PSO VARIANTS BASED OPTIMAL POWERFLOW FOR MULTIPLE OBJECTIVE MINIMIZATION

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ABSTRACT

Optimal power flow is an optimizing tool for power system operation analysis, scheduling and energy management. Use of the optimal power flow is becoming more important because of its capabilities to deal with various situations. The main purpose of an optimal power flow (OPF) programming is to determine the optimal operating state of a power system by optimizing a particular objective while meeting the constraints of economics and security. In this paper PSO variants method such as constriction factor approach PSO, adaptive PSO, and evolutionary PSO have been developed and presented. These PSO variants are combined with NR, Newton, and IPM to form hybrid method for the solution of OPF/volt-var optimization with different objective functions such as fuel cost minimization, voltage profile improvement, voltage stability enhancement, and real power loss minimization. These methods have been applied on IEEE-30 bus system and results have been ***obtained.***

Key words: *PSO, PSO variants, OPF, Newton method, IPM*

INTRODUCTION

The PSO technique is an evolutionary computation technique, but it differs from other well-known evolutionary computation algorithms such as the genetic algorithms. Although a population is used for searching the space, there are no operators inspired by the human DNA procedures applied on population. Instead, in PSO, the population dynamics simulates a ‘bird flock’s’ behavior, where social sharing of information takes place and individuals can profit form the discoveries and previous experience of all the other companions during the search forfood.

Thus, each companion, *called particle*, in the population, which is called *swarm*, is assumed to ‘fly’ over the search space in order to find promising regions of the landscapes. For example, in the minimization case, such regions possess lower function values than other, visited previously. In this context, each particle is treated as a point in a D-dimensional space, which its own ‘flying’ according to its flying experience as well as the flying experience of other particles (companions). In PSO, a particle is defined as moving point in hyperspace. For each particle, at the current time step, a record is kept of the position, velocity, and the best position found in search space so far.

PSO Variants

There are different variants of PSO. In this paper we considered three different types of PSO methods. They are:

- Constriction Factor Approach PSO (CFAPSO)method
- Adaptive PSO (APSO)method.
- Evolutionary PSO (EPSO)method.

Constriction Factor Approach PSO (CFAPSO)

The basic system equation of PSO (1, 2 and 3) can be considered as a kind of difference equation.

$$v_i^{k+1} = wv_i^k + c_1 rand_1 * (pbest_i - s_i^k) \quad + c_2 rand_2 * (gbest - s_i^k) \tag{1}$$

$$w = w_{max} - ((w_{max} - w_{min}) / (iter_{max})) * iter \tag{2}$$

$$s_i^{k+1} = s_i^k + v_i^{k+1} \tag{3}$$

Therefore, the system dynamics, that is, the search procedure, can be analyzed using eigen values of the difference equation. Actually, using a simplified state equation of PSO, Clerc and Kennedy developed CFA of PSO by eigen values [1, 3]. The velocity of the constriction factor approach (simplest constriction) can be expressed as follows instead of (1) and (2):

$$v_i^{k+1} = K[v_i^k + c_1 * rand_1 * (pbest_i - s_i^k) + c_2 * rand_2 (gbest - s_i^k)] \tag{4}$$

$$K = \frac{2}{2 - \varphi - \sqrt{\varphi^2 - 4\varphi}}, \text{ where } \varphi = c_1 + c_2, \varphi > 4 \tag{5}$$

where φ and K are coefficients.

For example, if φ=4.1, then K = 0.73. As w increases above 4.0, K gets smaller. For example, if φ=5.0, then K =0.38, and the damping effect is even more pronounced. The convergence characteristic of the system can be controlled by w. Namely, Clerc et al. found that the system behavior can be controlled so that the system behavior has the following features:

- The system does not diverge in a real-valued region and finally canconverge.
- The system can search different regions efficiently by avoiding premature convergence.

The whole PSO algorithms by IWA and CFA are the same except that CFA utilizes a different equation for calculation of velocity [(4) and (5)]. Unlike other EC methods, PSO with CFA ensures the convergence of the search procedures based on mathematical theory. PSO with CFA can generate higher-quality solutions for some problems than PSO with IWA [2, 4]. However, CFA only considers dynamic behavior of only one agent and studies on the effect of the interaction among agents. Understanding the effects of pbests and gbest in the system dynamics remains for futurework.

