

Fuzzy ranking based non-dominated sorting genetic algorithm-II for network overload alleviation

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Abstract: This paper presents an effective method of network overload management in power systems. The three competing objectives 1) generation cost 2) transmission line overload and 3) real power loss are optimized to provide pareto-optimal solutions. A fuzzy ranking based non-dominated sorting genetic algorithm-II (NSGA-II) is used to solve this complex nonlinear optimization problem. The minimization of competing objectives is done by generation rescheduling. Fuzzy ranking method is employed to extract the best compromise solution out of the available non-dominated solutions depending upon its highest rank. N-1 contingency analysis is carried out to identify the most severe lines and those lines are selected for outage. The effectiveness of the proposed approach is demonstrated for different contingency cases in IEEE 30 and IEEE 118 bus systems with smooth cost functions and their results are compared with other single objective evolutionary algorithms like Particle swarm optimization (PSO) and Differential evolution (DE). Simulation results show the effectiveness of the proposed approach to generate well distributed pareto-optimal non-dominated solutions of multi-objective problem.

Key words: non-dominated sorting genetic algorithm, generation rescheduling, particle swarm optimization, differential evolution, overload index

1. Introduction

Overloading in an electrical power system may occur due unexpected contingencies such as outage of lines, transformers, generators and sudden increase of load demand or failure of equipments. These overloads can be relieved through rescheduling the power outputs of generators, use of phase shifting transformers, switching the transmission network and load shedding. In general, power dispatch is a nonlinear programming problem. It is classified into

two parts namely real and reactive power dispatch. The reactive power dispatch in a system helps to reduce the overload more effectively but it cannot always be delivered from a source to an electrically remote sink. The real power dispatch is the most widely used control for network overload alleviation because of ease of control and require no additional reserves.

Optimal power flow (OPF) is an important tool for power system management. The aim of OPF problem is to optimize one or more objectives by adjusting the power system control variables while satisfying a set of physical and operating constraints such as generation and load balance, bus voltage limits, power flow equations, and active and reactive power limits. A variety of optimization techniques have been applied to solve the OPF problem such as gradient method [1], linear programming method [2] and interior point method. In conventional optimization methods, identification of global minimum is not possible. To overcome the difficulty, evolutionary algorithms like genetic Algorithm [3], particle swarm optimization [4], differential evolution [5], gravitational search algorithm [6], harmony search method [7] and artificial bee colony optimization [8] have been proposed.

In literature, several approaches have been proposed to alleviate the transmission line overloads in an electric power system. In [9], the authors' proposed a fuzzy logic based approach to alleviate the network overloads by generation rescheduling. The generation shift sensitivity factor (GSSF) was used to decide the changes in generation. The approach removes the overloaded lines in the considered test cases but could not remove the overload completely. In [10], the authors' proposed a static security enhancement through optimal utilization of thyristor-controlled series capacitors (TCSC). The ranking the system branches was based on determination of single contingency sensitivity (SCS) index which helps to decide on the best locations for the TCSCs. The objective of the optimization problem was to eliminate or minimize line overloads as well as the unwanted loop flows under single contingencies. In [11], the authors' proposed, the use of genetic algorithm (GA) and multi-objective genetic algorithm (MOGA) to alleviate the violations of the overloaded lines and minimize the transmission power losses for different operating conditions. In [12], the authors' proposed, multi-objective particle swarm optimization (MOPSO) method for transmission line overload management. The two competing objectives were considered for minimization such as line overloads and operating cost of generators. The overloads in a transmission network were alleviated by generation rescheduling. In [13], the authors' proposed a fuzzy particle swarm optimization (FPSO) based congestion management by optimal rescheduling of active powers of generators. The generators had been chosen based on the generator sensitivity to the congested line. The results were compared with fitness distance ratio particle swarm optimization (FDRPSO) and conventional PSO. In [14], the authors' proposed, graphical user interface (GUI) based on a genetic algorithm to determine the optimal location and sizing parameters of multi type FACTS devices for maximization of power system loadability in a transmission network. In [15], the authors' proposed an application of DEPSO algorithm to solve the maximum loadability problem. The results were compared with multi agent hybrid particle swarm optimization (MAHPSO) and differential evolution (DE). The algorithm improves the loadability margin with less number of iterations by consuming more time per iteration when compared to other algorithms.

