Multi-Objective Optimization using Evolutionary Computation Techniques

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ABSTRACT

In this paper an EP and PSO based optimization algorithms have been proposed for solving optimal power flow problems with multiple objective functions. These algorithms take into consideration all the equality and inequality constraints. The improvement in system performance is based on reduction in cost of power generation and active power loss. The proposed algorithms have been compared with the other methods reported in the literature. Simulation studies have been carried out for the optimal solutions of the IEEE 14-bus and IEEE 30-bus systems.

Keywords
EP, PSO, Active Power Loss

1. INTRODUCTION

The main objective of electric power utilities is to provide high quality reliable supply to the consumers at the lowest possible cost while operating to meet the limits and constraint imposed on the generating units. This formulates the well-known Economic Load Dispatch (ELD) problem for finding the optimal combination of the output power of all online generating units that minimizes the total fuel cost, while satisfying all constraints [1].

The Optimal Power Flow (OPF) is an important criterion in today's power system operation and control due to scarcity of energy resources, 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. Generally, most of the approaches apply sensitivity analysis and gradient-based optimization algorithms by linearizing the objective function and system constraints around an operating point. Unfortunately, the problems of OPF are highly nonlinear and a multi model optimization problems, i.e. there exist more than one local optimum. Therefore, conventional optimization methods that make use of derivatives and gradients are, in general, not able to locate or identify the global optimum [7].

ELD is solved traditionally using mathematical programming based on optimization techniques such as lambda iteration, gradient method and so on. Economic load dispatch with piecewise linear cost functions is a highly heuristic, approximate and extremely fast form of economic dispatch. Complex constrained ELD is addressed by intelligent methods. Among these methods, some of them are genetic algorithm (GA) and, evolutionary programming (EP), dynamic programming (DP), tabu search, hybrid EP, neural network (NN), adaptive Hopfield neural network (AHNN), particle swarm optimization (PSO) etc. For calculation simplicity, existing methods use second order fuel cost functions which involve approximation and constraints are handled separately, although sometimes valve-point effects are considered [13][15].

Intelligent methods are iterative techniques that can search not only local optimal solutions but also a global optimal solution depending on problem domain and execution time limit. They are general-purpose searching techniques based on principles inspired from the genetic and evolution mechanisms observed in natural systems and populations of living beings. These methods have the advantage of searching the solution space more thoroughly. The main difficulty is their sensitivity to the choice of parameters. Among intelligent methods, PSO is simple and promising. It requires less computation time and memory. It has also standard values for its parameters. In this, the Particle Swarm Optimization (PSO) is proposed as a methodology for economic load dispatch [2].

2. OPF BY EVOLUTIONARY COMPUTATION TECHNIQUES

2.1 Evolutionary Programming (EP)

Evolutionary Programming (EP) is an optimization technique based on the natural generation. It involves random number generation at the initialization process. The generated random numbers represent the parameters responsible for the optimization of the fitness value. In addition, EP also involves statistics, fitness calculation, mutation and the new generation will be bred by mode of selection. EP is a global optimization technique that starts with the population of randomly generated candidate solution and evolves a better solution over a number of generations or iterations. It is more suitable to effectively handle non-continuous and non-differentiable function. The main stage of this technique includes initialization, mutation, competition and selection [13].

EP Algorithm
i. An Initial population of N_p parent vectors is considered as the trial solution
ii. From these parents off springs are created by mutation, hence N_p off springs are obtained
iii. By combining the parents and off springs, $2N_p$ solutions are obtained
iv. Through competition and selection, first N_p optimal solutions are selected

v. The selected solutions are considered as parents for the next iteration

vi. After the required number of iterations, the best optimal solution is obtained.

2.2 Particle Swarm Optimization

PSO shares many similarities with evolutionary computation techniques such as Genetic Algorithms (GA). The system is initialized with a population of random solutions and searches for optima by updating generations. However, unlike GA, PSO has no evolution operators such as crossover and mutation [3].

Velocity of each agent can be modified by the following equation:

$$v_i^{k+1} = wv_i^k + c_1 rand_1 *(pbest_i - s_i^k) + c_2 rand_2 *(gbest - s_i^k)$$
(2.1)

$$w = w_{max} - ((w_{max} - w_{min})/(iter_{max}))*iter$$
(2.2)

The current position (searching point in the solution space) can be modified by the following equation

$$s_i^{k+1} = s_i^k + v_i^{k+1}$$
(2.3)

PSO Algorithm

Step 1: Generation of initial condition of each agent. Initial searching points (s_i^0) and velocities (v_i^0) of each agent are usually generated randomly within the allowable range. The current searching point is set to pbest for each agent. The best evaluated value of pbest is set to gbest, and the agent number with the best value is stored.