Adaptive PSO (APSO)

The following points are improved to the original PSO with IWA.

- The search trajectory of PSO can be controlled by introducing the new parameters (P1, P2) based on the probability to move close to the position of (pbest, gbest) at the followingiteration.
- The wv_i^k term of (1) is modified as (5). Using the equation, the center of the range of particle movements can be equal to gbest.
- When the agent becomes gbest, it is perturbed. The new parameters (P1, P2) of the agent are adjusted so that the agent may move away from the position of (pbest, gbest).
- When the agent is moved beyond the boundary of feasible regions, pbests and gbest cannot bemodified.
- When the agent is moved beyond the boundary of feasible regions, the new parameters (P1, P2) of the agent are adjusted so that the agent may move close to the position of (pbest,gbest).

The new parameters are set to each agent. The weighting coefficients are calculated as follows:

$$c_2 = \frac{2}{P_1}, \quad c_1 = \frac{2}{P_2} - c_2 \qquad (6)$$

The search trajectory of PSO can be controlled by the parameters (P_1, P_2). Concretely, when the value is enlarged more than 0.5, the agent may move close to the position of pbest/gbest.

$$w = gbest - \left(\left\{c_1(pbest - x) + c_2(gbest - x)\right\}/2 + x\right) \qquad (7)$$

Namely, the velocity of the improved PSO can be expressed as follows:

$$v_i^{k+1} = w_i + crand_1 * (pbest_i - s_i^k) + crand_2 * (gbest - s_i^k) \qquad (8)$$

The improved PSO can be expressed as follows (steps 1 and 5 are the same as PSO):

- *Generation of initial searching points*: Basic procedures are the same as PSO. In addition, the parameters (P1, P2) of each agent are set to 0.5 or higher. Then, each agent may move close to the position of (pbest, gbest) at the followingiteration.
- *Evaluation of searching points*: The procedure is the same as PSO. In addition, when the agent becomes gbest, it is perturbed. The parameters (P_1, P_2) of the agent are adjusted to 0.5 or lower so that the agent may move away from the position of (pbest, gbest).
- *Modification of searching points*: The current searching points are modified using the state equations (8), (3) of adaptivePSO.

Evolutionary PSO (EPSO)

The idea behind EPSO [5, 6] is to grant a PSO scheme with an explicit selection procedure and with self-adapting properties for its parameters. At a given iteration, consider a set of solutions or alternatives that we will keep calling particles. The general scheme of EPSO is the following:

- REPLICATION: each particle is replicated Rtimes
- MUTATION: each particle has its weightsmutated

- REPRODUCTION: each mutated particle generates an offspring according to the particle movementrule
- EVALUATION: each offspring has its fitnessevaluated
- SELECTION: by stochastic tournament the best particles survive to form a new generation.

The movement rule for EPSO is the following: given a particle s_i^k, a new particle s_i^{k+1} results from

$$s_i^{new} = s_i + v_i^{new} \tag{9}$$

$$v_i^{k+1} = w_{i0}^* v_i^k + w_{i1}^* \left(pbest_i - s_i^k\right) + w_{i1}^* \left(gbest^* - s_i^k\right) \tag{10}$$

So far, this seems like PSO—the movement rule keeps its terms of inertia, memory, and cooperation. However, the weights undergo mutation

$$w_{ik}^* = w_{ik} + \tau . N(0,1) \tag{11}$$

Where N (0, 1) is a random variable with Gaussian distribution, 0 mean, and variance 1; and the global best gbest is randomly disturbed to give

$$gbest^* = gbest + \tau' . N(0,1) \tag{12}$$

The τ, τ' are learning parameters (either fixed or treated also as strategic parameters and therefore also subject to mutation).

This scheme benefits from two "pushes" in the right direction, the Darwinist process of selection and the particle movement rule, and therefore it is natural to expect that it may display advantageous convergence properties when compared with ES or PSO alone. Furthermore, EPSO can also be classified as a self-adaptive algorithm, because it relies on the mutation and selection of strategic parameters, just as any evolution strategy.