In this paper, a fuzzy ranking based non-dominated sorting genetic algorithm-II for overload management in power system network is presented with illustrated example.

The organization of the paper is as follows: Section 2 presents the optimization problem formulation for transmission line management. Sections 3, 4, 5 and 6 explain the overview of PSO, DE, NSGA-II and Fuzzy ranking method. In section 7 the algorithm of proposed NSGA-II in solving the network overload alleviation is presented. The simulation results for different contingency cases in IEEE 30 and IEEE 118 bus systems are presented in section 8. Finally, conclusions are given in Section 9.

2. Problem formulation

The objective function of the proposed method is to find an optimum value of shift in active power generation along with network constraints so as to minimize the total generation cost, transmission line overload and real power loss simultaneously in the network. The problem of proposed algorithm may be stated as follows.

2.1. Objective functions

Objective 1 Minimize total generation cost

$$GC = \sum_{i=1}^{N_G} (a_i P_{gi}^2 + b_i P_{gi} + c_i), \quad (1)$$

where GC Generation cost, N_G Number of generators, P_{gi} Real power generation of i^{th} generator and a_i b_i c_i Cost coefficients of generator i .

Objective 2 Minimize transmission line overload by reducing Overload Index

$$OI = \sum_{i=1}^{N_L} (LF_i - L_{capi})^2, \quad (2)$$

where OI Overload Index, N_L Number of overloaded lines, LF_i MVA flow on line i and L_{capi} MVA capacity of line i .

Objective 3 Minimize real power loss

$$RPL = \sum_{i=1}^{N_G} P_{gi} - \sum_{i=1}^{N_D} P_{Di}, \quad (3)$$

where RPL Real power loss, N_D Number of participating loads, P_{Di} Real power demand at bus i , g Generator and D Demand.

2.2. Constraints

2.2.1. Equality constraints

Generation/load balance Equation:

$$\sum_{i=1}^{N_G} P_{gi} - \sum_{i=1}^{N_D} P_{Di} - P_L = 0, \quad (4)$$

where P_L – system real power loss.

2.2.2. Inequality constraints

(i) Voltage constraints

$$V_{i,\min} \leq V_i \leq V_{i,\max}, \quad (5)$$

where V_i – voltage magnitude at bus i , $V_{i,\max}$ – upper limit of voltage magnitude at bus i , $V_{i,\min}$ – lower limit of voltage magnitude at bus i .

(ii) Real power generation constraints

$$P_{gi,\min} \leq P_{gi} \leq P_{gi,\max}, \quad (6)$$

where P_{gi} – real power generation at generator bus i , $P_{gi,\max}$ – upper limit of real power generation at generator bus i , $P_{gi,\min}$ – lower limit of real power generation at generator bus i .

3. Overview of particle swarm optimization

PSO is a simple and efficient population-based optimization method [16]. PSO simulates the behaviors of bird flocking. It uses a number of agents (particles) that constitute a swarm moving around in the search space looking for the best solution. Each particle is treated as a point in an N-dimensional space which adjusts its “flying” according to its own flying experience as well as the flying experience of other particles. All particles have fitness values, which are evaluated by the fitness function to be optimized, and have velocities, which direct the flying of the particles.

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 two “best” values such as particle best ($pbest$) and global best ($gbest$). After finding the two best values, the particle updates its velocity and positions with following equation (7) and (8).

$$V_i^{(u+1)} = w * V_i^{(u)} + C_1 * rand() * (pbest_i - p_i^{(u)}) + C_2 * rand() * (gbest_i - p_i^{(u)}), \quad (7)$$

$$P_i^{(u+1)} = P_i^u + V_i^{(u+1)}, \quad (8)$$

where V_i – velocity of i^{th} particle, P_i – position of i^{th} particle.