Step 2: Evaluation of searching point of each agent. The objective function value is calculated for each agent. If the value is better than the current pbest of the agent, the pbest value is replaced by the current value. If the best value of pbest is better than the current gbest, gbest is replaced by the best value and the agent number with the best value is stored.

Step 3: Modification of each searching point. The current searching point of each agent is changed using eqns. (2.1), (2.2), and (2.3).

Step 4: Checking the exit condition. The current iteration number reaches the predetermined maximum iteration number, then exits. Otherwise, the process proceeds to step 2.

3. MATHEMATICAL FORMULATION 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 [4][5]

$$\text{Min } F(x,u)$$
(3.1)

Subject to $g(x,u) = 0$ (3.2)

$$h(x,u) \le 0$$
(3.3)

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

$$x^T = [P_{G_1}, V_{L_1}...V_{L_{NL}}, Q_{G_1}...Q_{G_{NG}}, S_l...S_{l_{nl}}] \quad (3.4)$$

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

$$u^T = [V_{G_1}...V_{G_{NG}}, P_{G_2}...P_{G_{NG}}, T_1...T_{NT}, Q_{C_1}...Q_{C_{NC}}] \quad (3.5)$$

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

Objectives

The objectives considered for minimization are as follows.

Objective Function 1: Fuel cost of generating units (f_1)

Objective Function 2: Active power loss (f_2)

Objective Function 3: Weighted multi objective function (f_3)

where

$$f_1 = \min(\sum_{i=1}^{NG}(a_i P_{Gi}^2 + b_i P_{Gi} + C_i)$$
(3.6)

$$f_2 = \min(\sum_{i=1}^{NL} G_{ij}(V_i^2 + V_j^2 - 2V_iV_j\cos(\delta_i - \delta_j)))$$
(3.7)

$$f_3 = w_1 * f_1 + w_2 * f_2$$
(3.8)

Here $w_1 + w_2 = 1$

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.

$$P_{Gi} - P_{Di} - \sum_{j=1}^{n}|V_i||V_j||Y_{ij}|\cos(\theta_{ij} - \delta_i + \delta_j) = 0$$
(3.9)

$$Q_{Gi} - Q_{Di} + \sum_{j=1}^{n}|V_i||V_j||Y_{ij}|\sin(\theta_{ij} - \delta_i + \delta_j) = 0$$
(3.10)

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 power outputs

$$P_{Gi}^{min} \le P_{Gi} \le P_{Gi}^{max}, i = 1,...,N_G$$
(3.11)

$$Q_{Gi}^{min} \le Q_{Gi} \le Q_{Gi}^{max}, i = 1,...,N_G$$
(3.12)

2) Voltage magnitudes at each bus in the network

$$V_i^{min} \le V_i \le V_i^{max}, i = 1,...,NL$$
(3.13)

3) transformer tap settings

$$T_i^{min} \le T_i \le T_i^{max}, i = 1,...,NT$$
(3.14)

4) Reactive power injections due to capacitor banks

$$Q_{Ci}^{min} \le Q_{Ci} \le Q_{Ci}^{max}, i = 1,...,CS$$
(3.15)

5) Transmission lines loading

$$S_i \le S_i^{max}, i = 1,...,nl$$
(3.16)

6) Voltage stability index

$$Lj_i \le Lj_i^{\max}, i = 1, \ldots, NL \qquad (3.17)$$

Handling of Constraints: There are different ways to handle constraints in evolutionary computation optimization algorithms. In this thesis, the constraints are incorporated into fitness function by means of penalty function method, which is a penalty factor multiplied with the square of the violated value of variable is added to the objective function and any infeasible solution obtained is rejected.

