

ADAPTIVE FUZZY PARTICLE SWARM OPTIMIZATION BASED CONGESTION MANAGEMENT USING OPTIMAL RESCHEDULING OF ACTIVE AND REACTIVE POWER

E. Muneender D.M. Vinodkumar

National Institute of Technology Warangal, AP, India
emuneender.nitw@gmail.com

Abstract: In a deregulated electricity market one of the most important tasks of System Operator is to manage congestion. Therefore, investigation of techniques for congestion free-wheeling power is of paramount interest. One of the most practical and obvious technique of congestion management is rescheduling the power outputs of generators in the system. In the present paper, the optimal rescheduling of reactive power generation of both generator and capacitor along with the rescheduling of active power is considered to relieve congestion. The optimal rescheduling of powers in a pool model is formulated as a nonlinear optimization problem. This paper proposes Adaptive Fuzzy Particle Swarm Optimization based Optimal Power Flow for solving the non linear optimization problem to minimize the Congestion Cost. For the better performance of Particle Swarm Optimization, in the proposed method, the inertia weight is dynamically adjusted using fuzzy IF/THEN rules to increase the balance between global and local searching abilities. The effectiveness of the proposed method has been tested on a 75-bus Indian Practical System and 39-bus New England system. The simulation experiments reveal that AFPSO performs better than other Evolutionary Algorithms such as Particle Swarm Optimization, Real and Binary Coded Genetic Algorithm and Conventional Optimization methods.

Key words: Congestion Management, Evolutionary Algorithms, Adaptive Fuzzy PSO, Optimal Power Flow and Transmission Congestion Distribution Factors.

1. Introduction

The privatization and deregulation of electricity markets have a very large impact on almost all power systems around the world. Competitive electricity markets are complex systems with many participants who buy and sell electricity. In any competitive market, system security plays a vital role from the market/system operator's point of view. When the producers and consumers of electric energy desire to produce and consume in amount that would cause the transmission system to operate at or beyond one or more transfer limits, then the system is said to be 'congested'. Congestion Management is about controlling the transmission system so that limits are

observed and is perhaps the most fundamental transmission management problem. One of the most critical and important tasks of System Operator (SO) is to manage congestion. Congestion before deregulation was treated in terms of steady state security and the basic objective was to control the generators' output so that system remained secure (no limits were violated) at the lowest cost as seen by the mutually agreeing Vertically Integrated Electric Utilities (VIEUs). But with deregulation, congestion has become a term in conjunction with power systems and competition. When there is congestion in a transmission system, locational prices can be significantly different from those of unconstrained optimal solution. Transmission congestion may prevent the existence of new contracts, lead to additional outages, increase the electricity prices in some regions of the electricity markets, and can threaten system security and reliability. The objective of the congestion management is to take actions or control measures to relieve the congestion of transmission networks.

Several methods of congestion management have been reported in literature [1]. Pool and bilateral contract dispatches and the priority arrangements for line congestion and curtailment strategies are discussed in [2]. Srivastava and Kumar [3] presented an OPF based model for reducing the congestion to minimize the curtailment of contracted power in a power market having bilateral and multilateral contracts. An efficient procedure minimizing the adjustments in preferred schedules to manage congestion is proposed in [4]. Optimal dispatch considering dynamic security constraints for congestion management is presented in [5]. Optimal dispatch model to manage congestion for the feasible contracts is presented in [6]. Nanda et al. [7] discuss an OPF algorithm developed using the Fletcher's quadratic programming method for congestion management to minimize the cost of congestion. Jian et al. [8] proposed an OPF based approach that minimizes cost of congestion and service cost. A congestion cluster based method, which

identifies the group of system users according to their impact on transmission constraints of interest, has been proposed in [9]. Here clusters of type 1, 2 and higher based on congestion distribution factors have been demarcated, with type 1 cluster consisting of those with strongest and non uniform effects on the transmission constraints of interest. Sudipta Dutta et al [10] proposed PSO based OPF for the optimal rescheduling of generators for congestion management using generator sensitivities. In this they discussed only the optimal re-dispatch of active power and the reactive power dispatch has not been taken into consideration. But, the reactive power will play a vital role in the congestion management in reducing the congestion cost. A Zonal model based on AC load flow was proposed in [11] and [12]. In these papers the zones/clusters are identified based on transmission congestion distribution factors and the optimal re-dispatch is done by Sequential Quadratic Programming (SQP) based OPF solution using GAMS software package. The SQP based OPF is a conventional deterministic optimization method. The conventional methods of solution of OPF are based on search direction determined from derivative of the objective function. Therefore it becomes imperative to express the problem in the form of continual differentiable function; otherwise, the methods become less efficient. To overcome this problem the present paper solves optimization problem using Evolutionary Algorithms such as Particle Swarm Optimization (PSO), Binary Coded Genetic Algorithm (BCGA) and Real Coded Genetic Algorithm (RCGA). The Standard PSO (SPSO) is more efficient in maintaining the diversity of the swarm, since all particles use the information related to most successful particle in order to improve themselves, whereas, in Genetic Algorithm (GA) the population evolves around a subset of the best individuals. The PSO technique can generate better quality solution within shorter calculation time and stable convergence characteristics than other stochastic methods like GA [15], [20] and [21]. If the parameters of Standard PSO (SPSO) are not properly tuned, it leads to premature convergence to local optima due to the imbalance between global and local searching capabilities [17]. For better performance of the SPSO search process, the inertia weight should be nonlinearly, dynamically changed to achieve better balance between global and local search abilities. The inertia weight is nonlinearly and dynamically changed using Adaptive Fuzzy Particle Swarm Optimization (AFPSO) [18]. The major contribution of this paper is that the Adaptive Fuzzy PSO based OPF is proposed

first time to solve Congestion Management problem using both the active and reactive power re-scheduling by considering all practical constraints with single and multi line congestion cases. In the present paper, the optimal rescheduling of both active and reactive power for Congestion Management problem is formulated as a nonlinear optimization problem with three different Congestion Cost (CC) functions for both single line and multi line congestion cases as follows:

- i) Case-1:* With change in real power generation.
- ii) Case-2:* With change in real and reactive power generation without capacitor reactive power support.
- iii) Case-3:* With change in real and reactive power generation with capacitor reactive power support.

To reduce the number of participating generators for congestion management in competitive power markets, the proposed method utilizes two sets of sensitivity indices, viz. Real Power Transmission Congestion Distribution Factors (PTCDFs) and Reactive Power Transmission Congestion Distribution Factors (QTCDFs). The most sensitive clusters/zones have been identified as the union of most sensitive zones obtained on the basis of real and reactive line flow sensitivity indices separately [11], [12]. The effectiveness of the proposed method has been tested on a 75-bus practical Indian system and 39-bus New England Test system and the results are compared with the other EAs such as SPSO, BCGA and RCGA based OPF methods. All the methods for Congestion Management problem have been implemented using MATLAB programming.

2. Congestion Management Problem Formulation

In the congestion management problem formulation, first it is required to find the optimal number of generators participating in the congestion alleviation process and then application of one of the available optimal power flow method to find minimum rescheduling cost or congestion cost to alleviate congestion. The effect of the generator and capacitor reactive support on the generator rescheduling has to be formulated. Thus congestion management problem formulation consists of two important steps as explained below:

- 1) Optimal number of generators participating in the congestion management
- 2) Optimal re-scheduling of real and reactive powers of generators with capacitor reactive support

For the optimal number of generators, this paper has utilized two sets of sensitivity indices termed as Real Power Transmission Congestion Distribution Factors (PTCDFs) and Reactive Power Transmission Congestion Distribution Factors (QTCDFs). The

procedure for the calculation of PTCDFs and QTCDFs is explained in the following section.

2.1 Transmission Congestion Distribution Factors (TCDFs)

Transmission congestion distribution factors (TCDFs) are defined as the change in power flow in a transmission line- k connected between $bus-i$ and $bus-j$ due to unit change in the power injection at $bus-i$. Mathematically the TCDF for the line- k can be written as:

$$\left. \begin{aligned} PTCDF_n^k &= \frac{\Delta P_{ij}}{\Delta P_n} \\ QTCDF_n^k &= \frac{\Delta Q_{ij}}{\Delta Q_n} \end{aligned} \right\} (1)$$

The $PTCDF_n^k$ and $QTCDF_n^k$ given in the above equations represent the real and reactive power flow sensitivities of line $i-j$ with respect to bus real and reactive power injections and have been termed as real and reactive power transmission congestion distribution factors respectively. The derivations for $PTCDF_n^k$ and $QTCDF_n^k$ are discussed in detail in [11].

