CHAPTER IV

SOLUTION BY INTERIOR POINT AND PARTICLE SWARM OPTIMIZATION METHODS

4.1. INTRODUCTION

The optimal power flow (OPF) provides good solutions for economic operation of the power system [47-59]. The OPF maximizes the social welfare in the power market by including consumer's benefits in the problem objective. Now a days, due to privatization of power markets, the multi-transaction is frequently involved with bilateral/multilateral contracts. This makes the formulation of OPF problem more complex. Also, the involvement of multi-transaction in market produces various technical challenges to transmission operators. All the participants of transactions try to maximize their profits by open access in the transmission system. The congestion management becomes an important operational issue in comparison to other operational issues due to multi-transaction operations. The congestion in the transmission system causes various security and reliability related problems in the power system. This also affects fair competition among the market participants. Sometimes, it causes various social and economic related problems in the system operations, such as distribution of transmission rights during contingent conditions and loss allocation due to each transaction.

This chapter represents the optimal rescheduling of active powers of generators and consumer's demands to solve the congestion management problems with maximum social welfare. The mathematical models of centralized and decentralized OPF based decision support have already been discussed in the previous chapter. In the present work, the congestion management has been solved using decentralized and centralized approaches. The test system models for studying the market operation is taken from refs. [100, 102]. The solution of the problem objective is obtained by interior point (IP) and particle swarm optimization (PSO) methods. The accuracy of the decentralized approach has been authenticated by comparing its results with the results of centralized approach. Modified IEEE-30 and modified IEEE-118 bus systems have been used to form the multi-transaction power market models for showing the performance of the IP and PSO methods. The test results reveal that the PSO provides better results as compared to the IP method.

4.2. OPTIMIZATION METHODS FOR OPTIMAL POWER FLOW

The OPF solution optimizes a selected objective function via optimal adjustment of power system control variables, while at the same time it satisfies the various equality and inequality constraints. These equality constraints are the power flow equations, whereas the inequality constraints are the limits of control variables and operating limits of power system dependent variables. A wide variety of optimization methods have been applied in the recent past for solving the OPF problems as reported in Chapter I which have their own advantages and limitations. In the present work, the IP and PSO methods have been considered among the reported techniques to solve the problem objective because of fast convergence of IP and better global solution capability of PSO.

4.2.1. Interior Point Optimization Method

Karmarkar proposed IP method for optimization problems of linear systems in 1984 [121]. The IP method is very popular among researchers to obtain the OPF solution in power system. This method has been extensively applied to solve large-scale OPF problems due to its fast computational speed and robustness. The gradient, Jacobean and Hessian matrices of objective functions (in IP) are considered as constraint functions which provides a fast convergence. This method also allows easy handing of simple bounds on the primal variables by incorporating the free variables in solution implementation. In the present work, the advantage of IP optimization based algorithm has been used to solve the congestion management problems while maximizing the social welfare in the bilateral multi-transaction power market. It is a known fact that in conventional nonlinear programming (NLP) optimization methods, some extreme points are visited before the optimum solutions during convergence. Therefore, it requires large number of iterations to reach to the optimum solution. On the other hand, in the IP based optimization solution process, a polynomial-time algorithm is used and it cuts across the interior of the solution space which results into fast convergence for extremely large programs [127-

129, 133-141]. The graphical representation of IP optimization algorithm is shown in Fig. 4.1.

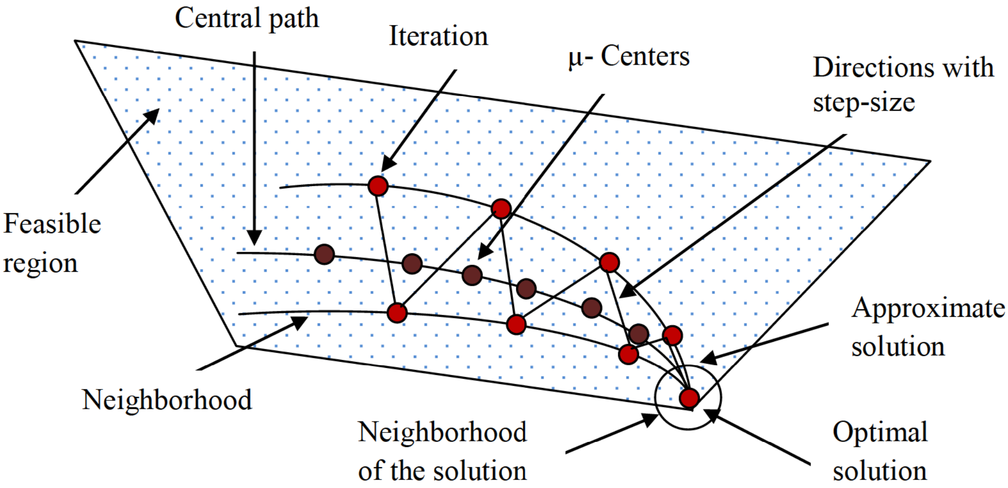


Fig. 4.1 Graphical representation of IP algorithm.

A non-linear optimization problem can be represented as follows:

$$\left.\begin{array}{ll} Minimize & f(x) \\ Subject\ to & h(x) = 0 \\ and & g_{min} \leq g(x) \leq g_{max} \end{array}\right\} \qquad (4.1)$$

The objective function *f(x)* generally represents the generation fuel cost, transmission loss, corrective controls, etc. In the present work the social welfare is considered as objective function for OPF formulation. The function *h(x)* represents the power flow equations and the function *g(x)* represents component and variable inequalities. The inequality constraints are transformed into equality constraints by the addition of non-negative slack variables. This modification reformulates Eq. (4.1) as

$$\left.\begin{array}{l} Minimize\ \ f(x) \\ Subject\ to\ \ h(x) = 0 \\ g(x) - z_1 - g_{min} = 0 \\ g(x) + z_u - g_{max} = 0 \\ z_1, z_u \geq 0 \end{array}\right\} \qquad (4.2)$$

where z_1 and z_u are slack variables.

The Lagrangian function of Eq. (4.2) can be written as

$$L = f(x) - \lambda^T h(x) - \pi_1^T(g(x) - z_1 - g_{min}) - \pi_u^T(g(x) + z_u - g_{max}) \qquad (4.3)$$

where λ, π_1 and π_u are the vectors of Lagrange multipliers.

The KKT optimal condition of this can be written as

$$\Delta_x L = \nabla f(x) - \nabla h(x)^T \lambda + \Delta g(x)^T \pi_1 - \nabla g(x)^T \pi_u = 0 \qquad (4.4)$$

$$\Delta_{\lambda} L = -h(x) = 0 \tag{4.5}$$

$$\Delta\pi_1 L = -(-g(x) + z_1 + g_{min}) = 0 \tag{4.6}$$

$$\Delta\pi_u L = -(g(x) + z_u - g_{max}) = 0 \tag{4.7}$$

$$\Delta_{z1} L = Z_1 \pi_1 = 0 \quad \pi_1, Z_1 < 0 \tag{4.8}$$

$$\Delta_{zu} L = z_u \pi_u = 0 \quad \pi_u, z_u < 0 \tag{4.9}$$

Due to complimentary conditions, Eqs. (4.8) and (4.9) are solved by introducing a perturbation factor, $\mu > 0$ in the Lagrangian function using a logarithmic barrier given by

$$L_{\mu} = f(x) - \mu \sum(\ln z_1 + \ln z_u) - \lambda^T h(x) - \pi_1^T (g(x) - z_1 - g_{min})$$
$$-\pi_u^T (g(x) + z_u - g_{max}) \tag{4.10}$$

When the KKT conditions are applied, Eqs. (4.8) and (4.10) are transformed as

$$\Delta_{z1} L_{\mu} = Z_1 \pi_1 - \mu e = 0 \tag{4.11}$$

$$\Delta_{zu} L_{\mu} = Z_u \pi_u - \mu e = 0 \tag{4.12}$$

where $e = [1, 1, 1, \ldots., 1]^T$ and μ is known as the barrier parameter. The original complementary conditions are satisfied by forcing the value of μ from a nonzero value to zero value as the iteration proceeds. After including the barrier parameter in Eqs. (4.4)-(4.7), (4.11) and (4.12), they are called the perturbed KKT conditions which on applying Newton's method gives

$$\begin{bmatrix} \pi_1 & 0 & z_1 & 0 & 0 & 0 \\ 0 & \pi_u & 0 & z_u & 0 & 0 \\ -z_1 & 0 & 0 & 0 & \nabla_{g(x)}^T & 0 \\ 0 & -z_u & 0 & 0 & -\nabla_{g(x)}^T & 0 \\ 0 & 0 & \nabla_{g(x)} & -\nabla_{g(x)} & \nabla_x^2 L_{\mu} & -\nabla h(x)^T \\ 0 & 0 & 0 & 0 & -\nabla h(x) & 0 \end{bmatrix} \times \begin{bmatrix} \Delta z_1 \\ \Delta z_u \\ \Delta \pi_1 \\ \Delta \pi_u \\ \Delta x \\ \Delta \lambda \end{bmatrix}$$
$$= -\begin{bmatrix} \nabla_{z_1} L_{\mu} \\ \nabla_{z_u} L_{\mu} \\ \nabla_{\pi_1} L_{\mu} \\ \nabla_{\pi_u} L_{\mu} \\ \nabla_x L_{\mu} \\ \nabla_{\lambda} L_{\mu} \end{bmatrix} \tag{4.13}$$

where$\nabla_x^2 L_{\mu} = \nabla_x^2 f(x) - \nabla_x^2 h(x)^T \lambda + \nabla_x^2 g(x)^T \pi_1 - \nabla_x^2 g(x)^T \pi_1 - \nabla_x^2 g(x)^T \pi_u$.

The Newton's direction is obtained by solving Eq. (4.2) directly or by solving the reduced system as

$$\begin{bmatrix} H & -J_h^T \\ -J_h & 0 \end{bmatrix} * \begin{bmatrix} \Delta x \\ \Delta \lambda \end{bmatrix} = -\begin{bmatrix} \psi \\ h(x) \end{bmatrix} \tag{4.14}$$

After finding Δx and $\Delta \lambda$, the variables $\Delta z_1, \Delta z_u, \Delta \pi_1$ *and* $\Delta \pi_u$ are given by

$$\left.\begin{aligned}\Delta z_1 &= \nabla g(x)^T \Delta x - \nabla_{\pi_1} L_\mu \\ \Delta z_u &= -\nabla g(x)^T \Delta x - \nabla_{\pi_u} L_\mu \\ \Delta \pi_1 &= z_1^{-1}(-\pi_1 \Delta z_1 - \nabla_{z_1} L_\mu) \\ \Delta \pi_u &= z_u^{-1}(-\pi_u \Delta z_u - \nabla_{z_u} L_\mu)\end{aligned}\right\} \tag{4.15}$$

Using Eq. (4.37); H, J_h and ψ are reformed as

$$\left.\begin{aligned}H &= \nabla_x^2 L\mu + \nabla g(x)(z_1^{-1}\pi_1 - z_u^{-1}\pi_u)\nabla g(x)^T \\ J_h &= \nabla h(x) \\ \psi &= -\nabla_x L_\mu - \nabla g(x)(z_1^{-1}\pi_1 - z_u^{-1}\pi_u)\nabla g(x)^T + z_1^{-1}\nabla_{z_1} L_\mu - z_u^{-1}\nabla_{z_u} L_\mu\end{aligned}\right\} \tag{4.16}$$

After computing Eq. (4.16), and then applying the new primal and dual variables theory, the value of μ and the variables Δx, $\Delta\lambda$, $\Delta z_1, \Delta z_u, \Delta\pi_1$ *and* $\Delta\pi_u$ are updated. These updated variables are as follows

$$\left.\begin{aligned}x^{Iter+1} &= x^{Iter} + \alpha_p^{Iter}\Delta x, & \lambda^{Iter+1} &= \lambda^{Iter} + \alpha_d^{Iter}\Delta\lambda \\ z_1^{Iter+1} &= z_1^{Iter} + \alpha_p^{Iter}\Delta z_1, & \pi_1^{Iter+1} &= \pi_1^{Iter} + \alpha_d^{Iter}\Delta\pi_1 \\ z_u^{Iter+1} &= z_u^{Iter} + \alpha_p^{Iter}\Delta z_u, & \pi_u^{Iter+1} &= \pi_u^{Iter} + \alpha_d^{Iter}\Delta\pi_u\end{aligned}\right\} \tag{4.17}$$

where α_p^{Iter} and α_d^{Iter} are primal and dual step length parameters. The maximum step length has been determined by Newton's direction as follows

$$\alpha_p^{Iter} = \min\left\{1, \gamma\, min\left\{-\frac{z_1^{Iter}}{\Delta z_1}/\Delta z_1 < 0, -\frac{z_u^{Iter}}{\Delta z_u}/\Delta z_u < 0\right\}\right\} \tag{4.18}$$

$$\alpha_d^{Iter} = \min\left\{1, \gamma\, min\left\{-\frac{\pi_1^{Iter}}{\Delta\pi_1}/\Delta\pi_1 < 0, -\frac{\pi_u^{Iter}}{\Delta\pi_u}/\Delta\pi_u < 0\right\}\right\} \tag{4.19}$$

To ensure that the next point satisfies the strict positivity conditions, γ is used as a safety factor. To reduce the complementary gap, the value of μ should be proportional to this gap and can be described as

$$\mu^{Iter+1} = \sigma^{Iter}\frac{\rho^{Iter}}{2p_{inq}} \tag{4.20}$$

where p_{inq} is number of inequality constraints, σ^{Iter} is a centering parameter which is given by $\sigma^{Iter} = max\,\{0.99\sigma^{Iter-1}, 0.1\}$, with $\sigma^0 = 0.2$ and ρ^{Iter} is a complementary gap and defined as

$$\rho^{Iter} = (z_1^{Iter})^T \pi_1^{Iter} + (z_u^{Iter})^T \pi_u^{Iter} \tag{4.21}$$

The solution convergence of Eq. (4.21) is terminated when the norm of right hand side vector scaled by summation of all variables and the complementary gap are sufficiently small or less than tolerance value ε for the algorithm ($\rho^{Iter} < \varepsilon$). The Eq. (4.21) can be rewritten as

$$\rho^{Iter} = \sum_{Iter=1}^{Iter_{max}} (z_1^{Iter})^T \pi_1^{Iter} + (z_u^{Iter})^T \pi_u^{Iter} \tag{4.22}$$

This method is also known as Primal-Dual Interior Point method (PD-IPM) [141].

