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SWARM INTELLIGENCE BASED ALGORITHM FOR WHEELING TRANSACTION IN DEREGULATED POWER INDUSTRY

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Abstract. *This paper proposes how to determine the optimal selection based on generation cost of power system network. For this purpose, an efficient PSO-optimal power flow algorithm has been proposed. In this proposed PSO-optimal power flow, Newton Raphson Method and Particle Swarm Optimization algorithm have been used for power flow and economic dispatch respectively. A Hybrid Particle Swarm Optimization (HPSO) algorithm has also been proposed for economic dispatch. Based on the power transfer capability and minimum generation cost, an optimal wheeling option will be suggested to both the owners of private non-utility generator (i.e., independent power producers or co-generators) and the utility. The proposed algorithm is independent of the cost characteristics of non-utility generators (NUGs). The proposed model has been tested on the IEEE 30 and Indian Uitility 69-bus test system with synthetic imposition of wheeling transactions. The solutions obtained are quite encouraging and useful in the present deregulated environment.*
Keywords: Optimal power flow, Particle Swarm Optimization (PSO), NUG, Wheeling

1. **Introduction.** Wheeling is the transaction of electrical energy from a seller to buyer through a transmission network owned by a third party [1]. As dependence on electricity grew, regulation on the federal and local level increased as well. However, the need for more efficiency in power production and delivery has led to a restructuring of the power sector in several countries traditionally under control of federal and state governments. In this, new environment of de-regulation, one common problem has been encouraged namely transmission congestion. Transmission congestion refers to the inability to dispatch additional generation from certain generators within the system due to transmission line limits. Generator rescheduling is one of the important ways to relieve congestion [15,16].

A wide variety of optimization techniques have been applied in solving the OPF problem such as nonlinear programming [2-7] Newton based techniques, genetic algorithm, Particle Swarm Optimization [13,14]. Recently a new evolutionary computation technique, called Hybrid Particle Swarm Optimization (HPSO) has been proposed. HPSO is a population based stochastic optimization technique. In HPSO search of optimal solution is conducted using a population of particles, each of which represents a candidate solution to the optimization problem. Particles change their position by flying round a multi-dimensional space by following current optimal particles until a relatively unchanged position has been achieved or until computational limitations are exceeded. Each particle adjusts its trajectory towards its own previous best position and towards its best position attained until now. HPSO is easy to implement, provides fast convergence for many optimization problems, and has gained lots of attention in power system application recently.

Under de-regulation, the generation patterns resulting from market activities can be quite different from the traditional one [18]. Further that any non-utility generator (NUG) in the system can sell all part of its output to single or multiple buyers located anywhere within the network, has made the problem very much complicated. NUGs include both independent power producers (IPPs) and co-generators. There is a need for an optimal system, which may balance the needs of energy providers, the resellers, the large industrial customers and residential consumers. Some methods and mathematical models have been reported in literature for solving above-mentioned problems.

The general concept of wheeling and optimization has been explained in [17]. The review of the major existing methods of wheeling has been discussed [8] and various existing models are in use in different countries. Privatizing and restructuring the state electricity boards has been proposed for the Indian power sector [9] and Norway's power sector [10]. The optimal approach explained in this paper, using PSO-OPF, in the proposed hybrid model, is simple and efficient under various complicated situations and system constraints. It can handle the generating plant with non-convex or any other cost characteristics. The proposed approach is free from mathematical complexity and suitable for highly complex environment. Hence, POPF has been used to determine most economical and suitable (satisfying various system constraints) options for wheeling transactions under de-regulated environment of power systems. The proposed algorithm is independent of cost characteristics of NUGs.

2. **Mathematical Formulation.** The selection of wheeling transaction is based on optimization of generation cost without violating system constraints [11,12]. So the optimization of cost of generation has been formulated based on classical OPF. The detailed problem formulation of the proposed approach is as follows:

Base case (optimal generation without any wheeling transaction). For a given power system network, the optimization cost of generation is given by the following equation

$$C = \min \sum_{i=1}^{Ng} f_i(pg_i) \tag{1}$$

The cost is optimized with the following power system constraint

$$\sum_{i=1}^{Ng} pg_i = p_D + pl \tag{2}$$

The power flow equation of the power network is

$$g(|v|, \phi) = 0 \tag{3}$$

where $|v|$ and ϕ are voltage magnitude and phase angles of different buses.

