FUEL COST MINIMIZATION USING AN IMPROVED PARTICLE SWARM OPTIMIZATION

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ABSTRACT

This paper deals about minimization of fuel cost using modified particle swarm Optimization (PSO) technique to solve optimal power flow (OPF) problems. The standard PSO algorithm is extended "passive congregation" to prevent premature convergence and refine the convergence performance. The proposed approach has been evaluated on an IEEE 6,14,30-bus test system which minimize fuel cost. The obtained results were compared with some other existing methods.

Index Terms - Optimal Power Flow, Particle Swarm Optimization (PSO), Passive Congregation.

I. INTRODUCTION

Now days the entire fuel source are going to exhaust within 20 years i.e.. around 2030. Hence saving the fuel is very essential aspects in today problem. With the help of this approach we can save some fuel without changing our net demands and only way to change is internal parameter. Now we taken the optimal power flow (OPF) problem was introduced by Carpentier [1] in 1962 as a network constrained economic dispatch problem. Since then, the OPF problem has been intensively studied and widely used in power system operation and planning [2]. The OPF problem aims to achieve an optimal solution of a specific power system objective function, such as fuel cost, by adjusting the power system control variables, while satisfying a set of operational and physical constraints. The control variables include the generator real powers, the generator bus voltages, the tap ratios of transformer and the reactive power generations of VAR sources. State variables are slack bus power, load bus voltages, generator reactive power outputs, and network power flows. The constrains include inequality ones which are the limits of control variables and state variables; and equality ones which are the power flow equations. The OPF problem can be formulated as a nonlinear constrained optimization problem. To solve OPF problem, a number of conventional optimization techniques have been applied. They include nonlinear programming (NLP) [3] [4], quadratic programming (QP) [5] [6], linear programming (LP) [7] [8], and interior point methods [9] [10] [11]. All these techniques rely on convexity to find the global minimum. But due to the non differential, nonlinearity and non convex nature of the OPF problem, the methods based on these assumptions do not guarantee to find the global optimum. These traditional techniques also suffer from bad starting points and frequently converge to local minimum or even diverge. In the past few decades, many stochastic optimization methods have been developed, such as Genetic Algorithms (GA), Evolutionary Programming (EP), and Evolution Strategies (ES). Their applications to global optimization problems become attractive because they have better global search abilities over conventional optimization algorithms. The OPF problem has been solved with Evolutionary Programming (EP) [12]. The proposed EP based OPF were evaluated on an IEEE 30-bus system and the obtained results were compared with those obtained using a conventional gradient-based method. In [13] an enhanced EP with gradient information was applied to the IEEE 30-bus system under different generator input-output curves. An enhanced GA with adaptive crossover and mutation based on the fitness statistics of population was applied to minimize the active power loss in the transmission network [14]. Recently, Bakirtzis et al. applied an enhanced GA to solve OPF problem [15]. In their study, advanced genetic operators such as fitness scaling, elitism and hill climbing and other problem specific operator are employed to improve the efficiency of simple GA. Particle Swarm Optimizer (PSO) is a newly proposed population based stochastic optimization algorithm which was inspired by the social behaviors of animals such as fish schooling and bird flocking [16]. Compared with other stochastic optimization methods, PSO has comparable or even superior search performance for some hard optimization problems with faster convergence rates [17]. It requires only few parameters to be tuned, which makes it attractive from an implementation view point. However, recent studies of PSO indicated that although the PSO outperforms other evolutionary algorithms in the early iterations, it does not improve the quality of the solutions as the number of generations is increased. In [18], passive congregation, a concept from biology, was introduced to the standard PSO to improve its search performance. Experimental results show that this novel hybrid PSO outperforms standard PSO on multi-model and high dimensional optimization problems. In this paper, we present a PSO with passive congregation (PSOPC) for the solution of OPF. The standard IEEE 30-bus power systems have been employed to carry out the simulation study. Particle Swarm Optimizer (PSO) is a newly proposed population based stochastic optimization algorithm which was inspired by the social behaviors of animals such as fish schooling and bird flocking [16]. Compared with other stochastic optimization methods, PSO has comparable or even superior search performance for some hard optimization problems with faster convergence rates [17]. It requires only few parameters to be tuned, which makes it attractive from an implementation viewpoint. 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II. OPTIMAL POWER FLOW PROBLEM FORMULATION

