32 Journal of Electrical Engineering & Technology Vol. 6, No. 1, pp. 32~41, 2011
DOI: 10.5370/JEET.2011.6.1.032

Fuzzy PSO Congestion Management using Sensitivity-Based Optimal Active Power Rescheduling of Generators

Ch Venkaiah† and D M Vinod Kumar*

Abstract – This paper presents a new method of Fuzzy Particle Swarm Optimization (FPSO)-based Congestion Management (CM) by optimal rescheduling of active powers of generators. In the proposed method, generators are selected based on their sensitivity to the congested line for efficient utilization. The task of optimally rescheduling the active powers of the participating generators to reduce congestion in the transmission line is attempted by FPSO, Fitness Distance Ratio PSO (FDR-PSO), and conventional PSO. The FPSO and FDR-PSO algorithms are tested on the IEEE 30-bus and Practical Indian 75-bus systems, after which the results are compared with conventional PSO to determine the effectiveness of CM. Compared with FDR-PSO and PSO, FPSO can better perform the optimal rescheduling of generators to relieve congestion in the transmission line.

Keywords: Congestion Management, Generator Sensitivity, PSO, FPSO, FDR-PSO

1. Introduction

A system is said to be congested when producers and consumers of electric energy desire to produce and consume in amounts that would cause the transmission system to operate at or beyond one or more transfer limits [1]. The principal challenge faced by the Independent System Operator (ISO) in a deregulated environment is to maintain the security and reliability of the power system by maximizing market efficiency when the system is congested. The ISO, therefore, has to create a set of transparent and robust rules that should not encourage aggressive entities to exploit congestion to create market power and maximize profits at the cost of the market. Congestion in a transmission system cannot be allowed beyond a short duration because this could lead to cascading outages with uncontrolled loss of load.

There are several methods to relieve congestion, such as using Flexible AC Transmission Systems (FACTS) devices [2], tapping transformers, re-dispatching power generation [3], and curtailing pool loads and/or bilateral contracts. In a deregulated environment, all the Generating Companies (GENCOs) and Distribution Companies (DISCOs) plan their transactions ahead of time. However, by the time of implementation of transactions, congestion may already be present in some of the transmission lines. Hence, ISO has to relieve the congestion so that the system remains in a secure state. ISO mainly uses two types of techniques to relieve congestion. These are listed below.

† Corresponding Author: Department of Electrical Engineering, National Institute of Technology, Warangal - 506 004 Andhra Pradesh, India. (ch.venkaiah@gmail.com)
* Department of Electrical Engineering, National Institute of Technology, Warangal - 506 004 Andhra Pradesh, India. (vinodkumar.dm@gmail.com)
Received: May 5, 2010; Accepted: July 25, 2010

i) Cost free means
  a. Out-aging of congested lines
  b. Operation of transformer taps/phase shifters
  c. Operation of FACTS [2] devices, particularly series devices
ii) Non-Cost free means
  a. Re-dispatching power generation [3] in a manner different from the natural settling point of the market. Some generators back down, while others increase their output. Consequently, generators no longer operate at equal incremental costs.
  b. Curtailment of loads and the exercise of (non-cost-free) load interruption options.

In this paper, Static Congestion Management by optimal rescheduling of active generator power selected based on their sensitivities to the congested line is attempted using Fuzzy Particle Swarm Optimization (FPSO) and Fixed Distance Ratio PSO (FDR-PSO). Test results are then compared with conventional PSO. This approach of relieving congestion in the transmission line is quite efficient because it is a non-cost free means technique.