The basic power flow equation on the congested line can be written as:

$$\left. \begin{aligned} P_{ij} &= V_i V_j Y_{ij} \cos(\theta_{ij} + \delta_j - \delta_i) - V_i^2 Y_{ij} \cos \theta_{ij} \\ Q_{ij} &= -V_i V_j Y_{ij} \sin(\theta_{ij} + \delta_j - \delta_i) + V_i^2 Y_{ij} \sin \theta_{ij} - \frac{V_i^2 Y_{sh}}{2} \end{aligned} \right\} (2)$$

Where V_i and δ_i are the voltage and phase angle respectively at i^{th} bus; Y_{ij} is the admittance of the line connected between buses i and j .

$$\left. \begin{aligned} PTCDF_n^k &= \left(\frac{\Delta P_{ij}}{\Delta \delta_i} \right) \left(\frac{\Delta \delta_i}{\Delta P_n} \right) + \left(\frac{\Delta P_{ij}}{\Delta \delta_j} \right) \left(\frac{\Delta \delta_j}{\Delta P_n} \right) \\ QTCDF_n^k &= \left(\frac{\Delta Q_{ij}}{\Delta V_i} \right) \left(\frac{\Delta V_i}{\Delta P_n} \right) + \left(\frac{\Delta Q_{ij}}{\Delta V_j} \right) \left(\frac{\Delta V_j}{\Delta P_n} \right) \end{aligned} \right\} (3)$$

$$\left. \begin{aligned} PTCDF_n^k &= a_{ij} m_{in} + b_{ij} m_{jn} \\ QTCDF_n^k &= c_{ij} n_{in} + d_{ij} n_{jn} \end{aligned} \right\} (4)$$

Where

$$\left. \begin{aligned} a_{ij} &= \frac{\Delta P_{ij}}{\Delta \delta_i} = V_i V_j Y_{ij} \sin(\theta_{ij} + \delta_j - \delta_i) \\ b_{ij} &= \frac{\Delta P_{ij}}{\Delta \delta_j} = -V_i V_j Y_{ij} \sin(\theta_{ij} + \delta_j - \delta_i) \\ c_{ij} &= \frac{\Delta Q_{ij}}{\Delta V_i} = -V_j Y_{ij} \sin(\theta_{ij} + \delta_j - \delta_i) + 2V_i Y_{ij} \cos(\theta_{ij}) - V_i Y_{sh} \\ d_{ij} &= \frac{\Delta Q_{ij}}{\Delta V_j} = -V_i Y_{ij} \sin(\theta_{ij} + \delta_j - \delta_i) \\ m_{in} &= \frac{\Delta \delta_i}{\Delta P_n} \quad \text{and} \quad m_{jn} = \frac{\Delta \delta_j}{\Delta P_n} \\ n_{in} &= \frac{\Delta V_i}{\Delta Q_n} \quad \text{and} \quad n_{jn} = \frac{\Delta V_j}{\Delta Q_n} \end{aligned} \right\} (5)$$

$PTCDF_n^k$ and $QTCDF_n^k$ are the real and reactive transmission congestion distribution factors corresponding to a $bus-n$ and a $line-k$ connected between $bus-i$ and $bus-j$. a_{ij} , b_{ij} , c_{ij} and d_{ij} are the coefficients which can be obtained using the partial derivatives of active and reactive power flows shown in equation (2).

After the calculation of PTCDFs and QTCDFs, these will be utilized for identifying congestion clusters (zones) for a given system. The congestion cluster of type-1 has been defined as the zone having large and non uniform Transmission Congestion Distribution Factors (TCDFs) and the congestion cluster of type 2 and higher has been defined as those having small or similar TCDFs. The transactions in the congestion Zone-1 have critical and unequal impact on the line flow. The congestion zones of type 2, 3 and higher are farther from the congested line of interest. Therefore, any transaction outside the most sensitive Zone-1 will contribute very little to the line flow. If more than one line congestion conditions are present in the system, the congestion zones can be obtained by superimposing the zones corresponding to the individual line congestion. Thus, the identification of congestion zones will reduce the computational burden, considerably, in both re-dispatching and physical curtailments necessary for the transmission loading relief (TLR) in case of emergency and the adjustment of system users themselves under normal conditions.

2.2 Optimal Power Flow (OPF) Problem Formulation

The optimal re-scheduling of active and reactive powers for Congestion Management in a pool model is formulated as a Optimal Power Flow (OPF) problem with three different Congestion Cost (CC) functions, for both single and multi line congestion cases, as

follows:

2.2.1 Optimal re-scheduling of real power

Case-1: Congestion Cost with real power adjustment

In this case the rescheduling of active power generator has been considered in the congestion cost function.

$$\text{Min } CC = \sum_g^{NG} C_{pg} (\Delta P_g) \Delta P_g \quad (6)$$

Subject to

$$\Delta P_g^{\min} \leq \Delta P_g \leq \Delta P_g^{\max} \quad g = 1, 2, \dots, NG \quad (7)$$

$$V_i^0 - V_i^{\min} \leq \Delta V_i \leq V_i^{\max} - V_i^0 \quad i = 1, 2, \dots, N_b \quad (8)$$

$$\left(P_{ij}^0 + \sum_g \text{PTCDF}_g^k * \Delta P_g \right) \leq (S_{ij}^{\max}) \quad ij \in N_l \quad (9)$$

$$\sum_g^{NG} \Delta P_g - \sum_g \frac{\partial P_L}{\partial P_g} \Delta P_g = 0 \quad (10)$$

2.2.2 Optimal re-dispatch of real and reactive power

The reactive power plays an important role in supporting real power transfer across the large scale transmission system. A sufficient reactive power support maintains the power flow within limits on transmission lines and voltage within limits at bus bars.

Therefore, procurement of reactive power support services is becoming important in the competitive electricity markets and thus, reactive power has been identified as one of the important ancillary services. Thus, the VAR support requirement from generators and capacitors to manage congestion along with real power re-scheduling poses great challenge to System Operator in an open electricity market. In the present work, the reactive support of generators and capacitors, in addition to the re-scheduling of real power generation, has been considered to manage the congestion. Based on the QTCDs, the generators from the most sensitive zone are selected for the reactive support. However, the optimal placement of capacitor is selected, in case there is no or insufficient capacitive reactive support in the system, at a bus which is having most negative QTCD with respect to congested line. The nonlinear optimization problem with the reactive power support of generators and capacitor are shown in case-2 and case-3 as follows.

Case-2: Congestion Cost with generator real and reactive power adjustment without capacitor reactive support

$$\text{Min } CC = \sum_g^{NG} C_{pg} (\Delta P_g) \Delta P_g + \sum_g^{NG} C_{qg} (\Delta Q_g) \Delta Q_g \quad (11)$$

Subject to

$$\Delta P_g^{\min} \leq \Delta P_g \leq \Delta P_g^{\max} \quad g = 1, 2, \dots, NG \quad (12)$$

$$\Delta Q_g^{\min} \leq \Delta Q_g \leq \Delta Q_g^{\max} \quad g = 1, 2, \dots, NG \quad (13)$$

$$V_i^0 - V_i^{\min} \leq \Delta V_i \leq V_i^{\max} - V_i^0 \quad i = 1, 2, \dots, N_b \quad (14)$$

$$\left(P_{ij}^0 + \sum_g \text{PTCDF}_g^k * \Delta P_g \right)^2 + \quad (15)$$

$$\left(Q_{ij}^0 + \sum_g \text{QTCD}_g^k * \Delta Q_g \right)^2 \leq (S_{ij}^{\max})^2 \quad ij \in N_l$$

$$\sum_g^{NG} \Delta P_g - \sum_g \frac{\partial P_L}{\partial P_g} \Delta P_g - \sum_g \frac{\partial P_L}{\partial Q_g} \Delta Q_g = 0 \quad (16)$$

$$\sum_g^{NG} \Delta Q_g - \sum_g \frac{\partial Q_L}{\partial Q_g} \Delta Q_g - \sum_g \frac{\partial Q_L}{\partial P_g} \Delta P_g = 0 \quad (17)$$