MATHEMATICAL MODEL OF OPF PROBLEM

The OPF problem is to optimize the steady state performance of a power system in terms of an objective function while satisfying several equality and inequality constraints. Mathematically, the OPF problem can be formulated as given

$$\text{Min } F(x,u) \tag{13}$$

Subject to

$$g(x,u) = 0 \tag{14}$$

$$h(x,u) \le 0 \tag{15}$$

where x is a vector of dependent variables consisting of slack bus power P_{G_1}, load bus voltages V_L, generator reactive power outputs Q_G, and the transmission line loadings S_l, Hence, x can be expressed as given

$$x^T = [P_{G_1}, V_{L_1} \ldots V_{L_{NL}}, Q_{G_1} \ldots Q_{G_{NG}}, S_{l_1} \ldots S_{l_{nl}}] \tag{16}$$

where NL, NG and nl are number of load buses, number of generators and number of transmission line respectively.

u is the vector of independent variables consisting of generator voltages V_G, generator real power outputs P_G except at the slack bus P_{G_1}, transformer tap settings T, and shunt VAR compensations Q_C. Hence u can be expressed as given

$$u^T = [V_{G_1} ... V_{G_{NG}}, P_{G_2} ... P_{G_{NG}}, T_1 ... T_{NT}, Q_{C_1} ... Q_{C_{NC}}] \quad (17)$$

Where *NT* and *NC* are the number of the regulating transformers and shunt compensators, respectively. *F* is the objective function to be minimized. g is the equality constraints that represents typical load flow equations and *h* is the system operating constraints

OBJECTIVE FUNCTIONS

In this paper, the objective(s)(J) is the objective function to be minimized, which is one of the following:

(i) Objective function-1 (Fuel costminimization)

It seeks to find the optimal active power outputs of the generation plants so as to minimize the total fuel cost. This can be expressedas

$$J = \sum_{i}^{NG} f_i (\$ / h) \quad (18)$$

where f_i is the fuel cost curve of the ith generator and it is assumed here to be represented by the following quadratic function:

$$f_i = a_i P_{G_i}^2 + b_i P_{G_i} + c_i (\$/h) \quad (19)$$

where a_i, b_i, and c_i are the cost coefficients of the i^{th} generator.

(ii) Objective function-2 (Voltage profile improvement)

Voltage profile is one of the quality measures for power system. It can be improved by minimizing the load bus voltage deviations from 1.0 per unit. The objective function can be expressed as

$$J = \sum_{i \in NL} |V_i - 1| \quad (20)$$

(iii) Objective function-3 (Voltage stabilityenhancement)

Voltage profile improvement does not necessary implies a voltage secure system. Voltage instability problems have been experienced in systems where voltage profile was acceptable [11]. Voltage secure system can be assured by enhancing the voltage stability profile throughout the whole power system.

An indicator *L*-index is used in this study to evaluate the voltage stability at each bus of the system. The indicator value varies between 0 (no load case) and 1 (voltage collapse) [12-14].One of the best features of the *L*-index is that the computation speed is very fast and so can be used for on-line monitoring of power system. Enhancing the voltage stability and moving the system far from voltage collapse point can be achieved by minimizing the following objective function

$$J = L_{\max} \quad (21)$$

where $L_{\max}$ is the maximum value of L-index as

$$L_{\max} = \max\{L_K, K = 1, ..., NL\} \quad (22)$$

(iv) Objective function-4 (Real power lossminimization)

The optimal reactive power flow problem to minimize active losses can be formulated as

$$\begin{aligned} &\min \quad J = f(Z) \\ &s.t \quad g(Z) = 0 \\ &\qquad Z_{\min} \le Z \le Z_{\max} \end{aligned} \tag{23}$$

Where $f(\cdot)$ Objective function for active losses

$g(\cdot)$ Nonlinear vectors function representing power flow equations

$Z = [xu]^T$ Vector of decision variables whose components are the vector of state variables x (voltage phase angles and magnitudes, etc.) and the vector of discrete control variables u (generator terminal voltages, tap position of OLTC transformers, number of connected shunt compensation devices etc.).

$Z_{\min}$ and $Z_{\max}$ vectors modeling operational limits on state and control variables

Constraints

The OPF problem has two categories of constraints:

Equality Constraints: These are the sets of nonlinear power flow equations that govern the power system, i.e,

$$P_{Gi} - P_{Di} - \sum_{j=1}^{n} |V_i||V_j||Y_{ij}| \cos(\theta_{ij} - \delta_i + \delta_j) = 0 \tag{24}$$

$$Q_{Gi} - Q_{Di} + \sum_{j=1}^{n} |V_i||V_j||Y_{ij}| \sin(\theta_{ij} - \delta_i + \delta_j) = 0 \tag{25}$$

where P_{Gi} and Q_{Gi} are the real and reactive power outputs injected at bus i respectively, the load demand at the same bus is represented by P_{Di} and Q_{Di}, and elements of the bus admittance matrix are represented by $|Y_{ij}|$ and θ_{ij}.