4.2.2. Particle Swarm Optimization

PSO is a heuristic global optimization model. This was originally presented by Kennedy and Berhrat in 1995 [146]. This method has been developed from swarm intelligence and bird and fish flock movement behaviour. While searching for food, the birds are either scattered or go together before they locate the place where they can find the food. When the birds are searching the food from one place to another, one bird smells the food and provides the information of food availability at that place. Since the information has been communicated to each bird and on the basis of good information, the birds will eventually flock to the place where food can be found. On the basis of this, the PSO algorithm was developed. The solution obtained by swarm optimization can be compared with bird swarm and the good information obtained by a bird is equivalent to optimal solution in the search space. In bird swarm, a single bird posses a relatively limited amount of intelligence, but the complex behaviour of the entire flock allows the birds to smell the food source. Similarly, each particles of PSO have their individual values, but there coordination provides a global optimal solution including equality and inequality constraints. PSO technique is based on computer science in addition to social science. It uses the swarm intelligence concept, which shows collective behaviour of swarm. The swarm interacts with the local environment and creates global functional patterns [147-148]. The swarm intelligence principles can be describes as

i. *Proximity Principle:* the population should be able to carry out simple space and time computations.
ii. *Quality Principle:* the population should be able to respond to quality factors in the environment.
iii. *Diverse Response Principle:* the population should not commit its activity along excessively narrow channels.
iv. *Stability Principle:* the population should not change its mode of behaviour every time the environment changes.
v. *Adaptability Principle:* the population should be able to change its behavioural mode when it is worth the computational price.

The term “particles” refers to population members which are mass-less and volume-less and are subjected to velocities and accelerations towards a better mode of behaviour. The PSO have numbers of advantages to solve the optimization problems. In this technique, the fitness functions and constraints are separately handled and simple manipulation is required to handle the constraints. Since a simple derivative free mathematical derivation is required for PSO, it is easier and simpler as compared to other conventional techniques. The PSO have also some other advantageous features such as easy to integrate with other optimization techniques, less sensitive to the nature of objective function (convexity or continuity) and operate without evaluating the operands such as crossover and mutation in genetic algorithm. These features make PSO a simpler, faster and efficient evolutionary optimization technique as compared to other evolutionary techniques.

4.2.1. Mathematical Formulation and Performance of PSO

The mechanism of PSO is based on the search technique. The particles are attracted towards both; on the area of highest concentration found by entire swarm and best position personally encountered by particles. In space, each individual possible solution can be modeled as a particle that moves through the problem hyperspace. If $X_i = (x_{i1}, \ldots\ldots, x_{in})$ and $V_i = (v_{i1}, \ldots\ldots, v_{in})$ denotes the coordinates and the corresponding flight speed of particle i in a search space respectively then the position of each particle is determined by the vector $x_i \in R^n$ and its movement is known as $v_i \in R^n$ [171] in the following equation.

$$x_i(t) = x_i(t) + v_i(t) \tag{4.23}$$

The information available for each individual is based on its own experience and knowledge of the performance of other individuals in its neighborhood. There acceleration and direction of movement towards the fittest locations can be expressed by the following equation.

$$V_i^{Iter+1} = V_i^{Iter} + c_1 rand_1 \times (P_{best}^{Iter} - X_i^{Iter}) + c_2 rand_2 \times (G_{best}^{Iter} - X_i^{Iter}) \tag{4.24}$$

where, c_1 and c_2 are two positive numbers and $rand_1$ and $rand_2$ are two random numbers with uniform distribution in the range of [0, 1]. Once the velocity is determined, it is simple to move the particle to its next location and a new coordinate X_i^{Iter+1} is computed for each of the D dimensions defined by the user by the following equation.

$$X_i^{Iter+1} = X_i^{Iter} + V_i^{Iter+1} \tag{4.25}$$

The velocity update of Eq. (4.24) has three major components.

i. The first component is known as inertia, momentum, or habit of the PSO. This represents the tendency of particle to continue in the same direction during travelling in the space.

ii. The second component is a linear attraction towards the best position ever found by the i^{th} particle known as $P^{Iter}{}_{best}$ of particle's best position until iteration $Iter^{th}$, which is scaled by a random weight c_1rand_1. This component is referred as memory or self knowledge.

iii. The third component of velocity update equation is a linear attraction towards the best position found by any group known as $G^{Iter}{}_{best}$ of group's best position until iteration $Iter^{th}$, which is scaled by a random weight c_2rand_2. This component is referred as group knowledge, social knowledge or shared information.

The Fig. 4.2 shows a graphical interpretation of the PSO algorithm in two-dimensional space. The new velocity V^{Iter+1} is the sum of a momentum that tends to keep the particle on its current path, an attraction towards its personal best position $P^{Iter}{}_{best}$ and then an attraction towards the global best position of all group members $G^{Iter}{}_{best}$. Finally, the new position x^{Iter+1} are the sum of the current position x^{Iter} and the velocity v^{Iter+1}. The performance of PSO depends upon structures of the social networks. Different social network structures have been developed for PSO [153] and these structures for PSO are ring topology, fully connected graph, star network, tree network, pyramid network, four clusters network, Von-Neuman network, etc. Each structure has their benefits over other topology. In general, the performance depends upon the size of the problem. One structure may perform more effectively for certain types of problems, yet not good for other problems.

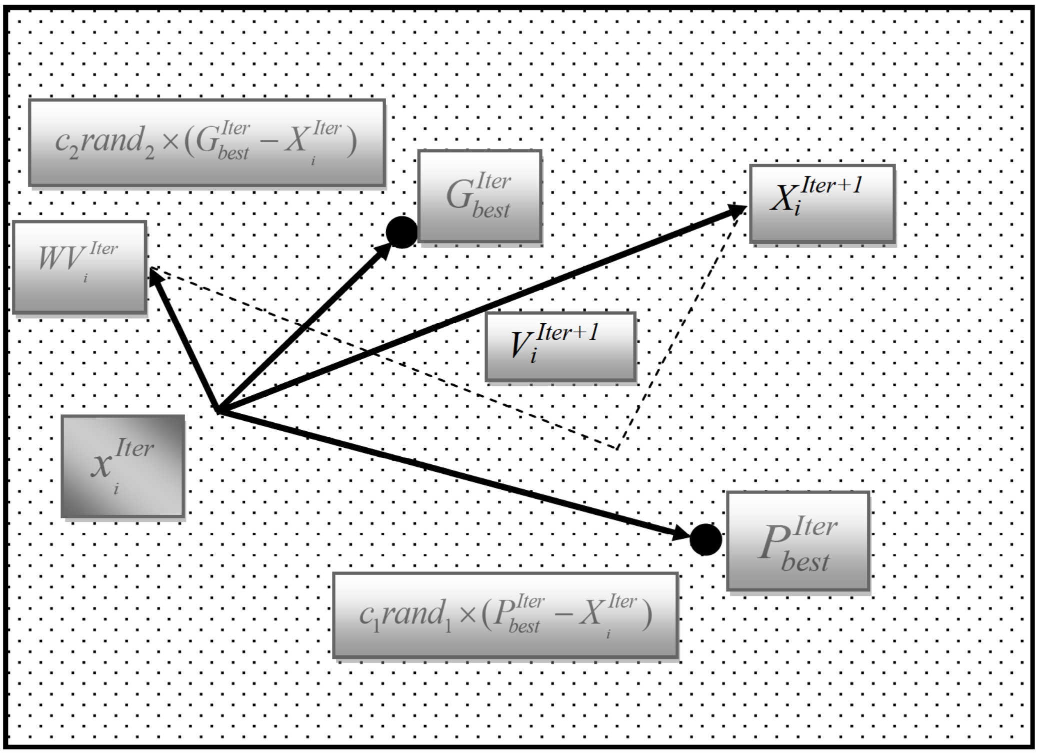


Fig. 4.2 Graphical representation of the PSO algorithm.

4.2.2. Parameter Selections for PSO

Several considerations must be taken into account to facilitate the convergence and to prevent against explosion of swarm during parameter selections of PSO. These considerations include various factors which affects the performance of the PSO such as maximum velocity limitation, selection of acceleration constants and the constriction factor or inertia weight.

4.2.2.1. Maximum Velocity Selection

The velocity of particles have been adjusted and bounded in between maximum and minimum values at each iteration step. If the velocity of particles is not bounded, then it creates an uncontrolled trajectory. In order to follow a wider cycles in the solution space, an appropriate velocity, v_i is introduced as given in ref. [153] which is

If $v_i > v_{max}$ *then* $v_i = v_{max}$

Else $v_i < -v_{max}$ *then* $v_i = -v_{max}$

Frequently, the value for v_{max} is selected according to the characteristics of the problem. If this parameter is high, then the particle move randomly and goes beyond a good solution. If this value is low, then the particle's movement is limited and the optimal solution may not be reached. To ensure uniform velocity throughout all dimensions, ref. [153] has proposed a maximum velocity given by

$$V_{max} = (x_{max} - x_{min})/N \tag{4.26}$$

where N is the number of interval in the d^{th} dimension selected by the user and x_{max} and x_{min} are the maximum and minimum values found by the particles up to then.

4.2.2.2. Selection of Acceleration Constants

Acceleration constant c_1 and c_2, with random vectors $rand_1$ and $rand_2$, control the stochastic influence of the cognitive and social component of the overall velocity of a particle. The acceleration constant c_1 and c_2 are also referred as trust parameters, wherein c_1 expresses the confidence of a particle and c_2 expresses the confidence a particle has with its neighbours. The conditions for c_1 and c_2 as follows

If	$c_1=c_2=0$	particles keep flying at their current speed until they hit a boundary;
	$c_1>0$ *and* $c_2 = 0$	all particles are independent hill climbers, they find the best position in its neighborhood by replacing the current best position if new position is better;
	$c_1=0, c_2>0$	entire swarm is attracted to a single point;
	$c_1=c_2$	particles are attracted towards the average of local and global best;
	$c_1>>c_2$	each particle is much more attracted to its own personal best position;
	$c_1<<c_2$	particles are most strongly attracted to the global best position.

In general, the maximum value for this constant should be equal to 4, which means $c_1+c_2=4$. A good proposed starting point is $c_1=c_2=2$ [153].

4.2.2.3. Selection of Constriction Factor or Inertia Constant

When the maximum velocity and acceleration constant are correctly defined, the particles may still diverge. This phenomenon is known as explosion of the swarm. This can be control by two methods [171].

(a) Constriction factor **–** As a general rule, when several particles are considered in a multi- dimensional problem space, it follows the following update rule [160] with a modification in Eq. (4.24) as

$$V_i^{Iter+1} = \chi\left\{V_i^{Iter} + c_1 rand_1 \times (P_{best}^{Iter} - X_i^{Iter}) + c_2 rand_2 \times (G_{best}^{Iter} - X_i^{Iter})\right\} \tag{4.27}$$

where $\chi = \dfrac{2\tau}{\left|2-\phi-\sqrt{\phi^2-4\phi}\right|}, \phi_1+\phi_2=\phi>4.0, \phi_1=c_1 rand_1, \phi_2=c_2 rand_2, \tau\in[0,1]$ and

equation (4.25) remains the same.

The constriction approach was developed as a natural, dynamic way to ensure convergence to a stable point, without the need for velocity clamping under the condition $\Phi \geq 4$ and $\tau \in [0, 1]$. In such a situation, the swarm is guaranteed to converge. The constriction coefficient, χ, evaluated to a value in the range [0, 1] implies that the velocity is reduced at each time step. The effect of τ on convergence is as follows.

If $\tau \approx 0$; fast convergence,

$\tau \approx 1$; slow convergence.

(b) Inertia weight **–** A parameter, W has been introduced in ref. [171] which is known as inertia weight constant. W is multiplied to the first term of right hand side of Eq. (4.24), instead of multiplying to the whole right hand side as in equation (4.27). The first term of equation (4.24) is the velocity of the particle in the previous time step. Thus, Eq. (4.24) is modified as

$$V_i^{Iter+1} = W \times V_i^{Iter} + c_1 rand_1 \times (P_{best}^{Iter} - X_i^{Iter}) + c_2 rand_2 \times (G_{best}^{Iter} - X_i^{Iter}) \tag{4.28}$$

The inertia constant can be selected as a fixed value or dynamically changing value as reported in [153] and [171]. Typically it is considered as 0.9 at initial stage and 0.4 at optimal stage during convergence. In the present work, the weighting factor is defined as follows

$$W = W_{\max} - \frac{W_{\max} - W_{\min}}{Iter_{\max}} \times Iter \tag{4.29}$$

where

W_{min} and W_{max} are the initial and final weights;

$Iter_{max}$ and $Iter$ are the maximum and current number of iteration.

4.3. SOLUTION FOR PROBLEM OBJECTIVE OF CONGESTION MANAGEMENT WITH SOCIAL WELFARE

The mathematical formulations of OPF based rescheduling of generation levels of generators and consumers demand for congestion management with social welfare maximization has already been explained in the Chapter III. The aim of this work is to obtain the maximum social welfare in the power market using optimal rescheduling of generators and demands. The solution of congestion management has been carried out in multi-transaction power market using IP and PSO based optimization methods for COPF and DOPF. In this market structure, all the generators and demands are coordinated to form a market for obtaining the optimal solution. The problem of congestion is resolved by taking the line limits into account while formulating the problem objective of social welfare maximization.

4.3.1. COPF based Approach

The mathematical formulation of centralized decision based multi-transaction power market has been carried out using Eqs. (3.18-3.24) (Chapter III). In COPF based problem objective, all the generators and the consumers mutually optimize their schedules for maximizing the total social welfare using OPF technique. The lines limits are taken into account for congestion management during optimal rescheduling of generators and consumers demand in the problem formulation. In this chapter, the solution of COPF problem has been solved using IP and PSO based OPF algorithms.

4.3.2. DOPF based Approach

In this approach, the COPF model is decomposed into DOPF model using RAWM $\alpha_l{}^k$ index as given in the Chapter III. As a result, all the transactions are independent from each other and they try to maximize the social welfare by solving the Eq. (3.25) (Chapter III). In this technique, each transaction solves their individual sub-problems of OPF under the limitations of $\alpha_l{}^k$, which is represented as $P_l^{k,max} \leq P_l{}^{max} . \alpha_l{}^k$. The appropriate RAWM $\alpha_l{}^k$ index is obtained for a congested line and then the total social welfare $w^k(u^k)$

for the system is determined as per DOPF based congestion management algorithm (Chapter III, section 3.6). In the present chapter, the solutions decomposed OPF sub-problems of Eq. (3.25) has been obtained using IP and PSO based OPF algorithms.

