

CONGESTION MANAGEMENT BASED ON OPTIMAL RESCHEDULING OF GENERATORS AND LOAD DEMANDS USING SWARM INTELLIGENT TECHNIQUES

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Abstract. *This paper presents the Congestion Management (CM) methodologies and how they get modified in the new competitive framework of electricity power markets. When the load on the system is increased or when some contingency occurs in the system, some of the lines may become overloaded. Thus, the loadability of the system should be increased by generating and dispatching the power optimally for the secure operation of power system. In this paper, the CM problem is solved by using the optimal rescheduling of generating units and load demands, and the Swarm intelligent techniques are used to handle this problem. Here, the CM problem is solved by using the Particle Swarm Optimization (PSO), Fitness Distance Ratio PSO (FDR-PSO) and Fuzzy Adaptive-PSO (FA-PSO). First, the generating units are selected based on sensitivity to the over-loaded transmission line, and then these generators are rescheduled to remove the congestion in the transmission line. This paper also utilizes the demand response offers to solve the CM problem. The effectiveness of the proposed CM methodology is examined on the IEEE 30 bus and Indian 75 bus test systems.*

Keywords

Congestion management, demand response offers, Generation rescheduling, Meta-heuristic algorithms, Swarm intelligent algorithms.

1. Introduction

In the deregulated power system, the challenge of Congestion Management (CM) for the transmission system operator is to create a set of rules that ensure sufficient control over producers and consumers (generators and

loads) to maintain an acceptable level of power system security and reliability in both the short term (real time operation) and the long term (transmission and generation construction) while maximizing the market efficiency. The system is said to be congested when the producers and consumers of electric energy desire to produce in amounts that would cause the transmission system to operate beyond one or more transfer limits. Congestion has direct impact on security and reliability of the system. Discrete changes in system configuration may result, due to some contingency or outage rendering the system, into an unsecured state and make other lines to undergo congestion too, resulting in dynamic congestion. Congestion Management (CM), that is controlling the transmission system so that the transfer limits are observed, is perhaps the fundamental transmission management problem [1].

When a generator is a price taker, it can be shown that maximizing its profit requires bidding its incremental cost. When a generator bids other than its incremental costs in an effort to exploit imperfections in the market to increase profits, its behavior is called strategic bidding. If the generator can successfully increase its profits by strategic bidding or by any other means than the lowering costs, it is said to have market power and one of the main cause of market power is congestion. Various approaches have been presented in the literature for solving the CM problem. The general methods adopted to relieve the congestion involve the rescheduling of generator power outputs, providing the reactive power support, and curtail the load demands/transactions. Optimal Power Flow (OPF) based CM techniques are widely available in the literature [2].

A new Particle Swarm Optimization (PSO) technique to relieve the line congestion with minimum rescheduling cost of generators is proposed in [3].

A new CM strategy by generator rescheduling using the Cuckoo Search algorithm is proposed in [4] to minimize the rescheduling cost of generators. A CM approach in a deregulated electricity market using improved inertia weight PSO has been proposed in [5]. Reference [6] proposes a technique for optimum selection of participating generators using generator sensitivities to the power flow on congested lines and minimizes the deviations of rescheduled values of generator power outputs from the scheduled levels. Reference [7] proposes an Artificial Bee Colony algorithm which was inspired by intelligent foraging behavior of honeybee swarm to solve the CM problem based on the generator rescheduling. Reference [8] proposes a CM approach using the generator rescheduling and genetic algorithm to identify the minimum cost of rescheduling. Reference [9] proposes an approach to alleviate the transmission congestion by using rescheduling of the active and reactive power output of generators. Reference [10] proposes a transmission CM approach in a restructured market environment using a combination of demand response and Flexible Alternating Current Transmission System (FACTS) devices. A new CM framework considering the dynamic voltage stability boundary of power system is proposed in [11].

Reference [12] presents an exhaustive and critical review on the topic of CM. This review focuses on the conventional methods of CM. A multi-objective CM framework while simultaneously optimizing the competing objective functions of CM cost, voltage security, and dynamic security is proposed in [13]. A rescheduling CM based strategy in hybrid electricity market structure for a combination of hydro and thermal units is proposed in [14]. Reference [15] proposes a one-step methodology for CM of a hybrid power market that consists of a power pool and bilateral contracts between the market participants. A new CM method based on the voltage stability margin sensitivities is proposed in [16]. Reference [17] presents a price volatility optimization methodology capable of assessing demand response and willingness to pay factor in real time by tracing each load for its competency to retain its place in the market without/optimized curtailment. A methodology of real-time CM of MV/LV transformers is proposed in [18]. Reference [19] proposes a generation rescheduling-based approach for CM in electricity market using a novel ant lion optimizer algorithm. Reference [20] investigates how the demand management contracts can help the electricity sector in both regulated and deregulated environments. A demand-side based CM approach for managing transmission line congestion has been proposed in [21] for pool based electricity market model.