The inequality constraint on real power generation Pg_i of each generation i

$$Pg_i^{\min} \le Pg_i \le Pg_i^{\max} \tag{4}$$

The inequality constraint on voltage of each PQ bus

$$V_i^{\min} \le V_i \le V_i^{\max} \tag{5}$$

Power limit on transmission line

$$MVAf_{p,q} \le MVAf_{p,q}^{\max} \tag{6}$$

where C is optimal cost of generation when the utility supplying its own load, $f_i(pg_i) =$ Generation cost function of the ith generator for pg_i generation. $pg_i =$ Power generation by the ith generator. $Ng =$ Number of generator connected network. $P_d =$ Total load of the system, $Pl =$ Transmission losses of the system (when the utility supplying its own load), $Pg_i^{\min}$ and $Pg_i^{\max}$ are respectively minimum and maximum value of real power generation allowed at generator i, $V_i^{\min}$ and $V_i^{\max}$ are respectively minimum and maximum voltage at bus i, $MVAf_{p,q}^{\max}$ is the maximum rating of transmission line connecting bus p and q.

3. **Wheeling Transaction and Its Loadability Limit.** A simultaneous wheeling transaction has been included in an 'n' bus system. The seller at the bus i and the buyer with a load at bus j. The corresponding wheeling transaction can be represented at WT (i-j), where i and j may be varied from 1 to n and i is not equal to j. Let us assume that an IPP is willing to supply the additional load demand at bus j through the utility transmission system by a wheeling transaction WT (i-j). Then, run the power flow program with all the generators of the utility being held at fixed optimal setting of base case under these conditions. The amount of wheeled power in the network must be within the limits of IPP and satisfy the transmission constraints. In general the algebraic sum of power delivered by the non-utility generators/Independent Power Producers is equal to the sum of power taken at different load points.

Suppose now real load is increased at load bus, which is virtually the load increasing at a bus j with unity power factor and it is a function of load parameter λ as

$$P_{dj} = \lambda P_{dj0} \quad j = 1, 2, \ldots, n_l \tag{7}$$

The zero subscript indicates base load at the buses. Now the load at bus j is varied until the system no longer has a solution. Therefore,

$$\lambda \ge \lambda^{\max} \tag{8}$$

The λ is the bifurcation parameter, where 'λ' is scalar parameter representing the increase in busload. $\lambda = 1$ corresponds to base case and $\lambda = \lambda^{\max}$ corresponds to the maximum load.

4. **Overview of HPSO.** The traditional PSO model has described by Dr. Kennedy and Dr. Eberhart in 1995. It consists of a number of particles moving around in the search space, each representing a possible solution to a numerical problem [20-22]. Each particle has a position Vector $X_i = (x_{i1}, x_{i2}, \ldots, x_{in})$, a velocity Vector $V_i = (v_{i1}, v_{i2}, \ldots, v_{in})$. In the PSO, the collective best position of all the particles taken together is termed as the global best position given as $Glbest_i = (glb_{i1}, glb_{i2}, \ldots, glb_{in})$ and the best position achieved by the individual particle is termed as the local best or position best and for ith particle given as $Pbest_i = (p_{i1}, p_{i2}, \ldots, p_{in})$. Particles use both of these pieces of information to update their positions and velocities are given in the following equations

$$V_i^{k+1} = \omega V_i^k + C_1 rand_1 (Pbest_i^k - X_i^k) + C_2 rand_2 (Glbest_i^k - X_i^k) \tag{9}$$

In each iteration, the position of each particle is updated. This is done by adding the velocity vector to the position vector, i.e.,

$$X_i^{k+1} = X_i^k + V_i^{k+1} \tag{10}$$

The accuracy and rate of convergence of the algorithm depends on the appropriate choice of particle size, maximum velocity of particle size and the inertia constant. If the velocity is higher than a certain limit, called $V^{\max}$, this limit will be used as the new velocity for this particle in this dimension, thus keeping the particle within the search space.

