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Enhanced Genetic Algorithm based computation technique for multi-objective Optimal Power Flow solution

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ABSTRACT

Optimal Power Flow (OPF) is used for developing corrective strategies and to perform least cost dispatches. In order to guide the decision making of power system operators a more robust and faster OPF algorithm is needed. OPF can be solved for minimum generation cost, that satisfies the power balance equations and system constraints. But, cost based OPF solutions usually result in unattractive system losses and voltage profiles. In the present paper the OPF problem is formulated as a multi-objective optimization problem, where optimal control settings for simultaneous minimization of fuel cost and loss, loss and voltage stability index, fuel cost and voltage stability index and finally fuel cost, loss and voltage stability index are obtained. The present paper combines a new Decoupled Quadratic Load Flow (DQLF) solution with Enhanced Genetic Algorithm (EGA) to solve the OPF problem. A Strength Pareto Evolutionary Algorithm (SPEA) based approach with strongly dominated set of solutions is used to form the pareto-optimal set. A hierarchical clustering technique is employed to limit the set of trade-off solutions. Finally a fuzzy based approach is used to obtain the optimal solution from the tradeoff curve. The proposed multi-objective evolutionary algorithm with EGA–DQLF model for OPF solution determines diverse pareto optimal front in just 50 generations. IEEE 30 bus system is used to demonstrate the behavior of the proposed approach. The obtained final optimal solution is compared with that obtained using Particle Swarm Optimization (PSO) and Fuzzy satisfaction maximization approach. The results using EGA–DQLF with SPEA approach show their superiority over PSO–Fuzzy approach.

1. Introduction

Optimal Power Flow (OPF) was first discussed by Carpentier in 1962 [1]. In the past two decades, OPF problem has received much attention, because of its ability to solve for the optimal solution that takes account of the security of the system. OPF is important software in Energy Management Systems (EMS).

OPF is a nonlinear, non-convex, large-scale, static optimization problem with both continuous and discrete control variables [2]. Even in the absence of discrete control variables, the OPF problem is non-convex due to the existence of the nonlinear (AC) power flow equality constraints.

To guide the decision making of the power system operator, the OPF solution should not be sensitive to selected starting points. Complexity of OPF problem must be reduced. OPF programs must be user friendly. Therefore, there is a need for more robust and faster OPF algorithm.

OPF can be used periodically to determine the optimal settings of the control variables to minimize the generation cost, minimization of losses in the transmission system. For a secure operation of the power system, it is also important to maintain required level of security margin. Therefore, the security indices related to bus voltage magnitudes can be derived and optimal control settings to minimize the security indices can also be determined.

When an optimization problem involves more than one objective function, the task of finding one or more optimum solutions is known as multi-objective optimization [3]. Since classical search and optimization algorithms use a point by point approach, the outcome of using a classical approach is a single optimized solution.

Evolutionary Algorithms (EA) such as Genetic Algorithms (GA) have become the method of choice for optimization problems that are too complex to be solved using deterministic techniques such as linear programming or gradient (Jacobian) methods. Because of their universality, ease of implementation, and fitness for parallel computing, EAs often take less time [4] to find the optimal solution than gradient methods. However, most real world problems involve simultaneous optimization of several often mutually concurrent objectives. Multi-objective EAs are able to find optimal trade-offs in order to get a set of solutions that are optimal in an overall sense. However, multi-objective EAs inherit all of the favorable properties from their single objective relatives.

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GAs has been successfully applied for solution of OPF problem as single objective optimization approaches [2], [5], [6]. Ref. [2] presents an Enhanced Genetic Algorithm (EGA) for solution of OPF. Particle Swarm Optimization (PSO) is also used to solve OPF [7] with different objectives that reflect fuel cost minimization and Voltage profile improvement. But the problem used the weighted sum of the objectives.

For multi-objective optimization the preference based approach requires multiple runs as many times as the number of desired optimal solutions. Ref. [8] presents a multi-objective Strength Pareto Evolutionary Algorithm (SPEA) for Optimal VAR dispatch problem considering simultaneous optimization of system transmission loss and bus voltage deviations.

In the present paper multi-objective optimization of three conflicting objectives: (i) generation costs (ii) system transmission loss and (iii) system voltage stability index is considered. OPF problem is formulated as simultaneous minimization of: (i) system generation cost and transmission loss (ii) generation cost and voltage stability index (iii) system transmission loss and voltage stability index and (iv) fuel cost, loss and voltage stability index. Enhanced Genetic Algorithm with Decoupled Quadratic Load Flow [12] solution is used to solve OPF. A Strength Pareto Evolutionary Algorithm (SPEA) [3] with strong-dominated solutions is used to form the pareto optimal set. A fuzzy based approach [8] is used to extract the best compromise solution from the tradeoff front. IEEE 30 bus system is considered to demonstrate the multi-objective optimization approach. Different cases have been studied with different combinations of above mentioned three objectives and the best compromise solution is reported.