To handle the inequality constraints of state variables including load bus voltage magnitudes and output variables with real power generation output at slack bus, reactive power generation output, and line loading, the extended objective function can be defined as:

$$OF = \sum_{i=1}^{N} F_i(P_{Gi}) + K_p h(P_{G1}) + K_q \sum_{i=1}^{N} h(Q_{Gi}) + K_v \sum_{i=1}^{NL} h(|V_i|) + K_s \sum_{i=1}^{NL} h(|S_i|) \qquad (3.18)$$

where

K_p, K_q, K_v, K_s are penalty constants for the real power generation at slack bus, the reactive power generation of all generator buses or PV buses and slack bus, the voltage magnitude of all load buses or PQ buses, and line or transformer loading, respectively. $h(P_{G1}), h(Q_{Gi})$, $h(|V_i|)$, $h(|S_i|)$ are the penalty function of the real power generation at slack bus, the reactive power generation of all PV buses and slack bus, the voltage magnitudes of all PQ buses, and line or transformer loading, respectively. NL is the number of PQ buses. The penalty function can be defined as:

$$h(x) = (x - x_{\max})^2 \text{, if } x > x_{\max}$$
$$= (x_{\min} - x)^2 \text{, if } x < x_{\min}$$
$$= 0 \qquad \text{, if } x_{\min} \le x \le x_{\max} \qquad (3.19)$$

where $h(x)$ is the penalty function of variable x, $x^{\max}$ and $x^{\min}$ are the upper limit and lower limit of variable x, respectively.

In this section i describe the dataset and how it is used to detect intrusions. I first examine what type of data was present in the dataset, what intrusion types were represented and what features were extracted.

4. COMPUTATIONAL PROCEDURE

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 EP/PSO parameters and randomly initialize k individuals within respective limits and save them in the archive.
Step 4: For each 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 EP/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 EP/PSO 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 4-15. Else go to step 16
Step 16: Print the results

There are two stopping criterion for the optimization algorithm. The algorithm can be stopped if the maximum number of generations is reached (Gen = Gen$_{max}$) or there is no solution improvement over a specified number of generations. The first criterion is used in this paper.

5. SIMULATION RESULTS

The proposed EP and PSO algorithms for solving optimal power flow problems are tested on standard IEEE 14 & IEEE 30-bus test systems. The EP and PSO parameters used for the simulation are summarized in Table 1

Table 1 Optimal parameter settings for EP and PSO

Parameter	EP	PSO
Population size	20	20
Number of iterations	250	150
Cognitive constant, c1	-	2
Social constant, c2	-	2
Inertia weight, W	-	0.3-0.95

5.1 IEEE 14-bus system results

Figures 1 shows the convergence characteristics of the three objective functions. It can be observed that the EP converge to lower values than PSO during initial evolutions and the PSO converge to a minimum value than EP after 20 iterations.

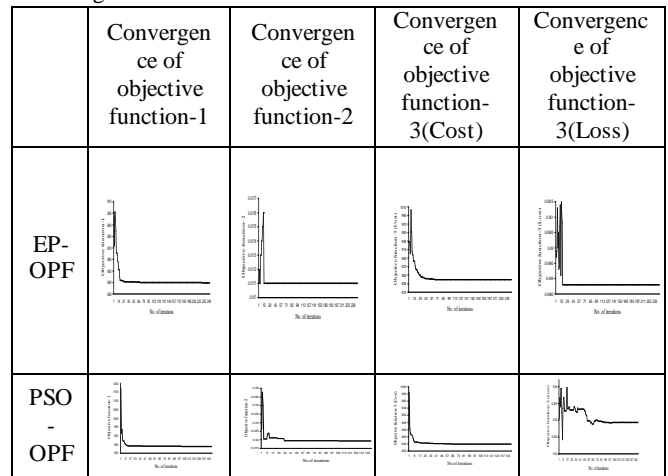|	Convergence of objective function-1	Convergence of objective function-2	Convergence of objective function-3(Cost)	Convergence of objective function-3(Loss)
EP-OPF				
PSO-OPF				