The term $rand() * (pbest_i - p_i^{(u)})$ is called particle memory influence. The term $rand() * (gbest_i - p_i^{(u)})$ is called swarm influence. $V_i^{(u)}$ is the velocity of i^{th} particle at iteration u must lie in the range.

$$V_{\min} \leq V_i^{(u)} \leq V_{\max}, \quad (9)$$

where V_{\max} – maximum velocity and V_{\min} – minimum velocity. The parameter V_{\max} determines the resolution, or fitness, with which regions are to be searched between the present position and the target position. If V_{\max} is too high, particles may fly past good solutions. If V_{\min} is too small, particles may not explore sufficiently beyond local solutions. The constants C_1 and C_2 pull each particle toward $pbest$ and $gbest$ positions. Suitable selection of inertia weight w provides a balance between global and local explorations, thus requiring less iteration on average to find a sufficiently optimal solution. In general, the inertia weight w is set according to the following equation.

$$w = w_{\max} - \left[\frac{w_{\max} - w_{\min}}{iter_{\max}} \right] \times iter, \quad (10)$$

where, w = inertia weighting factor, w_{\max} = maximum value of weighting factor, w_{\min} = minimum value of weighting factor, $iter_{\max}$ = maximum number of iterations and $iter$ = current number of iteration.

4. Overview of differential evolution

Differential Evolution is a stochastic direct search optimization method, which can be used to minimize nonlinear and non-differentiable continuous space functions with real-valued parameters. It was first proposed by Storn and Price. DE also relies on initial random population generation, which is then improved using selection, mutation, and crossover repeated through generations until the convergence criterion is met [17].

4.1. Differential evolution algorithm optimization process

4.1.1. Initialization

In the first step of the Differential Evolution Algorithm optimization process, the population of candidate solutions must be initialized. Typically, each decision parameter in every vector of the initial population is assigned a randomly chosen value from within its corresponding feasible bounds.

$$x_{j,i}^{(G=0)} = x_j^{\min} + rand_j(0,1).(x_j^{\max} - x_j^{\min}), \quad (11)$$

where $i = 1, \dots, N_p$, $j = 1, \dots, D$, N_p – particle size, D – number of control variables, $x_{j,i}^{(G=0)}$ is the initial value ($G = 0$) of the j^{th} parameter of the i^{th} individual vector. x_j^{\min} and x_j^{\max} are the lower and upper bounds of the j^{th} decision parameter respectively.

4.1.2. Mutation

The Differential Evolution Algorithm optimization process is carried out by applying the following three basic genetic operations; mutation, recombination (also known as crossover)

and selection. After the population is initialized, the operators of mutation, crossover and selection create the population of the next generation $P(G+1)$ by using the current population $P(G)$. The mutation operator generates mutant vectors ($V_i^{(G)}$) by perturbing a randomly selected vector (X_{r1}) with the difference of two other randomly selected vectors (X_{r2} and X_{r3}).

$$V_i^{(G)} = X_{r1}^{(G)} + F(X_{r2}^{(G)} - X_{r3}^{(G)}), i = 1, \dots, N_p, \quad (12)$$

where $r1, r2, r3$ are randomly chosen vector indices, which $r1, r2, r3 \in [1, \dots, N_p]$.

F is a user-defined constant known as the “scaling mutation factor”, which is typically chosen from within the range (0, 1).