Inequality Constraints: These are the set of constraints that represent the system operational and security limits like the bounds on the following:

1) generators real and reactive poweroutputs

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max}, i = 1, \ldots, N \tag{26}$$

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max}, i = 1, \ldots, N \tag{27}$$

2) voltage magnitudes at each bus in thenetwork

$$V_i^{\min} \le V_i \le V_i^{\max}, i = 1, \ldots, NL \tag{28}$$

3) transformer tapsettings

$$T_i^{\min} \le T_i \le T_i^{\max}, i = 1, \ldots, NT \tag{29}$$

4) reactive power injections due to capacitorbanks

$$Q_{Ci}^{\min} \le Q_{Ci} \le Q_{Ci}^{\max}, i = 1, \ldots, CS \tag{30}$$

5) transmission linesloading

$$S_i \le S_i^{\max}, i = 1, \ldots, nl \tag{31}$$

6) voltage stabilityindex

$$Lj_i \le Lj_i^{\max}, i = 1, \ldots, NL \tag{32}$$

The equality constraints are satisfied by running the power flow program. The generator bus terminal voltages (V_{gi}), transformer tap settings (t_k) and the reactive power generation of capacitor bank (Q_{Ci}) are the control variables and they are self-restricted by the representation itself. The active power generation at the slack bus (P_{gs}), load bus voltages (V_{Li}) and reactive power generation (Q_{gi}), voltage stability (L_j -index) are state variables which are restricted through penalty function approach.

OVERALL COMPUTATIONAL PROCEDURE FOR SOLVING THE PROBLEM

The implementation steps of the proposed IPM-APSO, IPM-CFAPSO and IPM-EPSO based hybrid algorithms can be written as follows;

Step 1: Input the system data for load flow analysis
Step 2: Run the power flow
Step 3: At the generation Gen =0; set the simulation parameters of hybrid OPF parameters and randomly initialize k individuals within respective limits and save them in the archive.
Step 4a: Run IPM based OPF with initial k individuals for getting highly evolved individuals.
Step 4b: For each highly evolved individual in the archive, run power flow to determine load bus voltages, angles, load bus voltage stability indices, generator reactive power outputs and calculate line power flows.
Step 5: Evaluate the penalty functions
Step 6: Evaluate the objective function values and the corresponding fitness values for each individual.
Step 7: Find the generation local best **xlocal** and global best **xglobal** and store them.
Step 8: Increase the generation counter Gen = Gen+1.
Step 9: Apply the PSO operators to generate new k individuals
Step 10: For each new individual in the archive, run power flow to determine load bus voltages, angles, load bus voltage stability indices, generator reactive power outputs and calculate line power flows.
Step 11: Evaluate the penalty functions
Step 12: Evaluate the objective function values and the corresponding fitness values for each new individual.
Step 13: Apply the selection operator of PSO variants and update the individuals.
Step 14: Update the generation local best **xlocal** and global best **xglobal** and store them.
Step 15: If one of stopping criterion have not been met, repeat steps 4-14. Else go to stop 16
Step 16: Print the results

SIMULATION RESULTS

The simulation results of the proposed hybrid OPF method for different objective functions (i.e. fuel cost minimization, voltage profile improvement, voltage stability enhancement, and real power loss minimization) have been applied to IEEE-30 bus system with NR-load flow, Newton-OPF and Interior Point-OPF Methods. The approach can be generalized and easily extended to large-scale systems.

The IEEE-30 bus system consists of six generators, four transformers, 41 lines, and nine shunt capacitors. In all these different PSO variants methods, the total control variables are 25: six unit active power outputs, six generator bus voltage magnitudes, four transformer tap settings, and nine bus shunt admittances. The PSO variants methods have been run for 20-populations and for 150-iterations.

To test the ability of the proposed hybrid algorithms for solving optimal power flow problem to reduce specified objective function, it was applied on selected bus system. Four objective functions are considered for the minimization using the proposed hybrid algorithm namely cost of generation, voltage profile improvement, voltage stability enhancement and real power loss minimization.