Christie et al. [1] in a study on Congestion Management (CM) has stated that controlling the transmission system so that transfer limits are observed is perhaps the fundamental transmission management problem. Fang et al. [4] considered an open transmission dispatch environment, in which pool and bilateral / multi lateral dispatches co-exist, and proceeded to develop a congestion management strategy for this scenario. Lo et al. [5] have presented congestion management techniques applied to various kinds of electricity markets. Ashwani Kumar et al. [6] have extensively reviewed literature reporting several techniques of congestion management and posited that congestion management is one of the major tasks of an ISO to ensure the operation of transmission system within operating limits. In the emerging electric power markets, congestion management has become extremely important as it can impose a barrier to electricity trading. Ashwani Kumar et al. [7] have proposed an efficient zonal congestion management approach using real and reactive power rescheduling based on AC Transmission Congestion Distribution factors considering the optimal allocation of reactive power resources. The impact of optimal rescheduling of generators and capacitors has been demonstrated in congestion management. Yamina et al. [8] have described a coordinating mechanism between generating companies and system operator for congestion management using Benders cuts. Capitanesu et al. [9] proposed two approaches for the unified management of congestions brought about by voltage instability and thermal overload in a deregulated environment. Fu et al. [10] discussed a combined framework for service identification and congestion management, in which a new approach has been applied to identify the services of reactive support and real power loss for managing congestion using upper bound cost minimization. Kennedy et al. [11] have described the PSO concept in terms of its precursors, briefly reviewed the stages of its development from social simulation to optimizer, and discussed the application of the algorithm to the training of artificial neural network weights. Meanwhile, Shi [12] surveyed the research and development of PSO in five categories, including algorithms, topology, parameters, hybrid PSO algorithms, and applications. The search process of a PSO algorithm should consist of both contraction and expansion so that it would have the ability to escape from local minima, eventually finding good solutions. On the other hand, Valle et al. [13] presented a detailed review of the PSO technique, the basic concepts and different structures and variants, as well as its applications to power system optimization problems. Chen et al. [14] introduced PSO for solving Optimal Power Flow (OPF), with which CM in the pool market is practically implemented on an IEEE 30-bus system; they have also proven that congestion relief using PSO is more effective compared with the Interior Point Method and Genetic Algorithm approach. Hazra et al. [15] have proposed a cost efficient generation rescheduling and/or load shedding approach for congestion management in transmission grids using Multi Objective Particle Swarm Optimization (MOPSO) method. Dutta et al. [3], meanwhile, proposed a technique for reducing the number of participating generators and optimum rescheduling of their outputs while managing congestion in a pool at minimum rescheduling cost; they also explored the ability of PSO technique in solving the congestion management problem. Vinod Kumar et al. [2] have obtained an optimal solution for static congestion management using the PSO-based OPF method. In their study, congestion has been created in the transmission line by loading the lines; this is then relieved by placing a Static Synchronous Series Compensator (SSSC) in an optimal location in the transmission line. Jeyakumar et al. [16] demonstrated the successful adaptation of the PSO algorithm to solve various types of economic dispatch (ED) problems in power systems, including Multi-Area ED with tie line limits, ED with multiple fuel options, Combined Environmental ED, and ED of Generators with prohibited operating zones. That their proposed PSO technique has better computation efficiency and convergence property demonstrates that it can be applied to a wide range of optimization problems. Gaing [17] has proposed a PSO method for solving the ED problem with the generator constraints and demonstrated that the PSO method can prevent premature convergence of the Genetic Algorithm (GA) method while obtaining higher quality solution with better computation efficiency and convergence property. In their work, Peram et al. [18] proposed the Fitness Distance Ratio PSO (FDR-PSO) algorithm, which combats the problem of premature convergence observed in many applications of PSO. It is accomplished by using the ratio of the relative fitness and the distance of other particles to determine the direction in which each component of the particle position needs to be changed. The FDR-PSO algorithm has performed significantly better than the original PSO algorithm and some of its variants on many different benchmark optimization problems. Gnanadass et al. [19] presented an application of the FDR-PSO algorithm to determine the optimal generation dispatch of power producers with dynamic security constraints and computed Dynamic Available Transfer Capability (DATC) for a practical Indian system with changing loads. Shi et al. [20] implemented a fuzzy system to dynamically adapt the inertia weight of the PSO algorithm; they demonstrated that the Fuzzy Adaptive PSO (FAPSO) is a promising optimization method for optimization problems within a dynamic environment. Saber et al. [21] proposed the FAPSO algorithm for the Unit Commitment (UC) problem, which is capable of tracking a continuously changing solution in a reliable and accurate manner. The fuzzy adaptive criterion is applied for the PSO inertia weight based on the diversity of fitness. Inertia weight is dynamically adjusted using fuzzy IF/THEN rules to increase the balance between global and local searching abilities.

In the literature survey on various approaches to congestion management, it can be observed that no researcher has made an attempt to dynamically adjust the inertia weight of the PSO for optimal rescheduling of the active powers of the participating generators by applying fuzzy criterion to inertia weight of the PSO in relieving congestion in the congested line. Further, no attempt has been made to learn from the experience of neighboring particles that have a better fitness value than the selected particle of PSO for updating the velocity of the particle to relieve congestion by effective rescheduling of active power of the generators. To incorporate innovation into congestion management, two new approaches, i.e., FPSO and FDR-PSO, are attempted to relieve congestion in the congested line by optimal rescheduling of active generator power.

Instead of selecting all the generators to relieve congestion, this paper proposes the selection of participating generators using generator sensitivities to the power flow on congested lines. Further, it is expected to solve the congestion management problem by optimal rescheduling of the active power of participating generators employing evolutionary algorithms, including FPSO and FDR-PSO. Subsequently, these two evolutionary algorithms are compared with the conventional PSO algorithm to test which among them gives the best optimal solution for rescheduling the active power of participating generators in order to relieve the congestion. This paper illustrates the effectiveness of the proposed methods on the congestion management problem using the IEEE 30-bus and the Practical Indian 75-bus systems.

This paper is organized as follows. Section II gives an insight into the evolutionary algorithms, such as FPSO and FDR-PSO. Section III details the problem formulation of CM by rescheduling the active power in participating generators; these have been selected based on their sensitivities with the congested line power flow and the methodology of implementation of the evolutionary algorithms. The effectiveness of these algorithms on the IEEE 30-bus and Practical Indian 75-bus systems is illustrated in Section IV. The conclusions are presented in Section V.

2. Proposed Evolutionary Algorithms

2.1 Fuzzy PSO

The velocity in the conventional PSO is constantly adjusted according to the corresponding particle's experience and that of the particle's companion. It is expected that the particles will move towards better solution areas. Mathematically, the particles are manipulated according to the following equations:

$$v_{id} = w * v_{id} + c_1 * rand(\ ) * (p_{id} - x_{id}) + c_2 * Rand(\ ) * (p_{gd} - x_{id}) \quad (1)$$

and

$$x_{id} = x_{id} + v_{id} \quad (2)$$

where c_1 and c_2 are positive constants; rand() and Rand() are two random functions in the range [0,1]; w is the inertia weight; $X_i = (x_{i1}, x_{i2} ... x_{id})$ represents the i^{th} particle; $P_i = (p_{i1}, p_{i2}, ..., p_{id})$ represents the best previous position (the position giving the best fitness value) of the i^{th} particle; g represents the index of the best particle in the population; and $V_i=(v_{i1}, v_{i2}, ... v_{id})$ represents the rate of the positive change (velocity) for particle i.

The balance between global and local search throughout the course of the run is critical to the success of an evolutionary algorithm. In PSO, inertia weight is used to balance the global and local search abilities. A large inertia weight facilitates a global search, while a smaller one facilitates a local search.

By changing the inertia weight, the search ability can be dynamically adjusted. For designing a mathematical model to adopt the inertia weight, the fuzzy system is a good candidate to tune the inertia weight of PSO. Given that inertia weight is a global variable in Equation (1), and it is applied to the entire population, a fuzzy system to adopt inertia weight dynamically is designed by taking variables that measure the performance of the PSO and the inertia weight as the inputs and change of the inertia weight as the output of the system.

