

Hybrid Particle Swarm Optimization Technique For Optimal Power Flow

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Abstract— The Optimal Power Flow (OPF) plays an important role in power system operation and control due to depleting energy resources, and increasing power generation cost and ever growing demand for electric energy. As the size of the power system increases, load may be varying. The generators should share the total demand plus losses among themselves. The sharing should be based on the fuel cost of the total generation with respect to some security constraints. Conventional optimization methods that make use of derivatives and gradients are, in general, not able to locate or identify the global optimum. Heuristic algorithms such as genetic algorithms (GA) and evolutionary programming and PSO have been proposed for solving the OPF problem. Recently, a new evolutionary computation technique, called Adaptive Particle Swarm Optimization (APSO), has been proposed and introduced. In this paper, a novel Adaptive PSO based approach is presented to solve Optimal Power Flow problem to satisfy objectives such as minimizing generation fuel cost and transmission line losses. A hybrid OPF is proposed by combining the positive aspects of Interior point method and APSO. The proposed algorithms are tested on IEEE 30 bus system using MATLAB.

Index Terms— Adaptive particle swarm optimization, Interior point method, Newton's raphson method, Optimal power flow, Particle swarm optimization.

1 INTRODUCTION

THE Optimal Power Flow problem can be traced back as early as 1920's when economic distribution of generation was the only concern. The economic operation of power system was achieved by dividing loads among available generator units such that their incremental generation costs are identical. The basic mission of a power system is to provide consumers with continuous, reliable and cost-efficient electrical energy. In order to achieve this aim, the system operators need for regularly adjustments of various controls such as generation outputs, transformer tap ratios, etc., to assure the continuous economic and secure system operations. This is a complex task that needs to depend highly on optimal power flow (OPF) function at power system control centers. The OPF problem optimize a selected objective function such as fuel cost via most favorable adjustment of the power system control variables while on the other side satisfying the various constraints such as the equality and inequality constraints. Different types of optimization techniques have been applied in solving the OPF problems [1-18] they are nonlinear programming [1-6], quadratic programming [7-8], linear programming [9-11], Newton based techniques [12-13],

sequential unconstrained minimization technique [14], and interior point methods [15-16]. The primary Interior Point (IP) is defined by the Frisch in 1955, which is a logarithmic barrier method that was later on broadly studied by Fiacco and McCormick to solve it into the nonlinearly inequality constrained problem in 1960. In 1979 Khachiyan presented an ellipsoid method that would solve a Linear Programming (LP) problem in polynomial moment. After 1984, several variants of Karmarkar's Interior Point (IP) method have been proposed and implemented. Recently, the research in OPF such as interior point (IP) using new optimization techniques, has been obtaining a better attention in power system operation [20-21].

Heuristic algorithms, such as Genetic Algorithms (GA) [17] and evolutionary programming [18], have been recently proposed for solving the OPF problem. The results reported were promising and encouraging for further research in this direction. Unfortunately, recent research has identified some deficiencies in GA performance [19]. This degradation in efficiency is apparent in applications with highly epistatic objective functions, i.e. where the parameters being optimized are highly correlated. In addition, the premature convergence of GA degrades its performance and reduces its search capability. Recently, a new evolutionary computation technique, called Particle Swarm Optimization (PSO), has been proposed and introduced [22-25]. This technique combines social psychology principles in socio cognition human agents and evolutionary computations. PSO has been motivated by the behavior of organisms such as fish schooling and bird flocking. Generally, PSO is characterized as simple in concept, easy to implement, and computationally efficient. Unlike the other heuristic techniques, PSO has a flexible and well-balanced mechanism to enhance and adapt to the global and local exploration abilities.

In this paper, a novel PSO based Hybrid approach is proposed to solve OPF problem. The problem is formulated as an

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optimization problem with mild constraints. In this study, the objective functions are generation fuel cost and line losses. The proposed approach has been tested on IEEE 30-bus system.