From the above literature, it is clear that the operational aspects of power systems pose some of the major challenging problems encountered in the restructured

power industry. The present paper focuses on the CM problem within an OPF framework in the restructured power market scenario. The objective of the conventional OPF problem is changed to include a mechanism which enables the electricity market players to compete and trade, while ensuring the system operation within the security limits. The motivation of this paper is to solve the CM problem by using the optimum rescheduling of generators and load demands. The participating generators are selected based on their sensitivity to the overloaded line, and then these generators are rescheduled to relieve the congestion in the transmission lines. The proposed CM problem is solved using the PSO, Fuzzy Adaptive PSO (FA-PSO) and Fuzzy Distance Ratio PSO (FDR-PSO) algorithms. The simulation results are performed on IEEE 30 and practical Indian 75 bus test systems.

The rest of the paper is organized as follows. Section 2. presents the Congestion Management (CM) problem formulation. The description of Swarm intelligent techniques (such as PSO, FA-PSO and FDR-PSO) are presented in Sec. 3. Section 4. presents the simulation results and discussion. Section 5. presents the contributions with concluding remarks.

2. Congestion Management (CM): Problem Formulation

There are two broad paradigms that may be employed to alleviate the congestion in the system. These are the cost-free and the not-cost-free paradigms [22]. The former includes actions like outaging of congested lines or operation of phase shifters, transformer taps, or FACTS devices. These means are termed as cost-free only because the marginal costs involved in their usage are nominal. The not-cost-free paradigm includes:

- *Generation Rescheduling:* This leads to generation operation at an equilibrium point away from the one determined by equal incremental costs. Mathematical models of pricing tools may be incorporated in the dispatch framework and the corresponding cost signals are obtained. These cost signals may be used for congestion pricing and as indicators for the market participants to rearrange their power injections/ extractions in order to avoid such congestion.
- *Prioritization and curtailment of loads/transactions:* A parameter termed as willingness-to-pay-to-avoid-curtailment was introduced in Reference [23]. This can be an effective instrument in setting the transaction curtailment strategies which may then be incorporated in the OPF framework.

These models can be used as part of a real-time open access system dispatch module [24]. The function of this module is to modify the system dispatch to ensure secure and efficient system operation based on the existing operating condition. It would use the schedulable resources and controls subject to their limits and determines the required curtailment of transactions to ensure uncongested operation of the power system [24].

Each generator in the power system has different sensitivity to the power flow in an overloaded/congested branch. A Generator Sensitivity (GS) to a line is described as the ratio of change in the active power flow in k^{th} transmission line connected between the buses i and j (i.e., ΔP_{ij}) due to the change in power generation by g^{th} generator (i.e., ΔP_g) [6], [7] and [8], and it is represented as:

$$GS_g = \frac{\Delta P_{ij}}{\Delta P_g}. \quad (1)$$

The generator sensitivity values are calculated considering the slack bus as reference. Therefore, the sensitivity of slack bus/slack generator to any congested transmission line in the system is always zero. Generators having the large and non-uniform values of sensitivities are selected for the participation in the CM by rescheduling their generation outputs. The basic power flow equation on congested line can be written as [6]:

$$P_{ij} = -V_i^2 G_{ij} + V_i V_j G_{ij} \cos(\theta_i - \theta_j) + V_i V_j B_{ij} \sin(\theta_i - \theta_j). \quad (2)$$

Neglecting the P-V coupling, the Eq. (1) can be expressed as:

$$GS_g = \frac{\partial P_{ij}}{\partial \theta_i} \frac{\partial \theta_i}{\partial P_g} + \frac{\partial P_{ij}}{\partial \theta_j} \frac{\partial \theta_j}{\partial P_g}. \quad (3)$$

In this paper, the CM problem is solved by considering the rescheduling of generating units, and also by using demand response offers provided by the load demands. The CM problem only by using the rescheduling of generating units is formulated as [6]:

minimize,

$$\sum_{g=1}^{N_g} C_p(\Delta P_g) \Delta P_g, \quad (4)$$

where $g = 1, 2, 3, \dots, N_g$. C_g is the incremental and decremental price bids submitted by the generating units. These are the electricity prices at which the generating units are willing to adjust their active power outputs.