To obtain better inertia weight under fuzzy environment, inputs (i.e., fitness of the current location and the current inertia weight) and outputs (i.e., correction of inertia weight) should all be expressed in fuzzy set notations. In this study, all the membership functions are triangular for simplicity; they are presented in three linguistic values (S, M, and L) for "Small," "Medium," and "Large," respectively. Simple plain-language IF/THEN rules are considered in calculating the amount of inertia weight correction in the fuzzy PSO process.

The fuzzy PSO aims to design a fuzzy system to dynamically adapt the inertia weight for the CM problem. The fuzzy IF/ THEN rules in Table 1 are used for the proposed fuzzy PSO method.

Table 1. Fuzzy Rules for inertia weight correction

W \ *NFIT*	S	M	L
S	ZE	PE	PE
M	NE	ZE	ZE
L	NE	NE	NE

S: Small; M: Medium; L: Large;
NE: Negative; PE: Positive; ZE: Zero

Normalized Fitness (NFIT): The fitness of the current solution (location) is very important in predicting the inertia weight for the right choice of velocity. Normalized fitness value is used as input to bind the limit between 0 and 1 as expressed by:

$$NFIT = \frac{C_{Cost} - C_{Cost_{min}}}{C_{Cost_{max}} - C_{Cost_{min}}} \quad (3)$$

In case of minimization problems, a lower NFIT value indicates a better solution. In the FPSO model, C_{Cost} from (12) at the first iteration may be used as $C_{Cost\text{-}max}$ for the next iterations. Only the cheapest unit with unlimited generation limits and without consideration for the constraints may be used to calculate the $C_{Cost\text{-}min}$ that satisfies the load demand.

Current inertia weight: Using inertia weight (w) is one of the most popular strategies for tuning the FPSO parameters. The value of the parameter *w* is large at the beginning of the search process and gradually becomes small as the iterations increase. Hence on the universe of discourse, range is selected between 1 (maximum) and 0.4 (minimum).

Current inertia weight correction: The change in inertia weight (Δw) requires both positive and negative corrections. To incorporate these, three linguistic variables, "Negative," "Zero," and "Positive" (NE, ZE and PE) are considered. Therefore, nine (3X3=9) fuzzy rules can be designed from Table 1; these are sufficient for fuzzification of the change in inertia weight (Δw). As the number of fuzzy rules increases, the complexity of the problem also increases. In this paper, (-0.1, +0.1) is considered on the universe of discourse because inertia weight correction (Δw) is small and requires both positive and negative corrections.

IF/THEN rules and defuzzification: Simple IF/THEN rules are shown in Table 1, which shows (3x3=9) possible rules for two input variables and three linguistic values of each input variable. Fuzzy control inputs are usually crisp. The degrees of fulfillment (DOF) of the rules that have been fired (Table 1) are evaluated using arithmetic product. For each rule, output (fuzzy inertia weight correction) is transformed (scaled) in accordance with DOF. The total output is the union of the results from the fired rules. Finally, the total output is defuzzified to a crisp value (Δw) using the centroid method as presented by:

$$w_{id} = w_{id} + \Delta w_{id} \,, \tag{4}$$

$$v_{id} = w_{id} * v_{id} + c_1 * rand(\ ) * (p_{id} - x_{id}) + c_2 * Rand(\ ) * (p_{gd} - x_{id}) \tag{5}$$

and

$$x_{id} = x_{id} + v_{id} \tag{6}$$

Binding Fitness: Fitness is an index used to evaluate the superiority of the particle. Traditionally, the objective function is regarded as the fitness function; the inequality constraints are converted to penalty functions and are then added to the objective function. One drawback, however, is that an excellent particle can be misjudged as inappropriate for the penalty factors. In addition, penalty parameters are usually assigned by empirical approach and are deeply affected by the problem model. To avoid this predicament, binary fitness has been used: one for the optimal objective and the other for the binding constraints. Optimal objective fitness is equal to the value of the expression (12), which represents the cost of active power rescheduling, and hence, the cost acquired to curb congestion or congestion cost. Binding constraints fitness value is adopted to scale the level of violation and can be calculated by:

$$IE_{ineqoon\_i}(ic) = \begin{cases} ic_{min} - ic & ic < ic_{min} \\ ic - ic_{max} & ic > ic_{max} \\ 0 & others \end{cases} , \tag{7}$$

where ic is the value of the inequality constraint, and ic_{max} and ic_{min} are the maximum and minimum limits of the inequality constraints, respectively. The fitness to the binding constraints of the particles are considered first, and a particle is regenerated if it does not satisfy the binding constraints. This generates feasible particles that guarantee the fulfillment of binding constraints that are superior to infeasible particles violating such constraints. Thus, entering into feasible region is considered before obtaining the global optimal solution, and there is no need to set up the penalty parameter.

2.2 Fitness Distance Ratio PSO

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 better fitness than itself. This changes the velocity update equation, although the position update equation remains unchanged. It selects only a single other particle at a time when updating each velocity dimension; this particle is chosen to satisfy the following two criteria:

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

The simplest way to select a nearby particle, which satisfies the criteria, is to maximize the ratio of the fitness difference to the one-dimensional distance. In other words, the d^{th} dimension of the velocity of the i^{th} particle is updated using a particle called the n_{best} with prior best position p_j. It is necessary to maximize the following FDR, which is given by:

$$\frac{Cost(p_j) - Cost(x_i)}{|p_{id} - x_{id}|} . \tag{8}$$

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

i. Previous best experience (i.e., P_{best} of the particle);
ii. Best global experience (i.e., g_{best}) considering the best P_{best} of all particles; and
iii. Previous best experience of the best nearest neighbour (i.e., n_{best})