The best results for APSO method combined with NR-load flow, Newton-OPF, and Interior Point method are compared and results are tabulated in Table 1. In this table, the optimal settings of the control variables and various performance parameters with four objective functions are presented. The optimal settings of the control variables and various performance parameters for CFAPSO and EPSO methods combined with NR-load flow, NETON-OPF and interior point methods are presented in Table 2 & Table 3. From these tables, it was found that all the state variables satisfy lower and upper limits. From the results it is evident that proposed IPM-EPSO hybrid method outperforms in achieving minimum of the specified objective when compared with other optimization methods.

CONCLUSIONS

In this paper PSO variants method such as constriction factor approach PSO, adaptive PSO, and evolutionary PSO have been developed and presented. These PSO variants are combined with NR, Newton, and IPM to form hybrid method for the solution of OPF/volt-var optimization with different objective functions such as fuel cost minimization, voltage profile improvement, voltage stability enhancement, and real power loss minimization. These methods have been applied on IEEE-30 bus system and results have been obtained. It has been observed that the EPSO-IPM gives better results when compared with other hybrid OPF methods for all different objectivefunctions.

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Table 1 Optimal settings of control variables of IEEE 30-bus system in APSO based OPF method

Control Variables	**Objective function-1 (cost)**			**Objective function-2 (V.D)**			**Objective function-3 (L-index)**			**Objective function-4 (loss)**		
	APSO-NR	**APSO-Newton**	**IPM-APSO**	**APSO-NR**	**APSO-Newton**	**IPM-APSO**	**APSO-NR**	**APSO-Newton**	**IPM-APSO**	**APSO-NR**	**APSO-Newton**	**IPM-APSO**
P_1	1.7738	1.7654	1.7651	1.3459	1.7998	1.7992	1.5234	1.6243	1.7940	0.7461	0.6186	0.3639
P_2	0.4886	0.4935	0.4935	0.5334	0.5107	0.4936	0.4558	0.4886	0.4935	0.8000	0.8000	0.8000
P_5	0.2146	0.2165	0.2165	0.3257	0.2067	0.2167	0.2800	0.2193	0.2165	0.5000	0.5000	0.5000
P_8	0.2150	0.2278	0.2278	0.2160	0.1281	0.1281	0.1635	0.1314	0.2278	0.1339	0.3000	0.3000
$P11$	0.1200	0.1200	0.1200	0.2016	0.1201	0.1200	0.2387	0.1831	0.1200	0.3434	0.4000	0.3500