Case-3: Congestion Cost with generator real and reactive power adjustment with capacitor reactive power support

$$\text{Min } CC = \sum_g^{NG} C_{pg} (\Delta P_g) \Delta P_g + \sum_g^{NG} C_{qg} (\Delta Q_g) \Delta Q_g + \sum_c^{NC} C_{qc} (\Delta Q_c) \Delta Q_c \quad (18)$$

Subject to

$$\Delta P_g^{\min} \leq \Delta P_g \leq \Delta P_g^{\max} \quad g = 1, 2, \dots, NG \quad (19)$$

$$\Delta Q_g^{\min} \leq \Delta Q_g \leq \Delta Q_g^{\max} \quad g = 1, 2, \dots, NG \quad (20)$$

$$\Delta Q_c^{\min} \leq \Delta Q_c \leq \Delta Q_c^{\max} \quad c = 1, 2, \dots, NC \quad (21)$$

$$V_i^0 - V_i^{\min} \leq \Delta V_i \leq V_i^{\max} - V_i^0 \quad i = 1, 2, \dots, N_b \quad (22)$$

$$\left(P_{ij}^0 + \sum_g \text{PTCDF}_g^k * \Delta P_g \right)^2 + \left(Q_{ij}^0 + \sum_g \text{QTCD}_g^k * \Delta Q_g + \sum_c \text{QTCD}_c^k * \Delta Q_c \right)^2 \leq (S_{ij}^{\max})^2 \quad ij \in N_l \quad (23)$$

$$\sum_g^{NG} \Delta P_g - \sum_g \frac{\partial P_L}{\partial P_g} \Delta P_g - \sum_g \frac{\partial P_L}{\partial Q_g} \Delta Q_g - \sum_c \frac{\partial P_L}{\partial Q_c} \Delta Q_c = 0 \quad (24)$$

$$\sum_g^{NG} \Delta Q_g - \sum_g \frac{\partial Q_L}{\partial Q_g} \Delta Q_g - \sum_g \frac{\partial Q_L}{\partial P_g} \Delta P_g - \sum_c \frac{\partial Q_L}{\partial Q_c} \Delta Q_c = 0 \quad (25)$$

Where

C_{pg} is the cost of active power generation and is modeled by quadratic function as follows:

$$C_{pg} (\Delta P_g) = a_i (\Delta P_g)^2 + b_i (\Delta P_g) + c_i \quad (26)$$

The second term in the objective function shown in (18) is the opportunity cost of the generator and it can be determine approximately as follows [13]:

$$C_{qg}(\Delta Q_g) = \left[C_{pg}(S_{G,\max}) - C_{pg} \left(\sqrt{S_{G,\max}^2 - \Delta Q_g^2} \right) \right] K \quad (27)$$

K is the profit rate of active power generation taken between 5% and 10%.

The third term in the objective function shown in (18) is the equivalent production cost for capital investment return on the capital investment of the capacitors, which is expressed as their depreciation rates for the life-span of 15 years as follows[13]:

$$\begin{aligned} C_c(\Delta Q_c) &= Q_c \times \frac{\text{Investment Cost}}{\text{Operating Hours}} \\ &= Q_c \times \frac{(\$11,600 / \text{MVar})}{(15 \times 365 \times 24 \times h)} \\ &= Q_c \times \$13.24 / (100\text{MVar}h) \end{aligned} \quad (28)$$

where h represents the average usage rate of capacitors taken as 2/3. Q_c is in per unit on the 100MVA base.

$$P_L = \sum_{j=1}^{N_b} \sum_{k=1}^{N_b} \left[\alpha_{jk}(P_j P_k + Q_j Q_k) + \beta_{jk}(Q_j P_k - P_j Q_k) \right] \quad (29)$$

$$Q_L = \sum_{j=1}^{N_b} \sum_{k=1}^{N_b} \left[\gamma_{jk}(P_j P_k + Q_j Q_k) + \xi_{jk}(Q_j P_k - P_j Q_k) \right] \quad (30)$$

$$\alpha_{jk} = \frac{r_{jk}}{V_j V_k} \times \cos(\delta_j - \delta_k); \quad \beta_{jk} = \frac{r_{jk}}{V_j V_k} \times \sin(\delta_j - \delta_k) \quad (31)$$

$$\gamma_{jk} = \frac{x_{jk}}{V_j V_k} \times \cos(\delta_j - \delta_k); \quad \xi_{jk} = \frac{x_{jk}}{V_j V_k} \times \sin(\delta_j - \delta_k) \quad (32)$$

P_L and Q_L are the total real and reactive power loss respectively. The second third and fourth terms in (24) and (25) incorporate the change in the losses in the system occurring due to re-dispatch of the generators and capacitors. The real and reactive power loss sensitivity with respect to change in real and reactive power injections can be derived by using (29) and (30). In the following sections various evolutionary computation methods are discussed to solve the above optimal power flow problems depicted in equation (6) to (32).

3. Evolutionary Algorithms

Evolutionary Algorithms (EAs) differ from the traditional optimization techniques in that EAs make use of a population of solutions, not a single point solution. An iteration of EA involves a competitive selection that weeds a poor solutions. Several Evolutionary search algorithms such as Binary Coded Genetic Algorithm (BCGA), Real Coded Genetic Algorithm (RCGA), Particle Swarm Optimization (PSO) and Differential Evolution (DE) were developed independently. These algorithms differ in selection, offspring generation and replacement mechanisms. For global functional optimization problems BCGA, RCGA and PSO are employed in this paper to discover

solutions for Congestion Management problem with three different objective functions depicted in (6) to (25).

3.1 Binary Coded Genetic Algorithm (BCGA)

GA operates on a population of potential solutions, applying the principle of survival of the fittest procedure to obtain better and better approximation to a solution. At each generation, a new set of better approximations is created by selecting individuals according to their fitness in the problem domain. This process leads to the evolution of populations of individuals that are better suited to their environment than the individuals from whom they were created [19]. Traditionally, solutions are represented in binary as strings of 0s and 1s, but other encodings are also possible. The evolution usually starts from a population of randomly generated individuals and happens in generations. In each generation, the fitness of every individual in the population is evaluated, multiple individuals are stochastically selected from the current population (based on their fitness), and modified (recombined and possibly randomly mutated) to form a new population. The new population is then used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population. In this paper, tournament selection, single point crossover and uniform mutation are employed.

3.2 Real Coded Genetic Algorithm (RCGA)

Real number encoding is best used for function optimization problems. It has been widely confirmed that real-number encoding performs better than binary or gray encoding for constrained optimization [21]. Owing to the adaptive capability, Simulated Binary Crossover (SBX) and Tournament selection is used as selection mechanism in order to avoid premature convergence. SBX crossover and non-uniform polynomial mutation are given below.

3.2.1 Simulated Binary Crossover (SBX)

In SBX crossover [21], two children solutions are created from two parents as follows:

Choose a random number $u_i \in [0,1]$ and calculate β_{qi} as given in (33)

$$\beta_{qi} = \begin{cases} \frac{1}{(2u_i)^{\eta_c+1}}, & u_i \leq 0.5 \\ \left(\frac{1}{2(1-u_i)} \right)^{\eta_c+1}, & \text{otherwise} \end{cases} \quad (33)$$

A spread factor β_{qi} is defined as the ratio of the

absolute difference in offspring values to that of the parents. η_c is the crossover index.

Then compute the offspring $x_i^{(1,t+1)}$ and $x_i^{(2,t+1)}$ as

$$\left. \begin{aligned} x_i^{(1,t+1)} &= 0.5 \left[(1 + \beta_{qi})x_i^{(1,t)} + (1 - \beta_{qi})x_i^{(2,t)} \right] \\ x_i^{(2,t+1)} &= 0.5 \left[(1 - \beta_{qi})x_i^{(1,t)} + (1 + \beta_{qi})x_i^{(2,t)} \right] \end{aligned} \right\} \quad (34)$$

3.2.2 Non-uniform polynomial mutation:

Newly generated offspring undergoes polynomial mutation operation. Like in the SBX operator, the probability distribution can also be a polynomial function, instead of a normal distribution. The new offspring $y_i^{(1,t+1)}$ is determined as follows

$$y_i^{(1,t+1)} = x_i^{(1,t+1)} + (x_i^U - x_i^L) \bar{\delta}_i \quad (35)$$

x_i^U and x_i^L are the upper and lower limit values.