Hence, the new velocity update equation becomes:

$$v_{id} = w_{id}.v_{id} + c_1.rand(p_{id} - x_{id}) + c_2.Rand(p_{gd} - x_{id}) + c_3.Rand1.(p_{nd} - x_{id}) \,, \tag{9}$$

where p_{nd} is the nearby particle that has better fitness, c_3 is a positive constant, and Rand1 is in the range [0,1].

$$x_{id} = x_{id} + v_{id} \tag{10}$$

3. Problem Formulation

The generators in the system under consideration have different sensitivities to the power flow on the congested line. A change in real power flow in a transmission line-k (connected between bus i and bus j) due to a change in power generation by generator g can be termed as generator sensitivity (GS) to the congested line. Mathematically, GS for line-k can be expressed as:

$$GS_g = \frac{\Delta P_{ij}}{\Delta P_g}, \tag{11}$$

where P_{ij} is the real power flow on the congested line-k, and P_g is the real power generated by generator g.

The GS values have been obtained using the slack bus as the reference. As such, the sensitivity of the slack bus generator to any congested line in the system is always zero. Further, by rescheduling their power outputs, it is advisable to select generators having non-uniform and large magnitudes of sensitivity values to participate in CM because these are the ones that are most sensitive to the power flow on the congested line. Based on the bids received from the participant generators, the amount of rescheduling required is computed by solving the following optimization problem:

$$C_C = Minimize \sum_g^{N_g} C_g(\Delta P_g)\Delta P_g \tag{12}$$

Subject to

$$\sum_{g=1}^{N_g}((\mathrm{GS_g})\Delta P_g) + \mathrm{PF_k^0} \le \mathrm{PF_k^{max}}, \tag{13}$$

$$k = 1, 2, 3.....N_{l,}$$

$$\Delta P_g^{min} \le \Delta P_g \le \Delta P_g^{max,} \tag{14}$$

$$\Delta P_g^{min} = P_g - P_g^{min,} \text{ and} \tag{15}$$

$$\Delta P_g^{max} = P_g^{max} - P_{g,} \tag{16}$$

where g= 1, 2, 3... $N_{g,}$ and

$$\sum_{g=1}^{N_g} \Delta P_g = 0\,. \tag{17}$$

In the above, ΔP_g is the real power adjustment at bus-g, and C_g refers to the incremental and decremented price bids submitted by the generators that are willing to adjust their real power outputs. In addition, power flow caused by all contracts requesting the transmission service is represented by PF_k^0; line flow limit of the line connecting bus-i and bus-j is represented by PF_k^{max}, the number of participating generators is represented by N_g; the number of transmission lines in the system is represented by N_l; and the minimum and maximum limits of generator outputs are denoted by P_g^{min} and P_g^{max}, respectively. Power flow solutions are not required during the process of optimization.

In applying evolutionary algorithms for optimization, each particle is considered with N variables, where N is the total number of generators taking part in CM. Each variable represents the output of participating generators submitting the bidding curves. Particle evolution, which is based on fitness of particles and selection operation of global best (g_{best}) and local best (p_{best}), is used to meet the constraints. Fitness is an index used to evaluate the superiority of the particle. Binary fitness is also used: one for optimal objective and another for the binding constraints. Optimal objective fitness is equal to the value of expression (12), which represents the cost of active power rescheduling, and hence, the cost acquired to curb congestion cost. Binding constraints fitness value is also adopted to scale the level of violation; this has been calculated as in expression (7).

The application of evolutionary algorithms for optimal rescheduling of the active power of participating generators for relieving congestion in the transmission line on the two test systems is detailed below.

3.1 FPSO Algorithm for CM by Optimal Rescheduling of Generators

The process flow for this approach is described below.

Step 1. Particles are randomly generated and initialized with random values of position and velocity. Each particle has N dimensions, where N denotes the number of participating generators. The values of these N variables are the amount of rescheduling required by generators to manage congestion.

Step 2. Equation (17) is tested based on the system states represented by an individual particle. The particle is regenerated if it does not satisfy the equality constraints.

Step 3. The fitness values of the binding constraints for the particles are determined. The particle is regenerated if it does not satisfy the fitness requirement.

Step 4. The optimal objective fitness values are calculated for all the particles. The values of position best and global best are determined.

Step 5. Input current inertia weight (w) and fitness (NFIT) to the fuzzy logic function in MATLAB fuzzy toolbox to obtain the change in inertia weight (Δw) as output.

Step 6. Update the inertia weight using Equation (4).

Step 7. Velocities and positions of particles are updated using Equations (5) and (6).

Step 8. If the maximum number of iterations is exceeded or converged, the program is stopped. Otherwise, go to Step 2.

3.2 FDR-PSO Algorithm for CM by Optimal Rescheduling of Generators

Step 1. Particles are randomly generated and initialized with random values of position and velocity. Each particle has N dimensions where N denotes the number of participating generators. The values of these N variables are the amount of rescheduling required by generators to manage congestion.

Step 2. Equation (17) is tested based on the system states represented by an individual particle. If that particle does not satisfy the equality constraints, it is regenerated.

Step 3. The binding constraints' fitness values for the particles are determined. If a particle does not satisfy the fitness requirement, it is regenerated.

Step 4. The optimal objective fitness values are calculated for all the particles. The values of position best and global best are then determined.

Step 5. Maximize Fitness Distance Ratio (FDR) using Equation (8).

Step 6. Select the best nearest neighbour to the current particle (i.e., maximum FDR).

Step 7. Velocity of each particle is updated using Equation (9).

Step 8. The position of each particle is updated using Equation (10).

Step 9. If the maximum number of iterations is exceeded or converged, the program is stopped. Otherwise, go to Step 2.