$P13$	0.1121	0.1000	0.1000	0.2911	0.1870	0.1936	0.2686	0.2628	0.1000	0.3500	0.2495	0.3500
V_1	1.0851	1.0863	1.0872	0.9984	0.9945	0.9963	1.0370	1.0467	1.0677	1.0659	1.0592	1.0608
V_2	1.0658	1.0672	1.0683	0.9901	1.0044	1.0032	1.0062	1.0497	1.0138	1.0584	1.0491	1.0565
V_5	1.0349	1.0361	1.0373	1.0152	1.0169	1.0177	1.0181	1.0590	1.0453	1.0369	1.0386	1.0443
V_8	1.0393	1.0406	1.0418	1.0017	1.0082	1.0071	1.0559	1.0504	1.0624	1.0394	1.0109	1.0460
$V11$	1.0466	1.0450	1.0299	1.0478	0.9916	0.9714	1.1000	1.0282	1.0535	1.0381	1.0308	1.0384
$V13$	1.0349	1.0300	1.0396	1.0675	1.0176	1.0115	1.0674	1.0280	1.0401	1.0483	1.0443	1.0447
$T11$	0.9761	0.9821	1.0051	0.9743	1.0019	0.9780	1.0983	1.0477	1.0007	0.9632	0.9543	1.0020
$T12$	1.0271	1.0063	0.9737	0.9903	0.9542	1.0100	1.0233	1.0458	1.0924	1.0472	1.0272	0.9650
$T15$	0.9593	0.9623	0.9674	1.0076	1.0152	1.0193	1.0822	0.9919	1.0466	0.9878	1.0198	0.9884
$T36$	0.9971	0.9766	0.9770	0.9793	0.9690	0.9812	0.9896	0.9825	0.9801	0.9872	0.9820	0.9859
$QC10$	0.0723	0.0581	0.0830	0.0465	0.0423	0.0788	0.0977	0.1000	0.1000	0.0399	0.1000	0.0601
$QC12$	0.0666	0.1000	0.0484	0.0804	0.0763	0.0344	0.1000	0.1000	0.1000	0.0749	0.1000	0.0653
$QC15$	0.0323	0.0437	0.0377	0.0837	0.0568	0.0662	0.0790	0.0915	0.1000	0.0245	0.0778	0.0755
$QC17$	0.0734	0.0710	0.0667	0.0668	0.0245	0.0498	0.1000	0.1000	0.1000	0.0672	0.0200	0.0695
$QC20$	0.0447	0.0418	0.0433	0.0927	0.0876	0.1000	0.1000	0.0843	0.1000	0.0497	0.1000	0.0000
$QC21$	0.0660	0.1000	0.1000	0.0766	0.0686	0.1000	0.1000	0.1000	0.1000	0.0931	0.0140	0.0756
$QC23$	0.0185	0.0180	0.0182	0.0426	0.0313	0.0674	0.0877	0.1000	0.1000	0.0070	0.0383	0.0246
$QC24$	0.0877	0.0759	0.0786	0.1000	0.0981	0.1000	0.1000	0.1000	0.1000	0.1000	0.1000	0.0720
$QC29$	0.0259	0.0247	0.0235	0.0393	0.0215	0.0350	0.0324	0.0306	0.0236	0.0339	0.0375	0.0246
Cost($/h)	**800. 3851**	**800. 3463**	**800. 2644**	832.3195	809.6815	809.4223	824.6611	807.0878	809.8743	929.4266	951.7429	955.5348
V.D	0.9081	0.9580	0.9523	**0. 0785**	**0. 0752**	**0. 0733**	1.0004	0.9840	1.0231	0.8763	0.8532	0.9052
L- Index	0.1250	0.1238	0.1241	0.1324	0.1338	0.1324	**0.1195**	**0.1192**	**0.1188**	0.1251	0.1241	0.1262
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	0.0901	0.0892	0.0890	0.0798	0.1184	0.1171	0.0960	0.0935	0.1178	**0. 0393**	**0. 0341**	**0. 0319**