Where the parameter $\bar{\delta}_i$ is calculated from the polynomial probability distribution.

$$P(\delta) = 0.5(\eta_m + 1)(1 - |\delta|)^{\eta_m}$$

$$\bar{\delta} = \begin{cases} (2r_i)^{1/(\eta_m+1)} - 1, & \text{if } r_i < 0.5 \\ 1 - [2(1 - r_i)]^{1/(\eta_m+1)}, & \text{if } r_i \geq 0.5 \end{cases} \quad (36)$$

Where, η_m is the mutation index.

3.3 Particle Swarm Optimization (PSO)

PSO is a novel optimization method developed by Kennedy, et al. [17]. It is a multi agent search technique that traces its evolution to the emergent motion of a flock of birds searching for food. It uses a number of particles that constitute a swarm. Each particle traverses the search space looking for the global minimum (or maximum). This Standard Particle Swarm Optimization (SPSO) is similar to the other evolutionary algorithms in which the system is initialized with a population of random solutions. However, each potential solution is also assigned a randomized velocity, and the potential solutions corresponding to individuals. Generally, the SPSO is characterized as a simple heuristic of well-balanced mechanism with flexibility to enhance and adapt to both global and local exploration abilities. SPSO has a more global searching ability at the beginning of the run and a local searching ability at the end of the run. Therefore, while solving problems with more local optima, there are more possibilities for the SPSO to explore local optima at the end of the run. In the SPSO system, particles fly around in a multidimensional search space. During flight, each particle adjusts its

position according to its own experience, and the experience of neighboring particles, making use of the best position encountered by itself and its neighbors. The swarm direction of a particle is defined by the set of particles neighboring to the particle and its history experience.

Let x and v denote a particle coordinates (position) and its corresponding flight speed (velocity) in a search space, respectively. The best previous position of a particle is recorded and represented as $pBest$.

The index of the best particle among all the particles in the group is represented as $gBest$. Finally, the modified velocity and position of each particle can be calculated as shown in the following formulae:

$$\begin{aligned} v_i^{k+1} &= w \times v_i^k + c_1 \times rand_1() \times (pBest_i - x_i^k) \\ &\quad + c_2 \times rand_2() \times (gBest - x_i^k) \end{aligned} \quad (37)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (38)$$

Where w is the inertia weight of the particle, C_1 and C_2 are two trust parameters, k is pointer of generations, x_i^k

is current position of particle at the k^{th} generation, v_i^k is velocity of particle at the k^{th} generation and $rand()$ is a uniform random value in the range $[0,1]$.

4. Adaptive Fuzzy Particle Swarm Optimization (AFPSO)

As evolution goes on, the swarm might undergo an undesired process of diversity loss. Some particles become inactive while they lose both global and local searching capabilities in the next generations. Considering Equations (37) and (38), there are three problem-dependent parameters, the inertia weight of the particle (w) and two trust parameters ($C1$ and $C2$). The inertia controls the exploration properties of the algorithm, with larger values facilitating a more global behavior and smaller values facilitating a more local behavior. The trust parameters indicate how much confidence the particle has in itself ($C1$) and how much confidence it has in swarm ($C2$). Therefore, for better performance, the inertia weight should be nonlinearly and dynamically changed to have better dynamics of balance between global and local searching abilities.

Due to the lack of knowledge of the searching process, it is very difficult to design a mathematical model to adapt the inertia weight dynamically [18]. The Adaptive Fuzzy Particle Swarm Optimization (AFPSO) is proposed in the subsequent part of this paper to design a fuzzy system to dynamically adapt the weight for the Congestion Management problem. Fuzzy IF/THEN rules in the Table 1 are used for the proposed

method. Here the number of linguistic variables is taken as 3. The number of fuzzy rules become $3 \times 3 = 9$. If number of linguistic variables is more than 3, the computation process will become tedious. If it is less than 3, the accuracy suffers. Hence, the optimal number of linguistic variables taken in the present work is as 3.

4.1 Fuzzy Formulation

To obtain a better inertia weight under the fuzzy environment, inputs: fitness of the current location (solution) and the current inertia weight, and output: the correction of inertia weight are all needed to express in fuzzy in fuzzy set notations. Here all membership functions are triangular in shape for simplicity. Each input is fuzzified as follows using three linguistic variables such as SM, M, L (Small, Medium and Large respectively). The values for the membership functions are chosen from the prior experience as shown in the Figure 2. Recall that, it is very difficult to develop a crisp mathematical model for adaptive PSO to dynamically change the inertia parameter. So, simple plain-language IF/THEN rules are suitable to calculate the amount of inertia weight correction in the adaptive fuzzy PSO process for the Congestion Management problem.

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

$$\text{as } \text{NormFIT} = \frac{CC - CC_{\min}}{CC_{\max} - CC_{\min}} \quad (39)$$

$$w_i^{t+1} = w_i^t + \Delta w_i^{t+1} \quad (40)$$

In case of minimization problem like congestion management problem, a lower value *NormFIT* indicates the better solution. CC_{\min} is a small value which is less than any acceptable feasible solution cost. CC_{\max} is a very large value which is greater than or equal to any acceptable feasible solution cost. Congestion Cost (CC) from equation (6), (11) and (18) at the first iteration may be used as CC_{\max} for the next iterations. The range of *NormFIT* has been chosen as 0 to 1.0 based on the prior experience as shown in Figure 2(a).

Current inertia weight: Inertia weight is between 0.4 and 1.0. This range is fitted to the shape of the triangular membership function as shown in Figure 2(b).

Current inertia weight correction: for the correction of the inertia weight both positive and negative corrections for the inertia weight has been considered. The change of the inertia weight is presented in 3 linguistic variables ‘Negative’, ‘Zero’ and ‘Positive’

(NE, ZE and PE). The range of change in inertia weight has been chosen as -0.1 to 0.1 for the inertia weight correction Δw from the prior experience as shown in Figure 2(c).

IF/THEN rules and defuzzification: simple IF/THEN rules are shown in Table 1 where there are $3 \times 3 = 9$ possible rules for two input variables and three linguistic variables of each input variable. Fuzzy control inputs are usually crisp. For the current Congestion Management problem, the degree of membership of NormFIT and w are calculated from the Figure 2(a) and 2(b), respectively.

Larsen product is used as the fuzzy implication operator for the individual rules. Using arithmetic product, the degrees of fulfillment of the rules in Table 1 that fire, are evaluated. So, the Degree Of Fulfillment (DOF) for rule r is $\text{DOF}_r = \mu_{\text{NormFIT}} \cdot \mu_w$. for each rule output will be transformed or scaled in accordance with the DOF. The total output is the union of the results from the fired rules. Finally, the total output is defuzzified to a crisp value (dw) by the centroid method. The process of Fuzzy control is shown visually in Figure 3 for an input set of (1, 0.7). The correction in inertia weight Δw obtained as output of Fuzzy Inference System (FIS) is added in the current iteration inertia weight value to obtain the inertia weight for next iteration as depicted in equation (40).

2.3 Algorithm for the AFPSO can be described as follows

Step 1: Initialize the parameters of PSO.

a) Learning factors C_1 and C_2 ; Inertia weight factor w ;
b) Population size; Maximum number of iterations;

Step 2: Randomly generate the initial positions (X_i) and velocities (V_i) of all particles in the population. These initial particles must satisfy the lower and upper limits of each variable.

Step 3: For each particle, set $p\text{Best}_i$ to the current position and set $g\text{Best}$ to the current best position of the swarm.

Step 4: iteration count starts $K=1$;

Step 5: a) Calculate the fitness value of each particle using objective function shown in equation (6), (11) and (18).

b) Update the $p\text{Best}_i$ and $g\text{Best}$ corresponding to the best solution.

c) Update the inertia weight (w) according to the equation $w_i^{t+1} = w_i^t + \Delta w_i^{t+1}$. Also modify the velocity and position of each particle according to equation (37) and (38).

Step 6: If iteration count reaches the maximum iterations, go to Step 7. Otherwise set $K=K+1$ and go to Step 5.

Step 7: The particle that generates the latest $g\text{Best}$ is the optimal value of Congestion Cost.

The detailed flow chart for the AFPSO based Congestion Management is given in Figure 4.