The breeding and subpopulation process is employed by the following equations:

$$child_1(x_i) = p_i * parent_1(x_i) + (1.0 - p_i) * parent_2(x_i) \tag{11}$$

$$child_2(x_i) = p_i * parent_2(x_i) + (1.0 - p_i) * parent_1(x_i) \tag{12}$$

where p_i is a uniformly distributed random value (between 0 and 1). The velocity vectors of the offspring are calculated as the sum of the velocity vectors of the parents normalized to the original length of each parent velocity vector.

$$child_1(\bar{v}) = \frac{parent_1(\bar{v}) + parent_2(\bar{v})}{|parent_1(\bar{v}) + parent_2(\bar{v})|} \, |parent_1(\bar{v})| \tag{13}$$

$$child_2(\bar{v}) = \frac{parent_1(\bar{v}) + parent_2(\bar{v})}{|parent_1(\bar{v}) + parent_2(\bar{v})|} \, |parent_2(\bar{v})| \tag{14}$$

The arithmetic crossover of positions and velocity vectors used were empirically tested to be the most promising. The arithmetic crossover of positions in the search space is one of the most commonly used crossover methods with standard real valued GAs, placing the offspring within the hypercube spanned by the parent particles. In this paper, mutation process is employed by the following equation:

$$mut(p[k]) = (p([k]) * -1) + \omega \tag{15}$$

where $p[k]$ is the random choice particle from the swarm, and ω is randomly obtained within the range $[rand(0, 0.1) * (x_{\max} - x_{\min})]$, representing 0.1 times the length of the search space, where $x_{\max}$ and $x_{\min}$ are the domains of the search space. Note that this does not restrict the values of x_i.

The structure of the hybrid model is illustrated below

```
Begin
    Initialize
        While (not terminate-condition) do
            Begin
                Evaluate
                    Calculate new velocity vectors
                        Move
                    Breeding
                Mutation
            End
End
```

Pseudo code for HPSO algorithm

5. **Algorithm for HPSO.** The step by step algorithm for the method is explained as follows:

1. Specify the maximum and minimum limits of generation power of each generating unit, maximum number of iterations to be performed and fuel cost co-efficient of each unit.
2. Specify the Bus data, Line data, Inertia weight, Acceleration constants, no of particles and the particle size.
3. Initialize randomly the individuals of the population of all units other than the reference unit according to the limit of each unit.
4. Calculate the evaluation value of each population P_g using the evaluation equation.

5. Compare each population's evaluation value with its *pbest*. The best evaluation value among the *pbest* is denoted as *gbest*.
6. Modify the velocity V of each individual P_{gi} using the Velocity Equation (9).
7. Modify the position of each individual according to the position Equation (10).
8. Perform Mutation using Equation (15).
9. If $p_{gid}^{(t+1)}$ violates the constraints then it must be set to the near margin of that particular unit.
10. If the evaluation value of each population is better than the previous p_{best} the current value is set to be p_{best}. If the best p_{best} is better than the g_{best} the value is set to be g_{best}.
11. If the number of iterations reaches the maximum then go to step 12, otherwise go to step 4.
12. The individual that generates the latest g_{best} is the optimal generation power of each unit.
13. The rescheduled power values of each generator corresponding to the minimum convergence value and the fuel cost of the same is displayed.
14. Using Newton-Raphson method the power flowing through all the lines of the system are determined.
15. Wheeling transaction is performed for each bus.
16. Stop.

6. **Results and Discussions.** The proposed method has been illustrated on IEEE 30-bus and Indian utility 69-bus utility systems. The influence of the PSO parameters, i.e., the inertia weight, and population size, constants C_1 & C_2, on the convergence of the algorithm has been studied. The size of particles has been increased from 10 to 100 in steps of 10 and the number of best particles for this problem is found to be 60. The inertia constant is varied from 0.4 to 0.9 and optimal value for this problem is found to be 0.5. Maximum number of iteration has been taken as 100. The minimum solution was obtained for 100 trial runs. Simulation studies have been conducted on Intel(R) core i5, CPU M430 @ 2.27 GHz processor under MatLab 7.6 environment. The adopted parameters for the algorithms are given in Table 1.