4.3.3. IP Method Implementation for Problem Solution

The problem objective of welfare with congestion management using OPF as given in Eq. (4.1) can be further represented as

$$maximize\ f\left(P_{D_j}, P_{G_i}\right) = \sum_{j=1}^{N_d} B_j\ \left(P_{D_j}\right) - \sum_{i=1}^{N_g} C_i\ \left(P_{D_i}\right) \tag{4.30}$$

Subjected to nonlinear equality constraints

$$P_i(x) = \sum_{i=1}^{N_G} P_{G_i} - \sum_{j=1}^{N_D} P_{D_j} - P_{Loss} = 0 \tag{4.31}$$

Nonlinear inequality constraints

$$h_i^{min} \le h_i(x) \le h_i^{max} \tag{4.32}$$

The OPF problem of Eqs. (4.30)-(4.32) can be transformed into equivalent OPF problem by applying the logarithmic barrier method of IP optimization technique and then the objective function becomes

$$Max\ \left\{f(x) - \mu \sum_{j=1}^{M} \ln(sl_i) - \mu \sum_{i=1}^{M} \ln(su_i)\right\} \tag{4.33}$$

Subject to the following constraints

$$P_i = 0 \tag{4.34}$$

$$h_i - sl_i - h_i^{min} = 0 \tag{4.35}$$

$$h_i + su_i - h_i^{max} = 0 \tag{4.36}$$

where $sl > 0$ and $su > 0$ are slack variables and the Lagrangian function for equalities optimization of Eqs. (4.33)-(4.36) is given as

$$L = f(x) - \mu \sum_{i=1}^{M} \ln(sl_i) - \mu \sum_{i=1}^{M} \ln(su_i) - \sum_{i=1}^{N} \lambda p_i\, P_i - \sum_{i=1}^{M} \pi l_i\left(h_i - sl_i - h_i^{min}\right)$$
$$- \sum_{i=1}^{M} \pi u_i(h_i - su_i - h_i^{max}) \tag{4.37}$$

where λp_i, λq_i, πl_i and πu_i are Langrang multipliers for the constraints of Eqs. (4.34)-(4.36). N and M represent the number of buses and the number of inequality constraints respectively, where $\mu > 0$. The Lagrangian functions of COPF and sub-problems of ORA based DOPF are formulated using Eq. (4.37) and then the IP optimization algorithm is applied to maximize the social welfare of the system.

4.3.4. IP based Solution Algorithm

The IP optimization algorithm is applied to obtain the optimal solution. Following are the steps for the IP based OPF solution algorithm.

Step 1) Identify the congested line using *PTDF* calculation and select the number of control variables which are participating to manage the congestion in the system.

Step 2) Initialize the algorithm by setting $Iter = 0$, $Iter_{max} = 20$, centering parameter $\sigma^{Iter} \epsilon (0,1)$ and tolerance $= 10^{-6}$, choose $[z_l, z_u]^T > 0$ and $[\pi_1 > 0, \pi_u < \ \ 0, \lambda = 0]$.

Step 3) Start the program ($Iter < Iter_{max}$)

Step 4) Compute complementary gap using Eq. (4.22).
If $\rho^{Iter} < \varepsilon$, *then* output is the optimal solution and go to step 9,
Else go to next step.

Step 5) Compute the perturbed factor μ using Eq. (4.20).

Step 6) Solve the correction Eq. (4.15) for $[\Delta x, \Delta\lambda]$, $[\Delta z_1, \Delta z_u]$ and $[\Delta\pi_1, \Delta\pi_u]$.

Step 7) Perform the ratio test to determine the maximum step length in primal and dual space using Eqs. (4.18) and (4.19).

Step 8) Update the primal and dual variables using Eqs. (4.17) and then go to step 4.

Step 9) STOP.

4.3.5. PSO Implementation for Problem Solution

The basic aim of PSO implementation is to obtain the global solution for the problem objective. It is well known that IP provides fast convergence, however it does not give a global solution always. In the present study, PSO has been used for obtaining a global solution for COPF and DOPF and the obtained results are compared with the results obtained using IP. The problem formulation for the objective of COPF and DOPF are same as in the previous chapter (Chapter III).

PSO algorithm has been used to solve the maximization problem, defined by the objectives of COPF and DOPF, whereas the constraint functions are considered as binding constraints. The PSO algorithm use moving particles which are scattered over the solution space to find the optimal solution. The particle is formed by collecting all the variables (active power of generators and demands) from problem objective. Initially, all the variables are randomly generated within the upper and lower bound values. The individual *i's* position of particles initially at $Iter = 0$ can be represented as

$$X_i^0 = (P_{Gi1}^0, P_{Gi2}^0 \dots\dots\dots\dots P_{GiN_G}^0, P_{Di1}^0, P_{Di2}^0 \dots\dots\dots\dots P_{DiN_D}^0) \qquad (4.38)$$

where N_G and N_D are the number of generators and demands. Similarly, the velocity of individual particles can be represented as

$$V_i^0 = (v_{i1}^0, v_{i2}^0 \dots\dots\dots\dots v_{iN_G}^0, v_{i1}^0, v_{i2}^0 \dots\dots\dots\dots v_{iN_D}^0) \qquad (4.39)$$

where V_i^0 having the D dimensions represents the position of particle in MW. In this way, these individual particles create a group which is called a population. During the iterative process, all the particles of the population are updated by the rule expressed in Eqs. (4.24) and (4.25) without violating their constraints. Subsequently the current searching points are modified by using Eq. (4.28) and is rewritten as

(for generators)

$$P_{G_i}^{k,Iter+1} = W \times P_{G_i}^{k,Iter} + c_1 rand_1 \times \left(P_{best}^{Iter} - P_{G_i}^{k,Iter}\right) + c_2 rand_2 \times \left(G_{best}^{Iter} - P_{G_i}^{k,Iter}\right) \qquad (4.40)$$

and

$$P_{G_i}^{k,Iter+1} = P_{G_i}^{k,Iter} + P_{G_i}^{k,Iter+1} \qquad (4.41)$$

(for demands)

$$P_{D_j}^{k,Iter+1} = W \times P_{D_j}^{k,Iter} + c_1 rand_1 \times \left(P_{best}^{Iter} - P_{D_j}^{k,Iter}\right) + c_2 rand_2 \times \left(G_{best}^{Iter} - P_{D_j}^{k,Iter}\right) \qquad (4.42)$$

and

$$P_{D_j}^{k,Iter+1} = P_{D_j}^{k,Iter} + P_{D_j}^{k,Iter+1} \tag{4.43}$$

The inequalities constraints of the system model are also handled in PSO based OPF formulation. In PSO, the fitness of particle indicates the superiority of the particle. The particle fitness and selection operation of global and local best positions are evaluated by constraints handling process. In this work, a dual fitness technique has been used to evaluate the fitness of particles for optimal objective and binding constraints. The optimal objective fitness is equal to the value of the objective function and the rescheduling values of active power of generators and loads to manage the congestion of the system. The binding constraints fitness value $fitness_{ineq\ constr}$ is adopted to scale the level of violation and its calculation is as follows

$$fitness_{ineq\ constr}\ (u) \begin{cases} u_{\ min} - u, & u < u_{min} \\ u - u_{max}, & u > u_{max} \\ 0, & else \end{cases} \tag{4.44}$$

where u is the value of inequality constraints, and u_{min} and u_{max} are the lower and higher limits of the inequality constraints. Now using Eqs. (4.44), the whole binding constraints fitness of the particle is given as

$$whole\ fitness_{ineq\ constr}\ (u) = \sum_{i=1}^{z} fitness_{ineq\ constr}\ (u) \tag{4.45}$$

where z is the total number of inequality constraints. If the particles do not satisfy the fitness to binding constraints, then it is regenerated. In this way, only those particles are generated which guarantee fulfillment of binding constraints. The inferior or the infeasible particles which do not qualify the binding constraints are violated during search mechanism. Thus, the feasible particles are considered before obtaining global optimal solution. This type of mechanism gives an advantage over the conventional optimization techniques. In fact, the traditional optimization technique converts the fitness functions and inequality constraints into a penalty function that are added to the objective function as in IP. The major limitation of this method is that an excellent particle is sometimes misjudged which not appropriate for the penalty factors. Besides this, penalty parameters are usually assigned by empirical approach and are deeply affected by the problem model. On the other hand there is no need to set up the penalty parameter in PSO.

4.3.6. PSO based Solution Algorithm

PSO has been applied to COPF and DOPF based problem objectives through the following steps:

Step 1) Identify the congested line and select the number of control variables which are participating.

Step 2) Set the maximum number of iterations, $Iter_{max}$ and choose the population size of PSO according to system model.

Step 4) Generate randomly *p* particles, $\{x_i\ (0),\ i = 1....p\}$ where $x_{ik}\ (0)$ is generated by randomly selecting a value with uniform probability over the k^{th} optimized parameter in search space $[x_{min}, x_{max}]$. Each particle has D dimensions that denotes the number of participating generators and demands. The values of these D variables are the amount of rescheduled levels of generators and demands requirements of consumers to manage the congestion. Similarly, generate the initial velocities of all the particles, $\{v_i\ (0),\ i = 1......p\}$, where $v_i\ (0)$ is generated by randomly selecting a value with uniform probability over the dimension $[-v_{min}, v_{max}]$.

Step 5) Test the conditions of equality based on the system states represented by individual particles using objective functions of COPF and DOPF formulations.

If the particle does not satisfy the equality constraints, *then* it is regenerated.

Step 6) Find the fitness values of particles for the inequality constraints of COPF and DOPF formulations.

If the particle does not satisfy the fitness requirement, *then* it is regenerated.

Step 7) Evaluate the fitness for each particle according to the objective function. The fitness function includes the total cost functions of active power generations and benefits functions of consumer's demands in a transaction for the problem objective.

Step 8) Calculate the optimal objective fitness values of each particle.

If the fitness value of each individual is better than the previous P_{best}, *then* current value is set to P_{best}.

If this P_{best} is better than the previous G_{best} , *then* the value is set to G_{best}, *else* go to step 11.

If previous G_{best} is better than G_{best}, *then* value is set to G_{best}.

Step 9) If maximum welfare of the fitness function or the maximum iteration number is reached, accept the individual generated latest G_{best} as the optimal solution and go to step 11, *else* go to next step.

Step 10) Update the velocity of each particle according to Eq. (4.28) and satisfy the following conditions:

$$If\ \ P_{G_i}^{k,Iter+1} > P_{G_i}^{k,max},\ then\ P_{G_i}^{k,Iter+1} = P_{G_i}^{k,max},$$

and

$$If\ P_{D_i}^{k,x+1} > P_{D_i}^{k,max},\ then \qquad P_{D_i}^{k,x+1} = P_{D_i}^{k,max}$$

Step 11) Generate new particle positions near the previous values of P_{best} and G_{best} using Eq. (4.25) and go to step 5.

$$If\ \ P_{G_i}^{k,Iter+1} > P_{G_i}^{k,max},\ then\ P_{G_i}^{k,Iter+1} = P_{G_i}^{k,max},$$

$$If\ P_{G_i}^{k,Iter+1} < P_{G_i}^{k,min},\ then\ P_{G_i}^{k,Iter+1} = P_{G_i}^{k,min}$$

and

$$If\ P_{D_i}^{k,Iter+1} > P_{D_i}^{k,max},\ then \qquad P_{D_i}^{k,Iter+1} = P_{D_i}^{k,max}$$

$$If\ P_{D_i}^{k,Iter+1} < P_{D_i}^{k,min},\ then \qquad P_{D_i}^{k,Iter+1} = P_{D_i}^{k,min}$$

Step 12) If maximum value of iteration number is reached, accept the individually that has generated the latest G_{best} as the optimal solution and STOP the program.

4.4. TEST RESULTS AND DISCUSSION

The IP and PSO algorithms for congestion management with social welfare using COPF and DOPF are implemented in MATLAB on Intel (R), Core 2 Duo, and 2.66 GHz processor. In order to demonstrate the effectiveness and performance of the proposed COPF and DOPF approaches, the modified IEEE-30 bus [100] and modified IEEE-118 bus [102] systems have been used to formulate the multi-transaction market structures. Each transaction has some certain number of generators and demands buses and they forms bilateral/multilateral coordination between them. In order to obtain the COPF based solution for problem objective, all the transactions participate collectively in the market operation. These transactions operate as a single transaction based market structure and tries to maximize the social welfare in the system. A centralized authority ISO manages the schedules of generators and demands without violating the system constraints.

In case of DOPF based solution for the total social welfare, all the transactions individually optimize their schedules for generators and demands of consumers on the basis of optimal resource allocation indices of transmission lines termed as RAWM index. Therefore, using this an improved competition is established among the participants who improve the market efficiency. In the proposed method, losses are also incorporated in the problem objective. The first generator of transaction T1 is considered as a slack bus in both the approaches. The losses due to other transactions are allocated on this generator to allocate additional generation cost of losses. The social welfare obtained reduces because of inclusion of cost of losses. The obtained total social welfare is the profit obtained by the market. In the present work; the system reliability, security and maintenance of equality constraints are related to congestion problem during their operation. The congestion is managed by system re-dispatch in this work.

4.4.1. Test Systems Details

The two test systems have been chosen to demonstrate the effectiveness and comparison of the suggested IP and PSO based COPF and DOPF approaches. In the present work, to study the problem objectives, these test systems are restructured as market models. The details of these systems are delineated in the following subsections.

4.4.1.1. Modified IEEE 30-Bus System

The standard modified IEEE-30 bus system consists of 6 generator buses and 24 load buses. In order to make a multi-transaction system for the present case study, the system is modified by considering all six generators and only nine demand buses. In the modified IEEE-30 bus system, all generators and loads form three sets of transactions T1, T2 and T3. It is assumed that each transaction has three loads and two generators. In this way there are nine demand and six generation bidders as shown in Fig. 4.3.