The Power Flow problem can be solved by the following formulae

$$\min \quad f(x,u) \qquad (1)$$

$$s.t \quad g(x,u) = 0 \qquad (2)$$

$$h(x,u) \le 0 \qquad (3)$$

where x is the vector of dependent variables such as slack bus power $PG1$, load bus voltage *VL*, generator reactive power outputs *QG* and apparent power flow *Sk*. x can be expressed as

$$x^T = [P_{G1}, V_{L1} ... V_{LN_L}, Q_{G1} ... Q_{GN_G}, S_1 ... S_{NE}] \qquad (4)$$

u is a set of the control variables such as generator real power outputs *PG* expect at the slack bus $PG1$, generator voltages *VG*, transformer tap setting *T*, and reactive power generations of

VAR sources *Qc*. Therefore, u can be expressed as

$$u^T = [P_{G2}, P_{GN_G}, V_{G1} ... V_{GN_G}, T_1 ... T_{N_T}, Q_{C_1} ... Q_{CN_C}] \quad (5)$$

The equality constraints *g*(x*;* u) are the nonlinear power

flow equations which are formulated as follows:

$$0 = P_{G_1} - P_{D_1} - V_i \sum_{j\varepsilon N_i} V_J (G_{IJ} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}) \qquad i\varepsilon N_O \quad (6)$$

$$0 = Q_{G_1} - Q_{D_1} - V_i \sum_{j\varepsilon N_i} V_J (G_{IJ} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}) \qquad i\varepsilon N_{PQ} \quad (7)$$

And the inequality constraints *h*(x*;* u) are limits of control variables and state variables which can be formulated as:

$$\begin{aligned}
&P_{G_i}^{\min} \le P_{G_I} \le P_{G_i}^{\max} i\varepsilon N_G \\
&Q_{G_i}^{\min} \le Q_{G_I} \le Q_{G_i}^{\max} i\varepsilon N_G \\
&Q_{C_i}^{\min} \le Q_{C_I} \le Q_{C_i}^{\max} i\varepsilon N_C \\
&T_K^{\min} \le T_K \le T_K^{\max} i\varepsilon N_T \\
&V_i^{\min} \le V_i \le V_i^{\max} i\varepsilon N_B \\
&|S_K| \le S_K^{\max} i\varepsilon N_E
\end{aligned} \quad (8)$$

To solve nonlinear constrained optimization problems, the most common method is using penalty functions to transform a constrained optimization problem into an unconstrained one.

The objective function equation (1), is generalized as follows:

$$F = f + \sum_{i\in N_V^{\lim}} \lambda_{V_I} (V_i - V_i^{\lim})^2 + \sum_{i\in N_V^{\lim}} \lambda_{G_I} (Q_{Gi} - Q_{Gi}^{\lim})^2 + \sum_{i\in N_E^{\lim}} \lambda_{S_I} (|S_i| - S_i^{\lim})^2 \quad (9)$$

Where $\lambda_{vi}, \lambda_{Gi} and \lambda_{si}$ are the penalty factors $V_i^{\lim}, Q_{G_i}^{\lim}$

are defined as

$$V_i^{\lim} = \begin{cases} V_i^{\max} if V_i > V_i^{\max} \\ V_i^{\min} if V_i < V_i^{\min} \end{cases} \quad (10)$$

$$Q_{G_i}^{\lim} = \begin{cases} Q_{G_i}^{\max} if Q_{G_i} > Q_{G_i}^{\max} \\ Q_{G_i}^{\min} if Q_{G_i} > Q_{G_i}^{\min} \end{cases} \quad (11)$$

III. STANDARD PARTICLE SWARM OPTIMIZATION

The recent techniques of PSO is a population-based optimization algorithm. Its population is called *swarm* and each individual is called a *particle*. For the *ith* particle at iteration *k*, it has the following two attributes:

1) A current position in an *N*-dimensional search space

$X_i^k = (x_{i,I}^k, ..., x_{i,n}^k, ..., x_{i,N}^k), where x_{i,n}^k \in [l_n, u_n], 1 \leq$

$n \leq N, l_n$ $n \leq N, l_n$ and u_n is the lower and upper bound for the *nth* dimension, respectively.