Table 2 Optimal settings of control variables of IEEE 30-bus system in CFAPSO based OPF method

Control Variables	**Objective function-1 (cost)**			**Objective function-2 (V.D)**			**Objective function-3 (L-index)**			**Objective function-4 (loss)**		
	CFAPSO-NR	**CFAPSO-Newton**	**IPM-CFAPSO**	**CFAPSO-NR**	**CFAPSO-Newton**	**IPM-CFAPSO**	**CFAPSO-NR**	**CFAPSO-Newton**	**IPM-CFAPSO**	**CFAPSO-NR**	**CFAPSO-Newton**	**IPM-CFAPSO**
P_1	1.7812	1.7827	1.7810	1.8452	1.4084	1.4940	1.6570	1.5351	1.7864	0.7721	0.5166	0.5141
P_2	0.4898	0.4897	0.4900	0.4545	0.4315	0.7975	0.2959	0.3902	0.3435	0.8000	0.8000	0.8000
P_5	0.2159	0.2146	0.2145	0.2340	0.3393	0.2379	0.1760	0.2044	0.1858	0.5000	0.5000	0.5000
P_8	0.2176	0.2175	0.2163	0.1082	0.1668	0.1846	0.1000	0.2089	0.1000	0.3000	0.3000	0.3000
$P11$	0.1200	0.1200	0.1223	0.1200	0.3388	0.1200	0.3439	0.2872	0.3233	0.4000	0.4000	0.4000
$P13$	0.1000	0.1000	0.1000	0.1906	0.2325	0.1000	0.3500	0.2900	0.2148	0.1000	0.3500	0.3500
V_1	1.0862	1.0875	1.0878	0.9959	0.9994	1.0001	1.0571	1.0446	1.0079	1.0675	1.0506	1.0622
V_2	1.0667	1.0682	1.0679	1.0039	1.0168	1.0063	1.0341	1.0378	1.0199	1.0605	1.0498	1.0581
V_5	1.0353	1.0379	1.0372	1.0174	1.0187	1.0183	1.0294	1.0267	1.0459	1.0377	1.0282	1.0385
V_8	1.0397	1.0412	1.0425	0.9968	1.0039	1.0040	1.0163	1.0514	1.0564	1.0440	1.0355	1.0449
$V11$	1.0556	1.1000	1.0214	1.0488	0.9500	0.9915	1.0830	1.0810	1.0712	1.0584	0.9880	1.0228
$V13$	1.0317	1.0222	1.0396	1.0166	0.9961	1.0193	1.0621	1.0302	1.0582	1.0422	1.0315	1.0401
$T11$	1.0047	1.0391	1.0125	1.0631	0.9557	1.0019	1.0518	1.0242	1.0373	1.0161	1.0813	0.9538
$T12$	0.9818	0.9528	0.9531	0.9352	1.0151	0.9736	1.0093	1.1000	1.0341	0.9720	0.9397	1.1000
$T15$	0.9520	0.9438	0.9654	1.0219	0.9797	1.0108	1.1000	1.0264	1.1000	0.9680	1.1000	0.9775
$T36$	0.9759	0.9767	0.9869	0.9782	0.9857	0.9807	0.9648	0.9871	0.9851	0.9780	1.0371	0.9812
$QC10$	0.0232	0.0000	0.0659	0.0319	0.0619	0.0802	0.0998	0.1000	0.1000	0.0821	0.1000	0.1000
$QC12$	0.0260	0.0700	0.0601	0.0455	0.0553	0.0386	0.1000	0.0990	0.1000	0.0201	0.0504	0.0729
$QC15$	0.0593	0.0418	0.0180	0.0733	0.0470	0.0536	0.1000	0.1000	0.0993	0.0509	0.1000	0.0535
$QC17$	0.1000	0.0529	0.0632	0.0239	0.0487	0.0199	0.1000	0.1000	0.1000	0.0722	0.0810	0.0987
$QC20$	0.0383	0.0360	0.4340	0.0893	0.1000	0.0989	0.1000	0.1000	0.1000	0.1000	0.0158	0.0535
$QC21$	0.0974	0.0716	0.1000	0.0604	0.1000	0.0733	0.1000	0.1000	0.1000	0.0000	0.0771	0.1000
$QC23$	0.0145	0.0223	0.0299	0.0413	0.0600	0.0360	0.1000	0.0983	0.1000	0.0158	0.0102	0.0000
$QC24$	0.0801	0.0769	0.0798	0.1000	0.1000	0.1000	0.1000	0.1000	0.1000	0.0728	0.0556	0.0987
$QC29$	0.0199	0.0223	0.0230	0.0371	0.0546	0.0362	0.0229	0.0297	0.0263	0.0272	0.0689	0.0238
Cost($/h) V.D	**800. 4045** 0.9511	**800. 3654** 0.9684	**800. 2690** 0.8964	809.9886 **0. 0764**	839.0542 **0. 0749**	827.5098 **0. 0734**	840.1029 0.9472	823.2082 1.0069	830.2930 1.0277	932.5302 0.9884	972.2034 0.3428	971.6062 0.9136

L- Index	0.1253	0.1260	0.1258	0.1343	0.1328	0.1338	**0. 1196**	**0. 1193**	**0. 1187**	0.1250	0.1348	0.1234
Ploss(pu)	0.0905	0.0905	0.0901	0.1185	0.0797	0.1001	0.0887	0.0818	0.1198	**0.0381**	**0.0326**	**0.0301**

Table 3 Optimal settings of control variables of IEEE 30-bus system in EPSO based OPF method