2. Problem formulation

The Optimal Power Flow (OPF) problem is to optimize the settings of control variables in terms of one or more objective functions while satisfying several equality and inequality constraints. In multi-objective OPF we have two or more objective functions to be optimized at the same time. As a consequence, there is no unique solution to multi-objective optimization problems, but we aim to find all of the trade-off solutions available (called as pareto-optimal set). The problem can be formulated as:

$$\text{Minimize } J_i(x,u) \quad i = 1,\ldots,N_{\text{obj}} \tag{1}$$

$$\text{Subjected to}: g(x,u) = 0 \tag{2}$$

$$h(x,u) \le 0 \tag{3}$$

where J_i is the ith objective function, and N_{obj} is the number of objectives. g is the equality constraints, represent the nonlinear power flow equations. h is the system operating constraints that include functional operating constraints and limits on control variables. 'x' is the vector of dependent variables consisting of load bus voltage magnitude limits, reactive capabilities of generators, slack bus active power and branch flow limits.

$$X^T = [V_{L1}\ldots V_{\text{LNL}}, Q_{G1}\ldots Q_{\text{GNG}}, P_{\text{Gslack}}, S_{L1}\ldots S_{L\text{nl}}] \tag{4}$$

where NL, NG and nl are number of load buses, number of generator buses and number of transmission lines, respectively.

u is the vector of control or independent variables consisting of generator-bus voltage magnitudes, active power generations, transformer-tap settings and reactive shunt compensators.

$$U^T = [V_{G1}\ldots V_{\text{GNG}}, P_{G2}\ldots P_{\text{GNG}}, T_1\ldots T_{\text{NT}}, Q_{c1}\ldots Q_{\text{cNC}}] \tag{5}$$

where NT and NC are the number of regulating transformers and shunt compensators, respectively.

The minimization function (objective function) can take different forms.

2.1. Objective functions

2.1.1. Case 1: generation cost or fuel cost (FC)

$$J = \sum_{i=1}^{\text{NG}} F_i \tag{6}$$

$$F_i = a_i + b_i P_{\text{G}i} + c_i P_{\text{G}i}^2 \tag{7}$$

where a_i, b_i, c_i are cost coefficients of unit i, $P_{\text{G}i}$ is real power generation of unit 'i'.

2.1.2. Case 2: real power losses (PLoss)

$$J = \sum_{i=1}^{\text{nl}} \text{Loss}_i \tag{8}$$

where nl is the number of branches, Loss_i is the power loss in branch i. Power loss in each branch is calculated from the power flow solution using the active power flow through the line.

2.1.3. Case 3: voltage stability enhancement index (VSEI)

To monitor the voltage stability in power system L-index [9] of the load buses is considered. This L-index uses the information from a normal load flow and is in the range of 0 (no load of the system) to 1 (voltage collapse). The control against voltage collapse is based on minimizing the sum of squared L-indices (index) for a given system operating condition.

$$J = \sum_{j=\text{NG}+1}^{n} L_j^2 \tag{9}$$

where NG is the number of generator buses, n is the total number of buses in the system.

$$L_j = \left| 1 - \sum_{i=1}^{\text{NG}} F_{ji} \frac{V_i}{V_j} \right| \quad j = \text{NG}+1,\ldots,n \tag{10}$$

All quantities with in the sigma in the RHS of (10) are complex quantities. The values F_{ji} are obtained from Y bus matrix. The L-indices for the given load condition are computed for all load buses and the maximum of L-indices gives the proximity of the system to voltage collapse.

2.1.4. The multi-objective OPF problem is defined as, simultaneous optimization of

Case 4: FC, PLoss
Case 5: FC, VSEI
Case 6: PLoss, VSEI and
Case 7: FC, PLoss, VSEI

2.2. Problem constraints

2.2.1. Equality constraints

These constraints are typical load flow equations

$$0 = P_{\text{G}i} - P_{\text{D}i} - V_i \sum_{j=1}^{n} V_j (G_{ij}\cos\delta_{ij} + B_{ij}\sin\delta_{ij}) \tag{11}$$

$$0 = Q_{\text{G}i} - Q_{\text{D}i} - V_i \sum_{j=1}^{n} V_j (G_{ij}\sin\delta_{ij} - B_{ij}\cos\delta_{ij}) \tag{12}$$

$i = 1\ldots n$. where n is the number of buses in the system. P_{Gi} and Q_{Gi} are active and reactive power generations at bus i, P_{Di} and Q_{Di} are corresponding active and reactive load demands. The present paper solves the equality constraints using a Decoupled Quadratic Load flow approach (DQLF), [11] which is proved to be very fast and reliable for well behaved and ill-conditioned power systems.

2.2.2. Inequality constraints

These constraints represent system operating limits.

