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Static security analysis of power system networks using soft computing techniques

D.Raaga Leela[1], Sairam Mannem[2] and Ch.Padmanabha Raju[3]
PVP Siddhartha institute of technology, EEE department, Vijayawada, A.P, India
Assistant Professor[1], M.Tech student[2], Professor[3]

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 fuzzy based network security. 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 30-bus systems.

Keywords

Evolutionary programming, Particle Swarm Optimization, fuzzy severity index, optimal power flow.

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[2-5]. 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[6]. 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 [8-10].

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

Step1: An Initial population of Np parent vectors is considered as the trial solution

Step2: From these parents off springs are created by mutation, hence Np off springs are obtained

Step3: By combining the parents and off springs, 2Np solutions are obtained

Step4: Through competition and selection, first Np optimal solutions are selected

Step5: The selected solutions are considered as parents for the next iteration

Step6: 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:

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

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

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

$$S_i^{k+1} = s_i^k + v_i^{k+1} \quad (3)$$

PSO Algorithm

Step 1: Generation of initial condition of each agent. Initial searching points (s_i^o) and velocities (v_i^o) 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. (1), (2), and (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.

2.3 Fuzzy Based Severity Index

The overall severity index is obtained using the parallel operated fuzzy inference systems, as shown in Fig.1, for the pre/post contingency operating conditions. The overall severity index for line loading, voltage profiles, and voltage stability indices are added and the sum is used as the Fuzzy Logic Composite Criteria (FLCC).

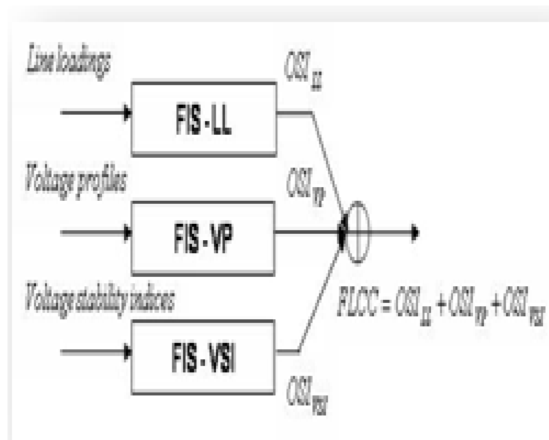

Fig.1: Parallel operation of fuzzy based system

Table I gives the fuzzy rules used for evaluating the Severity index.

Table 1: Fuzzy Rule Base For Determination Of Severity Index

Line Loadings					
Input	LL	NL	FL	OL	
Output	LS	BS	AS	MS	
Voltage profiles					
Input	LV	NV	OV		
Output	MS	BS	MS		
Voltage Stability Indices					
Input	VLI	LI	MI	HI	VHI
Output	VLS	LS	BS	AS	MS

3. Optimal Power flow problem formulation

Min $F(x,u)$ (4)

Subject to $g(x,u) = 0$ (5)

$h(x,u) \leq 0$ (6)

Where *x* is a vector of dependent variables consisting of slack bus power $P_{Gi,}$ 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

$$x^T = [P_{G_1}, V_{L_1} ... V_{L_{NL}}, Q_{G_1} .. Q_{G_{NG}}, S_l .. S_{l_{nl}}] \quad (7)$$

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_{G1} transformer tap settings *T*, and shunt VAR compensations Q_C Hence *u* can be expressed as given

$$u^T = [V_{G_1} ... V_{G_{NG}}, P_{G_2} ... P_{G_{NG}}, T_1 ... T_{NT}, Q_{C_1} ... Q_{C_{NC}}] \quad (8)$$

Where *NT* and *NC* are the number of the regulating 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: Fuzzy based severity index (f_2)

$$f_1 = \min\left(\sum_{i=1}^{NG} (a_i P_{Gi}^2 + b_i P_{Gi} + C_i\right) \quad (9)$$

$$`f_2 = \text{Min J2=min(FLCC)} \quad (10)$$

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.

$$P_{Gi} - P_{Di} - \sum_{j=1}^{n} |V_i||V_j||Y_{ij}| \cos(\theta_{ij} - \delta_i + \delta_j) = 0 \quad (11)$$

$$Q_{Gi} - Q_{Di} + \sum_{j=1}^{n} |V_i||V_j||Y_{ij}| \sin(\theta_{ij} - \delta_i + \delta_j) = 0 \quad (12)$$

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

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max}, i = 1, \ldots, N_G \quad (13)$$

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max}, i = 1, \ldots, N_G \quad (14)$$