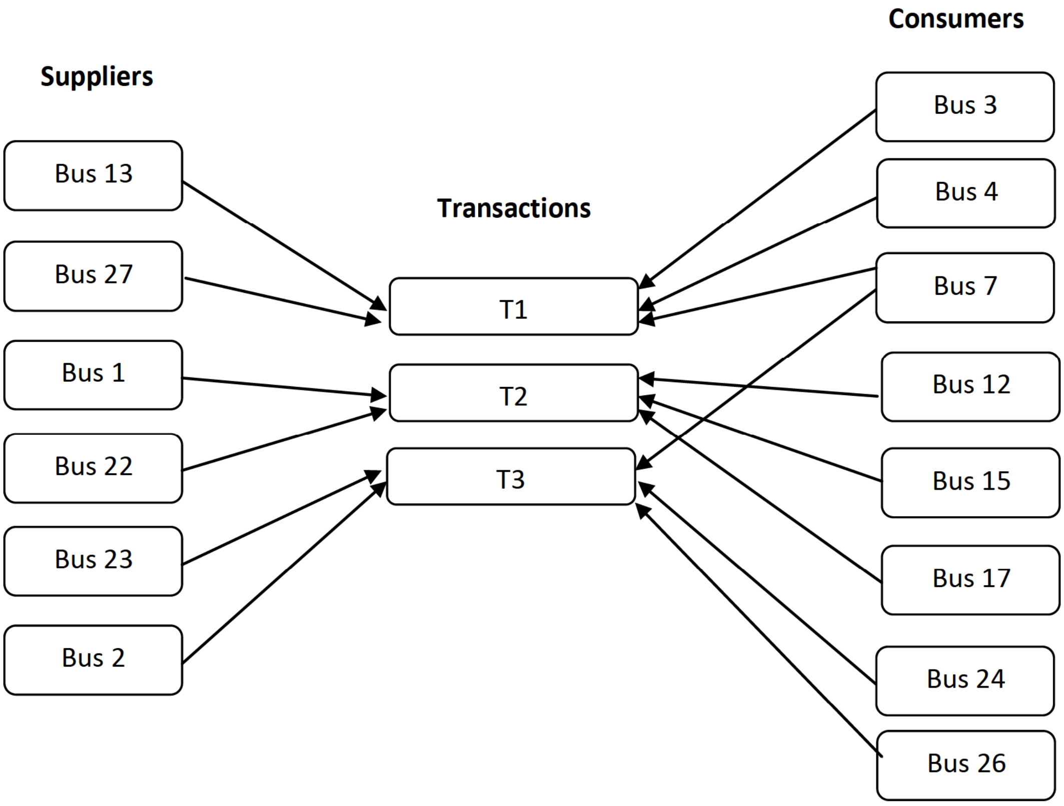


Fig. 4.3 Contracts among power producers and consumers of modified IEEE-30 bus system with multi-transaction

It can be observed that the power suppliers and consumers are connected with bilateral/multilateral contract as shown in Fig. 4.3. This figure shows that the generators 13, 27 and demand 3, 4, 7 belong to transaction T1; generators 1, 22 and demand 12, 15, 17 belong to transaction T2 and generators 23, 2 and demand 24, 26, 7 belong to transaction T3. The Fig. 4.3 shows that all the participants are connected with bilateral contract. However the consumer of bus 7 is connected with T1 and T2 both with multilateral contract in this system. The marginal cost functions of generators and marginal benefit functions of consumers are listed in Table 4.1 [100] and their connectivity in modified IEEE-30 bus system is shown in Fig. 4.4. In order to observe the congestion management in the system, the transfer limits of branches are considered in the problem formulations. The transfer limits of lines for the test system are given in Appendix I. In this work, the transfer limits of lines connected between buses 2-5, 4-12, 6-7 and 25-27 have been considered as 10, 30, 10, and 10 MW respectively for observing the performance of congestion management in modified IEEE-30 bus system.

Table 4.1

Cost and benefit function of utilities in using modified IEEE-30 bus system model

Transactions	Generator bus	Marginal function $/hr	Consumer bus	Consumer benefit function $/hr
T1	**13**	$20P+0.2P^2$	**3**	$38.8D-0.3D^2$
	27	$17.5P+0.1 P^2$	**4**	$38D-0.5 D^2$
			7	$38D-0.2 D^2$
T2	**1**	$17.5P+0.25 P^2$	**12**	$38D-0.4 D^2$
	22	$30P+0.25 P^2$	**15**	$39.5D-0.2 D^2$
			17	$37D-0.2 D^2$
T3	**23**	$18P+0.625 P^2$	**24**	$36D-0.3 D^2$
	2	$23P+0.283 P^2$	**26**	$38D-0.4 D^2$
			7	$37D-0.2 D^2$

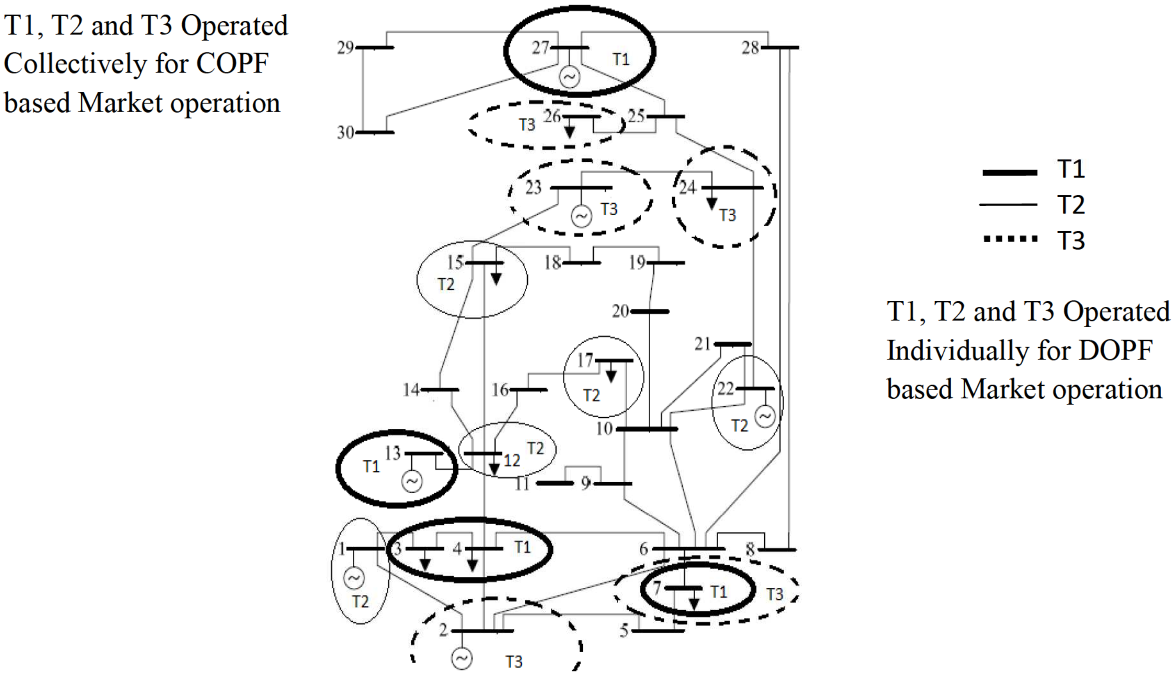


Fig. 4.4 Modified IEEE-30 bus system with multi-transaction power market model

4.4.1.2. Modified IEEE 118-Bus System

Similar to multi-transaction based modified IEEE-30 bus system, the modified IEEE-118 bus system is also partitioned into six transactions; T1, T2, T3, T4, T5 and T6 and a multi-transaction system is formulated as shown in Fig. 4.5. It is assumed that each transaction have three loads and two generators. In this way, eighteen demand and twelve generation bidders altogether are connected by bilateral/multilateral contract. The marginal cost functions of generators and marginal benefit functions of consumers are listed in Table 4.2 [102], where generators 4, 6 and demand 2, 3, 7 belong to transaction T1; generators 15, 24 and demand 14, 20, 23 belong to transaction T2; generators 34, 40 and demand 33, 35, 39 belong to transaction T3; generators 62, 70 and demand 67, 75, 78 belong to transaction T4; generators 85, 90 and demand 54, 20, 11 belong to transaction T5 and generators 107, 112 and demand 106, 108, 114 belong to transaction T6 as shown in Fig. 4.5. The modified IEEE-118 bus system with multi-transaction is shown in Fig. 4.6. Similar to the modified IEEE-30 bus system, the transfer limit of line 80-81 is considered as 30 MW to observe the congestion in the system in the modified IEEE-118 bus system.

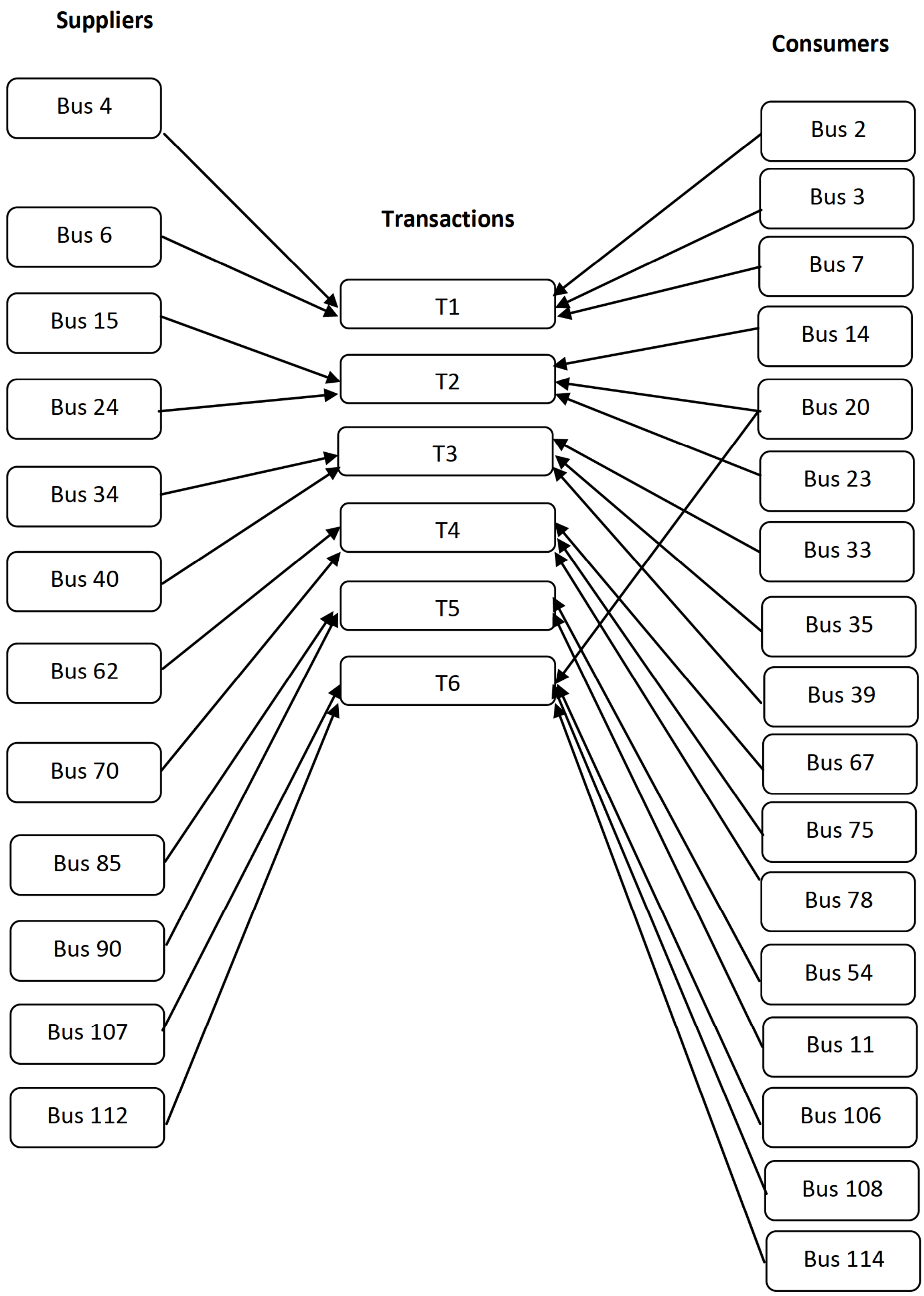


Fig. 4.5 Contracts among power producers and consumers of modified IEEE-118 bus system with multi-transaction.

Table 4.2

Cost and benefit function of market model using modified IEEE-118 bus system

Transactions	**Generator bus**	**Generation cost function ($/h)**	**Consumer bus**	**Consumer benefit function in ($/h)**
T1	**4**	$40P+0.01P^2$	**2**	$47.8D-0.03D^2$
	6	$40P+0.01\ P^2$	**3**	$47.8D-0.05D^2$
			7	$47.8D-0.02D^2$
T2	**15**	$40+0.01\ P^2$	**14**	$49.0D-0.04D^2$
	24	$40P+0.01\ P^2$	**20**	$48.5D-0.02D^2$
			23	$49.7D-0.02D^2$
T3	**34**	$40P+0.01\ P^2$	**33**	$49.0D-0.03D^2$
	40	$40P+0.01\ P^2$	**35**	$48.8D-0.04D^2$
			39	$48.8D-0.02D^2$
T4	**62**	$40P+0.01\ P^2$	**67**	$45.8D-0.03D^2$
	70	$40P+0.01\ P^2$	**75**	$45.8D-0.03D^2$
			78	$45.8D-0.02D^2$
T5	**85**	$40P+0.01\ P^2$	**54**	$48.0D-0.05D^2$
	90	$40P+0.01\ P^2$	**20**	$48.5D-0.03D^2$
			11	$47.8D-0.02D^2$
T6	**107**	$40P+0.01\ P^2$	**106**	$48.0D-0.02D^2$
	112	$40P+0.01\ P^2$	**108**	$48.0D-0.05D^2$
			114	$48.0D-0.02D^2$