The Non Utility generator is added at 24th bus for the IEEE 30-bus system. In Indian 69-utility bus has NUG at 24th bus, where its cost coefficients and power constraints are shown in Table 2.

6.1. **IEEE 30-bus system.** The numerical data for IEEE 30-bus system are taken from [19]. This system has 6 generators, 41 transmission lines. The generators are connected at

Table 1. Parameter values for PSO and HPSO for the two test systems

Parameters	IEEE 30-bus system		Indian 69-bus system	
	PSO	HPSOCM	PSO	HPSOCM
Population	100	100	100	100
Social Factor, C_1	2	2	2	2
Cognitive Factor, C_2	2	2	2	2
Minimum Inertia Weight Factor	0.4	0.4	0.4	0.4
Maximum Inertia Weight Factor	0.9	0.9	0.9	0.9
Cross over probability	–	0.8	–	0.8
Mutation probability	–	0.01	–	0.01
Iterations	100	100	100	100

the buses 1, 2, 13, 22, 23 and 27. For this system, bus 1 is slack bus and there are 24 load buses. IPP is interested to have a wheeling transaction of all load buses of 30-bus system. In each bilateral transaction, the algorithm conducts the OPF by satisfying all the power flow constraints and estimates the maximum load at each load (buyer) buses without violating transmission line limit constraint. To validate the superiority of the proposed HPSOCM approach, simulation results have been compared with PSO technique. Table 3 shows the base case and optimal generation (MW) of the generating units. From the results obtained, we infer that the total fuel cost for the IEEE 30-bus system is 789.635 \$/hr by using HPSO.

TABLE 2. IPP cost function

Test Systems	P_{min} (MW)	P_{max} (MW)	a_i \$/MW$^2 - h$	b_i \$/MW$-h$	c_i \$/h
IEEE 30-bus system	20	44	0.02	2	0
Indian 69-bus utility system	80	100	0.0035	3	0

TABLE 3. PSO and HPSO results for wheeling transaction (IEEE 30-bus system)

		PSO	HPSO
Total power demand		290.20 MW	290 MW
Power Generated	P1	174 MW	174 MW
	P2	26 MW	26 MW
	P5	24 MW	24 MW
	P8	20 MW	20 MW
	P11	13 MW	13 MW
	P13	33 MW	33 MW
Total Fuel Cost \$/hr		790.10	789.635
Execution Time		3.2190 sec	1.5480 sec