(a) *Generator constraints*: generator voltage magnitudes V_G, Generator active power P_G and reactive power Q_G are restricted by their lower and upper limits.

$$V_{Gi}^{\min} \le V_G \le V_{Gi}^{\max}, \quad i = 1, \ldots, \mathrm{NG} \tag{13}$$

$$Q_{Gi}^{\min} \le Q_G \le Q_{Gi}^{\max}, \quad i = 1, \ldots, \mathrm{NG} \tag{14}$$

$$P_{Gi}^{\min} \le P_G \le P_{Gi}^{\max}, \quad i = 1, \ldots, \mathrm{NG} \tag{15}$$

(b) *Transformer constraints*: transformer taps have minimum and maximum setting limits.

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

(c) *Switchable VAR sources*: the switchable VAR sources have restrictions as follows

$$Q_{ci}^{\min} \le Q_{ci} \le Q_{ci}^{\max}, i = 1, \ldots, .NC \tag{17}$$

(d) *Security constraints*: these include the limits on the load bus voltage magnitudes and line flow limits.

$$V_{Li}^{\min} \le V_{Li} \le V_{Li}^{\max}, \quad i = 1, \ldots, \mathrm{NL} \tag{18}$$

$$S_{Li} \le S_{Li}^{\max}, \quad i = 1, \ldots, \mathrm{nl} \tag{19}$$

A penalty function [5] is added to the objective function, if the functional operating constraints violate any of the limits. The initial values of the penalty weights are considered as in [10].

3. Multi-objective optimization, strength Pareto Evolutionary Algorithm (SPEA)

EAs are heuristics that use natural selection as their search engine to solve problems. One of the emergent areas in which EAs have become increasingly popular is multi-objective optimization.

For a multi-objective optimization problem, any two solutions x^1 and x^2 can have one of the two possibilities-one dominates the other or none dominates the other. In a minimization problem x^1 is said to dominate x^2 if following two conditions are satisfied.

$$\forall i \in \{1, 2, \ldots, N_{\mathrm{obj}}\} : J_i(x^1) \le J_i(x^2) \tag{20}$$

$$\exists j \in \{1, 2, \ldots, N_{\mathrm{obj}}\} : J_j(x^1) < J_j(x^2) \tag{21}$$

If x^1 dominates x^2, x^1 is called the non-dominated solution. The solutions that are non-dominated with in the entire search space are called pareto-optimal set.

In the present paper a strong dominated set of solutions is used to form pareto-optimal set. The solution is a strong-dominated solution if the following condition is satisfied.

$$\forall j \in \{1, 2, \ldots, N_{\mathrm{obj}}\} : J_j(x^1) < J_j(x^2) \tag{22}$$

Zitzler and Thiele (1998) proposed an elitist evolutionary algorithm, called Strength Pareto EA (SPEA) [3]. The features of the algorithm are as follows:

1) This algorithm introduces elitism by explicitly maintaining an external population.
2) This external population stores a fixed number of solutions.
3) It uses a clustering technique on external population members to maintain the size of the external set.
4) SPEA also uses these elites to participate in the genetic operations along with current population.

3.1. Multi-objective SPEA algorithm

Step 1: Initialize a population of chromosomes '*N*' and create an empty external pareto-optimal set $\overline{N}$.

Step 2: Search the population for strong-dominated solutions and copy them to the external set.

Step 3: If the size of the external set exceeds its maximum size $\overline{N}$, apply hierarchical clustering technique to reduce the size to maximum size.

Step 4: Assign fitness (called strength) to population members and external set members using SPEA[3] fitness assignment technique. The strength of each external member is proportional to the number n_i of the current population members that an external member dominates.

$$S_i = \frac{n_i}{N+1} \tag{23}$$

The fitness of current population member *j* is assigned as one more than the sum of the strength values of all external members which weakly dominate *j*:

$$F_j = 1 + \sum_{i \in \mathrm{Paretoset} \wedge i \preceq j} S_i \tag{24}$$

This method of fitness assignment suggests that a solution with smallest fitness is better.

Step5: Combine the external population and the population members. Use the assigned fitness values, apply tournament selection, a crossover and mutation operator to create new population of size *N* from combined population.

Step6: Repeat steps 2–5 until stopping criterion is reached.

3.2. Best compromise solution

Upon having the pareto-optimal set of non-dominated solution, the proposed approach [8] presents a best compromise solution to the decision maker. Due to the imprecise nature of the decision maker's judgement, the *i*th objective function J_i is represented by a membership function μ_i defined as

$$\mu_i = \begin{cases} 1 & J_i \le J_i^{\min} frac J_i^{\max} - J_i J_i^{\max} - J_i^{\min} J_i^{\min} < J_i < J_i^{\max} \\ 0 & J_i \ge J_i^{\max} \end{cases} \tag{25}$$

where $J_i^{\max}$ and $J_i^{\min}$ are the maximum and minimum values of the *i*th objective function among all non-dominated solutions.