4. Results and Discussions

4.1 Case A: IEEE 30-bus System

The IEEE 30-bus system consists of six generator buses and 24 load buses. The slack bus has been assigned to Bus 1. The network topology and the test data for the IEEE 30-Bus system can be found in http://www.ee.washington.edu/research/pstca. The single line diagram of the IEEE 30-Bus system is shown in Fig. 1. The system has six generating units; the characteristics of the generator units with their constraints are available in [22]. In this system, congestion is created by incrementally loading all the existing loads in small units until some line crosses its thermal limit. As can be seen, congestion occurred in Line 1 connecting Buses 1 and 2 when the system was loaded by 19% from their base case loads.

The unconstrained scheduled power flow of 132.60 MW is recorded in Line 1, whose power flow limit is 130.00 MW. Hence, congestion has to be relieved by optimally rescheduling the active power generation of the generators. Accordingly, GSs are computed for the congested Line 1 using Equation (11) for the system; these are plotted in Fig. 2.

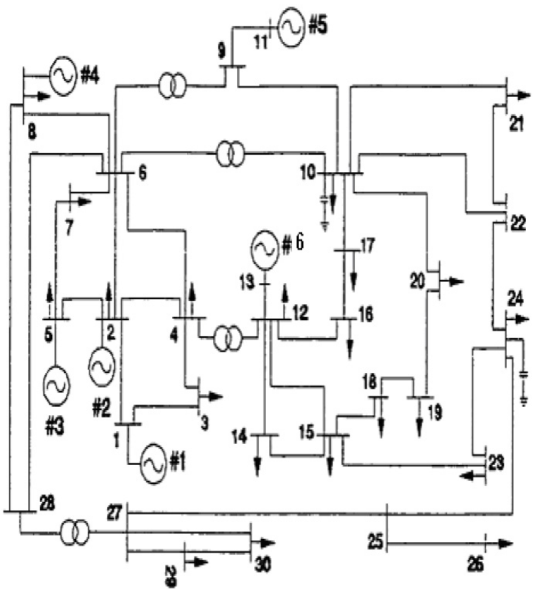

Fig. 1. Single Line Diagram for the IEEE 30-Bus System.

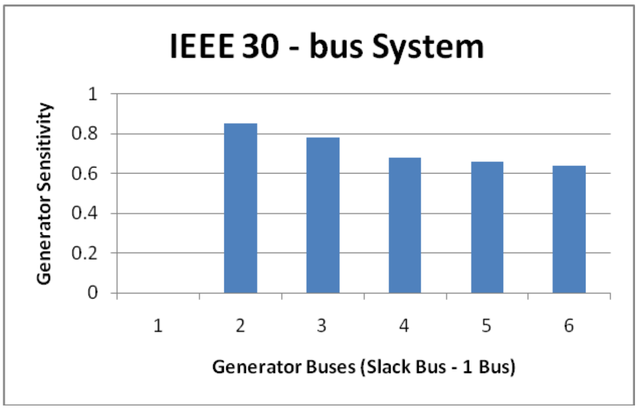

Fig. 2. Generator Sensitivity factors of Line 1 for IEEE 30-bus system.

In this test system, it has been observed that all the generators show strong influence on the congested line. This may be due to the very small system, which is very tightly connected electrically. Except for the slack bus, all generators participating in CM and evolutionary algorithms are employed to optimally reschedule the active power of the generators for relieving congestion in Line 1.

The parameters used for conventional PSO are as follows:

Swarm Size: 60; Positive Constants (i.e., $C_1 = C_2 = 2$);
Maximum Iterations: 500;
Maximum Inertia Weight W_{max}=0.9; and
Minimum Inertia Weight W_{min}=0.1

Table 2 gives the active power generation of the five participating generators before and after CM employing PSO, FPSO, and FDR-PSO.

Rescheduling of the active power of the participating generators by PSO, FPSO, and FDR-PSO are shown in Fig. 3 for comparison with active power generation before congestion management.

Table 3 shows the unconstrained scheduled power flow of 132.60 MW in the congested Line 1 (connecting Bus 1 and Bus 2 of IEEE 30-bus system) whose line flow limit is 130.00 MW before CM and the power flow in the congested line after relieving congestion through the PSO, FPSO, and FDR-PSO algorithms.

Table 2. Active power generation before and after congestion management for IEEE 30-bus system

Generator No.	Active Power Generation (pu) before Congestion Management	Active Power Generation (pu) after Congestion Management		
		PSO [3]	FPSO	FDR-PSO
2	0.5756	0.68375	0.66229	0.69899
3	0.2456	0.22883	0.15381	0.24755
4	0.3500	0.34421	0.34903	0.34858
5	0.1793	0.19925	0.24008	0.20447
6	0.1691	0.22052	0.20088	0.17236

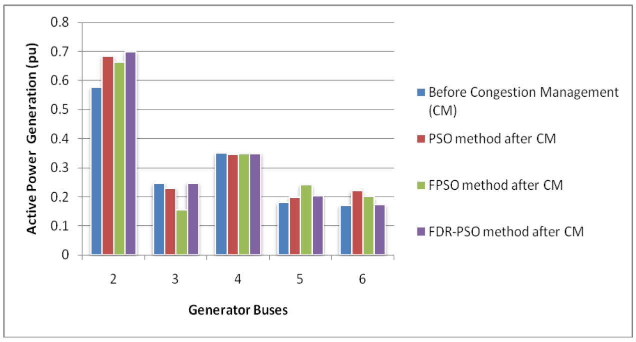

Fig. 3. Active Power Generation of Each Selected Generator for CM in the IEEE 30-Bus System.