2 Problem Formulation:

The economic optimal operation of power systems, considering transmission constraints and supplying load demand, requires to minimize two objective functions (total generation fuel cost and active power losses) while satisfying several equality and inequality constraints. The standard OPF problem can be formulated as a constrained optimization problem as follows:

$$\text{Objective} = \min j(x, u)$$

$$\text{Subject: } g(x, u) = 0, \text{ Equality constraints}$$

$$h(x, u) \leq 0, \text{ Inequality constraints}$$

Where x is the vector of dependent variable consisting of bus power P_{G_i} , load bus voltages V_L , generator reactive power outputs Q_{G_i} , and transmission line loadings S_{l_i} . Hence x can be expressed as

$$X^T = [P_{G_1}, V_{L_1}, Q_{G_1}, \dots, Q_{G_{NG}}, S_{l_1}, \dots, S_{l_{NL}}] \quad (1)$$

Where NG and NL are number of generators, and number of transmission lines respectively. U is the vector of independent variables consisting of generator voltages V_{G_i} , generator real power outputs P_{G_i} , except at the slack bus P_{G_1} , transformer tap settings T , and shunt VAR compensations Q_C . Hence, u can be expressed as

$$u^T = [V_{G_1}, \dots, V_{G_{NG}}, P_{G_2}, \dots, P_{G_{NG}}, T_1, \dots, T_{NT}, Q_{C_1}, \dots, Q_{C_{NC}}] \quad (2)$$

Where NT and NC are the number of the regulating transformers and shunt compensators, respectively. g and h are the load flow and operating constraints of the system respectively.

2.1 Objective function

A. Objective function-1(fuel cost minimization)

The most commonly used objective in the OPF problem formulation is the minimization of total fuel cost of real power generation. The individual cost of each generating unit is assumed to be function of active power generation and is represented by quadratic curve of second order. The objective function of entire power system can then be written as the sum of the quadratic cost model of each generator as given in eqn. (3)

$$\min c(x) = \min \sum_{i=1}^{n_g} a_i P_{g_i}^2 + b_i P_{g_i} + c_i \quad (3)$$

Where, $i=1, 2, 3, \dots, n_g$ and

n_g is the number of generators including the slack bus

P_{g_i} is the generated active power at bus i

a_i, b_i, c_i are the unit cost coefficients for i^{th} generator.

B. Objective function-II (Loss Minimization)

Active and reactive power loss occurs in transmission lines depending on the power to be transmitted. The active power loss equation for the k^{th} line between buses i and j can be given as in eqn. (4)

$$\min L(x) = P_{i-j} = G_j (V_i^2 + V_j^2 - 2V_i V_j \cos(\delta_i - \delta_j)) \quad (4)$$

Where

G_{ij} is i^{th} line conductance

B_{ij} is i^{th} line susceptance

V_i is voltage magnitude of i^{th} bus

δ_i is phase angle of i^{th} bus

2.2 Constraints

The OPF problem has two categories of constraints:

A. Equality constraints

The equality constraints $g(x)$ are the real and reactive power balance equations, expressed as follows:

$$P_{g_i} - P_{d_i} = V_i \sum_{j=1}^N V_j (g_{ij} \cos \delta_{ij} + b_{ij} \sin \delta_{ij}) \quad (5)$$

$$Q_{g_i} - Q_{d_i} = V_i \sum_{j=1}^N V_j (g_{ij} \sin \delta_{ij} + b_{ij} \cos \delta_{ij}) \quad (6)$$

P_{g_i}, Q_{g_i} are the active and reactive power generation at bus i ;

P_{d_i}, Q_{d_i} are the real and reactive power demand at bus i , V_j

is the voltage magnitude at bus j , respectively; δ_{ij} is the phase

angle difference between buses i and j , g_{ij} and b_{ij} are the real

and imaginary part of the admittance (Y_{ij}) and N is the total

number of buses.