2) A current velocity V_i^k ,

$V_i^k = (v_{I,i}^k, ..., v_{n,i}^k, ..., v_{N,i}^k)$ which is clamped to a maximum velocity

$V_{\max}^k = (v_{\max,1}^k, \ldots, v_{\max,n}^k, \ldots, v_{\max,N}^k).$

At each iteration, the swarm is updated by the following equations:

$$V_i^{k+1} = \omega V_i^k + c_1 r_1 (P_i^k - X_i^k) + c_2 r_2 (P_g^k - X_i^k) \quad (12)$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (13)$$

$$P_g \in \{P_0, P_1, ...P_m\} \big| f(P_g) = \min(f(P_o), f(P_1), ...f(P_m)) \quad (14)$$

where *f* is the objective function, *m* is the number of particles, *r*1 and *r*2 are elements from two uniform random sequence on the interval [0*;* 1]: *r*1 » *U*(0*;* 1) ; *r*2 » *U*(0*;* 1) and *!* is inertia weight [19] which is typically chosen in the range of [0,1].

A larger inertia weight facilitates the global exploration and a smaller inertia weight tends to facilitate the local exploration to fine-tune the current search area [20]. Therefore the inertia weight *!* is critical for the PSO's convergence behavior. A suitable value for the inertia weight *!* usually provides balance between global and local exploration abilities and consequently results in a better optimum solution. *c*1 and *c*2 are acceleration constants [21] which also control how far a particle will move in a single iteration. The maximum velocity V^{max} is set to be half of the length of the search space.

IV. PROPOSED METHODLOGY

The foundation of the development of PSO is based on the hypothesis: social sharing of information among conspecifics offers an evolutionary advantage [16]. The PSO model is based on [16]:

1) the autobiographical memory which remembers the best previous position of each individual (*pbest*) in the swarm and

2) the publicized knowledge which is the best solution

(*gbest*) currently found by the population.

From biology point of view, the sharing of information among conspecifics is achieved by employing the publicly available information *gbest*. There is no information sharing among individuals except that *gbest* give out the information to the other individuals. Therefore, for the *i*th particle, the search direction will only be affected by 3 factors as shown in Fig. 1: the inertia velocity *!V k i* , the best previous position *pbest*, and the position of global best particle *gbest*. The population is more likely to lose diversity and confine the search around local minima. From our experimental results, the performance of standard PSO is not sufficiently good enough to solve the OPF problem due to its high-dimensional and multi-model nature. Biologists have proposed four types of biological mechanisms that allow animals to aggregate into groups:

passive aggregation, active aggregation, passive congregation, and social congregation [22]. There are different information sharing mechanisms inside these forces. We found that the passive congregation model is suitable to be incorporated in the PSO model to improve the search performance. Passive congregation is an attraction of an individual to the entire group but do not display social behavior. It has been discovered that in spatially well-defined congregations, such as fish schools, individuals may have low fidelity to the group because the congregations may be composed of individuals with little to no genetic relation to each other [23]. In these congregations, information may be transferred passively rather than actively [24]. Such asocial types of congregations can be referred as passive congregation.

Biologists have discovered that group members in an aggregation can react without direct detection of an incoming signal from the environment, because they can get necessary information from their neighbors [22]. Individuals need to monitor both environment and their immediate surroundings such as the bearing and speed of their neighbors [22]. Therefore each individual in an aggregation have a multitude of potential information from other group members which may minimize the chance of missed detection and incorrect interpretations [22]. Such information transfer can be employed in the model of passive congregation. Inspired by this result, and to keep the model simple and uniform with the PSO, we propose a hybrid PSO with passive congregation (PSOPC):

$$V_i^{k+1} = \omega V_i^k + c_1 r_1 (P_i^k - X_i^K) + c_2 r_2 (P_g^k - X_i^K) + c_3 r_3 (R_i^k - X_i^K) \tag{15}$$

$$X_i^{k+1} = X_i^k + X_i^{k+1} \tag{16}$$

where *Ri* is a particle randomly selected from the swarm, *c*3 the passive congregation coefficient and *r*3 a uniform random sequence in the range (0,1): $r3 \sim U(0; 1)$. The interactions between individuals of PSOPC are shown in Fig. 1. The pseudo code for the PSOPC is listed in Table I.