Table 3. Active power flow in the congested line before and after congestion management for the IEEE 30-bus system

Branch Power Flow		Active Power flow (MW) Before Congestion Management	Active Power flow (MW) After Congestion Management		
From Bus	To Bus		PSO [3]	FPSO	FDR-PSO
1	2	132.604883	125.885171	129.47494	126.339796

The line flow in the congested line after relieving the congestion using the PSO, FPSO, and FDR-PSO algorithms are shown in Fig. 4 in comparison withunconstrained scheduled power flow. Evolutionary algorithms have been implemented ten times on the IEEE 30-Bus system in order to determine the robustness and effectiveness of the proposed methods.

Table 4 shows best, worst, and mean values after CM for optimal rescheduling of the active powers of the participating generators.

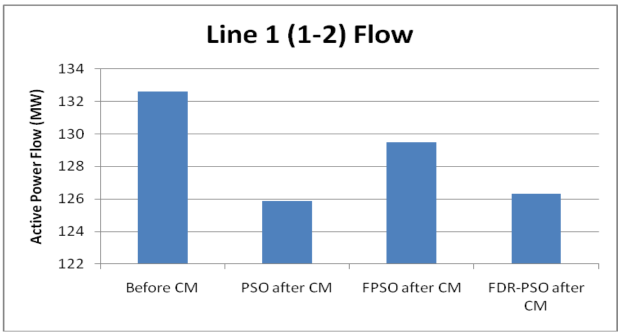

Fig. 4. Active Power Flow in Line 1 for the IEEE 30-Bus System.

Table 4. Comparisons of Congestion Management Methods for the IEEE 30-bus System

	PSO[3]	FPSO	FDR-PSO
Best(Rs/MWh)	956.8543	931.3373	950.9240
Worst(Rs/MWh)	988.9370	952.3600	977.4250
Mean(Rs/MWh)	962.4130	940.4810	958.6250
Time(Seconds)	0.0049	0.0166	0.0039
Losses(MW)	13.9765	13.9168	13.9615
SlackBus Power(MW)	183.3569	190.5672	184.0033

As can be seen above, the FPSO algorithm gives minimum cost for rescheduling the active power of participating generators to relieve congestion (Table 4). It is further observed that the losses incurred for relieving congestion are also comparatively low in the case of FPSO. However, the time taken for the best run among the ten runs of evolutionary algorithms for CM is less in the case of FDR-PSO.

4.2 Case B: Practical Indian 75-bus System

The Practical Indian 75-bus system consists of fifteen generator buses and 60 load buses. Bus 12 has been assigned as the Slack Bus. The single line diagram of the Practical Indian 75-Bus system is shown in Fig. 5. The characteristics of the generating units and their constraints are available in [22].

In this test system, congestion occurred in Line 71 connecting Bus 26 and Bus 41. When the base case power flows in various branches were computed, Line 71 was already overloaded. The unconstrained scheduled power flow of 401.65 MW is recorded in Line 71, whose power flow limit is 400.00 MW. Hence, congestion has to be relieved by rescheduling active power generation of the participating generators. Accordingly, GSs are computed for the congested Line 71 using Equation (11). This is plotted in Fig. 6.

Generators that are participating in CM must be selected depending on their sensitivities to the congested line. In this test system, only 10 generators have shown strong influence on the congested line; thus, these have been selected for congestion management.

The evolutionary algorithms are employed to optimally reschedule the active power of the selected generators for relieving congestion in Line 71. The parameters used for conventional PSO are as follows:

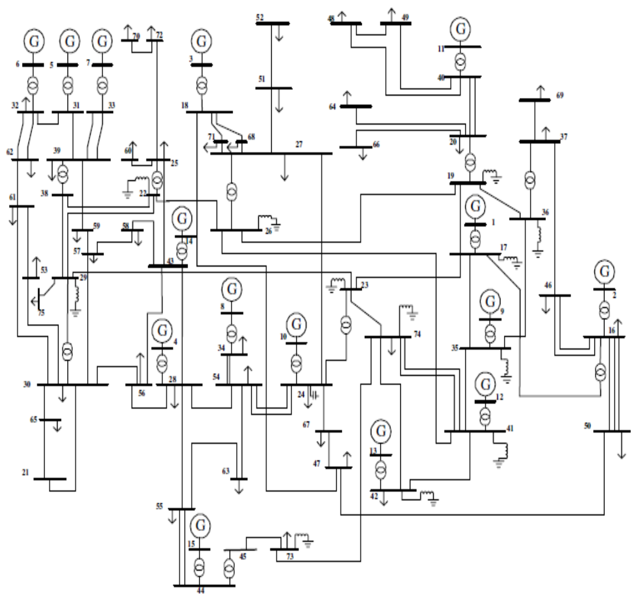

Fig. 5. Single Line Diagram [22] for the Practical Ind ian 75-Bus System.

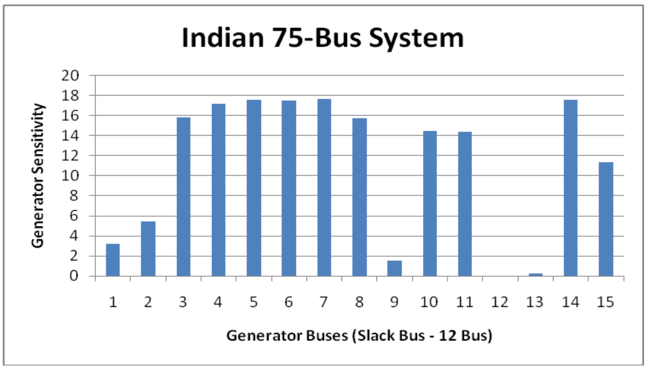

Fig. 6. Generator Sensitivity Factors of Line 71 for the Practical Indian 75-Bus System.

Swarm Size: 60; Positive Constants (i.e., $C_1 = C_2 = 2$);
Maximum Iterations: 500;
Maximum Inertia Weight W_{max}=0.9; and
Minimum Inertia Weight W_{min}=0.1

Table 5 gives the active power generation of the 10 participating generators before and after CM employing PSO, FPSO, and FDR-PSO.