The CM problem using the rescheduling of generating units and demand response offers is formulated as:

minimize,

$$\sum_{g=1}^{N_g} C_g(\Delta P_g) \Delta P_g + \sum_{k=1}^{N_D} C_k(\Delta P_{shd,k}) \Delta P_{shd,k}, \quad (5)$$

where $k = 1, 2, \dots, N_D$. The first term in the above objective function is the rescheduling cost of participating generators and it is expressed as [25]:

$$C_g(\Delta P_g) = a_g + b_g \Delta P_g + c_g \Delta P_g^2, \quad (6)$$

where a_i, b_i, c_i are the fuel cost coefficients of i^{th} generating unit. The second term is the demand response cost associated with the demand response offers provided by the load demands, and it is expressed as [25]:

$$C_k(\Delta P_{shd,k}) = a'_k + b'_k \Delta P_{shd,k} + c'_k \Delta P_{shd,k}^2, \quad (7)$$

where a'_k, b'_k, c'_k are the cost coefficients of demand response offers provided by the k^{th} load demand.

The above objective functions (i.e., Eq. (4) and Eq. (5)) are solved, subjected to the following constraints:

$$\sum_{i=1}^{N_g} [GS_g \Delta P_g] + F_l^0 \leq F_l^{\max}, \quad (8)$$

$$l = 1, 2, \dots, N_l,$$

where F_l^0 is the power flow caused by all contracts requesting the transmission line service. F_l^{\max} is maximum line flow limit of a transmission line connected between buses i and j .

$$(P_g - P_g^{\min} = \Delta P_g^{\min} \leq \Delta P_g \leq leq(\Delta P_g^{\max} = P_g^{\max} - P_g)), \quad (9)$$

where $g = 1, 2, 3, \dots, N_g$. P_g^{\max} and P_g^{\min} are maximum and minimum limits of generator power outputs. The power balance equation is expressed by using:

$$\sum_{i=1}^{N_g} \Delta P_g = 0. \quad (10)$$

The demand response offers provided by the k^{th} load demand are restricted by [25]:

$$0 \leq P_{shd,k} \leq P_{Dk} - \underline{P}_{Dk}, \quad (11)$$

$$K = 1, 2, \dots, N_d,$$

that is [26],

$$0 \leq P_{shd,k} \leq P_{shd,k}^{\max}, \quad (12)$$

$$K = 1, 2, \dots, N_d.$$

As mentioned earlier, in this paper, the proposed CM optimization problem is solved using the intelligent swarm techniques. The description of these techniques is presented below.

3. Swarm Intelligent Techniques

In this paper, Particle Swarm Optimization (PSO), FDR-PSO and FA-PSO are used to solve the CM problem. PSO is a population based stochastic optimization technique developed by Eberhart and Kennedy in 1995, inspired by social behavior of bird flocking or fish schooling [27]. PSO shares many similarities with evolutionary computation techniques like Genetic Algorithms (GAs). The system is initialized with a population of random solutions and searches for optimum by updating generations. In PSO, the particles fly through the problem space by following current optimum particles [28].

3.1. Particle Swarm Optimization (PSO)

PSO is initialized with a group of particles (solutions) and then searches for optimum through a number of generations. In each generation, each particle is updated by following two best stored values. First one is the best value that has seen so far, this is called p_{best} . Another best value tracked by the particle swarm optimizer is the best value obtained so far by any particle in the population, this is called as g_{best} . PSO procedures based on the above concept can be described as follows. Each particle tries to modify its position using the current velocity and the distance from p_{best} and g_{best} . The modification can be represented by the concept of velocity. Velocity of each particle can be modified by [29]:

$$V_k^{i+1} = V_k^i + c_1 r_1 (p_{best,k} - s_k^i) + c_2 r_2 (g_{best} - s_k^i). \quad (13)$$

Using the above equation, a certain velocity that gradually gets close to p_{best} and g_{best} can be calculated. The current position can be modified by using:

$$s_k^{i+1} = s_k^i + V_k^{i+1}. \quad (14)$$

This search procedure is called as Classical PSO. The work of PSO is explained with help of the flow chart shown in Fig. 1 [30].

Inertia weight parameter (ω): This parameter was introduced to improve the performance of the original PSO. This parameter plays the role in balancing the global and local search capability of PSO. It can be a positive constant or even a positive linear or non-linear function of time. A better chance of finding the global optimum within a reasonable number of iterations can be achieved by incorporating this parameter

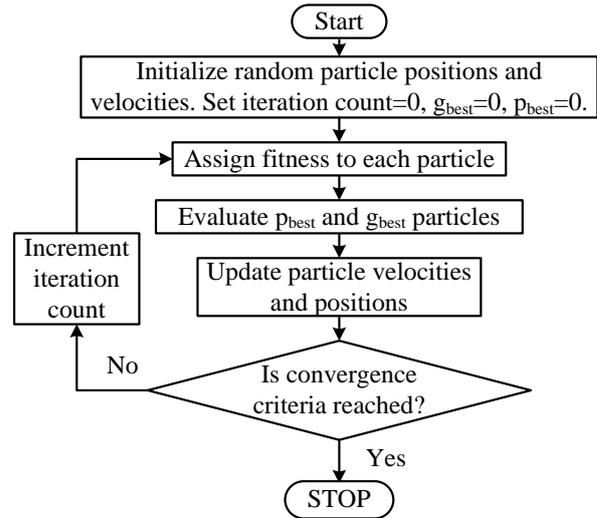


Fig. 1: Flow chart of PSO.