5. System Studies and Simulation Results

The proposed method AFPSO based Congestion Management in a pool model has been illustrated on a 75-bus Indian system and 39-bus New England system for both single and multi line congestion cases. And the results are compared with other evolutionary algorithms SPSO, RCGA and BCGA. All the EAs for the Congestion management problem are implemented using MATLAB 7.0 on a PC with a Intel Dual Core, 2.0GHz and 3GB RAM. Owing to the randomness of the EAs, their performance cannot be judged by the result of a single run. Many trials with independent population initializations should be made to acquire a useful conclusion of the performance of the algorithm. An algorithm is said to be robust, if it gives almost consistent result during the trials for all experiments. Hence, in this paper 25 independent trials are conducted. The best, worst and mean obtained in 25 trials are used to compare the performance of different EAs. The maximum number of function evaluations is set to 10000 for the population size of 50 for all the algorithms. Therefore, the number of iterations required for 10000 function evaluations is 200.

5.1 Parameter Selection

Optimal parameter combinations for different methods are determined by conducting a series of experiments with different parameter settings before conducting actual runs to collect the results. In RCGA, crossover probability P_c is varied between 0.4 and 0.9 in steps of 0.1 and for each P_c the performance is analyzed. Other parameters such as mutation probability (P_m), crossover index (η_c), mutation index (η_m) and penalty factor (PF) are selected as recommended by Deb [21]. It is found that the following parameter setting produces the best result in terms of best and mean.

$$P_c=0.8; P_m=1/n; \eta_c=5; \eta_m=20; PF=100.$$

In SPSO, there are two parameters namely V_{max} and inertia weight factor (w), to be adjusted for optimum performance besides swarm size. After series of experiments conducted, it is found that the following parameter setting produces the best result in terms of best and mean.

$$V_{max}=0.2; C_1=C_2=1; PF=100; w=0.4.$$

5.2 39-bus New England system

The 39-bus system is simplified representation of the 345-kV transmission system in the New England region having 10 generators and 29 load buses. The congestion cost has been determined for a pool based model by considering the reactive power support

provided by the generators and the optimally placed capacitors apart from real power scheduling of generation. The values of the generator PTCDFs and QTCDs for congested line 34-14 of 39-bus system are shown in Table 4. The plots of PTCDFs and QTCDs at each bus with respect to the congested line have been depicted in Figure 10. It can be seen from the Table 4 as well as Figure 10 that Zone-1 and 2 have the non-uniform values of PTCDFs and QTCDs to the congested line power flow. The magnitudes of the sensitivity values are also much larger. Thus the generators G3, G8 and G10 are selected for the congested line 34-14 from the most sensitive zones Zone-1 and 2 to participate in the congestion management based on the qualifying bids in the market. The capacitor has been located optimally on bus-14 based on its most negative reactive power flow sensitivity index value which has been found to be -0.3601. Whereas, the reactive power flow sensitivity indices at other buses are found to be less than the index at bus-14. In the multi line congestion case, the two lines 34-14 and 36-21 have been found to be congested. For managing the congestion the generators G3, G4, G6, G8 and G10 have been selected from the most sensitive Zone-1 and 2 based on the qualifying bids in the market.

The line ratings and base case line flows for 39-bus system are given as follows:

- Single line congestion:
- Line rating for line 34-14=2.500pu;
- Base case=2.67pu;
- Multi line congestion:

Line rating for line 34-14=2.500pu;

Base case=2.667pu;

Line rating for line 36-21=3.000pu;

Base case=3.195pu;

The different cases taken for the study are:

Case-1: With change in real power generation.

Case-2: With change in real and reactive power generation without capacitor reactive power support.

Case-3: With change in real and reactive power generation with capacitor reactive power support.

5.3 75-bus Indian system

The practical 75-bus Indian system represents a reduced network of Uttar Pradesh State Electricity Board's (UPSEB) network comprising of 400-kV and 200-kV buses with 15 generators, 24 transformers and 97 lines. The values of the generator PTCDFs and QTCDs for congested line 26-41 of 75-bus system are shown in Table 4. The plots of PTCDFs and QTCDs at each bus with respect to the congested line have

been depicted in Figure 11. It can be seen from the Table 4 as well as Figure 11 that Zone-1 has the non-uniform values of PTCDFS and QTCDFs to the congested line power flow. The magnitudes of the sensitivity values are also much larger. Thus the generators G3, G12 and G13 are selected for the congested line 26-41 from the most sensitive Zone-1 to participate in the congestion management based on the qualifying bids in the market. In the multi line congestion case, the two lines 26-41 and 19-36 have been found to be congested. For managing the congestion the generators G3, G9, G12 and G13 have been selected from the most sensitive Zone-1 based on the qualifying bids in the market.

The line ratings and base case line flows for 75-bus system are given as follows

a) Single line congestion:

Line rating for line 26-41=4.000pu;

Base case=4.030pu;

b) Multi line congestion:

Line rating for line 26-41=4.000pu;

Base case=4.030pu

Line rating for line 19-36=2.000pu;

Base case=2.055pu;

The different cases taken for the study are:

Case-1: With change in real power generation.

Case-2: With change in real and reactive power generation without capacitor reactive power support.

The optimal re-dispatch of active and reactive powers and Congestion Cost (CC) for 39-bus and 75-bus system using the proposed AFPSO based OPF and other EAs, for *Case-1*, *Case-2* and *Case-3*, are shown in Table 2(a), 2(b) and 2(c) respectively. From the simulation results shown in Table 2(a), 2(b) and 2(c), it is observed that the Congestion Cost (CC) and optimal change in real and reactive powers with the proposed AFPSO based OPF, for all cases, are smaller as compared to the other EAs. It can also be seen from the Table 2(c) that capacitor reactive support is more effective in reducing the congestion cost. The congestion cost is found to be minimum with both generator and capacitor reactive power support in the system.

It is also found that the generators are subjected to a lower magnitude of re-scheduling in the presence of reactive power provided by the generators and capacitors. From the Table 2(a), 2(b) and 2(c), it has been observed that the congestion cost for multi line congestion case is more as compared to single line congestion cases. Figure 5 to 8 shows the convergence characteristics of BCGA, RCGA, SPSO and AFPSO respectively. Figure 9 shows the comparison of the convergence characteristics of all the proposed

methods. From these figures it can be observed that the AFPSO is better among the other EAs in terms of solution quality to reach the global optimum solution. From the Table 3(a), the computation time for the proposed AFPSO based OPF is found to be slightly higher as compared to SPSO based OPF as it takes more time per iteration due to the Fuzzy evaluation process. And the line flows in the congested lines, shown in Table 3(a) are found to be less for the proposed AFPSO based OPF as compared to the other EAs. For the purpose of comparison, the results are directly taken from the respective papers [9] and [11]. From the Table 3(b), the Congestion Cost is found to be less with the proposed AFPSO based OPF method as compared to the other EAs such as BCGA, RCGA, SPSO based OPF and the methods proposed in [11] and [9].

Therefore from the Table 3(b) and Figure 12, it has been revealed that AFPSO based OPF provides the more economical solution to Congestion Management than the methods proposed in [11] and [9].

6. CONCLUSION

This paper has presented an optimal power dispatch model for congestion management and minimization of congestion cost using Adaptive Fuzzy PSO (AFPSO) based OPF. The proposed method is compared with other Evolutionary Algorithms, viz. BCGA, RCGA and SPSO based OPF methods. The studies are carried out on 75-bus Indian system and 39-bus New England Test System. The impact of reactive power support from both the generator and capacitor has also been studied. From the results presented in this paper, following main conclusions can be made.

- 1) The Congestion Cost with the proposed AFPSO based OPF method is found to be smaller as compared to the SPSO, RCGA and BCGA based OPF methods.
- 2) The congestion costs for cases employing reactive power support from generators and capacitors are considerably less than the cases without any reactive support.
- 3) The amount of rescheduling of real power transactions is reduced in the presence of reactive power support considered in the system for congestion management.
- 4) The Congestion Cost is significantly higher for multi line congestion case than single line congestion case.

Thus, the proposed AFPSO based optimal rescheduling method is more effective in reducing the congestion cost and it offers more economical solution to the congestion management as compared to the BCGA,

RCGA, SPSO and conventional optimization methods.