For each non-dominated solution *k*, the normalized membership function μ^k is calculated as

$$\mu^k = \frac{\sum_{i=1}^{\mathrm{Nobj}} \mu_i^k}{\sum_{k=1}^{M} \sum_{i=1}^{\mathrm{Nobj}} \mu_i^k} \tag{26}$$

where *M* is the number of non-dominated solutions. The best compromise solution is that having the maximum value of μ^k.

4. Multi-objective spea implementation

The OPF problem with different objectives is formulated as a multi-objective optimization problem. SPEA using EGA–DQLF model has been developed for simultaneous minimization of fuel cost and Transmission loss, fuel cost and voltage stability index and finally Transmission loss and voltage stability index. The developed SPEA uses population size of 200 chromosomes, and a pareto optimal set size of 30 chromosomes. A set of strong-dominated solutions is selected from a population of 200 chromosomes to form the pareto-optimal set. If the pareto set size exceeds maximum size, a hierarchical clustering technique is used to limit its size. Tournament selection is applied on the combined population members, and uniform crossover with a probability of 1.0 and mutation with a probability of 0.006 were used on all optimization runs. Maximum number of generations selected was 50.

5. PSO–Fuzzy satisfaction maximization approach

In order to validate the results obtained using EGA–DQLF–SPEA approach PSO–Fuzzy satisfaction maximization approach [13] is used. Various steps involved are presented in the flow chart shown in Fig. 1. The PSO parameters used are: Swarm size 60, Size of particle: 24, Maximum number of iterations: 100, acceleration constants C1 = C2 = 2.05, Inertia weight $w = 1.2$ and constriction factor 'χ' = 0.7295.

6. Results and discussions

The proposed approach is demonstrated on IEEE 30-bus, 41-branch system. The system data is taken from [5]. It has a total of 24 control variables as follows: Five unit active power outputs, six generator-bus voltage magnitudes, four transformer-tap settings, nine bus shunt admittances. The gene length for unit power outputs is 12 bits, generator voltage magnitude is eight bits, and they are both treated as continuous controls. The transformer-tap settings can take 17 discrete values, each one is encoded using five bits. The lower and upper limits are 0.9 p.u. and 1.1 p.u respectively, and the step size is 0.0125 p.u. The bus shunt admittances can take six discrete values, each one is encoded using three bits, the lower and upper limits are 0.0 and 0.05 p.u., respectively, and the step size is 0.01 p.u. (on system MVA basis). The lower and upper limits of load bus voltages are 0.95 and 1.05 p.u. respectively. The generator-bus voltage magnitude limits considered are 0.95 p.u and 1.1 p.u.

The problem is initially solved as single objective optimization and a comparison in the performance of the algorithms is made considering Simple Genetic Algorithms (SGA), Enhanced Genetic Algorithms (EGA) and Particle Swarm Optimization (PSO) techniques. It is observed that [12] Enhanced Genetic Algorithm (EGA) [2] with advanced and problem specific operators provides better optimal solution, both in terms of objective function values and convergence characteristics. Decoupled Quadratic Load Flow model (DQLF) [11] has been used for solution of equality constraints. String length of 155 bits, population size of 200 chromosomes was considered. Roulette wheel parent selection technique is used for reproduction. Uniform crossover with probability of 0.95, elitism index of 0.15, and mutation probability of 0.001 is used. However, for small population sizes ranging from 40 to 60, large mutation probabilities are recommended. The algorithm is stopped when all the population members assume similar fitness values. The results shown are the best values obtained over 20 runs.

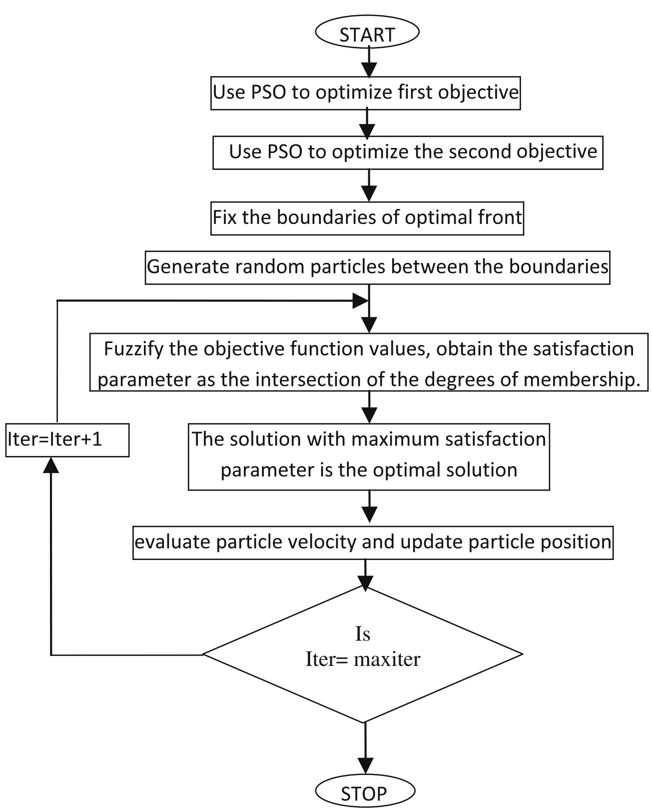

Fig. 1. Flow chart for PSO–Fuzzy satisfaction maximization approach.