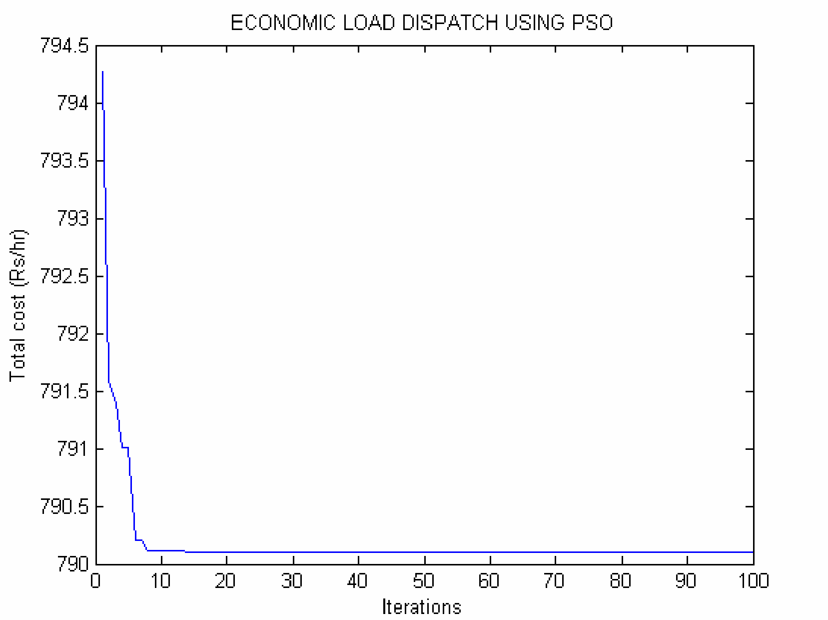

FIGURE 1. Iterations vs. Fuel Cost for IEEE 30-bus using PSO

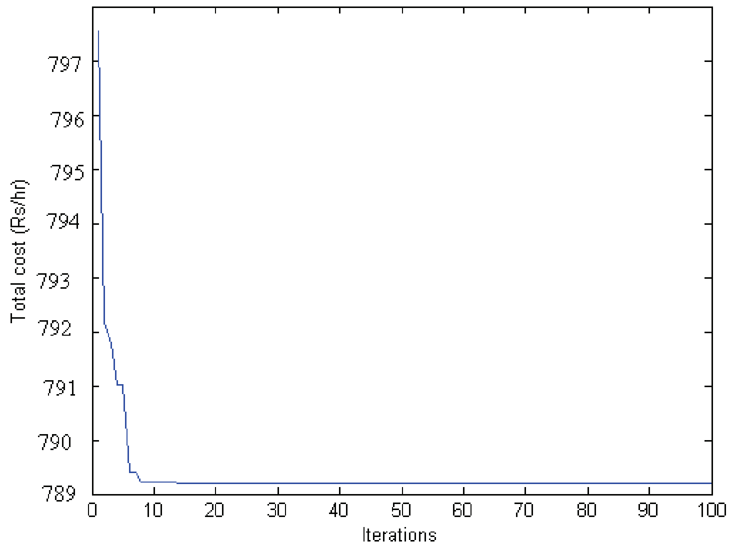

FIGURE 2. Iterations vs. Fuel Cost for IEEE 30-bus using HPSO

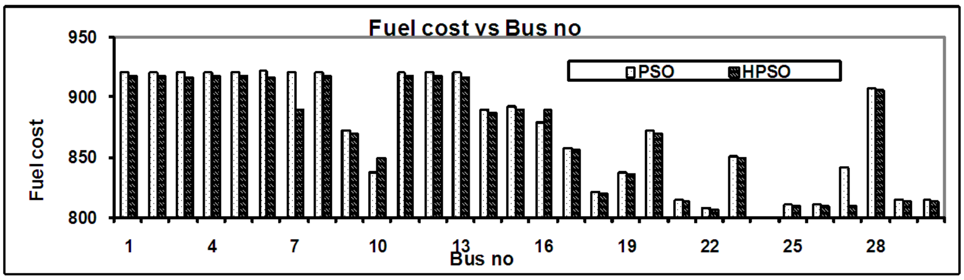

FIGURE 3. Bus No vs. Fuel Cost

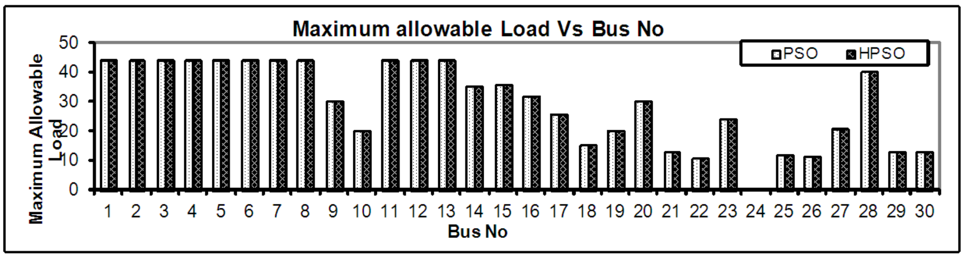

FIGURE 4. Bus No vs. maximum load

Figure 1 and Figure 2 show the graph drawn between Iterations vs. Fuel Cost. The minimum fuel cost converges at the 10th iteration.

Figure 3 shows the graph drawn between Bus No vs. Fuel Cost.

The maximum allowable load with respect to IPP is calculated and shown in Figure 4. We conclude that, the worst transaction takes place when the load is connected at 6th Bus. The best transaction takes place when the load is connected at 22nd Bus.

6.2. **Indian 69-bus utility system.** This utility system has 13 generators and 99 transmission lines and there are 57 load buses. The bus data for this system have been taken from TamilNadu Electricity Board report (2003-2004). Tamil nadu is one of the southern states of India and the entire power network is under the control of Tamil Nadu electricity Board, a state government owned Power Corporation.