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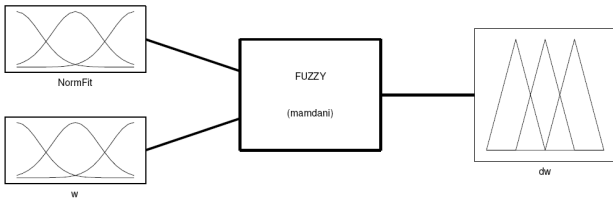


Figure 1. Fuzzy Control inputs and outputs

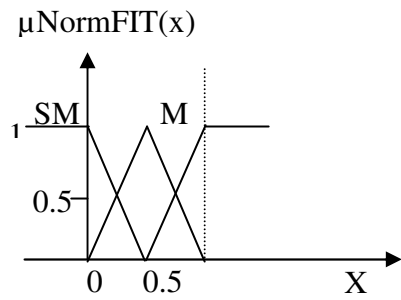


Figure 2(a). Membership of Normalized fitness

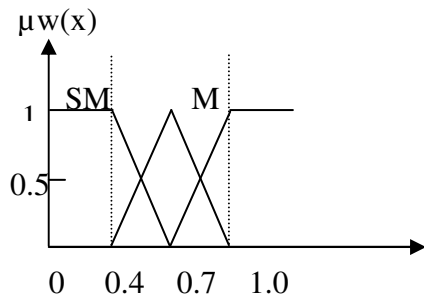


Figure 2(b). Membership of inertia weight

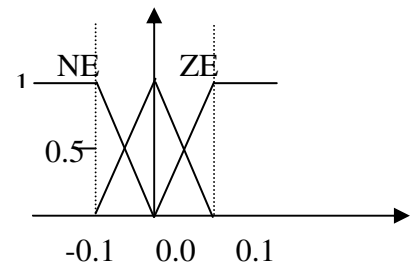


Figure 2(c). Membership of the change of inertia weight

Figure 2. Member ship function of Normalized fitness, Current inertia weight and change of inertia weight

TABLE 1: Fuzzy rules for Inertia weight correction

Rule No.	NormFIT	w	dw
1	S	S	ZE
2	S	M	NE
3	S	L	NE
4	M	S	PE
5	M	M	ZE
6	M	L	NE
7	L	S	PE
8	L	M	ZE
9	L	L	NE

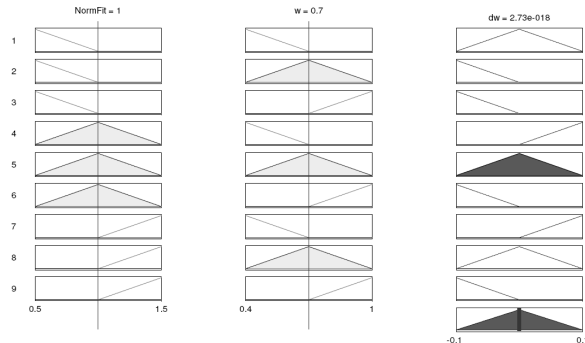


Figure 3. Fuzzy evaluation of the inertia weight correction for an input set of (1, 0.7) from MATLAB simulation.

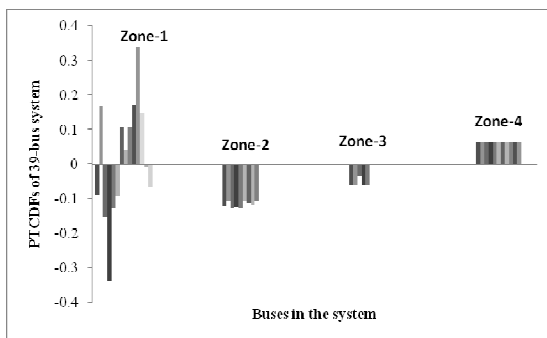


Figure 10(a). PTCDFs at all the buses in the 39-bus system

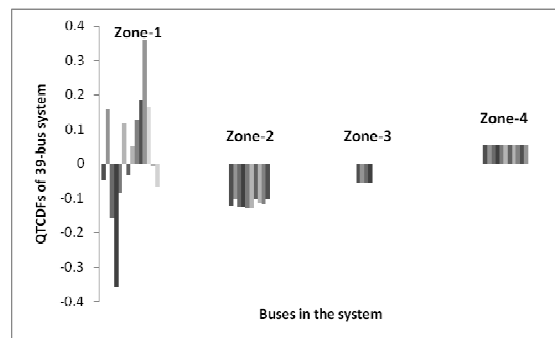


Figure 10(b). QTCDFs at all the buses in the 39-bus system

Figure 10: PTCDFs and QTCDFs of all busses in the 39-bus System for the congested line 34-14

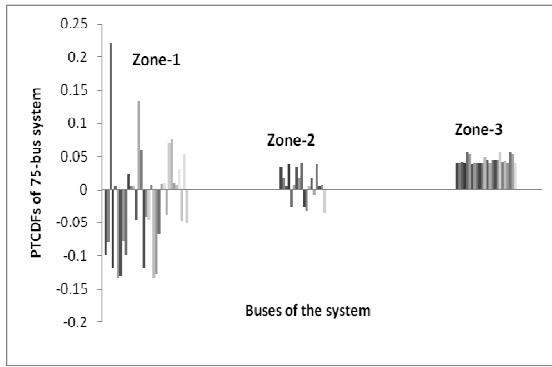


Figure 11(a). PTCDFs at all the buses in the 75-bus system

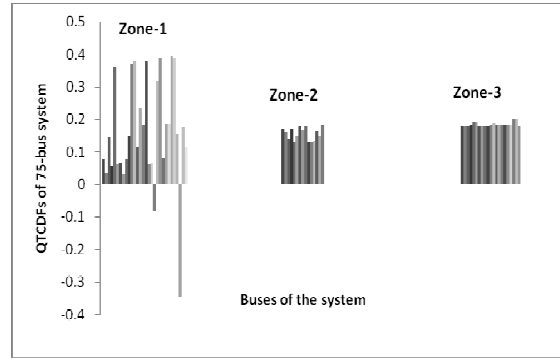


Figure 11(b). QTCDFs at all the buses in the 75-bus system

Figure 11: PTCDFs and QTCDFs of all busses in the 75-bus System for the congested line 26-41

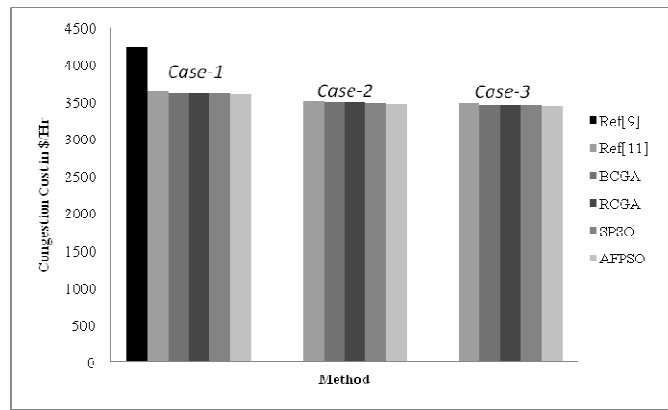


Figure 12. Comparison of Congestion Cost

Table 2(a): Change in active power generation, congestion cost and time for 39-bus system for *case-1*