Table 1 shows the control settings and objective function values for base case (without any optimization objective) and with single objective optimization using EGA–DQLF. In Tables 1–5, the bold values indicate the optimum value of the considered objective function for single objective and multi objective optimization cases.

Case 1: Minimization of fuel cost causes the system losses to increase to its maximum. The control settings corresponding to cost based OPF result in a reduction of 11.45% in fuel costs but causes the system losses to increase by 40.77% of base case values. The system stability index is reduced by 51.74%.

Case 2: Minimization of loss as objective in OPF results in reduction of 48.19% in losses, but the generation cost increased by 7.19% over the base case. The voltage stability index is reduced by 47.05%.

Case 3: Control settings based on Stability enhancement as objective in OPF results in a reduction of 54.78% in stability index, but results in loss reduction of only 1.39%. The fuel costs experience slight variation. Therefore, cost based OPF solutions are not attractive solutions from system stability or loss minimization point of view. Therefore such optimization objectives cannot be treated independently.

For Multi-objective SPEA with a population of 200 chromosomes and Pareto set size of 30 was considered for the study.

Table 1
Control variables for base case and single objective optimization.

Control variable	Base case	EGA–DQLF		
		Case 1	Case 2	Case 3
P_{G2} (MW)	80.0	48.11	80	79.94
P_{G5} (MW)	50.0	21.28	50	50
P_{G8} (MW)	20.0	20.93	35	35
P_{G11} (MW)	20.0	12.5	30	10.31
P_{G13} (MW)	20.0	12.0	40	12.0
$V_{G1(p.u.)}$	1.0	1.1	1.0435	1.0618
$V_{G2(p.u.)}$	1.0	1.081	1.04353	1.053
$V_{G5(p.u.)}$	1.0	1.053	1.02470	1.053
$V_{G8(p.u.)}$	1.0	1.062	1.03470	1.014
$V_{G11(p.u.)}$	1.0	1.095	1.07	1.0258
$V_{G13(p.u.)}$	1.0	1.088	1.043	1.046
$T_{6,9(p.u.)}$	1.0	0.95	1.0375	0.9125
$T_{6,10(p.u.)}$	1.0	1.0375	0.925	0.9
$T_{4,12(p.u.)}$	1.0	1.0	0.975	0.9
$T_{28,27(p.u.)}$	1.0	0.9750	0.975	0.925
$b_{sh10(p.u.)}$	0.00	0.04	0.05	0.0
$b_{sh12(p.u.)}$	0.00	0.02	0.03	0.0
$b_{sh15(p.u.)}$	0.00	0.05	0.0	0.0
$b_{sh17(p.u.)}$	0.00	0.0	0.01	0.03
$b_{sh20(p.u.)}$	0.00	0.02	0.04	0.02
$b_{sh21(p.u.)}$	0.00	0.04	0.02	0.05
$b_{sh23(p.u.)}$	0.00	0.04	0.05	0.02
$b_{sh24(p.u.)}$	0.00	0.03	0.05	0.05
$b_{sh29(p.u.)}$	0.00	0.01	0.05	0.03
FC ($/h)	902.9	**799.56**	967.86	898.817
Loss (MW)	6.178	8.697	**3.2008**	6.092
VSEI	0.230	0.111	0.12178	**0.10402**

The fuzzy approach explained in III.B presents a best compromise solution to the operator from the obtained pareto optimal front.

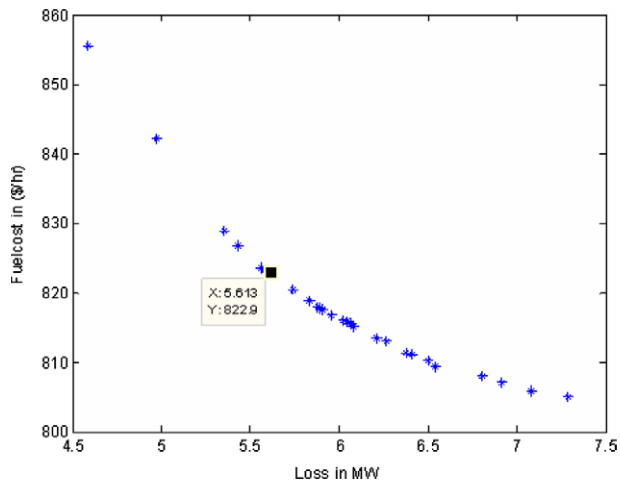

Fig. 2. Pareto optimal front of loss and fuel cost.