TABLE I

PSEUDO CODE FOR THE PSOPC ALGORITHM

Set $k = 0$;
Randomly initialize positions;;
Randomly initialize velocity;
WHILE (the termination conditions are not met)
    FOR (each particle i in the swarm)

Check feasibility:	Check the feasibility of the current particle. If X_i^k is outside the feasible region, then reset X_i to the previous position X_i^{k-1};
Calculate fitness:	Calculate the fitness value $f(X_i)$ of current particle;
Update ***pbest***:	Compare the fitness value of *pbest* with $f(X_i)$. If $f(X_i)$ is better than the fitness value of *pbest*, then set *pbest* to the current position X_i;
Update ***gbest***:	Find the global best position of the swarm. If the $f(X_i)$ is better than the fitness value of *gbest*, then *gbest* is set to the position of the current particle X_i;
Update R_i:	Randomly select a particle from the swarm as R_i;
Update velocities:	Calculate velocities V_i using equation (16);
Update positions:	Calculate positions X_i using equation (17);

    END FOR
    Set $k = k + 1$;
END WHILE

V. NUMERICAL RESULTS

The proposed PSOPC algorithm was tested on the standard IEEE 30-bus test system. The system line and bus data for 30-bus system were adopted from [3]. For all problems a population of 50 individuals is used. A time decreasing inertia

Fig. 1. Search direction of the *i*th particle in PSO

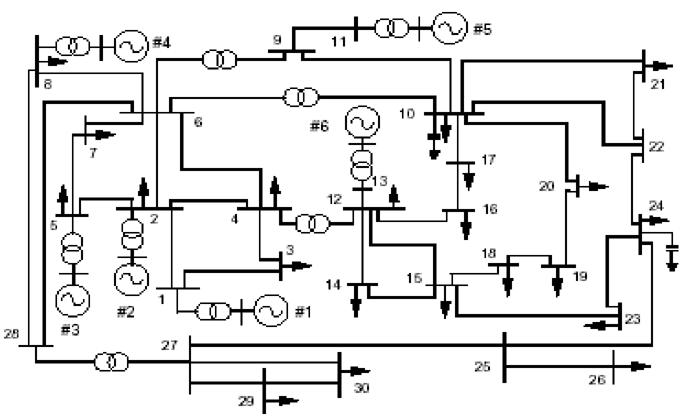


Fig. 3. IEEE 30-bus System

weight *!* which starts from 0.9 and ends at 0.4 was used. The default value of acceleration constants $c1$, $c2$ typically are set to 2.0. However with a setting of $c1 = c2 = 0{:}5$ better results were obtained. For each problem, 100 independent runs were carried out. The maximum generation was set to 500. The proposed algorithm was implemented in MATLAB 6.5 and executed on a Pentium 4, 2 GHz machine.

A. Case 1: Minimization of fuel cost

The objective of this example is to minimize the total fuel cost.

$$J = \sum_{i=1} fi \qquad (17)$$

Where *fi* is the fuel cost ($ /h) of the ith generator:

$$f_i = a_i + b_i P_{G_i} + c_i P_{G_i}^2$$

ai; bi and *ci* are fuel cost coefficients, *PGi* is the real power output generated by the *ith* generator.