Fig 1 Convergence of multiple objective functions by EP and PSO

Table 2 Optimal settings of control variables

Control variables	Objective function-1		Objective function-2		Objective function-3	
	EP	PSO	EP	PSO	EP	PSO
P_{G1}	1.1242	1.1279	0.2485	0.6138	1.1191	1.1278
P_{G2}	0.7000	0.7000	0.7000	0.3889	0.7000	0.7000
P_{G3}	0.2783	0.2749	0.8000	0.8000	0.2728	0.2748
P_{G4}	0.2605	0.2613	0.5424	0.5019	0.2746	0.2627
P_{G5}	0.2778	0.2746	0.3163	0.3049	0.2734	0.2739
Q_{G1}	0.0100	-0.0929	0.0741	0.1796	-0.0789	-0.0936
Q_{G2}	0.1108	0.0534	0.0506	-0.1906	0.1838	0.0574
Q_{G3}	0.1760	0.0373	0.1786	-0.0342	0.1688	0.0370
Q_{G4}	0.1283	0.0924	0.0044	0.1807	0.0322	0.1177
Q_{G5}	0.0995	0.1459	0.0505	0.0628	0.1177	0.1782
V_1	1.0700	1.0700	1.0700	1.0700	1.0700	1.0715
V_2	1.0567	1.0621	1.0644	1.0541	1.0609	1.0621
V_3	1.0275	1.0389	1.0541	1.0425	1.0321	1.0387
V_4	1.0137	1.0598	1.0491	1.0309	1.0564	1.0520
V_5	1.0480	1.0688	1.0326	1.0387	1.0571	1.0784
T_1	0.9543	1.0322	1.0260	1.0064	1.0331	1.0118
T_2	1.0879	0.9000	0.9665	0.9360	0.9017	0.9201
T_3	1.0157	0.9922	0.9669	1.0473	0.9617	1.0004

Q_{sh1}	0.0521	0.0260	0.0016	0.0183	0.0369	0.0500
Q_{sh2}	0.0975	0.0500	0.0105	0.0098	0.1000	0.0500
Q_{sh3}	0.0191	0.0351	0.0389	0.0348	0.0658	0.0218
Q_{sh4}	0	0.0500	0.0824	0.0178	0.0364	0.0208
Q_{sh5}	0.0306	0.0500	0.0787	0.0399	0.0551	0
Cost ($/hr)	840.114	839.0662	1105.4	1072.1	839.70	839.27
Loss p.u.MW	0.0509	0.0488	0.0583	0.0194	0.0499	0.0493
CPU Time	63.0150	35.5470	60.9060	39.7190	62.969	41.469

The above table presents the optimal settings of the control-variables with the three objective functions. From the Table 2, it was found that all the state variables satisfy their lower and upper limits.

It can be observed that the PSO algorithm is able to reduce the cost of generation less than that of the cost of generation obtained by the EP method. It is also evident from the results that particle swarm optimization technique outperforms in achieving minimum of the specified objective under different network contingencies when compared with evolutionary programming method.

	objective function-1	objective function-2	objective function-3
L-indices			
Line loadings			
Load voltages			

Fig 2 L-indices, Line loadings and Load voltages of 14 bus by EP and PSO for multiple objective functions

Figures 2 shows the percentage line loadings, load bus voltages and voltage stability indices after the optimization by EP and PSO methods with the three objective functions.

5.2 IEEE 30-bus system results

The proposed PSO algorithm was applied to find the optimal scheduling of the power system for the base case loading condition to minimize specified objective functions. Generator active-power outputs, generator terminal voltages, transformer tap settings and shunt reactive power compensating elements were taken as control variables. The control variables are represented as floating point numbers in the population. The upper and lower voltage limits of load buses were taken as 1.06 and 0.95 respectively.
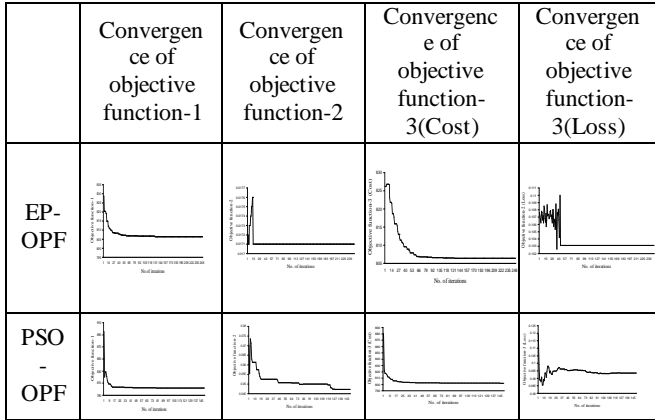
	Convergence of objective function-1	Convergence of objective function-2	Convergence of objective function-3(Cost)	Convergence of objective function-3(Loss)
EP-OPF				
PSO-OPF				

Fig 3 Convergence of multiple objective functions by EP and PSO

Figure 3 shows the convergence characteristics of the three objective functions. It can be observed that the EP converge to lower values than PSO during initial evolutions and the PSO converge to a minimum value than EP after 20 iterations.