B. Inequality Constraints

The inequality constraints $h(x, u)$ reflect the security limits, which include the following constraints as mentioned below:

Generator constraints

Upper and lower limits on the active power generations:

$$P_{g_i}^{\min} \leq P_{g_i} \leq P_{g_i}^{\max} \quad i=1, 2, \dots, NG \quad (7)$$

Upper and lower limits on the reactive power generations:

$$Q_{g_i}^{\min} \leq Q_{g_i} \leq Q_{g_i}^{\max} \quad i=1, 2, \dots, NG \quad (8)$$

Upper and lower limits on the generator bus voltage magnitude:

$$V_{g_i}^{\min} \leq V_{g_i} \leq V_{g_i}^{\max} \quad i=1, 2, \dots, NG \quad (9)$$

Transformer constraints:

Transformer tap settings are bounded as follows:

$$T_i^{\min} \leq T_i \leq T_i^{\max} \quad i=1, 2, \dots, NT \quad (10)$$

Shunt VAR constraints

Shunt VAR compensations are restricted by their limits as follows:

$$Q_{c_i}^{\min} \leq Q_{c_i} \leq Q_{c_i}^{\max} \quad i=1, 2, \dots, NC \quad (11)$$

3 Particle swarm optimization (PSO)

PSO is a population based stochastic optimization technique introduced by Kennedy and Eberhart. Like many biological inspired algorithms PSO also have natural motivation like bird flocking and fish schooling. PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. In every iteration each particle is updated by following two "best" values. The first one is the best solution (fitness) it has achieved so far, this value is called Pbest. Another "best" value that is tracked by the Particle swarm optimizer is the best value, obtained so far by any particle in the population; this best value is a global best and called Gbest. When a particle takes part of the population as its topological neighbors, the best value is a Pbest [26]. The number of parameters of the objective function is assumed to be n, and then the search space will be n-dimensional. The i^{th} particle has an n-dimensional position Vector

$X_i = (X_{i1}, X_{i2}, \dots, X_{in})^T$ and an n-dimensional velocity vector

$V_i = (V_{i1}, V_{i2}, \dots, V_{in})^T$ where i is a positive integer index of the particle in the swarm. The historical best position encountered by the i^{th} particle is denoted as $P_i = (P_{i1}, P_{i2}, \dots, P_{in})^T$. Let g denote the index of the particle that attained the best previous position among all the individuals of the swarm, and then the global best position can be denoted as $P_g = (P_{g1}, P_{g2}, \dots, P_{gn})^T$. The fitness, value of i^{th} particle can be calculated by $f(x_i)$, where f is the objective function. In the process of executing PSO algorithm, a swarm is initialized by random at first, and then the global best position may be updated during the each iteration. In each of the iterations, the position and the velocity of i^{th} particle are updated with eqns. (12) and (13) as follows [27] until the iteration termination is satisfied

$V_i(k+1) = wV_i(k) + c_1 r_{1i}(k)(P_i(k) - X_i(k)) + c_2 r_{2i}(k)(P_g(k) - X_i(k))$

$$(12)$$

$X_i(k+1) = X_i(k) + V_i(k+1)$

$$(13)$$

In the above equations, k denotes the iteration counter, w is called the inertia weigh which controls the impact of the previous velocity of the particle on its current one, coefficient c_1 and c_2 are the acceleration parameters which are commonly set to 2 [28], and the parameters r_{1i} and r_{2i} are random numbers uniformly distributed in the interval [0, 1]. The value of each component in every velocity vector can be clamped to the range [-vmax, vmax] to prevent the particles leaving the search space. By the same token, the value of each component in every position vector can be limited to the range [xmin, xmax].

A. Implementation of PSO Algorithm in OPF Problem

In this paper the solution to OPF using PSO algorithm is introduced, not only to minimize the generation fuel cost but also transmission line loss. Its implementation consists of the following six steps:

Step 1: Specify the number of generating units as the dimension. The particles are randomly generated between the maximum and minimum limits of the generators. If there are N units, the i^{th} particle is represented as follows:

$$(P_i = P_{i1}, P_{i2}, P_{i3}, \dots, P_{iN}).$$

Step 2: The particles velocities are generated randomly in the range of $[v_j^{\min}, v_j^{\max}]$.

The maximum velocity limit is set at 10-20 % of the dynamic range of the variables on each dimension [29, 30].

Step 3: Objective function values of the particles are evaluated using eqn. (3). These determined values are set as Pbest value of the particles.