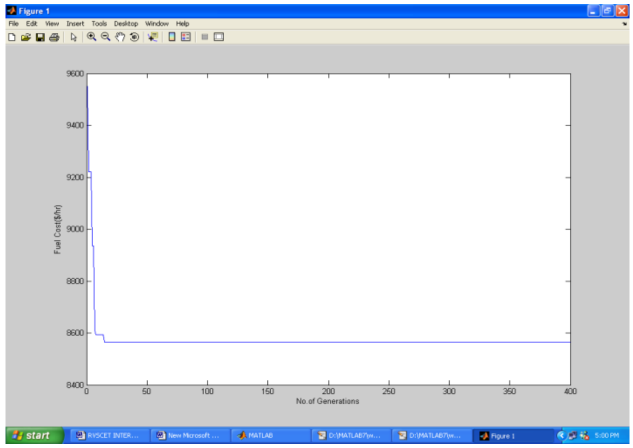
This problem was tackled using a gradient based optimization method [3]. The best-known result was obtained by

Bakirtzis et al. [15] using an enhanced GA (EGA). The PSO was implemented based on the algorithm presented in [20].

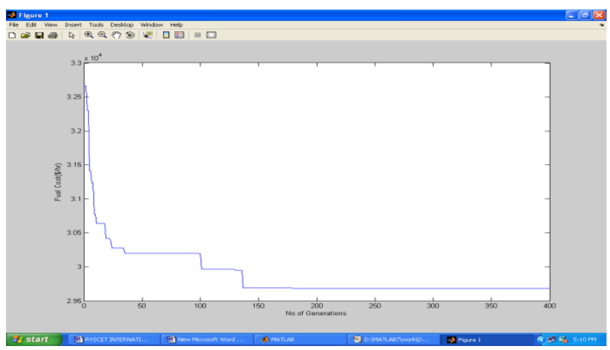
The best result of the PSOPC from 100 runs is tabulated in Table II in comparison to those obtained from techniques mentioned above.

6 Bus system results

6 Bus system Fuel cost graph



14 Bus system fuel cost graph



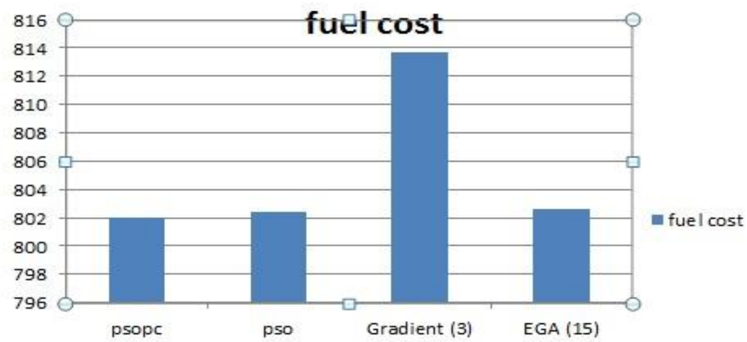
30 Bus systems fuel cost graph

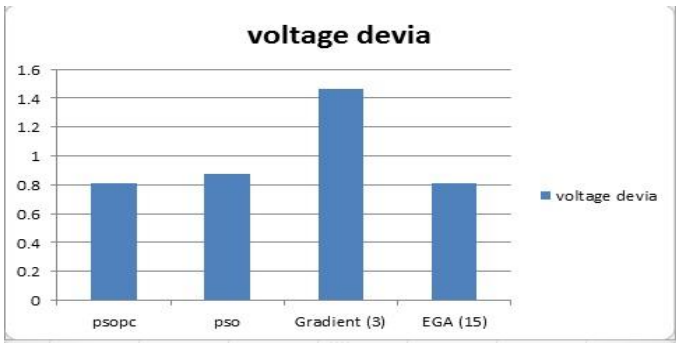
STATICAL TREPORT

TABLE II

BEST VALUES OF PSOPC, PSO, GRADIENT-BASED APPROACH AND EGA FOR CASE 1.