TABLE 4. PSO results for wheeling transaction (Indian utility 69-bus system)

PSO			HPSO
Total power demand		4647 MW	
Power Generated In MW	P1	800	800 MW
	P13	990	990 MW
	P14	350	350 MW
	P15	459.4	459.4 MW
	P21	250	250 MW
	P31	100	99 MW
	P36	120	120 MW
	P39	320	320 MW
	P52	812.5	812.5 MW
	P53	55	54 MW
	P57	150	150 MW
	P58	150	150 MW
	P60	90	89 MW
Total Fuel Cost Rs/hr		9408.80	9356.30
Execution Time		5 sec	3.422 sec

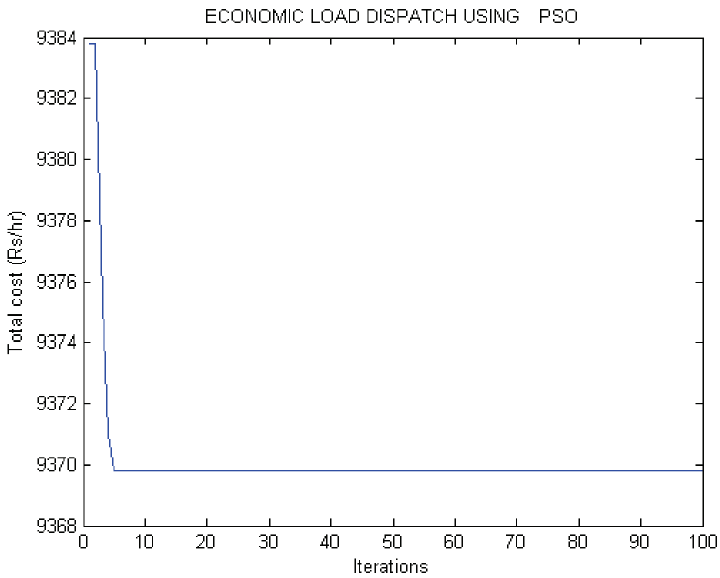

FIGURE 5. Iterations vs. Fuel Cost for Indian utility 69-bus system using PSO

From Table 4, we infer that the total fuel cost for the 69-bus systems is 9408.80 Rs /hr. From Figure 5 and Figure 6, the minimum fuel cost converges at the 5th iteration.

The maximum allowable load is calculated and shown in Figure 7. We conclude that, the worst transaction takes place when the load is connected at 67th Bus. The best transaction takes place when the load is connected at 28th Bus. Figure 8 shows the graph drawn between Bus No vs. Fuel Cost.

From the results obtained, we infer that the total fuel cost for the 69-bus system is 9356.3016 Rs/hr. Figure 5 shows the graph drawn between Iterations vs. Fuel Cost using PSO. From Figure 6, the minimum fuel cost converges at the 5th iteration in HPSO algorithm. The maximum allowable load is calculated and shown in Figure 7.