Rescheduling the active power of the participating generators by PSO, FPSO, and FDR-PSO for relieving congestion is shown in Fig. 7 for comparison with active power generation before CM.

Table 5. Active Power Generation Before and After CM for the Practical Indian 75-bus System

Generator No.	Active Power Generation (pu) before Congestion Management	Active Power Generation (pu) after Congestion Management		
		PSO[3]	FPSO	FDR-PSO
3	1.9248	1.7731	1.8000	1.9310
4	1.1653	0.9649	1.0000	0.9143
5	1.7572	1.9576	1.8000	1.9776
6	0.9680	1.0534	1.2000	1.0819
7	0.7005	0.5693	0.6000	0.9220
8	0.7469	0.9666	0.8000	0.8994
10	1.0237	0.7376	0.8000	0.6925
11	1.2258	1.2485	1.0900	1.0858
14	1.3312	1.3950	1.5000	1.2989
15	4.4229	4.5217	4.5400	4.4250

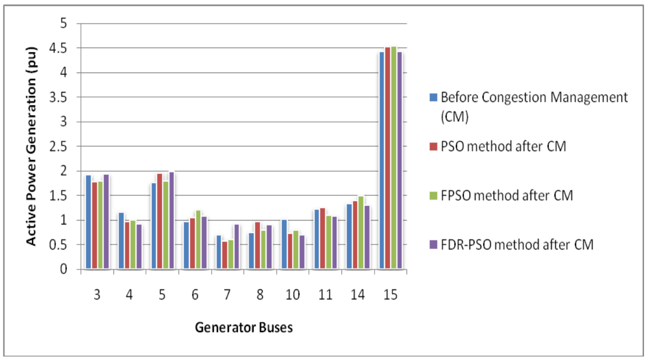

Fig. 7. Active Power Generation of Each Selected Generator for CM in the Indian 75-bus System.

Table 6 shows the unconstrained scheduled power flow of 401.65 MW in the congested Line 71 connecting Bus 26 and Bus 41 of the Practical Indian 75-bus system. Line flow limit is 400.00 MW before CM and the power flow in the congested line after relieving congestion by PSO, FPSO, and FDR-PSO algorithms.

The line flow in the congested line after relieving the congestion using PSO, FPSO, and FDR-PSO algorithms is shown in Fig. 8 in comparison with unconstrained scheduled power flow.

The evolutionary algorithms have been implemented ten times on the Practical Indian 75-bus system in order to determine the robustness and effectiveness of the proposed methods. Table 7 shows the best, worst, and mean values after CM for optimal rescheduling of the active powers of the participating generators.

It is observed from Table 7 that the FPSO algorithm gives minimum cost for rescheduling the active power of participating generators in relieving congestion. It is further observed that the losses incurred for relieving congestion are also comparatively low in the case of FPSO. However, the time taken for the best run among the 10 runs of evolutionary algorithms for congestion management is less in the case of FDR-PSO.

Table 6. Active Power Flow in the Congested Line Before and after CM in the Indian 75-bus System

Branch Power Flow		Active Power flow (MW) before Congestion Management	Active Power flow (MW) after Congestion Management		
From Bus	To Bus		PSO [3]	FPSO	FDRPSO
26	41	401.65	398.9037	397.558	398.67

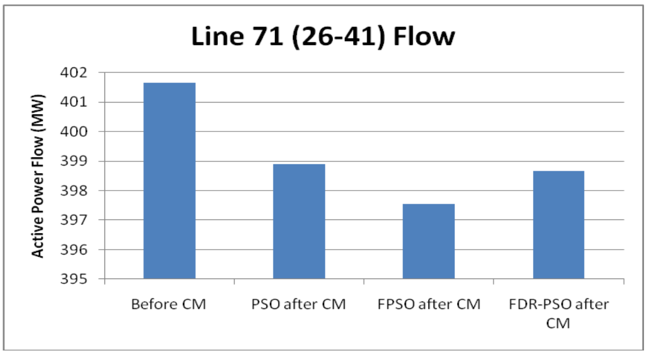

Fig. 8. Active Power Flow in Line 71 of the Practical Indian 75-Bus System.

Table 7. Comparison of CM Methods for the Practical Indian 75-bus system

	PSO [3]	FPSO	FDR-PSO
Best(Rs/MWh)	5189.47	5075.44	5189.1
Worst(Rs/MWh)	5243.81	5133.08	5213.77
Mean(Rs/MWh)	5203.92	5098.34	5198.36
Time(Seconds)	2.1207	2.4600	1.9573
Losses(MW)	207.8246	205.1068	206.6673
SlackBus Power(MW)	1793.975	1788.776	1792.843

The simulation was carried out using a PC running on Intel [R], Pentium [R] 4 CPU, 3.0 GHZ, 496 MB of RAM in the MATLAB environment.

5. Conclusion

In this paper, the CM problem has been solved through optimal rescheduling of active powers of generators utilizing Fuzzy FPSO and FDR-PSO. The generators have been chosen based on the generator sensitivity to the congested line. In this study, rescheduling has been carried out by taking minimization of cost and satisfaction of line flow limits into consideration. Results obtained by FPSO and FDR-PSO have been compared with conventional PSO and tested on the IEEE 30-bus and Practical Indian 75-bus systems. Based on the results, FPSO is the most cost-efficient solution to the CM problem compared with FDR-PSO and conventional PSO.

References

[1] Richard D Christie, Bruce F Wollenberg, Ivar Wangensteen, "Transmission Management in the Deregulated Environment", in *Proceedings of the IEEE*, Vol. 88, No. 2, pp. 170--194, February 2000.

[2] D M Vinod Kumar and Ch Venkaiah, "Swarm Intelligence based Security Constrained Congestion Management using SSSC", in *Proceedings of Asia Pacific Power and Energy Engineering Conference 2009*, March 28--31, 2009.