39-bus New England Test System									
Single line congestion case					Multi line congestion case				
	BCGA	RCGA	SPSO	AFPSO		BCGA	RCGA	SPSO	AFPSO
ΔP_{g_3}	-0.7289	-0.7294	-0.7278	-0.7261	ΔP_{g_3}	-0.0634	-0.0633	-0.0633	-0.0632
ΔP_{g_8}	0.3341	0.3335	0.3334	0.3326	ΔP_{g_4}	0.2000	0.2001	0.1994	0.1992
$\Delta P_{g_{10}}$	0.4003	0.3996	0.3987	0.3981	ΔP_{g_6}	-0.9997	-1.0006	-0.9972	-0.9960
					ΔP_{g_8}	0.4668	0.4664	0.4655	0.4649
					$\Delta P_{g_{10}}$	0.4001	0.4001	0.3993	0.3986
CC (\$/Hr)					CC (\$/Hr)				
Best	3625.6	3624.9	3618.3	3611.1	Best	5253.1	5252.1	5242.6	5232.1
Worst	3634.5	3630.8	3625.5	3616.1	Worst	5274.1	5267.9	5254.6	5242.5
Mean	3630.1	3627.0	3621.3	3613.6	Mean	5263.6	5261.7	5249.3	5237.2
75-bus Indian Practical System									
Single line congestion case					Multi line congestion case				
	BCGA	RCGA	SPSO	AFPSO		BCGA	RCGA	SPSO	AFPSO
ΔP_{g_3}	0.2046	0.2046	0.2040	0.2039	ΔP_{g_3}	0.4490	0.4492	0.4480	0.4472
$\Delta P_{g_{12}}$	-0.4236	-0.4236	-0.4230	-0.4214	ΔP_{g_9}	-0.5003	-0.4998	-0.4986	-0.4977
$\Delta P_{g_{13}}$	0.1999	0.1997	0.1996	0.1993	$\Delta P_{g_{12}}$	-0.1895	-0.1894	-0.1891	-0.1886
					$\Delta P_{g_{13}}$	0.1999	0.2000	0.1997	0.1991
CC (\$/Hr)					CC (\$/Hr)				
Best	1948.8	1948.4	1944.9	1941.0	Best	3098.6	3098.0	3092.4	3086.2
Worst	1954.6	1953.2	1949.3	1944.8	Worst	3107.9	3105.1	3098.5	3090.8
Mean	1950.8	1950.5	1946.5	1942.2	Mean	3101.7	3102.2	3095.6	3088.4

Table 2(b): Change in active and reactive generation, congestion cost for 39-bus system for *case-2*

39-bus New England Test System									
Single line congestion					Multi line congestion				
	BCGA	RCGA	SPSO	AFPSO		BCGA	RCGA	SPSO	AFPSO
ΔP_{g_3}	-0.7064	-0.7063	-0.7061	-0.6983	ΔP_{g_3}	0.1797	0.1797	0.1794	0.1793
ΔP_{g_8}	0.3142	0.3144	0.3136	0.3105	ΔP_{g_4}	-0.4505	-0.4511	-0.4501	-0.4488
$\Delta P_{g_{10}}$	0.3998	0.3998	0.3993	0.3950	ΔP_{g_6}	0.3346	0.3346	0.3340	0.3330
ΔQ_{g_3}	-0.5001	-0.5001	-0.4986	-0.4938	ΔP_{g_8}	0.3595	0.3593	0.3589	0.3581
ΔQ_{g_8}	0.6588	0.6594	0.6573	0.6512	$\Delta P_{g_{10}}$	-0.3905	-0.3901	-0.3894	-0.3886
$\Delta Q_{g_{10}}$	-0.2457	-0.2457	-0.2452	-0.2425	ΔQ_{g_3}	0.4667	0.4661	0.4658	0.4649
					ΔQ_{g_8}	-0.2528	-0.2527	-0.2523	-0.2519
					$\Delta Q_{g_{10}}$	0.1797	0.1797	0.1794	0.1793
CC (\$/Hr)					CC (\$/Hr)				
Best	3496.8	3496.1	3496.1	3482.8	Best	5072.2	5071.2	5062.0	5051.9
Worst	3507.3	3504.1	3496.7	3488.0	Worst	5087.4	5082.8	5072.1	5059.4
Mean	4501.5	3500.9	3492.0	3484.6	Mean	5078.9	5075.5	5065.2	5056.5
75-bus Indian Practical System									
Single line congestion					Multi line congestion				
	BCGA	RCGA	SPSO	AFPSO		BCGA	RCGA	SPSO	AFPSO
ΔP_{g_3}	0.2001	0.2001	0.1994	0.1992	ΔP_{g_3}	0.5685	0.5681	0.5674	0.5662
$\Delta P_{g_{12}}$	-0.4107	-0.4108	-0.4103	-0.4088	ΔP_{g_9}	-0.5003	-0.5003	-0.4985	-0.4982
$\Delta P_{g_{13}}$	0.1999	0.2000	0.1997	0.1992	$\Delta P_{g_{12}}$	-0.3473	-0.3478	-0.3468	-0.3459
ΔQ_{g_3}	-0.4996	-0.4994	-0.4993	-0.4978	$\Delta P_{g_{13}}$	0.2001	0.1998	0.1997	0.1992
$\Delta Q_{g_{12}}$	0.0346	0.0346	0.0345	0.0345	ΔQ_{g_3}	0.4474	0.4476	0.4467	0.4455
$\Delta Q_{g_{13}}$	0.3869	0.3865	0.3860	0.3848	$\Delta Q_{g_{12}}$	-0.4995	-0.5003	-0.4994	-0.4980
					$\Delta Q_{g_{13}}$	-0.4997	-0.4998	-0.4991	-0.4981
CC (\$/Hr)					CC (\$/Hr)				
Best	1917.5	1917.2	1913.7	1909.9	Best	3716.3	3715.5	3708.8	3701.4
Worst	1923.2	1921.6	1917.5	1912.7	Worst	3727.4	3724.0	3716.2	3706.9
Mean	1919.8	1919.9	1915.8	1910.5	Mean	3722.2	3719.5	3712.4	3703.5

Table 2(c): Change in active and reactive power generation, congestion cost and time for 39-bus system for *case-3*

39-bus New England Test System									
Single line congestion					Multi line congestion				
	BCGA	RCGA	SPSO	AFPSO		BCGA	RCGA	SPSO	AFPSO
ΔP_{g_3}	-0.7022	-0.7014	-0.6999	-0.6987	ΔP_{g_3}	-0.4997	-0.4994	-0.4992	-0.4977
ΔP_{g_8}	0.3083	0.3080	0.3077	0.3068	ΔP_{g_4}	0.2000	0.1998	0.1995	0.1992
$\Delta P_{g_{10}}$	0.3998	0.3996	0.3995	0.3985	ΔP_{g_6}	-0.4513	-0.4509	-0.4501	-0.4494
ΔQ_{g_3}	-0.3882	-0.3883	-0.3870	-0.3866	ΔP_{g_8}	0.3572	0.3570	0.3563	0.3559
ΔQ_{g_8}	0.3420	0.3422	0.3415	0.3405	$\Delta P_{g_{10}}$	0.3997	0.3996	0.3989	0.3983
$\Delta Q_{g_{10}}$	-0.3999	-0.3995	-0.3987	-0.3984	ΔQ_{g_3}	-0.4996	-0.5002	-0.4989	-0.4979
$\Delta Q_{c_{14}}$	0.3254	0.3255	0.3250	0.3244	ΔQ_{g_8}	0.3583	0.3577	0.3576	0.3567
					$\Delta Q_{g_{10}}$	-0.3625	-0.3619	-0.3617	-0.3612
					$\Delta Q_{c_{14}}$	0.3274	0.3271	0.3262	0.3257
CC (\$/Hr)					CC (\$/Hr)				
Best	3468.1	3467.4	3461.1	3454.2	Best	4632.3	4631.3	4623.0	4613.7
Worst	3478.5	3475.3	3468.0	3459.3	Worst	4646.2	4641.9	4632.2	4620.6
Mean	3474.4	3470.6	3464.5	3457.3	Mean	4639.9	4637.5	4628.7	4615.9

Table 3(a): Line flows for all methods for 39-bus system

	BCGA	RCGA	SPSO	AFPSO
Line flows				
Line 34-14	2.4995	2.4993	2.4990	2.4990
Line 36-21	2.5515	2.5514	2.5510	2.5510
Computation Time in (Sec)	40.12	32.23	29.55	31.30

Table 3(b): Comparison of Congestion cost for 39-bus system

	Case 1 as in ref. [9]	Case 1 as in ref. [11]	BCGA	RCGA	SPSO	AFPSO
Case-1	4242.8	3643.8	3625.6	3624.9	3618.3	3611.1
Case-2	-----	3514.4	3496.8	3496.1	3496.1	3482.8
Case-3	-----	3485.5	3468.1	3467.4	3461.1	3454.2

Table 4: PTCDFs and QTCDFs of generators indifferent Zones for bothe test systems