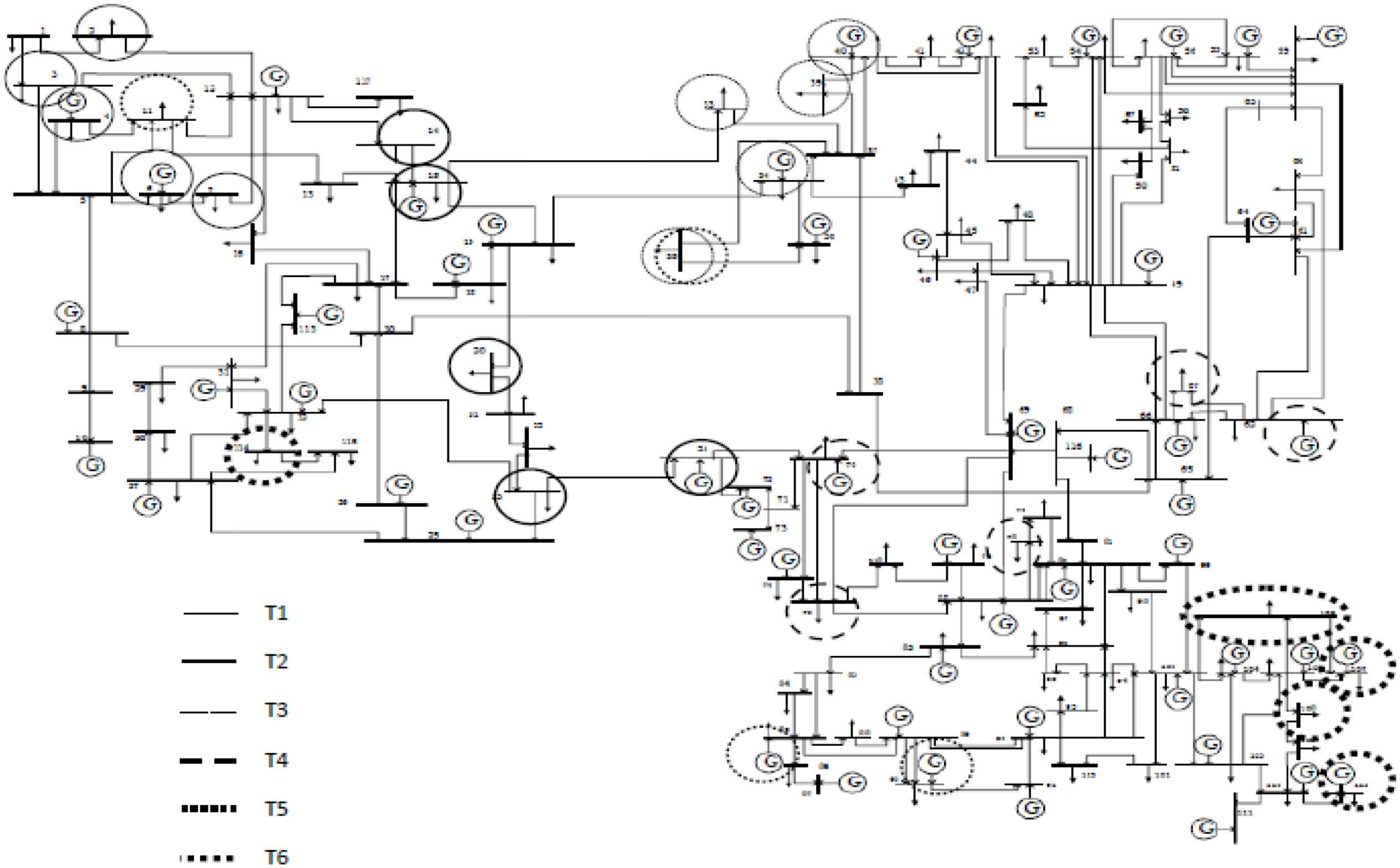


Fig. 4.6 Modified IEEE-118 bus system with multi-transaction power market model.

4.4.2. Selection of IP and PSO Parameters

In the present work, the suggested IP and PSO based solution technique are applied to obtain the optimal generation and demand schedules to alleviate the congestion in the lines using COPF and DOPF based decision supports. The mathematical formulation of IP method in Eqs. (4.3)-(4.22) reveals that the performance of this method depends upon initialization parameters such as maximum number of iteration, centering parameter and tolerance value. In the initialization of IP based OPF algorithm, the maximum number of iteration $Iter_{max} = 50$, centering parameter $= \sigma \epsilon (0,1)$ and tolerance $\varepsilon = 10^{-6}$.

In the present case study, during search mechanism, PSO parameters are varying according to system size. A generalized inertia weight, W considered for both the systems are 0.5 and the two positive constants c_1 and c_2 are fixed at widely use value 2. The other constants $rand_1$ and $rand_2$ selected are in the range of 0 and 1 and the velocity of each agent is updated according to Eq. (4.24). The selection of particle size and maximum number of iterations are also important parameters for achieving optimal solutions. There are no specific guide lines or rules for choosing the particle size and maximum number of iterations for any optimization problem. This can only be achieved by precise trials on any objective function. After a number of trials, it is observed that the increase in the number of iterations beyond a certain value does not provide better results. However, the increase in the particles provides a significant improvement in the solution. In each trail of COPF and DOPF approaches, the convergences of maximum value of objective function is achieved within 100 and 200 iterations with any value of particle size for modified IEEE-30 bus and modified IEEE-118 bus systems respectively. Thus, these respective values are considered as appropriate values of $Iter_{max}$ for both the test systems.

In this work, the particle size has been varied in the range of 20 to 2000. It has been observed that the value of objective function is maximum using COPF and DOPF for modified IEEE-30 bus system, when the particle size is 500. Similarly, in modified IEEE-118 bus system, the value of the particle size is 1000 to achieve the maximum value of objective function using COPF and DOPF. The tolerance value has been assumed to be 1×10^{-6} for objectives and coordinates in both the test systems. It can concluded that the selection of appropriate number of maximum iteration and particle size provide a significant effect on the convergence of global solution.

4.4.3. Case Studies

The following cases have been considered and carried out on modified IEEE-30 bus and modified IEEE-118 bus systems to find the effectiveness COPF and DOPF methods using IP and PSO methods.

Case 1: Initial schedules of generators and demands for COPF and DOPF before congestion management.

Case 2: COPF based economic rescheduling after congestion management using IP and PSO.

Case 3: DOPF based economic rescheduling after congestion management using IP and PSO.

4.4.3.1. Case 1: Initial Schedules of Generators and Demands for COPF and DOPF before Congestion Management

In this case, initial schedules of generators and consumers demands have been considered for COPF and DOPF. In case of COPF, all the participants of each transaction (in the multi-transaction system) are collectively operated as a single transaction in the system. The operations and controls are applied by a centralized authority and the schedules of generator and consumers demands are decided by this authority. These initial schedules are decided in such a way that the system can obtain the maximum social welfare. The initial schedules for generators and consumers demands for modified IEEE-30 bus system and modified IEEE-118 bus system are given in Tables 4.3 and 4.4. The power flows in the lines due to initial schedules are given in Table 4.7 for both the systems.

Similarly, in case of DOPF, each transaction independently schedules its generators and demand at load buses in multi-transaction system. The information given by the system operators is shared among transactions to achieve the schedules of the generators and consumers demand for managing the congestion from the system by fulfilling the problem objective. The serial computation is used for scheduling generators and demands of the transactions. The initial schedules of generators and consumers demands for modified IEEE-30 bus and modified IEEE-118 bus systems are given in Tables 4.8 and 4.9 respectively. The power flow in a particular line is obtained by summing the flows due to each transaction. The power flows due to transactions in the congested lines are given in Tables 4.12 and 4.13 for modified IEEE-30 bus and modified IEEE-118 bus systems respectively.

4.4.3.2. Case 2: COPF based Economic Rescheduling after Congestion Management using IP and PSO

In this case, all the constraints of system components and the transfer limits of the lines have been considered in the problem objective for studying congestion management. In the present case study, suggested IP and PSO methods have been used to obtain an optimal solution for both the test systems using COPF. All the generators and demand buses are chosen to participate in the problem objective of congestion management with maximum social welfare for both the test systems. The parameters selections for IP and PSO have been discussed in *Sub-section 4.4.2.* After application of COPF based optimal rescheduling using IP and PSO, the generation levels and consumers demands are increased or decreased in modified IEEE-30 bus and modified IEEE-118 bus systems for congestion management. The rescheduled values are given in Tables 4.3 and 4.4 for modified IEEE-30 bus and modified IEEE-118 bus systems respectively. The increments and decrements of generation levels of generators and demand levels of load buses after rescheduling with respect to initial schedules are given in Table 4.5 and 4.6 for both the systems. The positive values show the increments and negative values show the decrements of power levels. The line flows in congested lines are given in Table 4.7 for both the systems. In case of modified IEEE-30 bus system, it can be observed from Table 4.7 that the power flows in lines between buses 2-5, 4-12, 6-7 and 25-27 are 16.30, -33.66, 17.63 and -14.23 MW respectively of modified IEEE-30 bus system for Case 1. This indicates that the said lines are overflowing. Similarly, in the modified IEEE-118 bus system, the initial flow in the line between buses 80-81 is 39.85 MW which shows the case of congestion in the system. It can be observed from the obtained results that the generators output and demand at load buses are vary as compared to Case 1 (using IP and PSO). However, the congestion has been alleviated from the lines using rescheduling of generators and demands for both the test systems. The line flows in other lines using COPF are given in Appendix II. The obtained test results show that the COPF based rescheduling is an effective method for congestion management.

Table 4.3

Schedules of generators and demands modified IEEE-30 bus system using COPF

Cases	**Case 1 Before Congestion Management**	**Case 2 After Congestion Management**	
	Initial Solution	**IP**	**PSO**
Generator bus	**Generation Schedules (MW)**		
13	38.5700	14.2600	15.2500
27	21.7845	12.3887	11.1221
1	19.7458	50.3729	48.2553
22	4.5327	8.4283	9.9025
23	12.8305	10.5651	9.8938
2	15.5271	17.2596	18.7831
Loss	***1.1900***	***1.4800***	***1.4100***
Total Generation	**113.1600**	**113.5400**	**113.5600**
Load bus	**Demand Schedules (MW)**		
3	18.1287	16.3502	17.4812
4	16.5679	14.3823	14.1324
7	13.8737	10.1518	12.3787
12	10.3979	10.5145	10.5969
15	16.6773	20.1553	21.3479
17	11.6876	10.3984	9.8993
24	10.5696	19.5474	14.9761
26	13.8973	10.3001	10.9875
Total Demand	**111.8000**	**111.8000**	**111.8000**

Table 4.4

Schedules of generators and demands of modified IEEE-118 bus system using COPF

Cases	**Case 1 Before Congestion Management**	**Case 2 After Congestion Management**	
	Initial Solution	**IP**	**PSO**
Generator bus	**Generation Schedules (MW)**		
4	101.07	107.09	102.35
6	18.4232	17.0323	15.9021
15	70.3606	34.5236	31.9432
24	12.1120	2.3457	6.0914
34	70.1272	12.6476	13.2121
40	31.4836	81.5891	83.1103
62	93.8231	94.7485	98.1532
70	51.1017	45.2175	40.5423
85	18.5101	19.1263	20.8312
90	42.1635	68.5608	70.4231
107	10.6043	44.3345	44.0655
112	15.3412	10.2317	10.8800
Loss	*27.62*	*29.94*	*30.01*
Total Generation	**535.1205**	**537.4476**	**537.5044**
Load bus	**Demand Schedules (MW)**		
2	33.9815	24.7818	22.8769
3	19.8300	33.5015	32.6801
7	29.7385	14.4957	18.5487
14	18.8414	21.2748	23.9781
20	48.1015	40.5247	38.8384
23	8.8415	31.3787	16.9073
33	54.9743	20.5131	22.9870
35	11.7093	41.3745	34.3721
39	18.3715	24.8275	26.9802
67	32.5323	15.2826	28.8591
75	38.0277	47.3955	45.8672
78	49.2100	78.5866	73.9051
54	53.8354	51.7542	44.9387
11	16.7340	8.9675	21.9749
106	34.8301	39.2434	40.8960
108	25.9837	6.3535	5.9890
114	11.9573	7.2444	6.9012
Total Demands	**507.5000**	**507.5000**	**507.5000**

Table 4.5
Increments/decrements of active power levels after rescheduling using IP and PSO based COPF in Modified IEEE-30 bus system

	Generator bus	
Bus	**IP**	**PSO**
13	24.31	23.32
27	9.40	10.66
1	-30.63	-28.51
22	-3.90	-5.37
23	2.27	2.94
2	-1.73	-3.26
	Load bus	
3	1.78	0.65
4	2.19	2.44
7	3.72	1.50
12	-0.12	-0.20
15	-3.48	-4.67
17	1.29	1.79
24	-8.98	-4.41
26	3.60	2.91

Table 4.6
Increments/decrements of active power levels after rescheduling using IP and PSO based COPF in Modified IEEE-118 bus system

	Generator bus	
Bus	**IP**	**PSO**
4	-6.02	-1.28
6	1.3909	2.5211
15	35.837	38.4174
24	9.7663	6.0206
34	57.4796	56.9151
40	-50.106	-51.627
62	-0.9254	-4.3301
70	5.8842	10.5594
85	-0.6162	-2.3211
90	-26.397	-28.26
107	-33.73	-33.461
112	5.1095	4.4612
	Load bus	
2	9.1997	11.1046
3	-13.672	-12.85
7	15.2428	11.1898
14	-2.4334	-5.1367
20	7.5768	9.2631
23	-22.537	-8.0658
33	34.4612	31.9873
35	-29.665	-22.663
39	-6.456	-8.6087
67	17.2497	3.6732
75	-9.3678	-7.8395
78	-29.377	-24.695
54	2.0812	8.8967
11	7.7665	-5.2409
106	-4.4133	-6.0659
108	19.6302	19.9947
114	4.7129	5.0561

Table 4.7
Line flows in congested lines of modified IEEE-30 bus system and modified IEEE-118 bus systems using COPF (in MW)

Lines	Max. limit	Case 1 Before Congestion Management	Case 2 After Congestion Management	
		Initial Flow	IP	PSO
Modified IEEE-30 bus				
2-5	**10**	16.30	9.64	9.98
4-12	**30**	-33.80	25.06	23.80
6-7	**10**	17.63	7.59	6.49
25-27	**10**	-14.23	-7.49	-8.41
Modified IEEE-118 bus				
80-81	**30**	39.85	27.46	24.71

4.4.3.3. Case 3: DOPF based Economic Rescheduling after Congestion Management using IP and PSO

In the present case, the operation of system is based on DOPF is as given in Case 1 by including all the constraints of system components and the transfer limits of lines in the problem objective. The line limits are considered in the problem objective to observe the congestion management using DOPF. The global optimal solution is obtained using serial computation as in Case 1. In this work, the congestion in the system is identified using power transfer distribution factors (PTDFs) based sensitivity indices. The calculation of PTDFs indices have already been discussed in Chapter III, section 3.5. In the present work, these indices are directly used to find the power flows in the lines due to variations in generations or loads at any bus. Thus, the PTDFs of the system are useful for calculating the power flows and identifying the congested lines in the system without load flow study which results into fast convergence. The initial flows in congested lines of both the test systems are given in Tables 4.12 and 4.13 respectively. Therefore, DOPF based rescheduling using IP and PSO relieve the congestion from the system. Once the congested lines are identified in the system, ORA based congestion management strategy using DOPF is applied to obtain the solution for the problem objective. In DOPF, the RAWM indices are determined for the lines in both the test systems and then the main optimization problem is decomposed into sub-problems by using these indices. These indices are useful for allocating the maximum transmission capacities of the lines for the various transactions. The RAWM indices of lines for both the test systems are given in Appendix II. In the DOPF based congestion management strategy all the sub-problems of optimization are solved using IP and PSO.