into the velocity update expression, and it is shown below:

$$V_k^{i+1} = \omega V_k^i + c_1 r_1 (p_{best,k} - s_k^i) + c_2 r_2 (g_{best} - s_k^i). \quad (15)$$

The typical values of ω are in the range [0.9, 1.2]. Equation (15) consists of three terms [27]. The first term is the inertia velocity of particle, which reflects the memory behavior of particle; the second and third parts are utilized to change the velocity of the particle. Particle velocities in each dimension are limited to a maximum velocity V_{max} whenever particle velocity exceeds V_{max} . V_{max} is usually specified by the user.

3.2. Fitness Distance Ratio PSO (FDR-PSO)

In the original PSO, each particle learns from its own experience and the experience of the most successful particle. From the literature, it has been proved that the particle positions in PSO oscillate in damped sinusoidal waves until they converge to points between their previous P_{best} and g_{best} positions. During this oscillation, if a particle reaches a point which has better fitness than its previous best position, then the particle continues to move towards the convergence of the global best position discovered so far. All the particles follow the same behavior to converge quickly to a good local optimum of the problem.

In the FDR-PSO algorithm, in addition to the Socio-cognitive learning processes, each particle also learns from the experience of neighboring particles that have a better fitness than itself. This approach results in change in the velocity update equation, although the position update equation remains unchanged. This al-

Tab. 1: Fuzzy IF/THEN Rules for the Inertia Weight (ω) Correction.

Rule Number	Antecedent Normalised Fitness (NIFT)	Inertia Weight (ω)	Consequent Inertia Weight Correction ($\Delta\omega$)
1	S (Small)	S (Small)	ZE (Zero)
2	S (Small)	M (Medium)	NE (Negative)
3	S (Small)	L (Large)	NE (Negative)
4	M (Medium)	S (Small)	PE (Positive)
5	M (Medium)	M (Medium)	ZE (Zero)
6	M (Medium)	L (Large)	NE (Negative)
7	L (Large)	S (Small)	PE (Positive)
8	L (Large)	M (Medium)	ZE (Zero)
9	L (Large)	L (Large)	NE (Negative)

gorithm outperforms PSO and many of the recent improvements of the PSO algorithm on many benchmark problems, while being less susceptible to premature convergence [31]. It selects only one other particle at a time when updating each velocity dimension and that particle is chosen to satisfy the following two criteria:

- It must be near the current particle.
- It should have visited a position of higher fitness.

The simplest way to select a nearby particle that satisfies the above mentioned two criteria is to maximize the ratio of the fitness difference to the one-dimensional distance. In other words, the d_{th} dimension of the i_{th} particle’s velocity is updated using a particle called the n_{best} , with prior best position P_j . It is necessary to maximize the Fitness Distance Ratio (FDR), and it is expressed as [31]:

$$FDR = \frac{cost(P_j) - cost(s_i)}{|P_{id} - s_{id}|} \tag{16}$$

In FDR-PSO algorithm, the particle’s velocity update is influenced by the following three factors:

- Previous best experience i.e. P_{best} of the particle.
- Best global experience i.e. g_{best} , considering the best P_{best} of all particles.
- Previous best experience of the “best nearest” neighbor i.e. n_{best} .

Hence, the new velocity update equation becomes:

$$V_{id}^{k+1} = \omega V_{id}^k + c_1 rand_1 (P_{id} - s_{id}) + c_2 rand_2 (P_{gid} - s_{id}) + c_3 rand_3 (P_{nd} - s_{id}) \tag{17}$$

The position update equation remains the same as in Eq. (14).

3.3. Fuzzy Adaptive PSO (FA-PSO)

Fuzzy Adaptive PSO (FA-PSO) [32] is developed to design a fuzzy system to dynamically adapt the inertia

weight (Ω) for the CM problem. Table 1 presents the Fuzzy IF/THEN rules. Equation (19), Eq. (20) and Eq. (21) are used for the proposed FA-PSO algorithm.

To get a better Ω under fuzzy environment, the inputs i.e., fitness of current inertia weight, current location (i.e., solution); and the output: correction of inertia weight ($\Delta\Omega$) are required to represent in fuzzy set notations. All membership functions are considered in triangular shape, and they are expressed in 3 linguistic variables (S, M and L) for ‘Small’, ‘Medium’ and ‘Large’, respectively, as shown in Fig. 2. The values of X_S , X_M and X_L are selected from the previous experience. As mentioned earlier, it is most difficult to form a crisp mathematical model for the adaptive PSO to change the inertia dynamically. Therefore, a simple IF/THEN rules are suitable to determine $\Delta\Omega$ in the FA-PSO process.