39-bus New England Test System for congested line 34-14								75-bus Indian System for congested line 26-41					
PTCDFs								PTCDFs					
Zone 1		Zone 2		Zone 3		Zone 4		Zone 1		Zone 2		Zone 3	
Gen No.	PTCDFs	Gen No.	PTCDFs	Gen No.	PTCDFs	Gen No.	PTCDFs	Gen No.	PTCDFs	Gen No.	PTCDFs	Gen No.	PTCDFs
1	-0.0891	2	-0.1201	9	-0.0599	4	0.0621	1	-0.1001	4	0.0340	5	0.0398
3	0.1691	8	-0.1069			5	0.0621	2	-0.0789	8	0.0171	6	0.0398
		10	-0.128			6	0.0629	3	0.2212	10	0.0061	7	0.0420
						7	0.0629	9	-0.1178	14	0.0389		
								11	0.0048	15	-0.0269		
								12	-0.1329				
								13	-0.1309				
QTCDFs								QTCDFs					
Zone 1		Zone 2		Zone 3		Zone 4		Zone 1		Zone 2		Zone 3	
Gen No.	QTCDFs	Gen No.	QTCDFs	Gen No.	QTCDFs	Gen No.	QTCDFs	Gen No.	QTCDFs	Gen No.	QTCDFs	Gen No.	QTCDFs
1	-0.0499	2	-0.1221	9	-0.0566	4	0.0538	1	0.0769	4	0.0340	5	0.0398
3	0.1590	8	-0.1049			5	0.0538	2	0.0348	8	0.0171	6	0.0398
		10	-0.1248			6	0.0531	3	0.1455	10	0.0061	7	0.0420
						7	0.0538	9	0.0538	14	0.0389		
								11	0.3588	15	-0.0269		
								12	0.0629				
								13	0.0648				

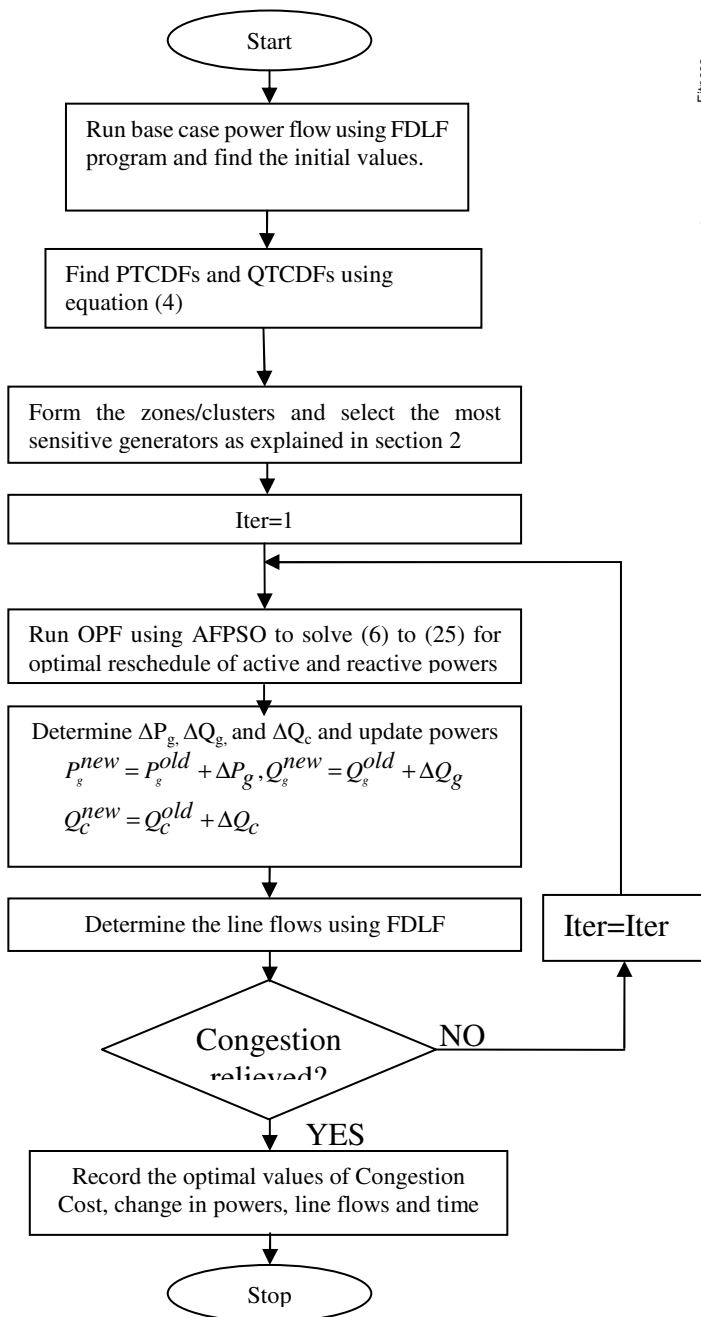


Figure 4. Flow chart for proposed AFPSO based congestion

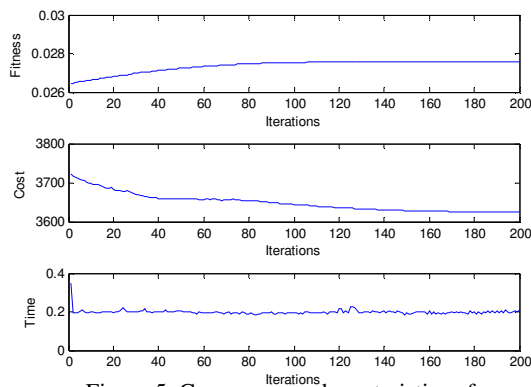


Figure 5. Convergence characteristics of BCGA based OPF

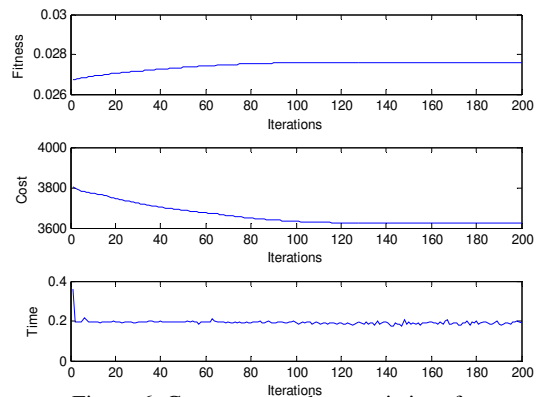


Figure 6. Convergence characteristics of RCGA based OPF

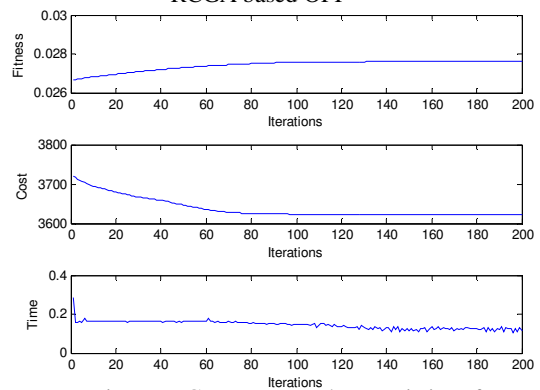


Figure 7. Convergence characteristics of SPSO based OPF

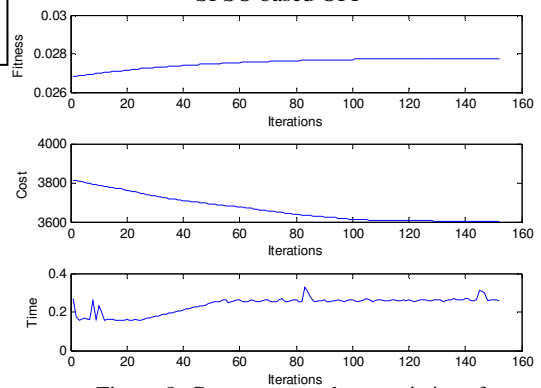


Figure 8. Convergence characteristics of AFPSO based OPF

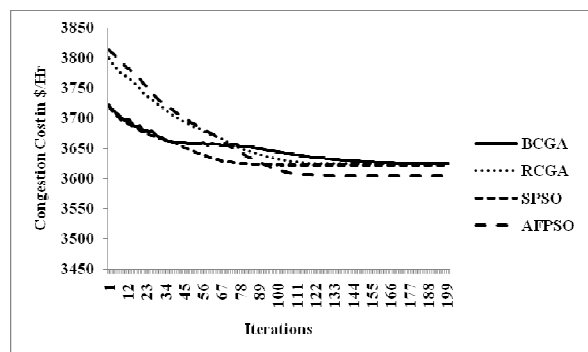


Figure 9. Comparison of Convergence characteristics of BCGA, RCGA, SPSO and AFPSO