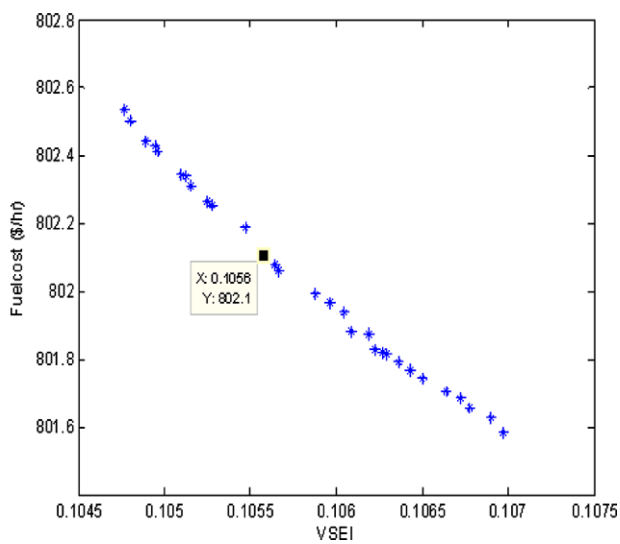

Fig. 3. Pareto optimal front of index and fuel cost.

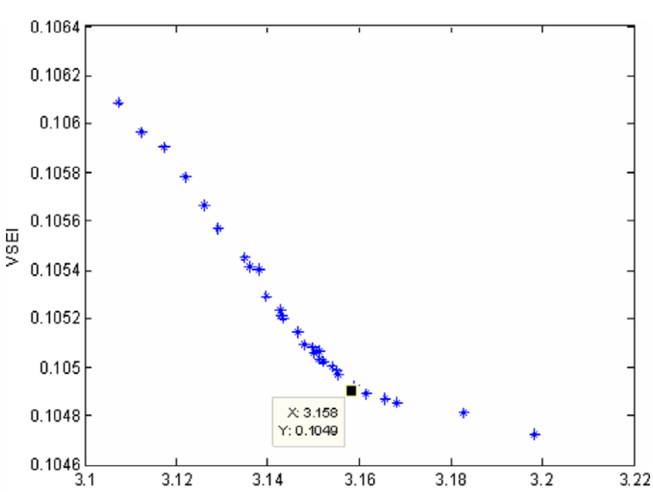

Fig. 4. Pareto optimal front loss and index.

Case 4: Fuel cost and loss minimization:

Fig. 2 shows the pareto optimal front for fuel cost and loss minimization. The best compromise solution obtained is 822.9$/h and 5.613 MW, which shows 8.9% reduction in FC and 9.15% reduction in losses.

Case 5: Fuel cost and index minimization:

Fig. 3 shows the pareto optimal front obtained with fuel cost and voltage stability Index minimization. The best compromise solution obtained is 802.06$/h and 0.10567, which shows 11.2% reduction in fuel cost and 54% reduction in index. The fuel cost and Index both are very close to the optimized values using single objective optimization.

Case 6: Loss and index minimization:

Fig. 4 shows the pareto optimal front obtained for loss and Index minimization. The best compromise solution obtained is 3.158 MW and 0.10490, which shows 48.9% reduction in loss and 54.4% reduction in index. The best compromise solution is almost

Table 2
Control variables for best compromise solution using multi-objective SPEA with strong dominated sorting.

Control variable	Case 4	Case 5	Case 6	Case 7
$P_{G2(MW)}$	49.5	48.586	79.98	48.55
$P_{G5(MW.)}$	30.06	21.33	49.96	41.11
$P_{G8(MW)}$	34.98	21.55	34.95	34.0
$P_{G11(MW)}$	23.96	12.13	30	20.95
$P_{G13(MW)}$	21.374	12.00	39.96	12.19
$V_{1(p.u.)}$	1.096	1.1	1.1	1.1
$V_{2(p.u.)}$	1.0806	1.096	1.1	1.0994
$V_{5(p.u.)}$	1.058	1.077	1.0865	1.0806
$V_{8(p.u.)}$	1.065	1.0917	1.1	1.1
$V_{11(p.u.)}$	1.053	1.1	1.1	1.1
$V_{13(p.u.)}$	1.094	1.1	1.0994	1.1
$T_{6,9(p.u.)}$	0.9875	0.925	0.9125	0.9125
$T_{6,10(p.u.)}$	0.9625	0.9	0.9125	0.9
$T_{4,12(p.u.)}$	1.0125	0.9	0.9	0.9
$T_{28,27(p.u.)}$	1.0125	1.0125	1.0125	1.0125
$b_{sh10(p.u.)}$	0.04	0.03	0.03	0.03
$b_{sh12(p.u.)}$	0.03	0.03	0.05	0.01
$b_{sh15(p.u.)}$	0.0	0.01	0.05	0.02
$b_{sh17(p.u.)}$	0.04	0.02	0.0	0.04
$b_{sh20(p.u.)}$	0.05	0.03	0.02	0.03
$b_{sh21(p.u.)}$	0.05	0.01	0.01	0.02
$b_{sh23(p.u.)}$	0.03	0.05	0.02	0.02
$b_{sh24(p.u.)}$	0.05	0.04	0.05	0.02
$b_{sh29(p.u.)}$	0.05	0.04	0.02	0.03
FC ($/h)	**822.87**	**802.06**		**844.5**
Loss(MW)	**5.613**		**3.1581**	**5.69**
VSEI		**0.1056**	**0.1049**	**0.1084**