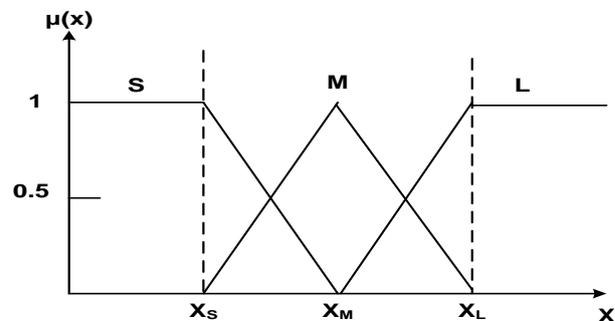


Fig. 2: Triangular membership function.

Normalized Fitness: The fitness of current solution (i.e., location) is the most important to predict ω for the right choice of velocity. Here, we used Normalized Fitness (NFIT) value as an input to bound the limit between 0 & 1. Normalized Fitness (NFIT) is defined as:

$$NFIT = \frac{TC - TC_{min}}{TC_{max} - TC_{min}} \tag{18}$$

In the minimization problems, minimum value of NFIT denotes a better solution. In the FA-PSO algorithm, Total Cost (TC) from Eq. (4) and Eq. (5) at first iteration may be used as TC_{max} for the next iterations. Only the least cost generator with unlimited

power limits and without considering the constraints is used to determine the TC_{\min} that satisfies the demand.

Inertia Weight: Inertia weight (ω) is between 0.4 & 1. This range is fitted to the shape of triangular membership function.

Current Inertia Weight Correction ($\Delta\omega$): We require both negative and positive corrections for ω . The change in inertia weight ($\Delta\omega$) is described in three linguistic variables (NE, ZE and PE) for ‘Negative’, ‘Zero’ and ‘Positive’ corrections instead of (S, M and L). The selected range for $\Delta\omega$ is between -0.1 to 0.1 .

IF/THEN Rules and Defuzzification: The simple IF/THEN rules for the inertia weight correction are presented in Tab. 1. There are 9 rules (3×3) for 2 input variables and 3 linguistic variables for every input variable. Generally, the fuzzy control inputs are crisp. Utilizing the arithmetic product, the degrees of fulfillment of the rules that are activated in Tab. 1, are determined. For every rule, the output (fuzzy $\Delta\omega$) is scaled in accordance with the DOF [32]. The final output value is the arithmetic sum of results obtained from activated rules. By using the Centriod Method, the final output is defuzzified to a crisp value ($\Delta\omega$).

$$\omega_{ij} = \omega_{ij} + \Delta\omega_{ij}, \quad (19)$$

$$v_{ij} = \omega_{ij} \cdot v_{ij} + c_1 \cdot \text{rand} \cdot (p_{bestij} - s_{ij}) + c_2 \cdot \text{rand} \cdot (g_{bestj} - s_{ij}), \quad (20)$$

$$s_{ij} = s_{ij} + v_{ij}, \quad (21)$$

Binding Fitness: Fitness is an index which is used to determine the superiority of an individual in the swarm. Generally, the objective function is considered as the fitness function and inequality constraints are changed to penalty terms, and these are added to the objective function. The main drawback of this approach is that the best particle/individual can be misjudged as inappropriate for the penalty factors. However, usually, the penalty factors are assigned by an empirical method and are deeply affected by the problem model. To overcome this drawback, a binary fitness has been used; one for the optimum objective function and the other for binding constraints. Optimal objective fitness is equal to the value of Eq. (4) or Eq. (5), which describes the active power rescheduling cost, therefore the congestion cost, i.e., the cost to relieve the congestion. The fitness value of binding constraints is used to scale the level of violation, and is calculated using:

$$\text{Binding Fitness } (Z) = \begin{cases} Z_{\min} - Z & \text{if } Z_{\min} < Z, \\ Z - Z_{\max} & \text{if } Z > Z_{\max}, \\ 0 & \text{otherwise,} \end{cases} \quad (22)$$

where Z is value of inequality constraint. Z_{\min} and Z_{\max} are minimum and maximum limits of inequality constraints.

4. Results and Discussion

In this paper, IEEE 30 [33] and practical Indian 75 bus [34] test systems are selected to show the effectiveness and the suitability of the proposed algorithms applied to solve the CM problem. The parameters selected for PSO are: swarm/population size is 60, acceleration constants C_1 and C_2 are 2, maximum number of generations is 500, maximum and minimum limits of inertia weight are 0.9 and 0.1, respectively.