Step 4: The best value among all the Pbest values is identified and denoted as Gbest.

Step 5: New velocities for all the dimensions in each particle are calculated using eqn. (12). Then the position of each particle is updated using eqn. (13).

Step 6: The objective function values are calculated for the updated positions of the particles. If the new value is better than the previous Pbest, the new value is set to Pbest, if the stopping criteria are met, the positions of particles represented by Gbest are the optimal solution, and otherwise the procedure is repeated from step 4.

4 ADAPTIVE PSO (APSO)

The basic eqns of PSO (14), (15) and (16) can be considered as a kind of difference equation.

$$v_i^{k+1} = wv_i^k + c_1 rand_1 * (pbest_i - s_i^k) + c_2 rand_2 * (gbest - s_i^k) \quad (14)$$

$$w = w_{\max} - \left(\frac{(w_{\max} - w_{\min})}{(iter_{\max})} \right) * iter \quad (15)$$

$$s_i^{k+1} = s_i^k + v_i^{k+1} \quad (16)$$

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 [28, 29]. The velocity can be expressed as follows instead of eqns. (14) and (15):

$$v_i^{k+1} = K \left[v_i^k + c_1 * rand_1 * (pbest_i - s_i^k) + c_2 * rand_2 * (gbest - s_i^k) \right] \quad (17)$$

$$K = \frac{2}{2 - \varphi - \sqrt{\varphi^2 - 4\varphi}},$$

where $\varphi = c_1 + c_2$, $\varphi > 4$ (18)

Where φ and K are coefficients.

The following points are improved to the original PSO with Inertia Weight Approach (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 (Pbest, Gbest) at the following iteration.
- The wv_i^k term of (14) is modified as (17). 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 may move away from the position of (Pbest, Gbest).
- When the agent is moved beyond the boundary of feasible regions, Pbests and Gbest cannot be modified.
- 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).
- When the agent is moved beyond the boundary of feasible regions, Pbests and Gbest cannot be modified.
- 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:

$$C_2 = \frac{2}{P_1}, C_1 = \frac{2}{P_2} - C_2 \quad (19)$$

The search trajectory of PSO can be controlled by the parameters (P1, P2). Concretely, when the value is enlarged more than 0.5, the agent may move close to the position of Pbest/Gbest.

$$w = gbest - \left(\frac{\{c_1 (pbest - x) + c_2 (gbest - x)\}}{2} + x \right) \quad (20)$$

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

$$v_i^{k+1} = w_i + c_1 rand_1 * (pbest_i - s_i^k) + c_2 rand_2 * (gbest - s_i^k) \quad (21)$$

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 following iteration.
- *Evaluation of searching points:* The procedure is the same as PSO. In addition, when the agent becomes Gbest, it is perturbed. The parameters (P1, P2) 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 eqns. (21) and (17) of adaptive PSO.

5 OVERALL COMPUTATION PROCEDURE FOR SOLVING THE PROBLEM

The implementation steps of the proposed hybrid method combining IPM with APSO based algorithm can be written as follows:

Step1: Input the system data for load flow analysis

Step2: Run the power flow

Step3a: Basically the hybrid method involves two steps.

Step3b: The first step employs IPM to solve OPF approximated as a continuous problem and introduced into the initial populations of APSO.

Step3c: The second part uses APSO to obtain the final optimal solution.

Step4: In initial population, all individuals (obtained from IPM) are produced randomly. The main

reason for using IPM is that it is often closer to optimal solutions than other random individuals.

- Step5: For each individual in this method, run power flow to determine generator active and reactive power outputs, shunt VAR compensators, load bus voltages, angles, tap settings can be calculated.
- Step6: Evaluate the objective function values and the corresponding fitness values for each individual
- Step7: Find the generation local best xlocal and global best xglobal and store them
- Step8: Increase the generation counter Gen = Gen+1
- Step9: Apply the APSO operators to generate new k Individuals
- Step10: For each new individual in this method, run power flow to determine the generator active and reactive power outputs, shunt VAR compensators, load bus voltages, angles, tap settings can be calculated.
- Step11: Evaluate the objective function values and the corresponding fitness values for each new individual
- Step12: Update the generation local best xlocal and global best xglobal and store them
- Step13: If one of stopping criterion have not been met repeat steps 5-12. Else go to step14
- Step14: Print the results.