The optimal schedules for generators and demands in transactions have been obtained by IP and PSO methods under the RAWM indices and subjected to the system constraints. The parameters of IP and PSO have selected according to system model and this has already been discussed in *Sub-section 4.4.2.* The suggested IP and PSO are applied to reschedule the generators and demands at load buses in each transaction for managing the congestion in the system as given in Tables 4.8 and 4.9. It can be observed that the suggested IP and PSO based DOPF method has succeeded in managing the congestion in both modified IEEE-30 bus and modified IEEE-118 bus systems with bilateral contracts. Similar to Case 2, the generators outputs and demands at load buses are increased or decreased due to rescheduling. The incremented or decremented values of generation levels and demands of various buses for both the test systems are given in Tables 4.10 and 4.11. The power flows of congested lines due to the transactions in modified IEEE-30 bus and modified IEEE-118 bus systems are given in Tables 4.12 and 4.13. The power flows in all the lines using DOPF are given in Appendix III. The results show that the power flows in congested lines are overflowing for Case 1 in both the test systems. Conversely, after rescheduling of generators and demands using DOPF, the congestion has been alleviated from the lines in both the test systems (Case 3). The obtained results reveal that the DOPF based rescheduling has also successfully managed the congestion in the system, while all the transactions have rescheduled their generators and demands individually. This feature makes DOPF an efficient method of congestion management which promotes fair competition and independent scheduling operations among the transactions in comparison to COPF.

Table 4.8
Schedules of generators and demands modified IEEE-30 bus system using DOPF

Transactions	**Bus**	**Case 1**	**Case 3**	
		Before Congestion Management	**After Congestion Management**	
		Initial	**IP**	**PSO**
		Generation Schedules (MW)		
T1	**13**	22.3283	21.1119	14.3233
	27	23.3709	22.5217	27.4778
	Total	**45.6385**	**43.6336**	**41.8011**
	Allocated Loss	*0.76*	*0.73*	*0.69*
T2	**1**	26.4731	30.6397	29.1678
	22	12.2871	10.2291	10.8254
	Total	**37.7602**	**40.8688**	**39.9932**
	Allocated Loss	*0.63*	*0.65*	*0.64*
T3	**23**	11.4822	19.2472	19.5798
	2	17.9577	9.9104	12.3189
	Total	**29.4399**	**29.1576**	**31.8987**
	Allocated Loss	*0.66*	*0.49*	*0.57*
Total Generations		**112.8386**	**113.66**	**113.693**
Total Loss		***2.05***	***1.86***	***1.89***
		Demand Schedules (MW)		
T1	**3**	18.1287	18.8292	17.6256
	4	17.5674	11.9608	12.7357
	7	8.9038	10.9836	9.5468
	Total	**44.5999**	**41.7736**	**39.9081**
T2	**12**	10.3953	7.7894	8.5978
	15	15.6773	23.6201	21.4879
	17	11.6876	9.4593	9.9075
	Total	**37.7602**	**40.8688**	**39.9932**
T3	**24**	9.5694	16.8923	16.9765
	26	13.7412	8.3316	10.9885
	7	6.1293	3.9337	3.9337
	Total	**29.4399**	**29.1576**	**31.8987**
Total Loads		**111.8**	**111.8**	**111.8**

Table 4.9

Schedules of generators and demands of modified IEEE-118 bus system using DOPF

Transactions	bus	Case 1	Case 3	
		Before Congestion Management	After Congestion Management	
		Initial Schedule	IP	PSO
		Generation Schedules (MW)		
T1	**4**	64.4500	63.7000	59.3800
	6	43.0187	49.2100	42.9771
	Total	***107.4687***	***112.9100***	***102.3571***
	Allocated Loss	*5.60*	*5.88*	*5.11*
T2	**15**	41.2114	28.1168	28.7328
	24	20.2011	16.5847	26.5231
	Total	**61.4125**	**44.7015**	**55.2559**
	Allocated Loss	*3.61*	*2.63*	*3.29*
T3	**34**	12.7687	24.2001	12.0002
	40	65.9305	62.4	72.0006
	Total	**78.6992**	**86.6001**	**84.0008**
	Allocated Loss	*6.43*	*6.67*	*6.92*
T4	**62**	86.0489	79.1989	85.0083
	70	34.0461	64.6891	63.2276
	Total	**120.095**	**143.888**	**148.2359**
	Allocated Loss	*8.19*	*9.16*	*9.53*
T5	**85**	53.9638	37.4493	37.9383
	90	41.487	52.2191	53.4697
	Total	**95.4508**	**89.6684**	**91.408**
	Allocated Loss	*4.89*	*4.40*	*4.48*
T6	**107**	51.9772	28.0186	29.8796
	112	22.9027	31.0734	25.9471
	Total	**74.8799**	**59.092**	**55.8267**
	Allocated Loss	*3.91*	*2.95*	*2.82*
Total Generations		**540.1154**	**539.2007**	**539.6636**
Total *Loss*		***32.62***	***31.70***	***32.16***
		Demand Schedules (MW)		
T1	**2**	31.2679	23.9815	22.3156
	3	18.2631	39.83	32.6913
	7	27.4316	19.7385	17.7658
	Total	**76.9626**	**83.55**	**72.7727**
T2	**14**	21.2443	18.8415	25.3394
	20	27.2364	15.9885	11.2634
	23	12.9318	9.8715	18.6531
	Total	**61.4125**	**44.7015**	**55.2559**
T3	**33**	51.2348	25.5193	23.5987
	35	11.1349	32.7093	33.2698
	39	16.3295	28.3715	27.1323
	Total	**78.6992**	**86.6001**	**84.0008**
T4	**67**	31.5691	27.5363	28.6549
	75	38.2692	46.0877	45.5976
	78	50.2567	70.264	73.9834
	Total	**120.095**	**143.888**	**148.2359**
T5	**54**	54.293	50.7138	42.6719
	20	23.8614	22.5176	26.3894
	11	17.2964	16.437	22.3467
	Total	**95.4508**	**89.6684**	**91.408**
T6	**106**	35.9671	40.8512	41.2378
	108	26.3491	5.9819	6.3495
	114	12.5637	12.2589	8.2394
	Total	**74.8799**	**59.092**	**55.8267**
Total Demands		**507.5**	**507.5**	**507.5**

Table 4.10
Increments/decrements of active power levels after rescheduling using IP and PSO based DOPF in Modified IEEE-30 bus system

Transactions	Generator bus		
	Bus	**IP**	**PSO**
	13	1.22	8.01
T1	**27**	0.85	-4.11
	1	-4.17	-2.69
T2	**22**	2.06	1.46
	23	-7.77	-8.10
T3	**2**	8.05	5.64
	Load bus		
	3	-0.70	0.50
T1	**4**	5.61	4.83
	7	-2.08	-0.64
	12	2.61	1.80
T2	**15**	-7.94	-5.81
	17	2.23	1.78
	24	-7.32	-7.41
T3	**26**	5.41	2.75
	7	2.20	2.20

Table 4.11
Increments/decrements of active power levels after rescheduling using IP and PSO based DOPF in Modified IEEE-118 bus system

Transactions	Generator bus		
	Bus	**IP**	**PSO**
	4	0.75	5.07
T1	**6**	-6.1913	0.0416
	15	13.0946	12.4786
T2	**24**	3.6164	-6.322
	34	-11.431	0.7685
T3	**40**	3.5305	-6.0701
	62	6.85	1.0406
T4	**70**	-30.643	-29.182
	85	16.5145	16.0255
T5	**90**	-10.732	-11.983
	107	23.9586	22.0976
T6	**112**	-8.1707	-3.0444
	Load bus		
	2	7.2864	8.9523
T1	**3**	-21.567	-14.428
	7	7.6931	9.6658
	14	2.4028	-4.0951
T2	**20**	11.2479	15.973
	23	3.0603	-5.7213
	33	25.7155	27.6361
T3	**35**	-21.574	-22.135
	39	-12.042	-10.803
	67	4.0328	2.9142
T4	**75**	-7.8185	-7.3284
	78	-20.007	-23.727
	54	3.5792	11.6211
T5	**20**	1.3438	-2.528
	11	0.8594	-5.0503
	106	-4.8841	-5.2707
T6	**108**	20.3672	19.9996
	114	0.3048	4.3243

Table 4.12

Line flows in congested lines of modified IEEE-30 bus systems using DOPF

Lines	**Max. limit**	**Initial Flows (Case 1)**				**After Congestion Management (Case 3)**							
						IP				**PSO**			
		T1	**T2**	**T3**	**Total**	**T1**	**T2**	**T3**	**Total**	**T1**	**T2**	**T3**	**Total**
2-5	**10**	-17.04	-14.09	44.55	13.42	-8.72	-7.21	22.81	6.87	-8.46	-6.99	22.11	6.66
4-12	**30**	0.94	25.99	4.07	31.00	0.74	20.35	3.19	24.27	0.65	17.85	2.80	21.29
6-7	**10**	1.52	5.61	4.56	11.68	1.05	3.89	3.16	8.11	0.89	3.30	2.68	6.87
25-27	**10**	-21.80	-13.85	20.92	-14.73	-13.47	-8.55	12.92	-9.10	-12.45	-7.91	11.94	-8.41

Table 4.13

Line flows in congested line 80-81 of modified IEEE-118 bus systems using DOPF approach

Maximum Limit 30 MW		**T1**	**T2**	**T3**	**T4**	**T5**	**T6**	**Total**
Initial Flows (Case 1)		0.52	-33.08	-0.59	0.38	-0.12	-0.25	-33.14
After Congestion Management (Case 3)	**IP**	0.37	-23.52	-0.42	0.27	-0.08	-0.18	-23.56
	PSO	0.32	-20.17	-0.36	0.23	-0.07	-0.15	-20.21

4.4.4. Analysis of Social Welfares using COPF and DOPF

The generation cost and benefits of consumers in modified IEEE-30 bus and modified IEEE-118 bus systems are given in Tables 4.14-4.17 for COPF and DOPF. The social welfares (profits of the system) offered by COPF and DOPF approaches in both the test systems have also been given in these tables. The results show that the social welfare by COPF and DOPF approaches are in close proximity. Initially, the social welfares obtained in modified IEEE-30 bus system for Case 1 using COPF and DOPF approaches are 899.2317 $/hr and 920.0927 $/hr respectively before congestion management. Similarly, in modified IEEE-118 bus system the social welfare using COPF and DOPF approaches are 1722.2217 $/hr and 2675.1638 $/hr respectively. In main aim of this work is to maximize the social welfare in the multi-transaction system during congestion. The results show that the social welfare offered by COPF and DOPF approaches in both the test systems reduce after the congestion management as given in Tables 4.14 and 4.15 for Case 2 (COPF) and Tables 4.16 and 4.17 for Case 3 (DOPF). In fact, during rescheduling of generators and demands in each transaction for congestion management, some of the costly generators supplies more power as compared to economical generators which results into the increment of total generation cost. At the same time, the demands are also rescheduled to manage the congestion in the lines. However, because of rescheduling of demands, some of the less beneficial load buses get more power as compared to more beneficial buses. It is a known fact that the consumer’s benefit is a function of active power load on a load bus. Therefore, if any less beneficial load bus takes more power, then the overall benefit offered by the system reduces which results into reduced social welfare of the system. It has also been observed that the IP based solution method gives inferior solutions compared to PSO based solution method for both the test systems.

The costs of losses are also incorporated in the problem formulation of social welfare with congestion management (Chapter III). These costs have been included in the obtained social welfare of the test systems using COPF and DOPF approaches. In both the approaches, the total power loss cost has been allocated on the slack bus of both the test systems. To allocate the loss costs, bus 13 and bus 4 are considered as slack bus of the modified IEEE-30 bus and modified IEEE-118 bus systems respectively. Therefore, due to allocation of losses on slack bus, the generation cost of slack bus generator is increased in comparison to its offered value. The COPF provides total losses of the system and this is allocated on the slack bus. Therefore, this approach cannot identify the contribution of transactions in total loss. This results into problem of calculation of actual welfares of the transactions which can be considered as a major disadvantage of COPF method. The problem of loss allocation due to individual transaction in multi-transaction system for obtaining the actual welfares of the various transactions can be overcome by using DOPF method. In DOPF, the losses due to individual transactions have been allocated by DOPF. The cost corresponding to the losses have been allocated on the slack bus which is deducted from the welfares obtained by the various transactions. This procedure provides a solution for calculation of actual welfares of transactions and the social welfare offered by the system. The results of Tables 4.14-4.17 also include the costs of losses in the cost of slack bus generation. In COPF, the total cost of losses is allocated on the slack bus. However, in case of DOPF, the individual allocated cost of losses caused by various transactions are allocated in the generation cost of their respective transactions.

In ref. [102], the total social welfare obtained did not include the cost of losses of the system. Thus, it can be stated that the results of this work does not provide actual social welfare for modified IEEE-118 bus system. On the other hand, the results of this work included the cost of losses in the problem formulations. This ascertains that the results obtained by this work provide actual social welfare of the system as compared to reported work [102]. The comparisons of generation costs, demand benefits and the social welfare obtained by COPF using IP and PSO for the modified IEEE-30 bus and modified IEEE-118 bus systems are shown in Figs. 4.7 and 4.8 respectively. Also, the comparisons based on DOPF are shown in Fig. 4.9 and 4.10 for both the test systems. These figures show that the PSO based DOPF approach provides more social welfare with congestion management as compared to IP method for both the test systems. The social welfares using PSO based DOPF for modified IEEE-30 bus system is 901.8887 $/hr and for modified IEEE 118 bus system it is 2656.6777 $/hr, whereas for IP based DOPF for modified IEEE 30 bus system it is 887.0904 $/hr and for modified IEEE 118 bus system it is 2583.0451 $/hr. Therefore, PSO based DOPF gives more social welfare as compared to IP based DOPF.