4.1. Simulation Results on IEEE 30 Bus Test System

IEEE 30 bus test system [33] consists of 6 generating units, 24 load demands and 41 branches. It should be noted, that the obtained generator sensitivity values are the reference with respect to the slack bus. Therefore, the sensitivity of the slack bus generator to any congested line in the system is always zero. Here, two case studies are performed, one is based on only generation rescheduling, and the other one is based on both generators and load demands rescheduling. These case studies are presented further:

1) Case 1: CM Based on Optimal Rescheduling of Generators

In this case, only the participating generators are considered to be rescheduled to alleviate the congestion in the system. The generator sensitivity factors for this system are depicted in Fig. 3. Generators which are participating in the CM are selected depending upon their sensitivity to the overloaded/congested line. In IEEE 30 bus system, all the generating units have nearly same sensitivity to the line because it is a small system. Here, the slack bus is selected by default as it is the reference bus.

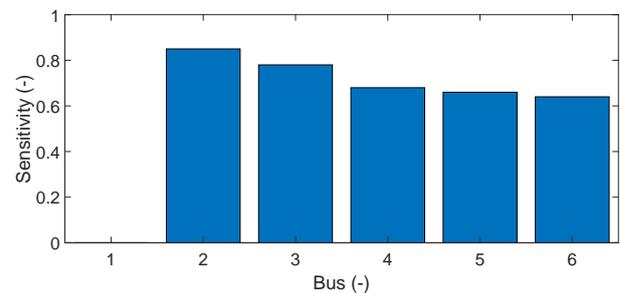


Fig. 3: Sensitivity factors of generators for line 1 in IEEE 30 bus system.

In this case study, the system is over-loaded by 19 % to perform the CM. The scheduled power generation at each selected bus before and after the CM is presented in Tab. 2.

Tab. 2: Scheduled power generation before and after the CM for IEEE 30 bus system.

Scheduled Generation	Before the CM	After the Congestion Management (CM)		
	Original	PSO	FA-PSO	FDR-PSO
P_{G1} (MW)	138	164.36	163.78	162.76
P_{G2} (MW)	57.56	68.36	66.23	69.90
P_{G5} (MW)	24.56	22.88	15.38	24.76
P_{G8} (MW)	35	34.42	34.90	34.86
P_{G11} (MW)	17.93	19.93	24.01	20.45
P_{G13} (MW)	16.91	22.05	20.09	17.24

Figure 4 depicts the scheduled power generation in per unit values before and after the CM using the PSO, FDR-PSO and FA-PSO.

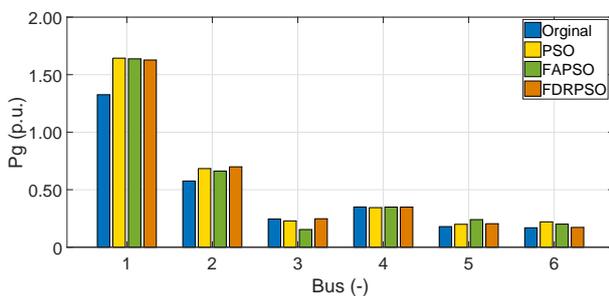


Fig. 4: Scheduled active power generation in p.u. before and after the CM in IEEE 30 bus system.

The simulation results after performing the CM are presented in Tab. 3, Tab. 4 and Tab. 5. Table 3 presents the line flows in a congested line in MVA before and after the CM. From Tab. 3, it can be seen that the power flow in a line connected between buses 1 and 2 before the CM is 132.6 MVA (but the maximum line flow limit is 130 MVA), whereas after the CM using PSO, FA-PSO and FDR-PSO algorithms are 125.89 MVA, 129.47 MVA and 126.34 MVA, respectively.

Tab. 3: Line flow in the congested line before and after the CM for Case 1.

Overloaded line flows (in MVA)	Before the CM	After the CM		
		PSO	FA-PSO	FDR-PSO
Line 1 (between buses 1 and 2)	132.6	125.89	129.47	126.34

Table 4 presents the optimum cost, execution time per iteration, total system losses and slack bus power for IEEE 30 bus test system. The minimum operating cost obtained using the PSO, FDR-PSO and FA-PSO algorithms are 956.85 \$/hr, 950.92 \$/hr and 931.34 \$/hr, respectively. The execution time per generation for PSO, FA-PSO and FDR-PSO are 0.00487 s, 0.01658 s and 0.00393 s, respectively. Table 5 presents the active and reactive flows in the congested line before and after the CM.

Tab. 4: Optimum cost, time per iteration, losses and slack bus power after the CM for IEEE 30 bus system.