	Case 1			
	PSOPC	PSO	Gradient [3]	EGA [15]
Fuel cost ($/h)	**802.0477**	802.41	813.74	802.6087
$\sum$ voltage deviations	**0.8089**	0.8765	1.4602	0.8073
L_{max}	**0.1383**	0.1381	0.1384	0.1394





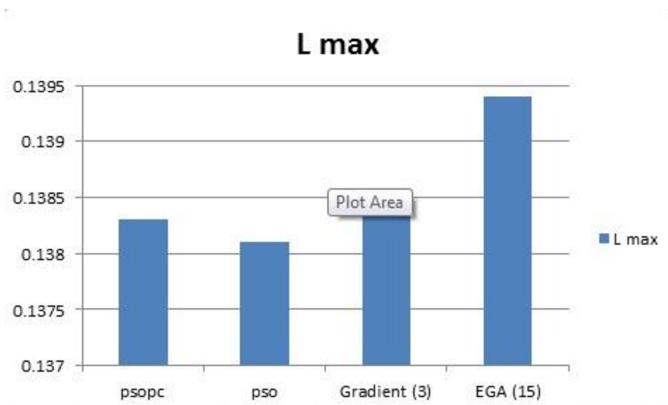
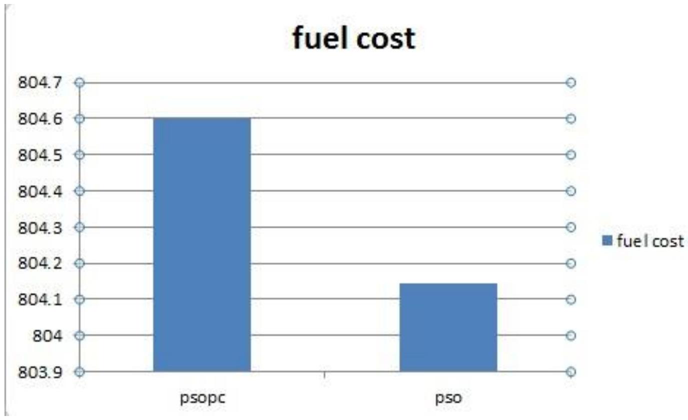
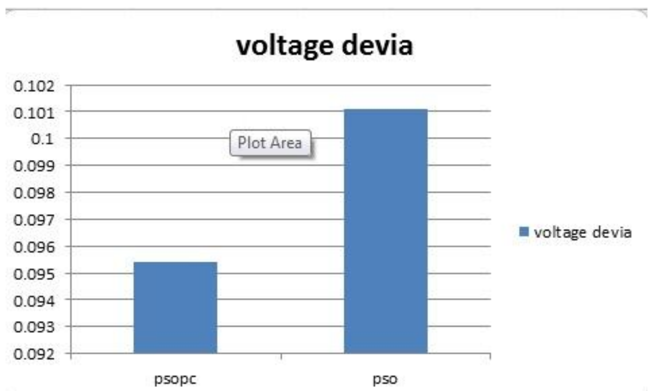


TABLE III

BEST VALUES OF PSOPC AND PSO FOR CASE 2

	Case 2	
	PSOPC	PSO
Fuel cost ($/h)	**804.0650**	804.1426
$\sum$ voltage deviations	**0.0954**	0.1011





B. Case 2: Voltage profile improvement

This example aims at minimizing fuel cost with a flatter voltage profile. The objective function is modified to minimize the fuel cost while at the same time to improve voltage profile by minimizing the load bus voltage deviations from 1.0 per unit. The objective function can be express as:

$$J = \sum_{i=1}^{NG} f_i + \omega \sum_{i \in NL} |V_i - 1.0| \qquad (18)$$

where ω is the weighting factor.

The best result of the PSOPC from 100 runs is tabulated in Table III in comparison to the result obtained from the standard PSO.

C. Case 3: Voltage stability enhancement

This example minimizes fuel cost and enhances voltage stability profile through out the whole network. *L* is the stability indicators at every bus of the system and *L*max is the maximum value of *L*-index defined as [25]:

$$L_{\max} = \max\{L_k, K = 1, \cdots, NL\} \tag{19}$$

And *L* can be calculated from following equation:

$$L_j = \left|1 + \frac{V_{0j}}{V_j}\right| = \left|\frac{S_j^+}{Y_{jj}^{+*} \cdot V_j^2}\right| \tag{20}$$

And *L* can be calculated from following equation:

$$L_j = \left|1 + \frac{V_{0j}}{V_j}\right| = \left|\frac{S_j^+}{Y_{jj}^{+*} \cdot V_j^2}\right| \tag{21}$$

Where Y_{jj}^+ is the transformed admittance, $Y_{jj}^+ = 1/Z_{jj}; V_j$ is the consumer node voltage; $S_j^+ = S_j + S_j^{\cos}$;and $S_j^{\cos}$ is given by

$$S_j^{\cos} = \left[\sum_{i \in \alpha}\left(\frac{Z_{ji}^*}{Z_{ij}^*}\right) \cdot \left(\frac{S_i}{V_i}\right)\right] \cdot V_j \tag{22}$$

and α_L is the set of consumer nodes .