6 SIMULATION RESULTS

The proposed hybrid algorithms for solving OPF problem are tested on standard IEEE-30 bus system using MATLAB software and results are tabulated.

The IEEE-30 bus system consists of 30 buses, out of which six are Generator buses. The network has total active power load of 283.4 MW and reactive power load of 126.2 MVAR. Totally there are 19 control variables which consist of six Generator Bus voltages, four Tap changing transformers and nine Shunt compensators.

The PSO parameters used for simulation are summarized in Table-I

Here we have considered two objective functions, Objective function-1 is the Cost Minimization and Objective function-2 is the Loss Minimization.

TABLE – I
OPTIMAL PARAMETER SETTING FOR PSO

Parameter	Value
Population size	15
Number of iterations	100
Cognitive constant, c1	2
Social parameter, c2	2
Inertia weight, W	0.5-1.5

The proposed hybrid PSO algorithm were applied to find the optimal scheduling of the power system for the base case loading condition to minimize specified objective functions.

Table II presents the optimal setting of the control variables with objective function 1. It is observed that minimum cost was obtained using APSO-IPM method when compared

TABLE II
OPTIMAL SETTINGS OF CONTROL VARIABLES WITH GENERATION FUEL COST MINIMIZATION

Control variables	PSO-NR	APSO-NR	APSO-IPM
Real power generation (p.u)	1.7773	1.7753	1.7652
	0.4928	0.4879	0.4935
	0.2122	0.2170	0.2278
	0.1200	0.1200	0.1200
	0.2128	0.2138	0.2165
Generator voltages (p.u)	0.1099	0.1106	0.1000
	1.0783	1.0842	1.0877
	1.0590	1.0639	1.0685
	1.0351	1.0385	1.0417
	1.0621	1.0368	1.0472
Transformer Tap	1.0296	1.0325	1.0371
	1.0490	1.0507	1.0401
	0.9920	0.9606	1.0039
	1.0003	1.0163	0.9837
	0.9864	0.9762	0.9613
Shunt reactive power	0.9721	0.9760	0.9777
	0.0596	0.0726	0.0624
	0.0623	0.0267	0.0177
	0.0687	0.0492	0.0384
	0.0694	0.0191	0.0642
	0.0433	0.0364	0.0454
	0.0663	0.0554	0.0919
	0.0000	0.0504	0.0183
	0.0786	0.0621	0.0859
	0.0246	0.0294	0.0241
Cost(\$/hr)	800.5736	800.5282	800.2771
Loss(MW)	0.0911	0.0905	0.0890