	PSO	FA-PSO	FDR-PSO
Best Cost (\$/MWh)	956.85	931.34	950.92
Worst Cost (\$/MWh)	988.94	952.36	977.43
Mean Cost (\$/MWh)	962.41	940.48	958.63
Time per Iteration (s)	0.00487	0.01658	0.00393
Total System Losses (MW)	13.98	13.92	13.96
Slack Bus Power (MW)	183.36	190.57	184

Tab. 5: Active and reactive power flows in the congested line before and after the CM.

Line No.	Before the CM		After the CM using PSO	
	Active power flow (P_{ij}) (MW)	Reactive power flow (Q_{ij}) (MVAR)	Active power flow (P_{ij}) (MW)	Reactive power flow (Q_{ij}) (MVAR)
1	128.87	24.25	109.57	60.68

The above simulation results clearly indicate that FA-PSO provides us with best solution since the costs and losses in the system are lower when compared to PSO and FDR-PSO.

2) Case 2: CM Based on Optimal Rescheduling of Generators and Demand Response Offers

As mentioned earlier, in this sub-section both generators and load demands are rescheduled to alleviate the congestion in the system. In this case study, the system load has been increased to 145 % to create the congestion in the system. IEEE 30 bus system has 6 generating units and 21 load demands. In this paper, it is assumed that the System Operator (SO) receives the generator bids and demand response/load shedding offers from customers to perform the CM analysis [26]. In this case study, it is assumed that the amount of load shed at i^{th} bus cannot be more than 30 % of load demand at that bus.

Table 6 presents the optimal generation schedules before and after the CM analysis for Case 2 using PSO, FA-PSO and FDR-PSO algorithms. The line flows in the congested lines before and after the CM are presented in Tab. 7. In this case, the transmission lines 1, 10 and 18 are overloaded/congested, and their power flows are 143.13 MVA, 43.82 MVA and 36.08 MVA, respectively. Whereas, the maximum power flow limits of lines 1, 10 and 18 are 130 MVA, 32 MVA and 32 MVA, respectively. To overcome this situation, generation rescheduling and demand response are used.

By using this, the congestion in the system has been removed, and the power flows after the CM are presented in Tab. 7.

Tab. 6: Scheduled power generations before and after the CM for IEEE 30 bus system (for Case 2).

	PSO	FA-PSO	FDR-PSO
Best Cost (\$/MWh)	956.85	931.34	950.92
Worst Cost (\$/MWh)	988.94	952.36	977.43
Mean Cost (\$/MWh)	962.41	940.48	958.63
Time per Iteration (s)	0.00487	0.01658	0.00393
Total System Losses (MW)	13.98	13.92	13.96
Slack Bus Power (MW)	183.36	190.57	184

Tab. 7: Line flow in the congested line before and after the CM for Case 1.

Overloaded line flows (in MVA)	Before the CM	After the CM		
		PSO	FA-PSO	FDR-PSO
Line 1 (between buses 1 and 2)	143.18	128.36	128.54	127.93
Line 10 (between buses 9 and 4)	43.82	31.40	31.82	31.57
Line 18 (between buses 13 and 15)	36.08	30.11	30.84	29.98

As mentioned earlier, in this paper, the CM has been performed by using the PSO, FDR-PSO and FA-PSO algorithms. Optimum total cost and losses obtained after the CM are presented in Tab. 8. The optimum costs obtained by using PSO, FDR-PSO and FA-PSO algorithms are 1413.7 \$/hr, 1412.4 \$/hr and 1408.5 \$/hr, respectively.

Tab. 8: Optimum total cost and losses obtained after the CM for IEEE 30 bus system (for Case 2).

Scheduled Generation	Before the CM	After the Congestion Management (CM)		
		Original	PSO	FA-PSO
P_{G1} (MW)	138	164.36	163.78	162.76
P_{G2} (MW)	57.56	68.36	66.23	69.90
P_{G5} (MW)	24.56	22.88	15.38	24.76
P_{G8} (MW)	35	34.42	34.90	34.86
P_{G11} (MW)	17.93	19.93	24.01	20.45
P_{G13} (MW)	16.91	22.05	20.09	17.24

4.2. Simulation Results on Practical Indian 75 Bus Test System

The Indian 75 bus system [34] has 97 branches, 15 generators, 24 transformers and 12 shunt reactors. The generator sensitivity factors for this system are depicted in Fig. 5. The generating units which participate in the CM are selected depending upon their sensitivity to the overloaded line.

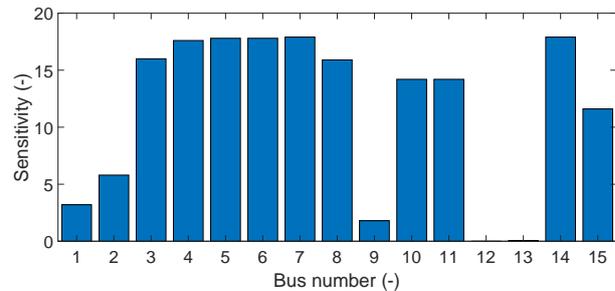


Fig. 5: Generator sensitivity factors for line 71 in practical Indian 75 bus test system.