One way of determining L is:

$$L = \max_{j \in \alpha L}\left|1 - \frac{\sum_{i \in \alpha c} F_{ij} \cdot V_i}{V_j}\right| \tag{23}$$

where αL is the set of load buses αG is the set of generator buses . V_j is the voltage at load bus j ; V_i is the complex voltage at generator bus i; F_{ij} is the element of matrix [F] determoined by

$$[F] = -\frac{[Y_{LL}]}{[Y_{LG}]} \qquad (24)$$

Where $[Y_{LL}]$ and $[Y_{LG}]$ are sub-matrices of the Y-bus matrix The objective function can be express as

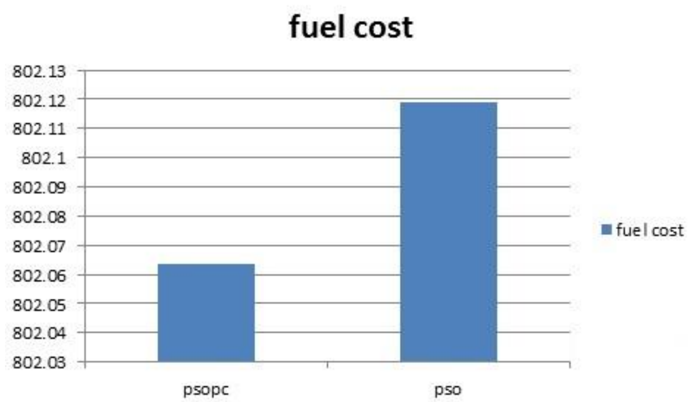
$$J = \sum_{i=1}^{NG} f_i + \omega L_{\max}$$

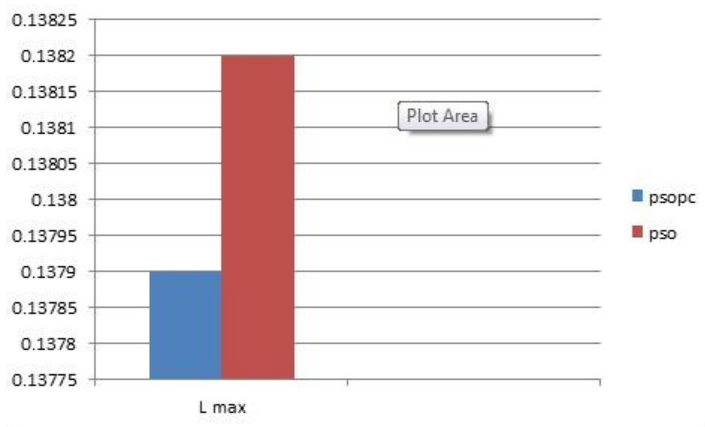
The best results of the PSOPC and the stand PSO from 100 runs are tabulated in Table IV.

TABLE IV

BEST VALUES OF PSOPC AND PSO FOR CASE 3

	Case 3	
	PSOPC	PSO
Fuel cost ($/h)	**802.0638**	802.1190
$L_{\max}$	**0.1379**	0.1382





VI. CONCLUSIONS

With the help of this approach we can minimize the fuel cost at same time we have to maintain the voltage stability and system stability also In this study, a novel PSO with passive congregation (PSOPC) extended from the standard PSO was applied to tackle OPF problems. By introducing the passive congregation, information can be transferred among individuals which will help individuals to avoid misjudging information and trapping by poor local minima. Numerical experiments were carried out on an IEEE 30-bus for three different fuel cost minimization problems. So far, our algorithm provides better results than those obtained from the other optimization techniques in terms of accuracy and convergence speed.

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