2) Voltage magnitudes at each bus in the network

$$V_i^{\min} \le V_i \le V_i^{\max}, i = 1, \ldots, NL \quad (15)$$

3) transformer tap settings

$$T_i^{\min} \le T_i \le T_i^{\max}, i = 1, \ldots, NT \quad (16)$$

4) reactive power injections due to capacitor banks

$$Q_{Ci}^{\min} \le Q_{Ci} \le Q_{Ci}^{\max}, i = 1, \ldots, CS \quad (17)$$

5) Transmission lines loading

$$S_i \le S_i^{\max}, i = 1, \ldots, nl \quad (18)$$

6) Voltage stability index

$$Lj_i \le Lj_i^{\max}, i = 1, \ldots, NL \quad (19)$$

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

$$OF = \sum_{i=1}^{N} F_i(P_{Gi}) + K_p h(P_{G1}) + K_q \sum_{i=1}^{N} h(Q_{Gi}) + K_v \sum_{i=1}^{NL} h(|V_i|) + K_s \sum_{i=1}^{NL} h(|S_i|) \quad (20)$$

defined as:

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:

$$h(x) = (x - x_{\max})^2 \text{, if } x > x_{\max}$$
$$= (x_{\min} - x)^2 \text{, if } x < x_{\min} \qquad (21)$$
$$= 0 \quad \text{, if } x_{\min} \le x \le x_{\max}$$

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. **I**n 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
Step3: 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.
Step4: For each individual in the archive, run power flow under selected contingency 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.
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 EP/PSO operators to generate new k individuals
Step10: 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.
Step11: Evaluate the penalty functions
Step12: Evaluate the objective function values and the corresponding fitness values for each new individual.
Step13: Apply the selection operator of EP/PSO and update the individuals.
Step14: Update the generation local best **xlocal** and global best **xglobal** and store them.
Step15: If one of stopping criterion have not been met, repeat steps 4-15. Else go to step 16
Step16: 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 = Genmax) 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 30-bus test systems. The EP and PSO parameters used for the simulation are summarized in below table.

Table 1: Optimal parameter settings for EP and PSO

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

The table 2 presents the optimal settings of the control variables with the two 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.

Table 2: Optimal Settings of Control Variables under selected contingency

Control Variable	COST		Fuzzy based severity index	
	EP	PSO	EP	PSO
Pg1	1.7292	1.7169	1.4126	1.0911
Pg2	0.4806	0.4714	0.2	0.5332
Pg3	0.2637	0.2707	0.2696	0.2788
Pg4	0.1494	0.1411	0.2488	0.2213
Pg5	0.2486	0.2579	0.4991	0.5008
Pg6	0.12	0.1274	0.2942	0.2886
Qg1	-0.1086	-0.2	0.2359	0.2338
Qg2	0.1153	0.1913	-0.0987	-0.1561
Qg3	0.4869	0.0649	0.2953	0.1219
Qg4	0.1574	0.3162	0.1034	0.1791
Qg5	0.3072	0.1466	0.2822	0.1511
Qg6	0.0166	0.3357	0.0023	0.0093
Qsvc1	0.0784	0.0144	0	0.0247
Qsvc2	0.0167	0.0286	0.0631	0.0336
Qsvc3	0.0846	0.0448	0.0669	0.0408
Qsvc4	0.1	0.05	0.0727	0.0191
Qsvc5	0.0553	0.0374	0.0451	0.05
Qsvc6	0.0074	0.05	0.0459	0.0288
Qsvc7	0.0573	0.05	0.0465	0.0184
Qsvc8	0.0606	0.05	0.067	0.0243
Qsvc9	0.0794	0.0391	0.0856	0.0423
tap1	0.9877	1.0392	1.0436	1.0447
tap2	1.0648	0.9548	0.9311	0.9964
tap3	1.0103	1.0379	1.0278	0.9432
tap4	0.99	0.9719	0.9729	0.9666
V1	1.05	0.9857	1.05	1.0578
V2	1.0373	1.0482	1.0241	1.0212
V3	1.0192	1.0261	0.9985	1.0127
V4	1.0565	1.1	1.0054	1.0124
V5	0.9591	0.9774	0.9664	0.988
V6	1.0126	1.0933	0.9903	1.0194
COST	827.5017	826.3019	898.6594	896.5202
Fuzzy based severity index	0.1618	0.1581	0.1336	0.132