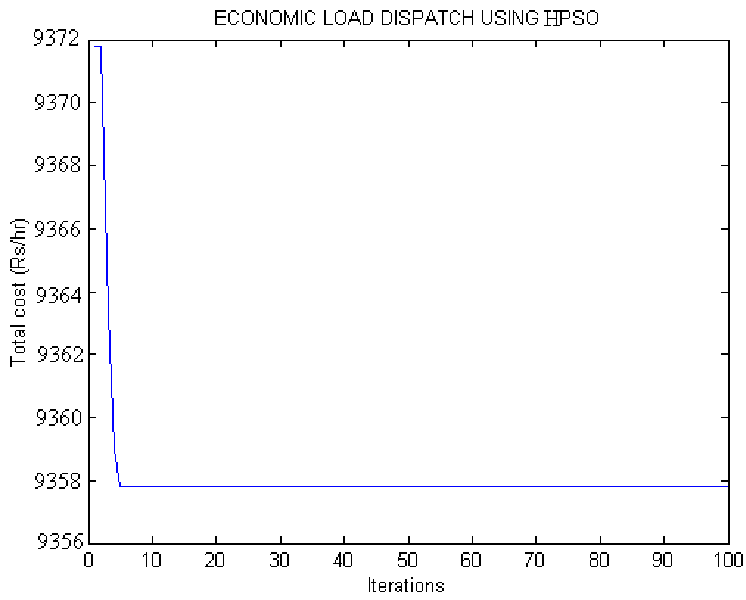

FIGURE 6. Iterations vs. Fuel Cost for Indian utility 69-bus system using HPSO

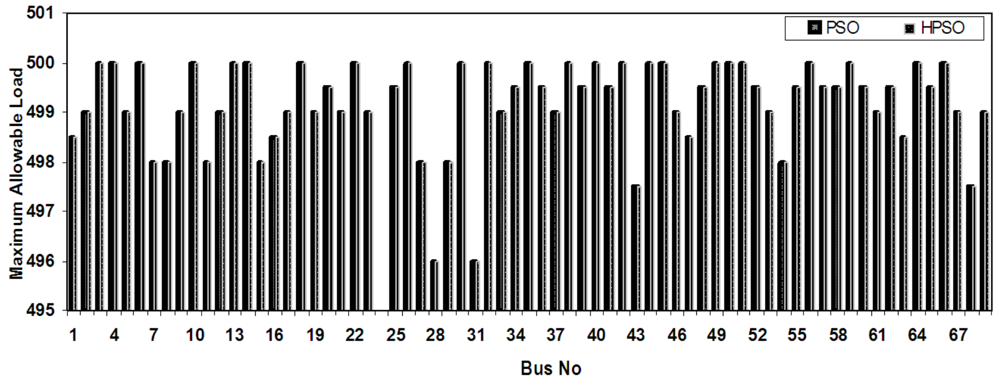

FIGURE 7. Bus No vs. maximum load for Indian utility 69-bus system

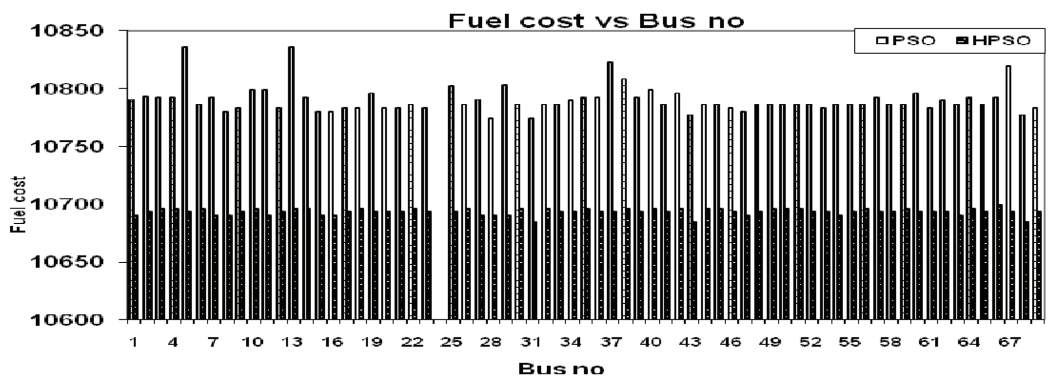

FIGURE 8. Bus No vs. Fuel Cost

From Table 4 we conclude that, the worst transaction takes place when the load is connected at 66th Bus. The best transaction takes place when the load is connected at 31st Bus. Figure 8 shows the graph drawn between Bus No vs. Fuel Cost for the Indian utility 69 bus system.

7. **Conclusion.** A PSO & HPSO based approach for optimal selection of wheeling option from the various feasible options of power system considering various system constraints has been proposed under de-regulated environment. The rescheduling of generators is in a manner that congestion does not occur in any part of the transmission line. The maximum load is determined at each bus when a non-utility generator comes into operation. This paper presents an approach to solve optimal power flow problem, which aims at minimizing fuel cost. Our proposed approach satisfactorily finds global optimal solution within a small no of iteration. Thus, the algorithm is very fast and can be applied online. However, as the other evolutionary methods HPSO also has the drawback of not converging to exactly the same value all the time due to its stochastic nature. However, in this case HPSO has returned almost the same result for most of the cases.

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