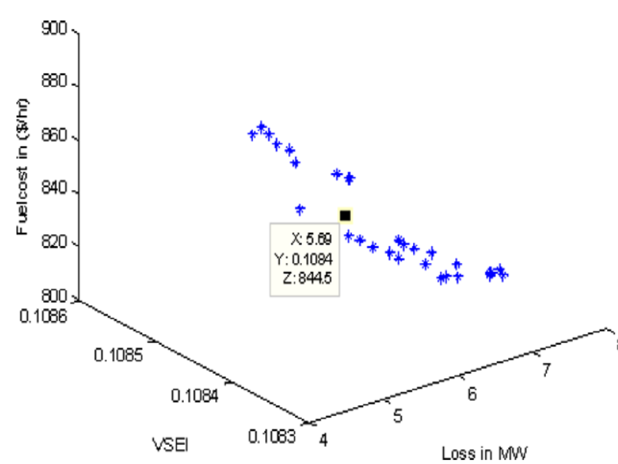

Fig. 5. Pareto optimal front of three objective minimization.

Table 3
Comparison of OPF control variables for single objective optimization using PSO.

Control variable	Base case	Case 1 PSO	Case 2 PSO	Case 3 PSO
$P_{G2(\mathrm{MW})}$	80.0	48.706	79.06	55.0
$P_{G5(\mathrm{MW})}$	50.0	22.21	50	37.858
$P_{G8(\mathrm{MW})}$	20.0	23.93	35	29.02
$P_{G11(\mathrm{MW})}$	20.0	12.58	29.53	19.586
$P_{G13(\mathrm{MW})}$	20.0	12.0	36.134	16.92
$V_{G1(\mathrm{p.u.})}$	1.0	1.0	1.0	1.00
$V_{G2(\mathrm{p.u.})}$	1.0	0.989	0.996	1.034
$V_{G5(\mathrm{p.u.})}$	1.0	0.966	0.978	1.046
$V_{G8(\mathrm{p.u.})}$	1.0	0.973	0.98	1.02
$V_{G11(\mathrm{p.u.})}$	1.0	1.062	1.032	1.0117
$V_{G13(\mathrm{p.u.})}$	1.0	1.0708	1.0415	1.0528
$T_{6,9(\mathrm{p.u.})}$	1.0	0.9	0.9	0.9
$T_{6,10(\mathrm{p.u.})}$	1.0	0.9625	1.0	0.95
$T_{4,12(\mathrm{p.u.})}$	1.0	0.9625	0.95	0.925
$T_{28,27(\mathrm{p.u.})}$	1.0	0.9	0.9375	0.925
$b_{sh10(\mathrm{p.u.})}$	0.00	0.04	0.05	0.04
$b_{sh12(\mathrm{p.u.})}$	0.00	0.04	0.05	0.04
$b_{sh15(\mathrm{p.u.})}$	0.00	0.04	0.03	0.03
$b_{sh17(\mathrm{p.u.})}$	0.00	0.02	0.04	0.05
$b_{sh20(\mathrm{p.u.})}$	0.00	0.05	0.05	0.01
$b_{sh21(\mathrm{p.u.})}$	0.00	0.01	0.02	0.04
$b_{sh23(\mathrm{p.u.})}$	0.00	0.03	0.02	0.02
$b_{sh24(\mathrm{p.u.})}$	0.00	0.05	0.06	0.04
$b_{sh29(\mathrm{p.u.})}$	0.00	0.02	0.04	0.01
FC ($/h)	**902.923**	**802.19**	956.45	837.06
Loss (MW)	6.1787	10.083	**3.6294**	8.8209
VSEI	0.230974	0.12256	0.1286	**0.11055**

Table 4
Optimal objective function values and control variables for multi-objective optimization using PSO and fuzzy satisfaction maximization approach.