In practical Indian 75 bus system, 11 out of 15 generators are selected for participation in the CM problem. Here, the slack bus is selected by default as it is the reference bus. Power generated at each selected bus before and after the CM is shown in Tab. 9.

Tab. 9: Active power output before and after the congestion management for Indian 75 bus system.

Scheduled Generation	Before the CM	After the Congestion Management (CM)		
	Original	PSO	FA-PSO	FDR-PSO
P_{G3} (MW)	192	177	180	193
P_{G4} (MW)	117	96	100	91
P_{G5} (MW)	176	196	180	198
P_{G6} (MW)	97	105	120	108
P_{G7} (MW)	70	57	60	92
P_{G8} (MW)	75	97	80	90
P_{G10} (MW)	102	74	80	69
P_{G11} (MW)	123	125	109	109
P_{G14} (MW)	133	140	150	130
P_{G15} (MW)	442	452	454	443

Indian 75 bus system is already overloaded as line 71 is congested. The simulation results after performing the CM are shown in Tab. 10 and Tab. 11. The power

Tab. 10: Line flow in the overloaded line before and after the CM for Indian 75 bus system.

Overloaded line flows (in MVA)	Before the CM	After the CM		
		PSO	FA-PSO	FDR-PSO
Line 1 (between buses 1 and 2)	132.6	125.89	129.47	126.34

Tab. 11: Cost, time per iteration, losses and slack bus power after the CM for Indian 75 bus system.

	PSO	FA-PSO	FDR-PSO
Best Cost (in R_s /MWh)	5189.47	5075.44	5189.1
Worst Cost (in R_s /MWh)	5243.81	5133.08	5213.77
Mean Cost (in R_s /MWh)	5203.92	5098.34	5198.36
Time per Iteration (s)	2.12	2.24	1.96
Total System Losses (MW)	207.82	205.11	206.67
Slack Bus Power (in MW)	1793.98	1788.78	1792.84

flow in the transmission line connected between buses 26 and 41 before the CM is 401.65 MW, whereas after the CM using the PSO, FA-PSO and FDR-PSO is 398.9 MW, 397.56 MW and 398.67 MW, respectively. The optimum cost obtained using the PSO, FDR-PSO and FA-PSO is 5189.47 R_s MWh, 5189.1 R_s MWh and 5075.44 R_s MWh, respectively. However, the execution time per generation for PSO, FA-PSO and FDR-PSO algorithms is 2.12 s, 2.24 s and 1.96 s, respectively.

From the above simulation results on IEEE 30 bus and Indian 75 bus systems, it can be observed that FA-PSO algorithm provides us with best solution since the costs and losses in the system are lower when compared to PSO and FDR-PSO algorithms. But, the FDR-PSO algorithm takes less time to find a solution. FA-PSO takes more time as it has to solve the fuzzy logic block for each iteration.

5. Conclusion

Congestion Management (CM) using the optimal rescheduling of active power generation and load demands/demand response with Particle Swarm Optimization (PSO), Fitness Distance Ratio-PSO (FDR-PSO) and Fuzzy Adaptive-PSO (FA-PSO) algorithms has been solved in this paper. Here, the generator rescheduling is performed by taking into account the minimization of generation scheduling cost while satisfying all the line flow limits. Generators are selected in accordance with their sensitivity to the overloaded transmission line. The CM problem is modelled as an optimization problem, and it is solved by using the PSO, FDR-PSO and FA-PSO. The proposed CM methodology is implemented on IEEE 30 bus and practical Indian 75 bus test systems. The simulation results show that the FA-PSO gives optimum cost when compared to other swarm intelligent algorithms, whereas FDR-PSO takes lesser computational time to solve this CM problem.

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Appendix A Nomenclature

Tab. 12: Nomenclature.

P_g	Active power output of generator g
P_{ij}	Power flow on congested line ' k ' connected between the bus i and bus j
$P_{shd,k}$	Amount of demand response provided by the k^{th} load demand
V_i, θ_i	Voltage magnitude and phase angle at i^{th} bus
G_{ij}, B_{ij}	Conductance and susceptance of the line connected between the buses i and j
N_g	Number of participating generators
N_D	Number of loads/demands
N_l	Number of transmission lines
ΔP_g	Active power adjustment of generator g
P_{Dk}	Lower bound on the decreased or curtailed level of power consumption
P_{Dk}	Power demand from k^{th} load demand
$P_{shd,k}^{\max}$	Maximum amount of load shed by k^{th} load
P_{nd}	Nearby particle which has better fitness
c_1, c_2	Constants
r_1, r_2	Random numbers between 0 and 1