[3] Sudipta Dutta, S P Singh, "Optimal Rescheduling of Generators for Congestion Management Based on Particle Swarm Optimization", *IEEE Transactions on Power Systems*, Vol. 23, No. 4, pp. 1560--1569, November 2008.

[4] R S Fang, A K David, "Transmission Congestion Management in an Electricity Market", *IEEE Transactions on Power Systems*, Vol. 14, No. 3, pp. 877--883, August 1999.

[5] K L Lo, Y S Yuen, L A Snider, "Congestion Management in Deregulated Electricity Markets", in Proceedings of IEEE International Conference on Electric Utility Deregulation and Restructuring and Power Technologies 2000, City University, London, pp. 47--52, April 4--7, 2000.

[6] Ashwani Kumar, S C Srivastava, S N Singh, "Congestion Management in Competitive Power Market: A Bibliographical survey", *Electric Power Systems Research*, Vol. 76, pp. 153--164, 2005.

[7] Ashwani Kumar, S C Srivastava, S N Singh, "A Zonal Congestion Management Approach Using Real and Reactive Power Rescheduling", *IEEE Transactions on Power Systems*, Vol. 19, No. 1, pp. 554--562, February 2004.

[8] H Y Yamina, S M Shahidehpour, "Congestion Management Coordination in the deregulated power market", *Electric Power Systems Research*, Vol. 65, pp. 119--127, 2003.

[9] Florin Capitanescu, Thierry Van Cutsem, "A Unified Management of Congestions due to voltage instability and thermal overload", *Electric Power Systems Research*, Vol. 77, pp. 1274--1283, 2007.

[10] Jian Fu, John W Lamont, "A Combined Framework for Service Identification and Congestion Management", *IEEE Transactions on Power Systems*, Vol. 6, No. 1, pp. 56--61, February 2001.

[11] James Kennedy, Russell Eberhart, "Particle Swarm Optimization", in *IEEE Proceedings*, pp. 1942--1948, 1995.

[12] Yuhui Shi, "Particle Swarm Optimization", in *Proceedings of IEEE Neural Networks Society*, pp. 8--13, February 2004.

[13] Yamille del Valle, Ganesh Kumar Venayagamoorthy, Salman Mohagheghi, Jean-Carlos Hernandez, Ronald G Harley, "Particle Swarm Optimization: Basic Concepts, Variants and Applications in Power Systems", *IEEE Transactions on Evolutionary Computation*, Vol. 12, No. 2, pp. 171--195, April 2008.

[14] Zhi xu Chen, Li zi Zhang, Jun Shu, "Congestion Management Based on Particle Swarm Optimization", in *Proceedings of IEEE, The 7th International Power Engineering Conference 2005*, Vol. 2, pp. 1019--1023, Nov. 29 2005–Dec. 2 2005.

[15] Jagabondhu Hazra, Avinash K Sinha, "Congestion Management Using Multiobjective Particle Swarm Optimization", *IEEE Transactions on Power Systems*, Vol. 22, No. 4, pp. 1726–1734, November 2007.

[16] D N Jeyakumar, T Jayabarathi, T Raghunathan, "Particle Swarm Optimization for various types of economic dispatch problems", *Electrical Power and Energy Systems*, Vol. 28, pp. 36--42, 2006.

[17] Zwe-Lee Gaing, "Particle Swarm Optimization to Solving the Economic Dispatch Considering the Generator Constraints", *IEEE Transactions on Power Systems*, Vol. 18, No.3, pp. 1187--2123, August 2003.

[18] Thanmaya Peram, Kalyan Veeramachaneni, Chilukuri K Mohan, "Fitness-Distance-Ratio Based Particle Swarm Optimization", in *Proceedings of Swarm Intelligence Symposium 2003*, pp. 174--181, 2003.

[19] R Gnanadass, Venkataramana Ajjarapu, "Assessment of Dynamic Available Transfer Capability using FDR PSO Algorithm", *ELEKTRIKA*, Vol.10, No.1, pp. 20--25, 2008.

[20] Yuhui Shi, Russell C. Eberhart, "Fuzzy Adaptive Particle Swarm Optimization", in *Proceedings of the 2001 Congress on Evolutionary Computation*, pp. 101--106, 2001.

[21] A Y Saber, T Senjyu, A Yona and T Funabashi, "Unit Commitment computation by fuzzy adaptive particle swarm optimization", *IET Transactions on Generation, Transmission and Distribution*, Vol.1, No. 3, pp. 456--465, 2007.

[22] I Jacob Raglend and Narayana Prasad Padhy, "Solutions to Practical Unit Commitment Problems with

Operational Power Flow and Environmental Constraints", in *Proceedings of IEEE*, pp. 1--6, 2006.

Ch Venkaiah received his B.Tech. degree in Electrical and Electronics Engineering from JNTUCOE, Kakinada. He received his M.Tech. degree in Computer Science and Engineering from the National Institute of Technology (NIT), Warangal. He is currently pursuing his Ph.D. degree in Electrical Engineering at NIT, Warangal. He is an Associate Professor of Electrical Engineering at NIT, Warangal. His current research interests include Power System Deregulation and Artificial Intelligence Technique applications in Power Systems.

D M Vinod Kumar received his B.E. degree in Electrical Engineering and his M.E. degree in Power Systems Engineering from the University College of Engineering, Osmania University, Hyderabad, Andhra Pradesh, India. He received his Ph.D degree in Electrical Engineering from the Indian Institute of Technology (IIT), Kanpur, India. At present, he is the Dean for Academic Affairs and a Professor of Electrical Engineering at the National Institute of Technology, Warangal. His current research interests include power system deregulation, AI technique applications in power systems, power system stability, energy management systems (EMS), and flexible AC transmission systems (FACTS).