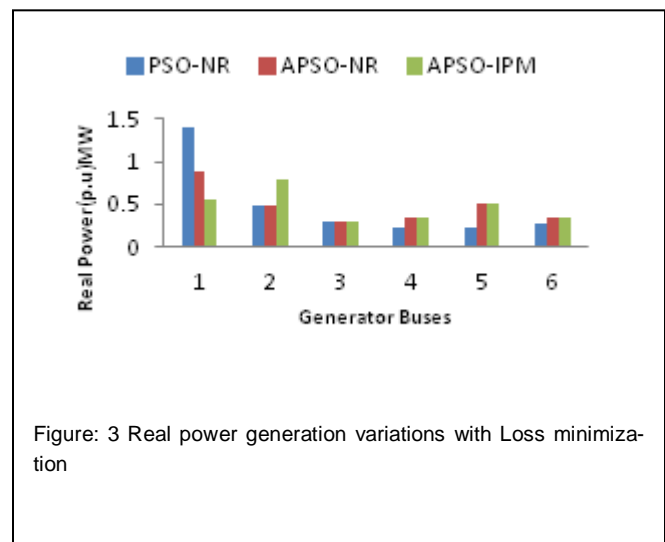
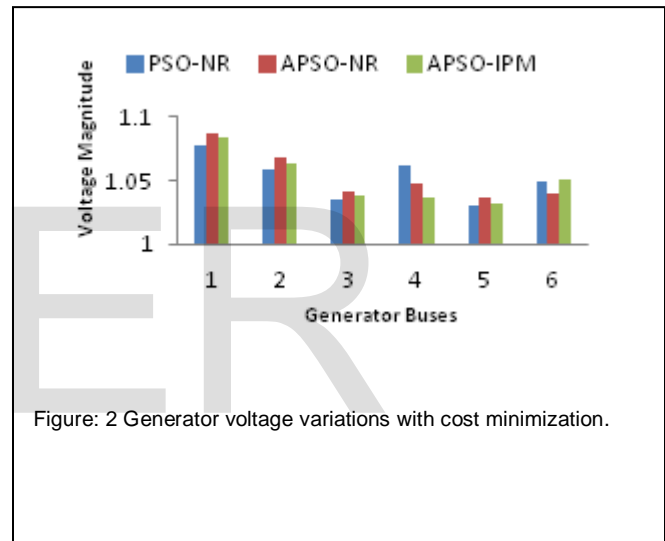
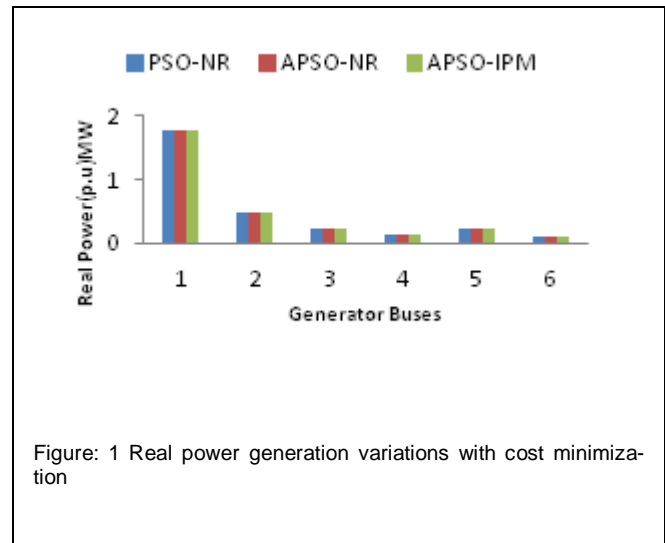
with other two Hybrid methods.

Table III presents the optimal setting of the control variables with objective function 2. It is observed that minimum loss value was obtained using APSO-IPM method when compared with other two Hybrid methods.

Fig 1-4 shows the variation of control variables with fuel cost and transmission line losses minimization using different Hybrid OPF techniques.

TABLE III
OPTIMAL SETTINGS OF CONTROL VARIABLES WITH LINE LOSS
MINIMIZATION

Control variables		PSO-NR	APSO-NR	APSO-IPM
Real power generation (p.u)	P_{G1}	1.3993	0.8789	0.5662
	P_{G2}	0.4937	0.4936	0.8000
	P_{G3}	0.2936	0.3000	0.3000
	P_{G4}	0.2350	0.3490	0.3496
	P_{G5}	0.2165	0.5000	0.5000
	P_{G6}	0.2645	0.3489	0.3500
Generator voltages (p.u)	V_{G1}	1.0773	1.0695	1.0623
	V_{G2}	1.0590	1.0586	1.0572
	V_{G3}	1.0302	1.0449	1.0430
	V_{G4}	1.0031	1.0389	1.0425
	V_{G5}	1.0258	1.0368	1.0378
	V_{G6}	1.0501	1.0301	1.0390
Trans-former Tap	Tap-1	0.9871	0.9890	0.9969
	Tap-2	1.0144	1.0224	0.9904
	Tap-3	0.9926	0.9572	0.9811
	Tap-4	1.0061	0.9811	0.9788
Shunt re-active power	Q_{SVC1}	0.0808	0.0486	0.0479
	Q_{SVC2}	0.0752	0.0613	0.0866
	Q_{SVC3}	0.0561	0.0421	0.0431
	Q_{SVC4}	0.0444	0.0710	0.0677
	Q_{SVC5}	0.0317	0.0376	0.0384
	Q_{SVC6}	0.0905	0.0735	0.1000
	Q_{SVC7}	0.0677	0.0382	0.0459
	Q_{SVC8}	0.0725	0.1000	0.0613
	Q_{SVC9}	0.0233	0.0103	0.0226
Cost(\$/hr)		818.9696	911.2535	955.4140
Loss(MW)		0.0685	0.0365	0.0318