Table 4.14

Social welfare of modified IEEE-30 bus system using COPF approach ($/hr)

Cases	Case 1 Before Congestion Management	Case 2 After Congestion Management	
	Initial	IP	PSO
Total Generation Cost	2836.2213	3069.3824	3055.2898
Total Demand Benefit	3735.4531	3723.7449	3750.4562
Social Welfare	**899.2317**	**654.3626**	**695.1664**

Table 4.15

Social welfare of modified IEEE-118 bus system using COPF approach ($/hr)

Cases	Case 1 Before Congestion Management	Case 2 After Congestion Management	
	Initial	IP	PSO
Total Generation Cost	21759.2526	21877.2143	21876.16577
Total Demand Benefit	23481.4743	23416.2359	23439.2305
Social Welfare	**1722.2217**	**1539.0217**	**1563.0648**

Table 4.16

Social welfare of modified IEEE-30 bus system using DOPF approach

Transactions		Case 1 Before Congestion Management	Case 2 After Congestion Management	
		Initial	IP	PSO
T1	Generation Cost	999.2363	948.007	873.4102
	Demand Benefit	1440.5419	1400.4403	1338.0824
	Welfare	**441.3056**	**452.4333**	**464.6722**
T2	Generation Cost	1022.7973	1092.9427	1063.1143
	Demand Benefit	1319.1768	1413.4278	1389.7755
	Welfare	**296.3795**	**320.4851**	**326.6612**
T3	Generation Cost	806.6559	843.5661	929.7882
	Demand Benefit	989.0635	957.7382	1040.3435
	Welfare	**182.4076**	**114.1721**	**110.5553**
Total Generation Cost		**2828.6896**	**2884.5159**	**2866.3127**
Total Demand Benefit		**3748.7823**	**3771.6063**	**3768.2014**
Social Welfare		**920.0927**	**887.0904**	**901.8887**

Table 4.17

Social welfare of modified IEEE-118 bus system using DOPF approach

Transactions		Case 1	Case 2	
		Before Congestion Management	After Congestion Management	
		Initial	IP	PSO
T1	Generation Cost	3363.1226	3643.8244	3170.9380
	Demand Benefit	3617.7549	3889.3230	3403.8470
	Welfare	**254.6323**	**245.4986**	**232.9090**
T2	Generation Cost	2477.5646	1798.7161	2225.5265
	Demand Benefit	2968.4127	2168.0276	2679.7851
	Welfare	**490.8481**	**369.3116**	**454.2586**
T3	Generation Cost	3193.0667	3508.7980	3413.3129
	Demand Benefit	3761.7253	4152.7569	4028.2534
	Welfare	**568.6586**	**643.9589**	**614.9405**
T4	Generation Cost	4889.4355	5860.0915	6041.6774
	Demand Benefit	5376.0021	6404.8601	6592.7260
	Welfare	**486.5666**	**544.7686**	**551.0486**
T5	Generation Cost	3864.3646	3628.0288	3699.3032
	Demand Benefit	4235.7886	3990.4775	4109.2557
	Welfare	**371.4240**	**362.4486**	**409.9525**
T6	Generation Cost	3027.4576	2381.1860	2248.7284
	Demand Benefit	3530.4919	2798.2448	2642.2969
	Welfare	**503.0343**	**417.0588**	**393.5685**
Total Generation Cost		**20815.0117**	**20820.6448**	**20799.4864**
Total Demand Benefit		**23490.1755**	**23403.6900**	**23456.1641**
Social Welfare		**2675.1638**	**2583.0451**	**2656.6777**

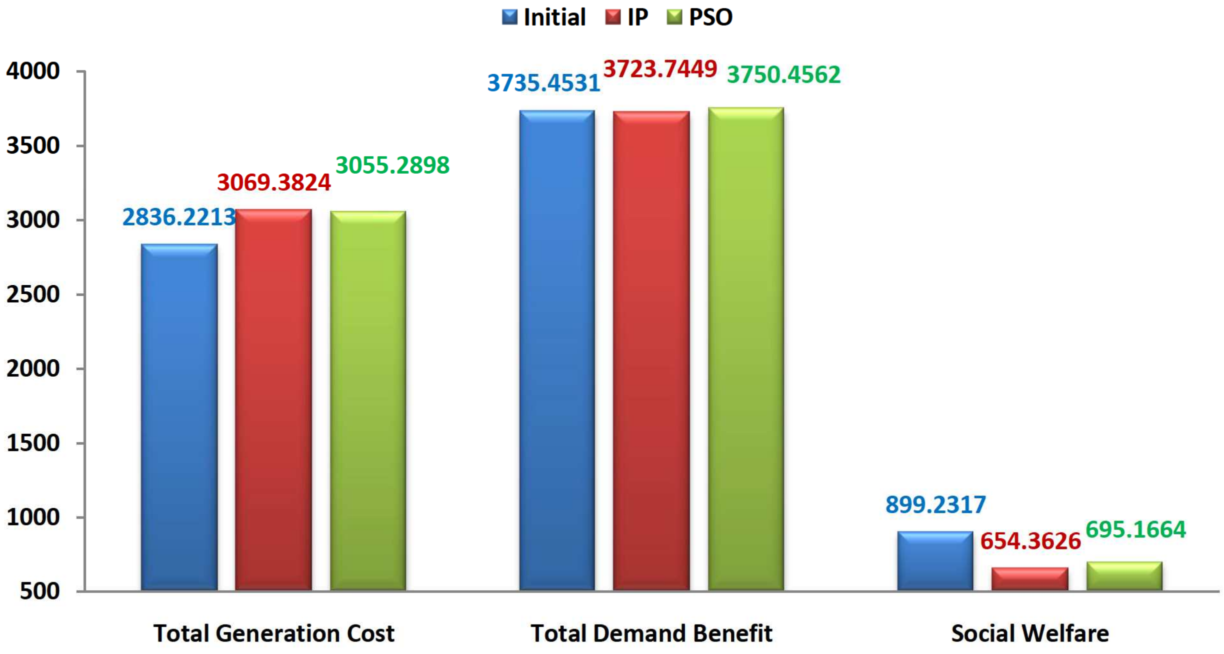


Fig. 4.7 Comparisons of generation cost, demand benefits and social welfares in modified IEEE-30 bus system using COPF approach

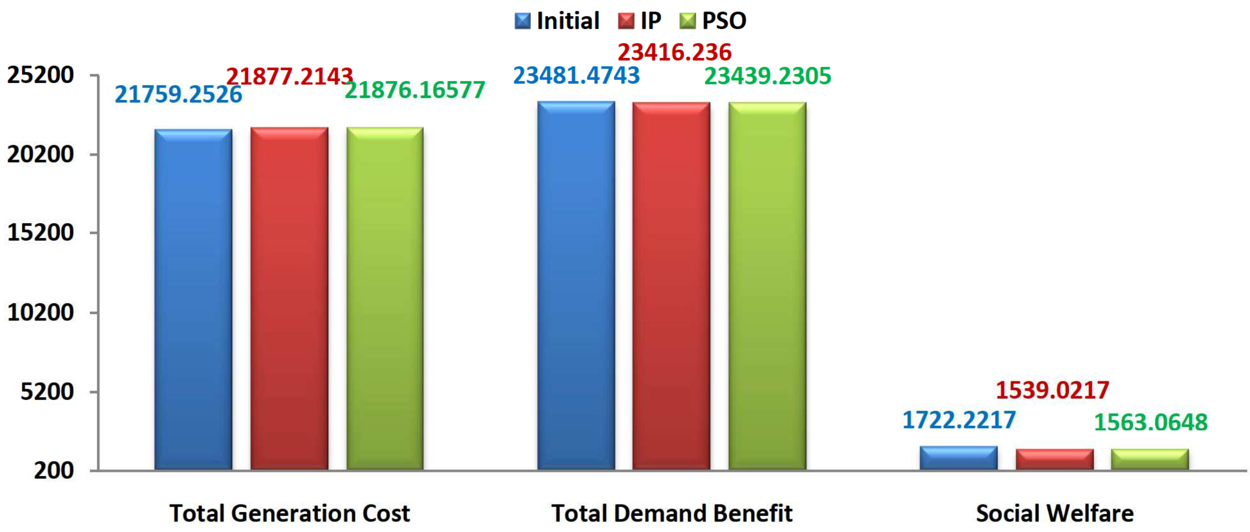


Fig. 4.8 Comparisons of generation cost, demand benefits and social welfares in modified IEEE-118 bus system using COPF approach

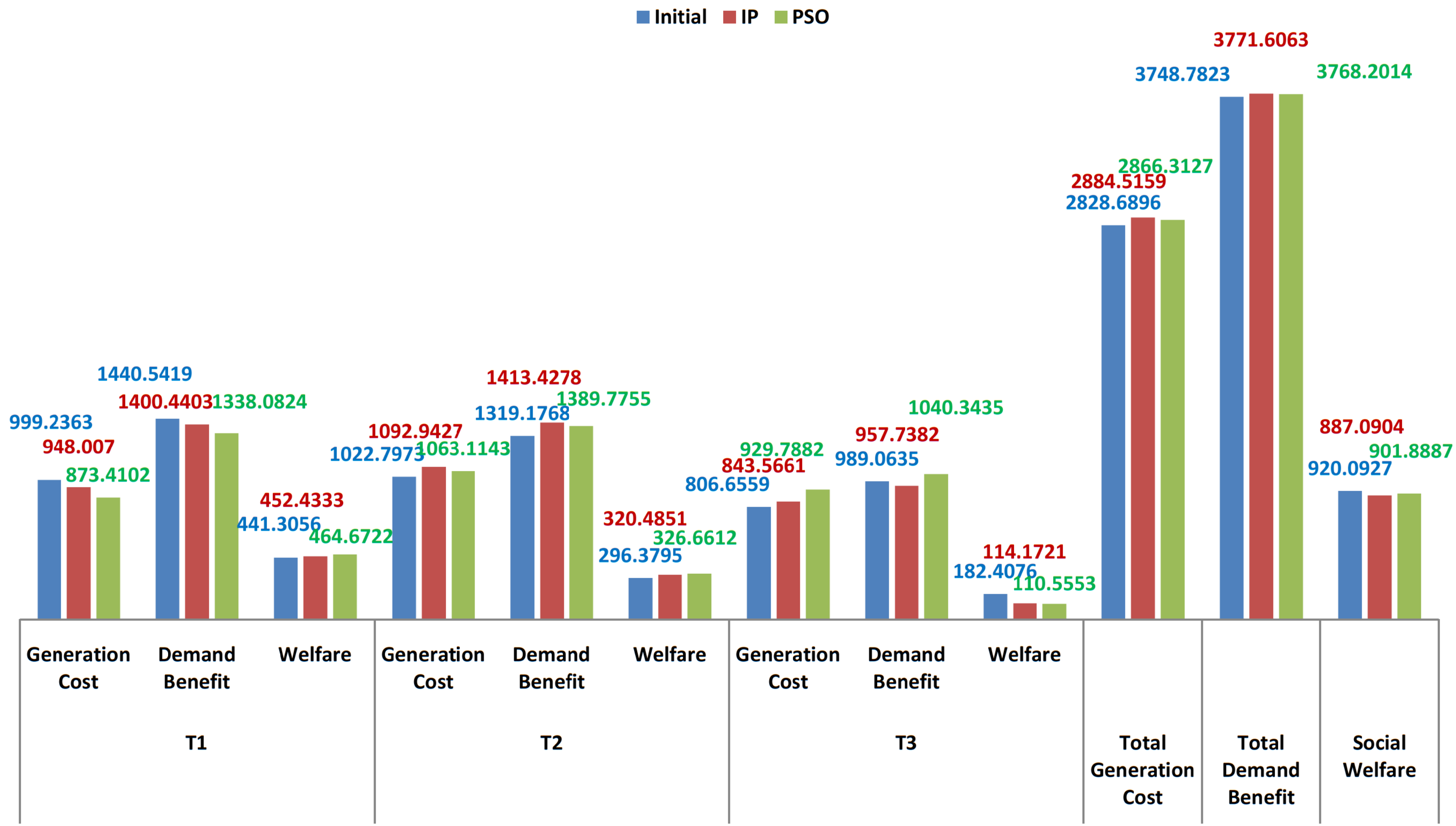
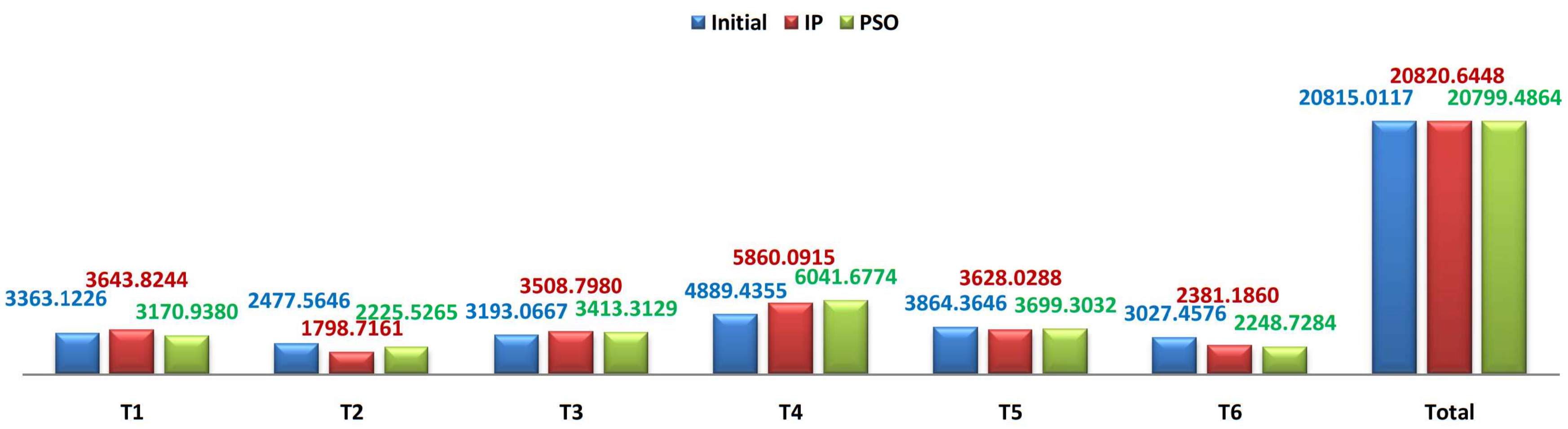
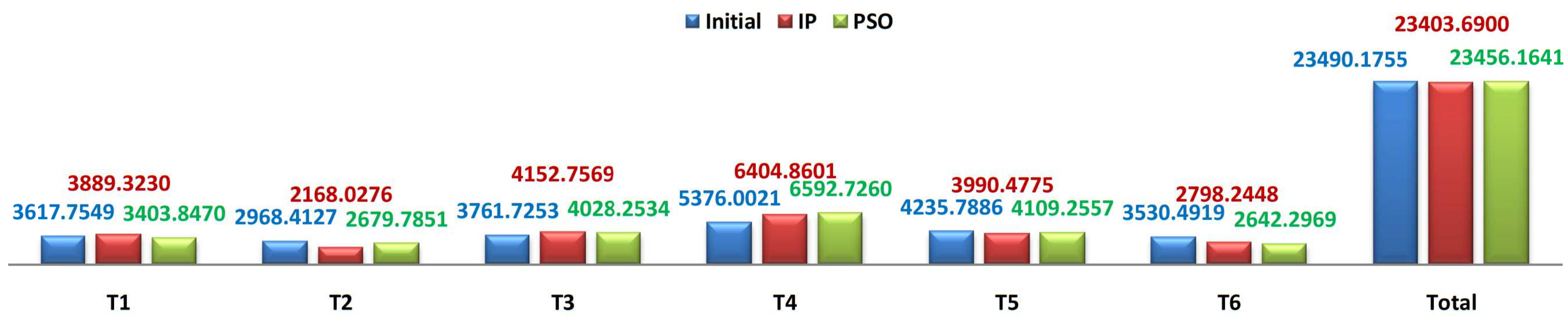