Control Variables	**Objective function-1 (cost)**			**Objective function-2 (V.D)**			**Objective function-3 (L-index)**			**Objective function-4 (loss)**		
	EPSO-NR	**EPSO-Newton**	**IPM-EPSO**	**EPSO-NR**	**EPSO-Newton**	**IPM-EPSO**	**EPSO-NR**	**EPSO-Newton**	**IPM-EPSO**	**EPSO-NR**	**EPSO-Newton**	**IPM-EPSO**
P_1	1.7836	1.7695	1.7769	1.7989	1.5087	1.7889	1.1265	1.3971	1.9874	0.7184	0.5159	0.5140
P_2	0.4908	0.4856	0.4867	0.4937	0.3944	0.4937	0.5867	0.8000	0.3091	0.8000	0.8000	0.8000
P_5	0.2116	0.2162	0.2112	0.2165	0.3739	0.2165	0.3516	0.1500	0.1978	0.5000	0.5000	0.5000
P_8	0.2125	0.2179	0.2289	0.1281	0.1436	0.1310	0.1703	0.1692	0.2188	0.1044	0.3000	0.3000
$P11$	0.1200	0.1200	0.1200	0.1261	0.2396	0.1262	0.4000	0.1303	0.1350	0.4000	0.4000	0.4000
$P13$	0.1065	0.1144	0.1000	0.1936	0.2584	0.1936	0.2556	0.2792	0.1002	0.3500	0.3500	0.3500
V_1	1.0855	1.0886	1.0884	0.9865	0.9951	0.9956	1.0509	1.0559	1.0504	1.0640	1.0586	1.0613
V_2	1.0678	1.0690	1.0694	1.0067	1.0007	1.0054	1.0500	1.0325	1.0298	1.0576	1.0555	1.0575
V_5	1.0377	1.0374	1.0383	1.0189	1.0173	1.0183	1.0471	1.0325	1.0429	1.0354	1.0333	1.0375
V_8	1.0426	1.0417	1.0438	1.0065	1.0004	1.0036	1.0490	1.0549	1.0487	1.0402	1.0399	1.0434
$V11$	1.0376	1.0297	1.0559	0.9500	1.0167	0.9802	1.0121	1.0731	1.1000	1.0520	0.9513	1.0208
$V13$	1.0405	1.0348	1.0322	1.0330	1.0095	1.0190	1.0280	1.0162	1.0472	1.0310	1.0444	1.0402
$T11$	1.0001	0.9992	0.9916	0.9600	1.0256	0.9871	0.9913	1.1000	1.1000	1.1000	1.0071	0.9570
$T12$	0.9623	0.9645	0.9886	0.9903	0.9852	1.0091	1.0365	0.9558	1.0184	0.9235	0.9495	1.0627
$T15$	0.9730	0.9698	0.9635	1.0536	1.0084	1.0155	1.0299	1.0237	1.0631	0.9748	0.9989	0.9864
$T36$	0.9839	0.9940	0.9880	0.9877	0.9772	0.9797	0.9823	0.9906	0.9854	0.1002	1.0048	0.9795
$QC10$	0.0504	0.0421	0.0334	0.0918	0.0435	0.0671	0.0902	0.1000	0.1000	0.0588	0.0726	0.1000
$QC12$	0.0332	0.0509	0.0674	0.0388	0.0380	0.0457	0.1000	0.1000	0.1000	0.0713	0.1000	0.1000
$QC15$	0.0548	0.0810	0.0527	0.0548	0.0810	0.0583	0.1000	0.1000	0.1000	0.0351	0.0696	0.0543
$QC17$	0.0208	0.0669	0.0747	0.0327	0.0610	0.0562	0.1000	0.1000	0.1000	0.1000	0.0899	0.1000
$QC20$	0.0228	0.0499	0.0224	0.1000	0.1000	0.1000	0.1000	0.1000	0.1000	0.0644	0.1000	0.0483
$QC21$	0.0726	0.0590	0.0842	0.0785	0.0839	0.1000	0.0954	0.1000	0.1000	0.0359	0.0563	0.1000
$QC23$	0.0436	0.0566	0.0466	0.0559	0.0334	0.0379	0.1000	0.1000	0.1000	0.0511	0.1000	0.0000
$QC24$	0.0583	0.0360	0.0530	0.1000	0.1000	0.1000	0.1000	0.1000	0.1000	0.0672	0.0801	0.0912
$QC29$	0.0241	0.0345	0.0277	0.0516	0.0358	0.0362	0.0306	0.0322	0.0285	0.0554	0.0726	0.0243

Cost($/h)	**800. 3884**	**800. 3577**	**800. 2573**	811.5123	836.9765	809.2338	859.0078	832.1599	813.4000	939.3039	927.0347	971.5937
V.D	0.7941	0.8580	0.9364	**0. 0759**	**0. 0738**	**0. 0722**	1.0084	1.0106	1.0336	0.7849	0.8645	0.9348
L- Index	0.1298	0.1260	0.1262	0.1330	0.1329	0.1326	**0.1196**	**0.1193**	**0.1185**	0.1262	0.1249	0.1231
Ploss(pu)	0.0909	0.0896	0.0897	0.1229	0.0847	0.1158	0.0567	0.0918	0.1144	**0.0388**	**0.0319**	**0.0300**