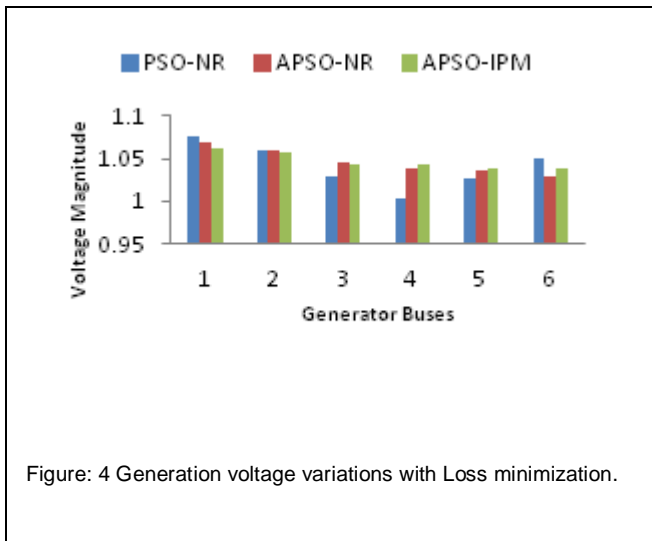


Figure: 4 Generation voltage variations with Loss minimization.

7 CONCLUSION

An Adaptive particle swarm optimization algorithm to solve the OPF problem in a power system is presented in this paper. As a representative method of swarm intelligence, APSO supplies a novel thought and solution for nonlinear, non-differential and multi-modal problem. For solving the OPF problem, numerical results on the 30-bus system demonstrate the feasibility and effectiveness of the proposed APSO method.