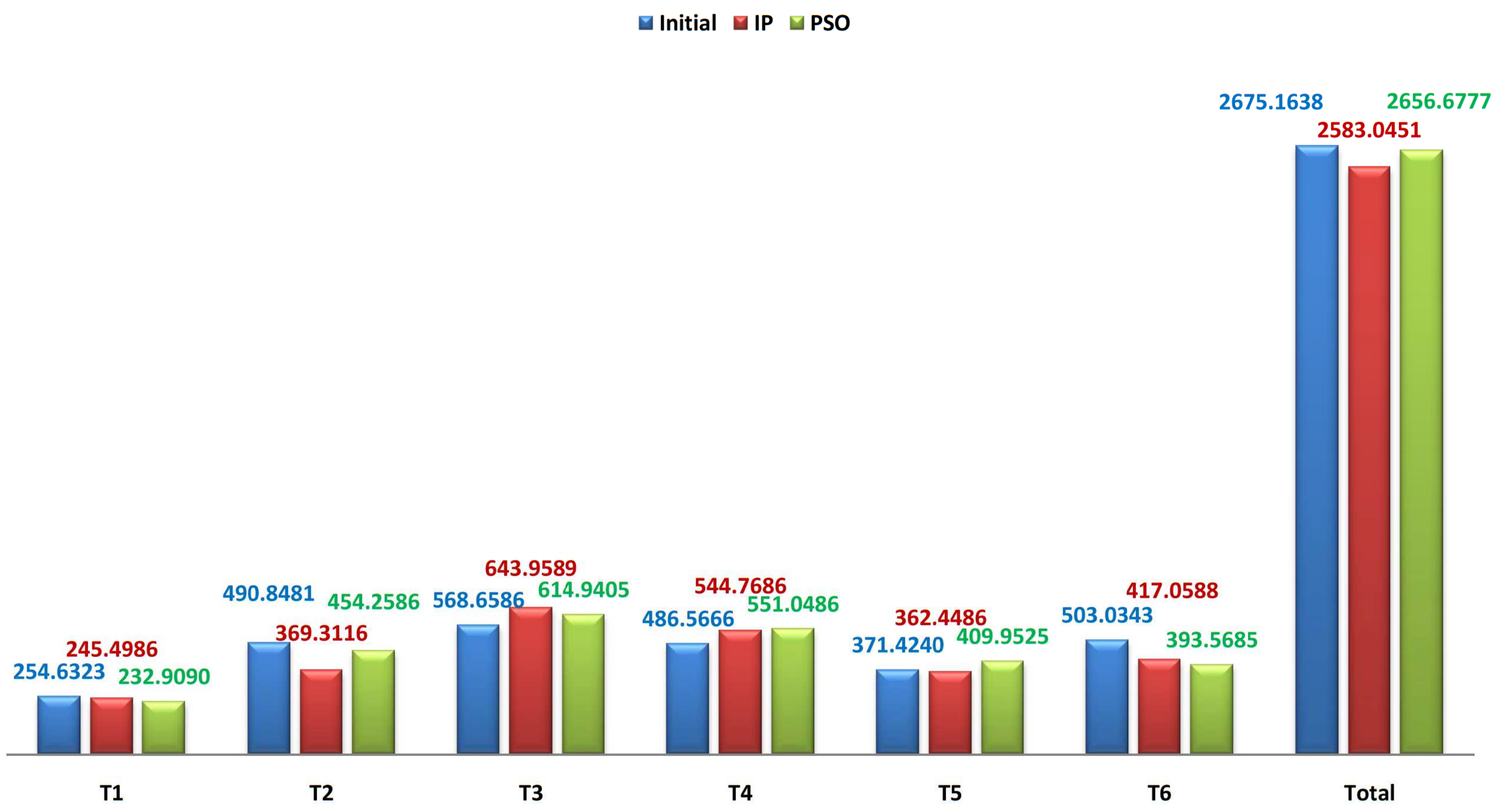
Fig. 4.9 Comparisons of generation cost, demand benefits and social welfares in modified IEEE-30 bus system using DOPF approach



(a) Generation cost



(b) Demand benefits

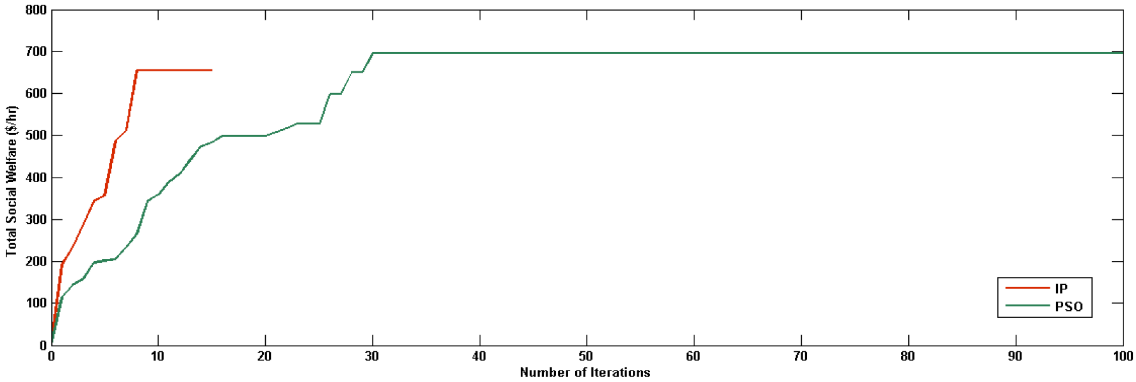


(c) Social welfares

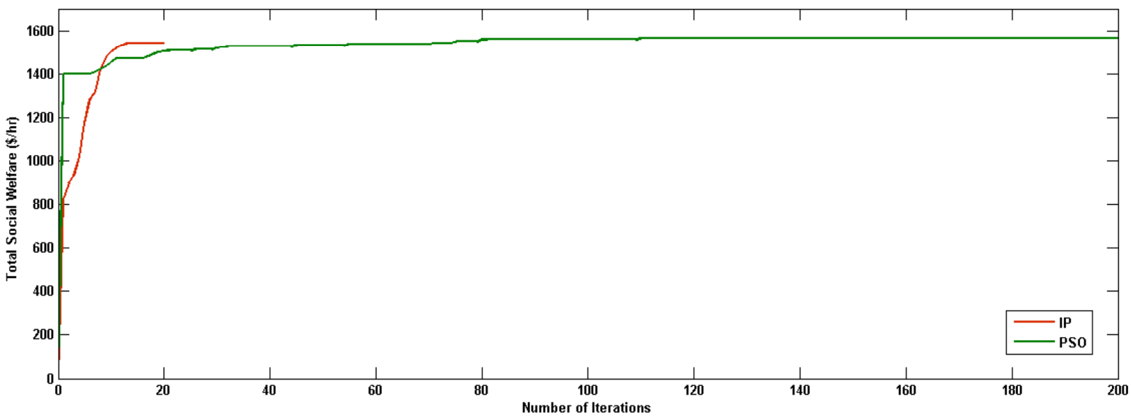
Fig. 4.10 Comparisons in modified IEEE-118 bus system using DOPF approach

4.4.5. Comparison of Computational Times of IP and PSO

This section presents the comparison of computational behaviour of IP and PSO methods for COPF and DOPF approaches. The convergence of IP and PSO based solution using COPF and DOPF for both the test systems are shown in Figs. 4.11 and 4.12 respectively. The computational times and number of iteration required for the solution using both the approaches for modified IEEE-30 bus and modified IEEE-118 bus systems are given in Table 4.18. It has been observed from the test results that IP converges very fast but the solution obtained by this technique is inferior as compared to PSO. On the other hand, PSO provides a good solution as compared to IP in terms of global solution and convergence.

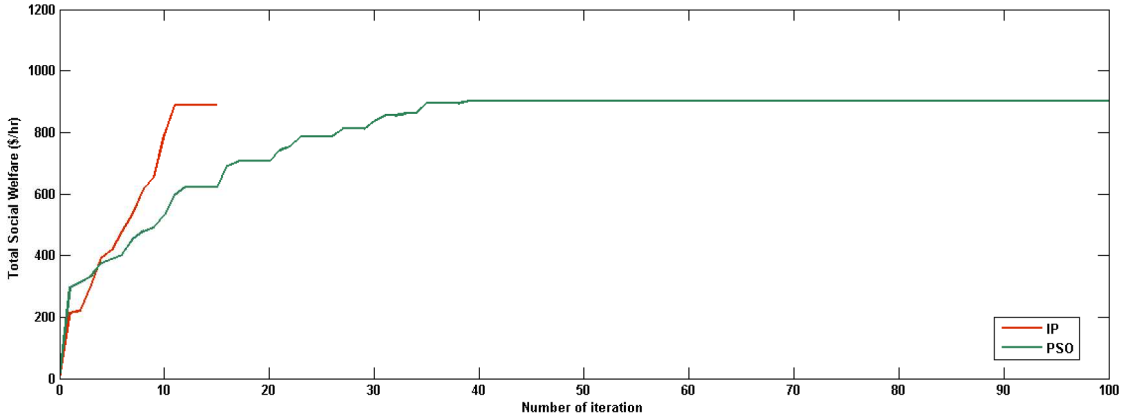


(a) Modified IEEE-30 bus system

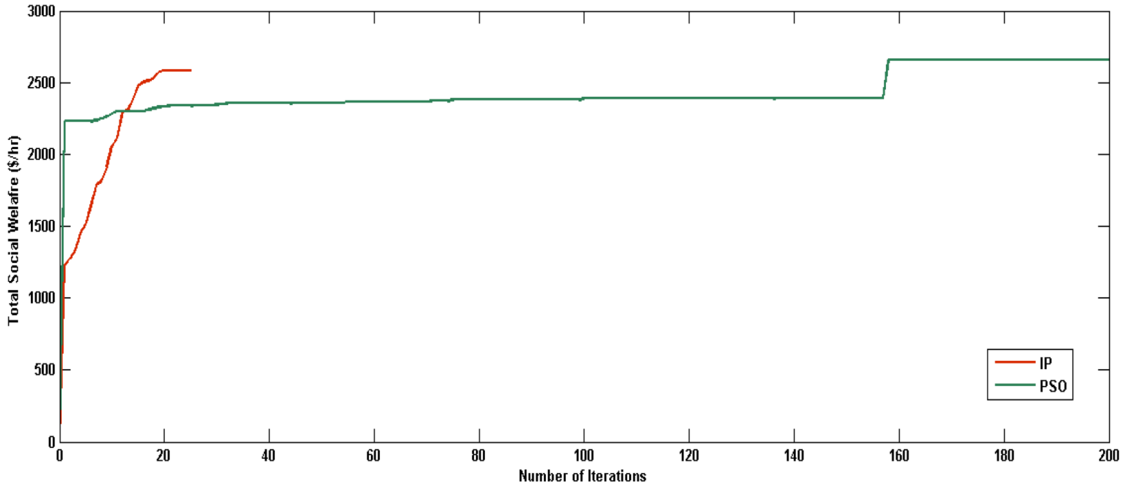


(b) Modified IEEE-118 bus system

Fig.4.11 Convergence of COPF by IP, PSO



(a) Modified IEEE-30 bus system



(b) Modified IEEE-118 bus system

Fig.12 Convergence of DOPF by IP, PSO

Table 4.18

Computational times and number of iterations

	System	Method	Number of Iterations	CPU Time (s.)
COPF	Modified IEEE-30 bus System	IP PSO	8 30	56.71 323.16
	Modified IEEE-118 bus System	IP PSO	13 110	68.82 358.19
DOPF (Series Computation)	Modified IEEE-30 bus System	IP PSO	10 39	93.32 841.67
	Modified IEEE-118 bus System	IP PSO	20 158	126.61 892.57

4.5. CONCLUSION

This chapter presents the centralized and decentralized decision support based optimal power flow operations of power market. The congestion in transmission system with social welfare in multi-transaction is considered as a problem objective. In this work, IP and PSO methods are used for social welfare maximization during congestion in the transmission system. The solution for congestion management with social welfare maximization has been obtained by optimal rescheduling of generators and demands using COPF and DOPF approaches. These approaches have been applied in modified IEEE-30 bus and modified IEEE-118 bus systems to observe the effectiveness of the solution methodologies. The congestion in transmission lines have been identified using power transfer distribution factors and then the congestion has been alleviated from the system by optimal rescheduling. In this work, the allocation of losses due to transactions in multi-transaction power system has also been considered in test results. The test results reveal that the PSO based DOPF approach provides superior results as compared to PSO based COPF based approach. The effects of loss allocation on social welfare have also been analyzed in the present work. The results of ref. [102] are also compared with results of the present work for modified IEEE-118 bus system. This comparison shows that the proposed technique provides actual social welfare in the power market as compared to results of ref. [102] by including the losses of transactions.