Control variable	Case 4	Case 5	Case 6	Case 7
$P_{G2(\mathrm{MW})}$	59.88	47.283	53.94	66.56
$P_{G5(\mathrm{MW})}$	34.62	21.387	47.66	29.8
$P_{G8(\mathrm{MW})}$	33.40	18.8	25.08	27.42
$P_{G11(\mathrm{MW})}$	30.0	14.53	24.87	21.59
$P_{G13(\mathrm{MW})}$	23.56	20.67	34.81	24.27
$V_{G1(\mathrm{p.u.})}$	1.000	1.0	1.0	1.01
$V_{G2(\mathrm{p.u.})}$	0.996	1.017	1.007	1.006
$V_{G5(\mathrm{p.u.})}$	0.979	1.024	0.998	0.993
$V_{G8(\mathrm{p.u.})}$	0.989	1.045	1.018	1.015
$V_{G11(\mathrm{p.u.})}$	1.0535	1.069	1.0362	1.083
$V_{G13(\mathrm{p.u.})}$	1.0302	1.083	1.06	1.0574
$T_{6,9(\mathrm{p.u.})}$	0.9	0.9	0.9	0.9
$T_{6,10(\mathrm{p.u.})}$	1.0125	0.95	0.9	0.9625
$T_{4,12(\mathrm{p.u.})}$	0.9625	0.9	0.9	0.9
$T_{28,27(\mathrm{p.u.})}$	0.9625	0.9375	0.9625	0.9325
$b_{sh10(\mathrm{p.u.})}$	0.01	0.03	0.04	0.04
$b_{sh12(\mathrm{p.u.})}$	0.03	0.04	0.05	0.03
$b_{sh15(\mathrm{p.u.})}$	0.04	0.03	0.03	0.02
$b_{sh17(\mathrm{p.u.})}$	0.06	0.02	0.04	0.05
$b_{sh20(\mathrm{p.u.})}$	0.02	0.05	0.04	0.05
$b_{sh21(\mathrm{p.u.})}$	0.06	0.05	0.02	0.04
$b_{sh23(\mathrm{p.u.})}$	0.02	0.04	0.03	0.05
$b_{sh24(\mathrm{p.u.})}$	0.03	0.03	0.05	0.03
$b_{sh29(\mathrm{p.u.})}$	0.04	0.03	0.05	0.01
FC ($/h)	**847.011**	**809.79**		**836.96**
Loss (MW)	**5.6658**		**5.5779**	**7.2207**
VSEI		**0.1146**	**0.1140**	**0.10910**

close to the optimized values with single objective approach. The minimum loss obtained is less than what is obtained in case 2. Observation of the Tables 1 and 2 reveal the fact that, a better system voltage profile (at generator buses and also at load buses) is observed when the index and loss are minimized simultaneously, than in loss minimization case alone. However, the reduction in loss and increase in index from the single objective optimization case are marginal. The results and corresponding control settings are shown in Table 2.

Case 7: Fuel cost, loss and index minimization:

With simultaneous minimization of all the objectives fuel cost is reduced by 6.46%, the transmission loss is reduced by 7.89% and voltage stability index is reduced by 52.8% from the base case values. Fig. 5 shows the optimized pareto optimal front. The optimized objective function values and corresponding control settings are shown in Table 2.

Now Particle Swarm Optimization (PSO) is used to solve OPF as a single objective optimization problem. Table 3 presents the optimal control settings and objective function values obtained when OPF is treated as single objective optimization problem.

Multi-objective OPF is then solved using PSO–Fuzzy satisfaction maximization approach. The results obtained are presented in Table 4. Table 5 provides comparison between the results obtained with EGA–DQLF–SPEA and PSO–Fuzzy approaches.

The results reveal that SPEA using EGA–DQLF model provides better optimal solution compared to PSO–Fuzzy approach for multi-objective OPF solution.

7. Conclusions

The purpose of the OPF is to calculate recommended set points for power system controls that are a tradeoff between security and economy. Optimizing the network for costs alone will result in increased system losses. Because all the optimization objectives are inter related, system controls cannot be recommended based on individual optimizations alone. In the present paper an attempt is made to simultaneously optimize all the conflicting objectives, and suggest the power system operator a set of controls which are the best compromise controls with respect to all the objectives. System voltage stability index, (L-index) has been formulated as an objective and sum squared L-indices is minimized to improve system stability margin. Multi-objective SPEA has been successfully applied on the three conflicting objectives. EGA with new DQLF algorithm is proposed to determine optimal control settings. Further, SPEA is implemented considering strong-dominated solutions. The algorithm presents a diverse pareto-optimal set in just 50 generations.

SPEA using EGA–DQLF provides a better optimal solution when compared to PSO–Fuzzy satisfaction maximization approach. The proposed algorithm can act as decision supporting tool for power system operators. Though the paper concentrated on the steady state network cost, loss and voltage stability index minimization, the dynamic and transient stability constraints can also be included into the multi-objective optimization problem and can be taken up as future work.

Table 5
Comparison of best compromise solution obtained using SPEA EGA–DQLF and PSO–Fuzzy approaches for multi-objective optimization.

	FC & Loss		FC & VSEI		Loss & VSEI		FC, Loss & VSEI		
	FC ($/h)	Loss (MW)	FC ($/h)	VSEI	Loss (MW)	VSEI	FC ($/h)	Loss (MW)	VSEI
SPEA using EGA–DQLF	**822.9**	**5.613**	**802.06**	**0.1057**	**3.158**	**0.1049**	**844.5**	**5.69**	**0.1084**
PSO–Fuzzy	847.01	5.666	809.79	0.1146	5.578	0.1140	836.96	7.22	0.1091

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