References

- [1] Alsac O, Stott B. "Optimal load flow with steady state security". IEEE Transactions on Power Apparatus and Systems; vol. PAS-93: pp.745-51. 1974.
- [2] Dommel H, Tinny W. "Optimal power flow solution". IEEE Transactions on Power Apparatus and Systems; vol.PAS-87(10): pp.1866-76. 1968.
- [3] Happ HH. "Optimal power dispatch: a comprehensive survey". IEEE Transactions on Power Apparatus and Systems; vol.PAS-96: pp.841-54. 1977.
- [4] Mamandur KRC. "Optimal control of reactive power flow for improvements in voltage profiles and for real power loss minimization". IEEE Transactions on Power Apparatus and Systems; vol. PAS-100(7): pp.3185-93. 1981.
- [5] Shoults R, Sun D. "Optimal power flow based on P-Q decomposition". IEEE Transactions on Power Apparatus and Systems; vol. PAS-101(2): pp.397-405. 1982.
- [6] Habiabollahzadeh H, Luo GX, Semlyen A. "Hydrothermal optimal power flow based on a combined linear and nonlinear programming methodology". IEEE Transactions on Power Apparatus and Systems; vol. PWRS-492: pp.530-7. 1989.
- [7] Burchett RC, Happ HH, Vierath DR. "Quadratically convergent optimal power flow". IEEE Transactions on Power Systems; vol. PAS-103: pp.3267-76. 1984.
- [8] Aoki K, Nishikori A, Yokoyama RT. "Constrained load flow using recursive quadratic programming". IEEE Transactions on Power Systems; vol.2 (1): pp.8-16. 1987.
- [9] Abou El-Ela AA, Abido MA. "Optimal operation strategy for reactive power control, Modelling, simulation and control" vol. 41(3).pp.19-40. AMSE Press, 1992p
- [10] Stadlin W, Fletcher D. "Voltage versus reactive current model for dispatch and control". IEEE Transactions on Power Systems; vol. PAS-101(10): pp.3751-8. 1982.
- [11] Mota-Palomino R, Quintana VH. "Sparse reactive power scheduling by a penalty-function linear programming technique". IEEE Transactions on Power Apparatus and Systems; vol.1 (3): pp.31-39. 1986.
- [12] Sun DI, Ashely B, Brewer B, Hughes A, Tinney WF. "Optimal power flow by Newton approach". IEEE Transactions on Power Apparatus and Systems; vol. PAS-103(10): pp.2864-75. 1984.
- [13] Santos A, da Costa GR. "Optimal power flow solution by Newton's method applied to an augmented lagrangian function". IEEE Proc Generation Transmission Distribution; vol.142 (1): pp.33-36. 1995.
- [14] Rahil M, Pirotte P. "Optimal load flow using sequential unconstrained minimization technique (SUMT) method under power transmission losses minimization". Electric Power Systems Res; vol.52: pp.61-64. 1999.
- [15] Yan X, Quintana VH. "Improving an interior point based OPF by dynamic adjustments of step sizes and tolerances". IEEE Transactions on Power Systems; vol.14 (2): pp.709-17. 1999.
- [16] Momoh JA, Zhu JZ. "Improved interior point method for OPF problems". IEEE Transactions on Power Systems; vol. 14(3): pp.1114-20. 1999.
- [17] Lai LL, Ma JT. "Improved genetic algorithms for optimal power flow under both normal and contingent operation states". Int J Electrical Power Energy Systems; vol.19 (5): pp.287-92. 1997.
- [18] Yuryevich J, Wong KP. "Evolutionary programming based optimal power flow algorithm". IEEE Transactions on Power Systems; vol.14 (4): pp.1245-50. 1999.
- [19] Fogel DB. "Evolutionary computation toward a new philosophy of machine intelligence". New York: IEEE Press, 1995.
- [20] J.A. Momoh, L.G. Dias, Guo, and R.A. Adapa, "Economic operation and planning of multi-area interconnected power system," IEEE Transactions on Power System, vol. 10, pp. 1044-1051, 1995.
- [21] S. Granville, J. C. O. Mello, and A. C. G. Melo, "Application of interior point methods to power flow, unsolvability," IEEE Transactions on Power System, vol. 11, pp. 1096-1103, 1996.
- [22] Kennedy J. "The particle swarm: social adaptation of knowledge". Proc 1997 IEEE International Conference Evolutionary Computation ICEC, 97, Indianapolis, IN, USA: pp.303-8. 1997.
- [23] Angeline P. "Evolutionary optimization versus particle swarm optimization": philosophy and performance differences. Proc 7th Annual Conference on Evolutionary Programming: pp.601-10. 1998.
- [24] Shi Y, Eberhart R. "Parameter selection in particle swarm optimization". Proc 7th Annual Conference Evolutionary Programming: pp.591-600. 1998.
- [25] Ozean E, Mohan C. "Analysis of a simple particle swarming optimization system". Intel Engineering Systems and Artificial Neural Networks; vol. 8: pp.253-8. 1998.
- [26] J. Kennedy, and R. Eberhart, "Particle swarm optimization," IEEE International Conference on Neural Networks, vol. 4, pp. 1942-1948, Perth, Australia, 1995.
- [27] Y. Shi, and R. C. Eberhart, "A Modified Swarm Optimizer", In Proceedings of IEEE International Conference on Evolutionary Computation, Piscataway, NJ: IEEE Press, pp.303-308, 1998.
- [28] R. C. Eberhart, P. Simpson, and R. Dobbins, Computational Intelligence PC Tools: Academic, ch.6, pp. 212-226. 1996.
- [29] S. Kirkpatrick, C. D. Gellat, and M. P. Vecchi. "Optimization by Simulated Annealing, Science". Vol. 220, pp. 671-680, 1983.
- [30] M.M. El Metwally, A.A. El Emary, F.M. El Bendary and M.I. Mosaad. "Optimal Power Flow Using Evolutionary Programming Techniques." MEPCON'2008 Power Systems, pp. 260-264, 2008.

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