSA***	***FFA [15]***	***PSO [23]***	***RSM [23]***	***SA [23]***
Total Congestion Cost ($/h)	2596.1161	2618.1	3117.6	3717.9	4072.9
Power flow (MW) on previously congested line 2–3	19.8091	19.79	19.88	20	18.43
ΔP_{G1}(MW)	+0.5844	+0.3704	NR	NR	NR
ΔP_{G2}(MW)	-21.3304	-27.5084	NR	NR	NR
ΔP_{G3}(MW)	+33.3714	+31.6294	NR	NR	NR
ΔP_{G4}(MW)	+0.3264	+0.3308	NR	NR	NR
ΔP_{G5}(MW)	-1.9315	-2.2549	NR	NR	NR
ΔP_{G6}(MW)	+1.9672	-1.9354	NR	NR	NR
ΔP_{G7}(MW)	+1.9921	-0.5101	NR	NR	NR
Total generation rescheduled (MW)	61.5034	64.5393	76.314	89.320	97.887

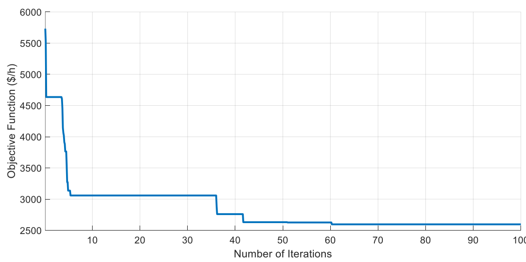

Fig. 8. The convergence graph of the CSA for case 2 of modified IEEE 57-bus test system

8. Conclusion

In this study, using the CSA, it was attempted to determine the optimal generation rescheduling of GenCos in order to minimize the cost of network congestion. All constraints related to the network, transmission lines and GenCos are also contemplated. Contingencies such as line outage and sudden load variations are assumed to create congestion and CSA was executed for optimal generation rescheduling. The proposed method is implemented in the IEEE 30 and IEEE 57-bus systems.

The results obtained for the various simulation considered cases, indicate the superiority of the proposed method based on the CSA in finding the optimal solution. In order to verify the accuracy and efficiency of the proposed approach, the results were compared with those of the other methods presented in the literature. This comparison determined that the proposed method could attain the optimal solution in such a way that the cost of congestion is less than other methods and thus the accuracy and strength of the proposed method.

References

[1] Sharma, A.K., Mittapalli, R.K. & Pal, Y. J. Inst. Eng. India Ser. B (2016) 97: 339. https://doi.org/10.1007/s40031-015-0211-7.

[2] Siddiqui, A.S. & Deb, T. Int J Syst Assur Eng Manag (2016) 7: 387. https://doi.org/10.1007/s13198-014-0262-1.

[3] Khan, M.T. & Siddiqui, A.S. Int J Syst Assur Eng Manag (2017) 8(Suppl 1): 1. https://doi.org/10.1007/s13198-014-0258-x.

[4] M. Afkousi-Paqaleh, A. Abbaspour Tehrani Fard, and M. Rashidi-Nejad, "Distributed generation placement for congestion management considering economic and financial issues" Electrical Engineering (Springer), Vol. 92, No. 6, pp. 193-201, 2010.

[5] M. Afkousi-Paqaleh, A. Abbaspour-Tehrani fard, M. Rashidinejad and K. Y. Lee, "Optimal placement and sizing of distributed resources for congestion management considering cost/benefit analysis," IEEE PES General Meeting, Providence, RI, 2010, pp. 1-7.

[6] M. Afkousi-Paqaleh, A. R. Noory, A. Abbaspour T. F. and M. Rashidinejad, "Transmission Congestion Management Using Distributed Generation Considering Load Uncertainty," 2010 Asia-Pacific Power and Energy Engineering Conference, Chengdu, 2010, pp. 1-4.

[7] Z. Liu, B. Tessema, G. Papaefthymiou and L. van der Sluis, "Transmission expansion planning for congestion alleviation using constrained locational marginal price," IET Conference on Reliability of Transmission and Distribution Networks (RTDN 2011), London, 2011, pp. 1-6.

[8] J. A. C. Miclat, A. J. S. Patubo, R. D. del Mundo, W. R. D. Tarnate and A. E. D. C. Tio, "Using the Transmission Congestion Expectation (TCE) in optimal transmission expansion planning," 2016 IEEE 16th International Conference on Environment and Electrical Engineering (EEEIC), Florence, 2016, pp. 1-4.

[9] Pantos M. Market-based congestion management in electric power systems with increased share of natural gas dependent power plants. Energy, 2011;36(7):4244e55.

[10] Dutta S, Singh SP. Optimal rescheduling of generators for congestion management based on particle swarm optimization. Power Syst IEEE Trans 2008;23(4):1560e9.

[11] Grgic D, Gubina F. Congestion management approach after deregulation of the Slovenian power system. Power Eng Soc Summer Meet 2002 IEEE 2002;3: 1661e5.

[12] Esmaili M, Shayanfar HA, Amjady N. Multi-objective congestion management incorporating voltage and transient stabilities. Energy 2009;34(9):1401e12.

[13] Esmaili M, Amjady N, Shayanfar HA. Stochastic congestion management in power markets using efficient scenario approaches. Energy Convers Manag 2010;51(11):2285e93.

[14] S.T. Suganthi, D. Devaraj, K. Ramar, S. Hosimin Thilagar, An Improved Differential Evolution algorithm for congestion management in the presence of wind turbine generators, Renewable and Sustainable Energy Reviews, Volume 81, 2018, Pages 635-642.

[15] Sumit Verma, V. Mukherjee, Firefly algorithm for congestion management in deregulated environment, Engineering Science and Technology, an International Journal, Volume 19, Issue 3, 2016, Pages 1254-1265.

[16] Mohammad Mahmoudian Esfahani, Ahmed Sheikh, Osama Mohammed, Adaptive real-time congestion management in smart power systems using a real-time hybrid optimization algorithm, Electric Power Systems Research, Volume 150, September 2017, Pages 118-128.

[17] Yadav, N.K. Soft Comput (2017). https://doi.org/10.1007/s00500-017-2792-3.

[18] Sophia Jasmine, G. & Vijayakumar, P. Wireless Pers Commun (2017) 94: 2665. https://doi.org/10.1007/s11277-016-3878-4.

[19] Sumit Verma, Subhodip Saha, V. Mukherjee, "Optimal rescheduling of real power generation for congestion management using teaching-learning-based optimization algorithm," Journal of Electrical Systems and Information Technology, 2016.

[20] D.P. Kothari, J.S. Dhillon, Power System Optimization, PHI, New Delhi, 2011.

[21] M. Afkousi-Paqaleh and S. H. Hosseini, "Transmission constrained energy and reserve dispatch by harmony search algorithm," 2009 IEEE Power & Energy Society General Meeting, Calgary, AB, 2009, pp. 1-8.

[22] H. Saadat, Power System Analysis, Tata McGraw Hill Ltd, New Delhi, 2002.

[23] S. Balaraman, N. Kamaraj, Transmission congestion management using particle swarm optimization, J. Electr. Syst. 7 (1) (2011) 54–70.