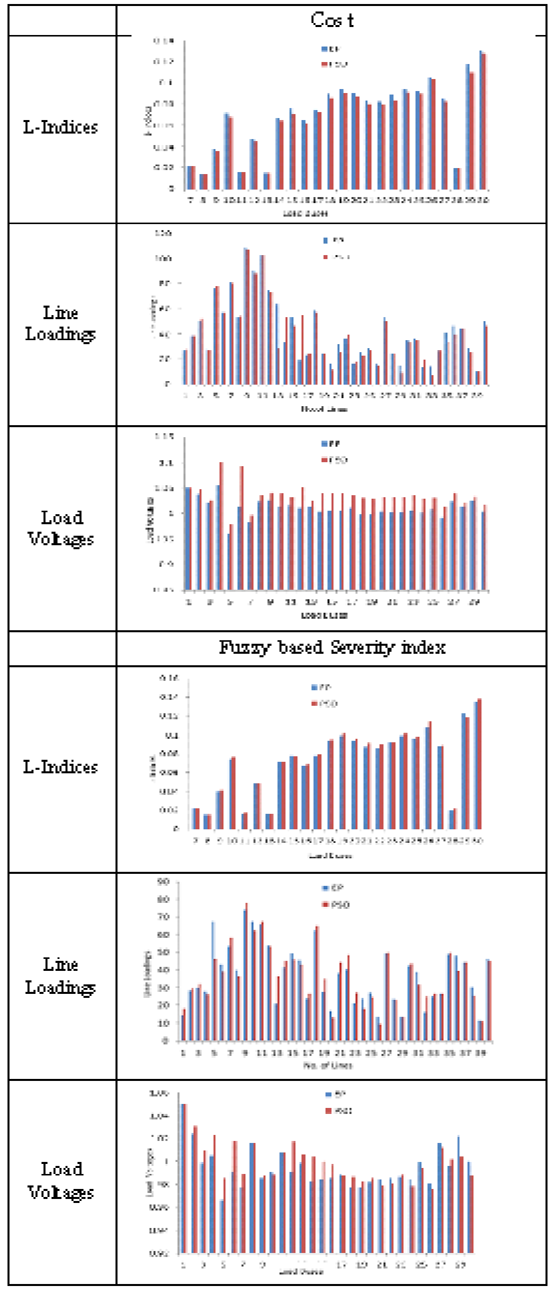

Fig 2: L-indices, Line loadings and Load voltages of 30bus by EP and PSO for two objective functions

Figures 2 shows the percentage line loadings, load bus voltages and voltage stability indices after the optimization by EP and PSO methods with the two objective functions under the selected network contingency condition. From the Figures 2 it can be observed that line flows are within their permissible limits during minimization of fuzzy based objective function. But line flow violations are observed during minimization of objective function-1(cost of generation) even though cost of generation has been decreased considerably when compared with fuzzy based 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 fuzzy based network security. Simulation studies have been carried out for the optimal solutions of the IEEE 30-bus system. 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.

References

[1] Kennedy J, Eberhart R. "Particle swarm optimization" Proceedings of IEEE International Conference on Neural Networks (ICNN'95) Perth, Australia: IEEE Press; 1995 Vol. IV. p. 1942–1948.

[2] Shi Y, Eberhart R. "A modified particle swarm optimizer" Proceedings of IEEE International Conference on Evolutionary Computation (ICEC'98). Anchorage: IEEE Press; 1998. p. 69–73.

[3] Shi Y, Eberhart R. "Parameter selection in particle swarm optimization" Proceedings of the 1998 Annual Conference on Evolutionary Programming. San Diego: MIT Press;1998.

[4] Fukuyama Y. et al. "A particle swarm optimization for reactive power and voltage control considering voltage security assessment". IEEE Trans Power Systems 2000; 15(4):1232–1239.

[5] Naka S, Genji T, Yura T, Fukuyama Y. "A hybrid particle swarm optimization for distribution state estimation" IEEE Trans Power Systems 2003; 18(1):60–68.

[6] IEEE Special Publication 90TH 0358-2PWR, "Voltage Stability of Power Systems: Concepts, Analytical Tools and Industry Experience", The IEEE Working Group on Voltage Stability, 1990.

[7] A J Wood and B F Wollenberg, "Power generation operation and control", John Wiley and Sons Inc.Singapore, 1984.

[8] Brian Stott, Ongun Alsac, and Alcir J. Monticelli, "Security analysis and optimization", Proc. of IEEE, Vol.75, No.12, December 1987, pp.1623-1644.

[9] Parker, C.J., I. F Morrison, and D. Sutanto, "Application of an optimization method for determining the reactive margin from voltage collapse in reactive power planning", IEEE.Trans. on Power Systems, Vol.11, No. 3, August 1996, pp.1473-1481.

[10] Venikov, V.A., V.A Stroev, V.I. Idelchick, and V.I. Tarasov, "Estimation of electric power system steady state Stability in load flow calculations", IEEE Trans. on PAS, Vol.PAS-94, No.3, May/June 1975, pp.1034-1040.

D.Raga Leela[1] pursued M.Tech in power systems. Currently working as Sr.Assistant Professor in the Department of E.E.E, Prasad.v. Potluri Siddhartha Institute of Technology, Vijayawada.A.P.

Sairam Mannem received B.Tech degree in Electrical and Electronics Engineering from JNTU Hyderabad in the year 2008, presently pursuing M.Tech in Power system control and Automation in Prasad.V.Potluri Siddhartha Institute of Technology, Vijayawada.A.P.

Dr. Ch. Padmanabha Raju B.E, M.Tech (Power Systems), Ph.D., He has Published several National and International Journals and Conferences. Currently he is working as a professor in the Department of E.E.E, Prasad.V.Potluri Siddhartha institute of technology, Vijayawada. A.P.