Table 3 Optimal settings of control variables

Control variables	Objective function-1		Objective function-2		Objective function-3	
	EP	PSO	EP	PSO	EP	PSO
P_{G1}	1.7814	1.7616	0.5304	0.9421	1.7778	1.7618
P_{G2}	0.4990	0.4885	0.7940	0.6868	0.4985	0.4884
P_{G3}	0.1961	0.2207	0.3500	0.2480	0.2008	0.2212
P_{G4}	0.1200	0.1217	0.3000	0.1768	0.1167	0.1220
P_{G5}	0.2242	0.2150	0.5000	0.4870	0.2277	0.2151
P_{G6}	0.1206	0.1200	0.4000	0.3405	0.1200	0.1200
Q_{G1}	-0.196	-0.162	- 0.186	-0.056	-0.143	-0.200
Q_{G2}	0.1451	0.1268	0.1183	-0.0017	0.1859	0.0698
Q_{G3}	0.3189	-0.012	0.3264	0.1036	0.2465	0.0956
Q_{G4}	0.1496	0.2631	0.0022	0.1485	0.0308	0.2648
Q_{G5}	0.4744	0.0988	0.3885	0.0538	0.4489	0.0889
Q_{G6}	0.1218	0.2056	0.0912	0.2138	0.2000	0.4472
V_1	1.0500	1.0500	1.0500	1.0500	1.0500	1.0500
V_2	1.0364	1.0379	1.0500	1.0418	1.0345	1.0385
V_3	1.0284	1.0189	1.0444	1.0282	1.0175	1.0196
V_4	1.0649	1.1000	1.0330	1.0538	1.0375	1.1000
V_5	1.0148	1.0109	1.0349	1.0209	1.0080	1.0121
V_6	1.0634	1.0768	1.0571	1.0432	1.0577	1.1000
T_1	1.0331	1.0049	1.0115	1.0000	0.9769	0.9956
T_2	0.9327	0.9591	0.9544	0.9964	1.0058	0.9819
T_3	0.9891	1.0064	1.0041	1.0473	1.0240	1.1000
T_4	0.9611	0.9592	0.9842	0.9616	0.9812	0.9755
Q_{sh1}	0.0054	0.0282	0.0154	0.0166	0.0342	0
Q_{sh2}	0.0057	0.0443	0.0237	0.0239	0.0238	0.0231
Q_{sh3}	0.0127	0.0365	0.0605	0.0259	0.0709	0.0495
Q_{sh4}	0.0641	0.0414	0.0560	0.0321	0.0415	0.0447
Q_{sh5}	0.1000	0.0389	0.0461	0.0168	0.0491	0.0336
Q_{sh6}	0.0581	0.0415	0.0913	0.0378	0.0544	0.0500
Q_{sh7}	0.0507	0.0339	0.0410	0.0205	0.0419	0.0234
Q_{sh8}	0.0495	0.0500	0.0243	0.0269	0.0200	0.0500
Q_{sh9}	0.0275	0.0326	0.0283	0.0257	0.0761	0.0500
Cost ($/hr)	806.3633	801.9525	968.6317	899.1088	806.619	802.268
Loss p.u.MW)	0.1703	0.0936	0.0494	0.0472	0.1075	0.0944
CPU Time	145	92.172	134.0320	129.6410	120.263	90.9330

Table 3 presents the optimal settings of the control-variables with the three objective functions. From the Table 3, it was found that all the state variables satisfy their lower and upper limits.

From the Table 5.3, it can be observed that the PSO algorithm is able to reduce the cost of generation less than that of the cost of generation obtained by the EP method. It is also evident from the results that particle swarm optimization technique outperforms in achieving minimum of the specified objective under different network contingencies when compared with evolutionary programming method.
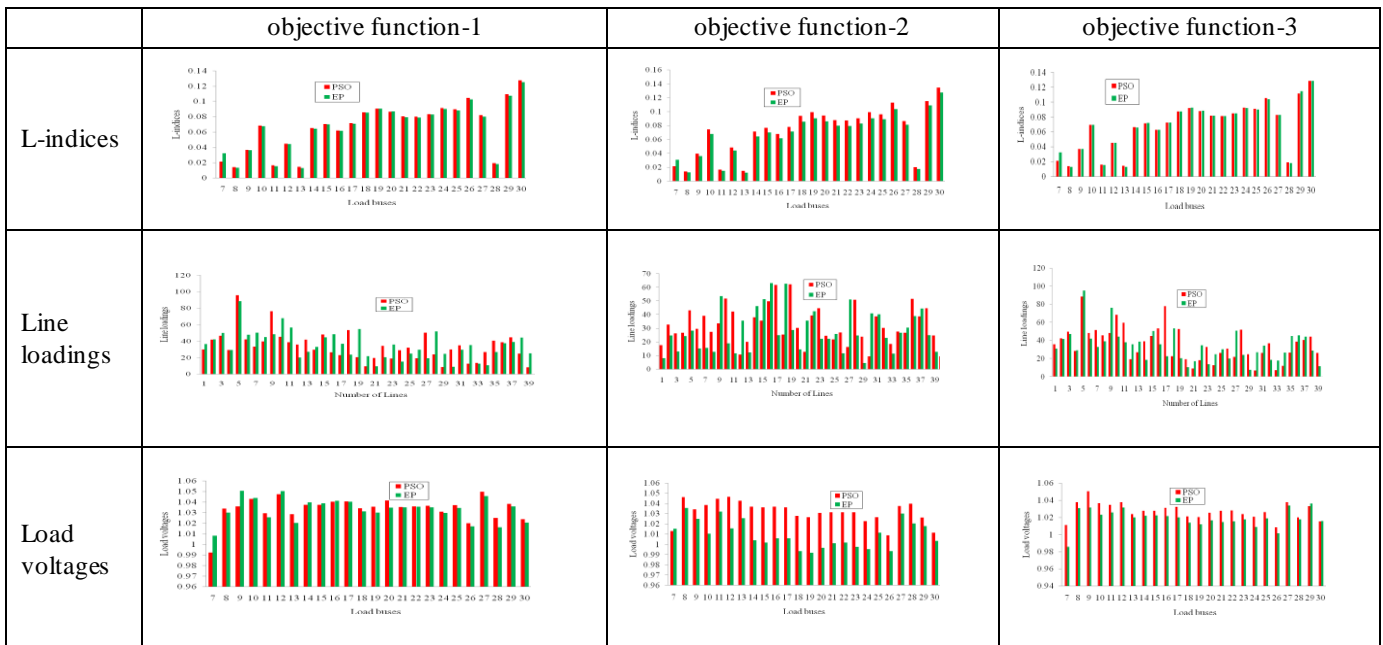
	objective function-1	objective function-2	objective function-3
L-indices			
Line loadings			
Load voltages			

Fig 4 L-indices, Line loadings and Load voltages of 14 bus by EP and PSO for multiple objective functions

Figure 4 shows the percentage line loadings, load bus voltages and voltage stability indices after the optimization by EP and PSO methods with the three objective functions.

The comparison of fuel cost of the proposed methods with those of the methods reported in the literature for IEEE 30-bus system is given in Table 4. It can be seen from the Table 5.4 that the PSO algorithm gives less cost of generation compared with the cost of generation obtained with other methods.

Table 4 Comparison of fuel costs

Method	Fuel Cost ($/hr)
EP [13]	802.9070
TS [13]	802.5020
TS/SA [13]	802.7880
ITS [13]	804.5560
IEP [13]	802.4650
SADE_ALM [15]	802.4040
OPFPSO [14]	800.4100
MDE-OPF [16]	802.3760
Genetic Algorithm [17]	803.05
Gradient method [18]	802.43
PSO (proposed)	801.9525

Here an IEEE-30 bus system is considered. Evolutionary programming (EP) method has been applied on the IEEE-30 bus system. Here we have considered three objective functions. Objective function1 is the cost objective function. Objective function 2 is the loss objective function. Objective function 3 is the multi objective function i.e. both cost and losses are taken as objectives. The fitness function is taken as the reciprocal of the objective function.

6. CONCLUSION

An EP and PSO based optimization algorithms have been proposed for solving optimal power flow problems with different objective functions. These algorithms take into consideration all the equality and inequality constraints. The improvement in system performance is based on reduction in cost of power generation and active power loss. The proposed algorithms have been compared with the other methods reported in the literature. Simulation studies have been carried out for the optimal solutions of the IEEE 14-bus and IEEE 30-bus systems. It was observed that the results obtained by the proposed algorithms can be implemented in real life power systems for operation and analysis.

Based on the overall observations from the results obtained on various IEEE test systems, it can be concluded that the proposed methods for optimal solutions are suitable for implementing in modern power system operation.

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