4.1.3. Crossover

Crossover operation helps to increase the diversity among the mutant parameter vectors. At the generation G , the crossover operation creates trial vectors (U_i) by mixing the parameters of the mutant vectors (V_i) with the target vectors (x_i) according to a selected probability distribution.

$$U_i^{(G)} = U_{j,i}^{(G)} = \begin{cases} V_{j,i}^{(G)} & \text{if } rand_j(0, 1) \leq CR \\ x_{j,i}^{(G)} & \text{otherwise} \end{cases}, \quad (13)$$

where CR is the crossover probability, which is usually selected from within the range (0, 1) and $rand_j$ is a uniformly distributed random number within the range (0, 1) generated a new for each value of j

4.1.4. Selection

The selection operator chooses the vectors that are going to compose the population in the next generation. This operator compares the fitness of the trial vector and the corresponding target vector and selects the one that provides the best solution. The fitter of the two vectors is then allowed to advance into the next generation according to Equation (14).

$$X_i^{(G+1)} = \begin{cases} U_i^{(G)} & \text{if } f(U_i^{(G)}) \leq f(X_i^{(G)}) \\ X_i^{(G)} & \text{otherwise} \end{cases}. \quad (14)$$

5. Overview of NSGA-II

NSGA II is an elitist non-dominated sorting Genetic Algorithm to solve multi-objective optimization problem. It was proposed by Srinivas and Deb [18]. It is a popular non-dominance based genetic algorithm for multi-objective optimization. It is a very effective algorithm but has been generally criticized for its computational complexity, lack of elitism and for choosing the optimal parameter value for sharing parameter σ_{share} . A modified version, NSGA-II was developed [19], which has a better sorting algorithm, incorporates elitism and no sharing parameter needs to be chosen prior.

5.1. Procedure for NSGA-II

- 1) Initialize the population P_t using equality and inequality constraints.
- 2) Create offspring population Q_t from the current population P_t .
- 3) Combine the two populations P_t and Q_t to form R_t . $R_t = P_t \cup Q_t$.
- 4) Determine all non-dominated fronts F_i of R_t .
- 5) Initiate the new population P_{t+1} , $i = 1$.
- 6) While $P_{t+1} + F_i \leq N$, do:
- 7) $P_{t+1} = P_{t+1} \cup F_i$, $i = i + 1$.
- 8) Sort the last front F_i using the crowding distance in descending order and choose the first $(N - P_{t+1})$ elements of F_i .
- 9) Use selection, crossover and mutation operators to create the new offspring population Q_{t+1} size N_{obj} .

6. Overview of fuzzy ranking method

Fuzzy ranking method is employed to extract the best compromise solution out of the available non-dominated solutions depending upon its highest rank. In real applications, due to imprecision of judgments by decision makers a fuzzy membership functions adopted to provide best compromise solution out of the pareto-optimal solutions which satisfies different goals to some extent [20, 21]. The membership value '0' indicates incompatibility with the sets, while '1' means full compatibility. In other words, the membership value indicates the degree of satisfaction of the solution for an objective. $\mu(F_i)$ is a strictly monotonic decreasing function defined as:

$$\mu(F_i) = \begin{cases} 1; & F_i \leq F_i^{\min} \\ \frac{F_i^{\max} - F_i}{F_i^{\max} - F_i^{\min}}; & F_i^{\min} \leq F_i \leq F_i^{\max} \\ 0; & F_i \geq F_i^{\max} \end{cases} \quad (15)$$

where F_i is the membership value of i^{th} objective function and F_i^{\min} and F_i^{\max} are the expected minimum and maximum values of i^{th} objective function.

The value of the membership function indicates how much (in scale from 0 to 1) a solution is satisfying the i^{th} objective F_i . The best solution can then be selected using fuzzy min-max proposition.

$$\mu_{\text{bestsolution}} = \max \left\{ \min [\mu(F_j)]^k \right\}, \quad (16)$$

where min is the minimum membership value of objective functions, max is the maximum membership value among the calculated minimum, j is the number of objectives to be minimized and k is the number of pareto-optimal solutions obtained.

7. Proposed Fuzzy ranking based NSGA-II algorithm for network overload alleviation

The flow chart of the proposed NSGA-II algorithm is shown Figure 1 and their steps are given below.

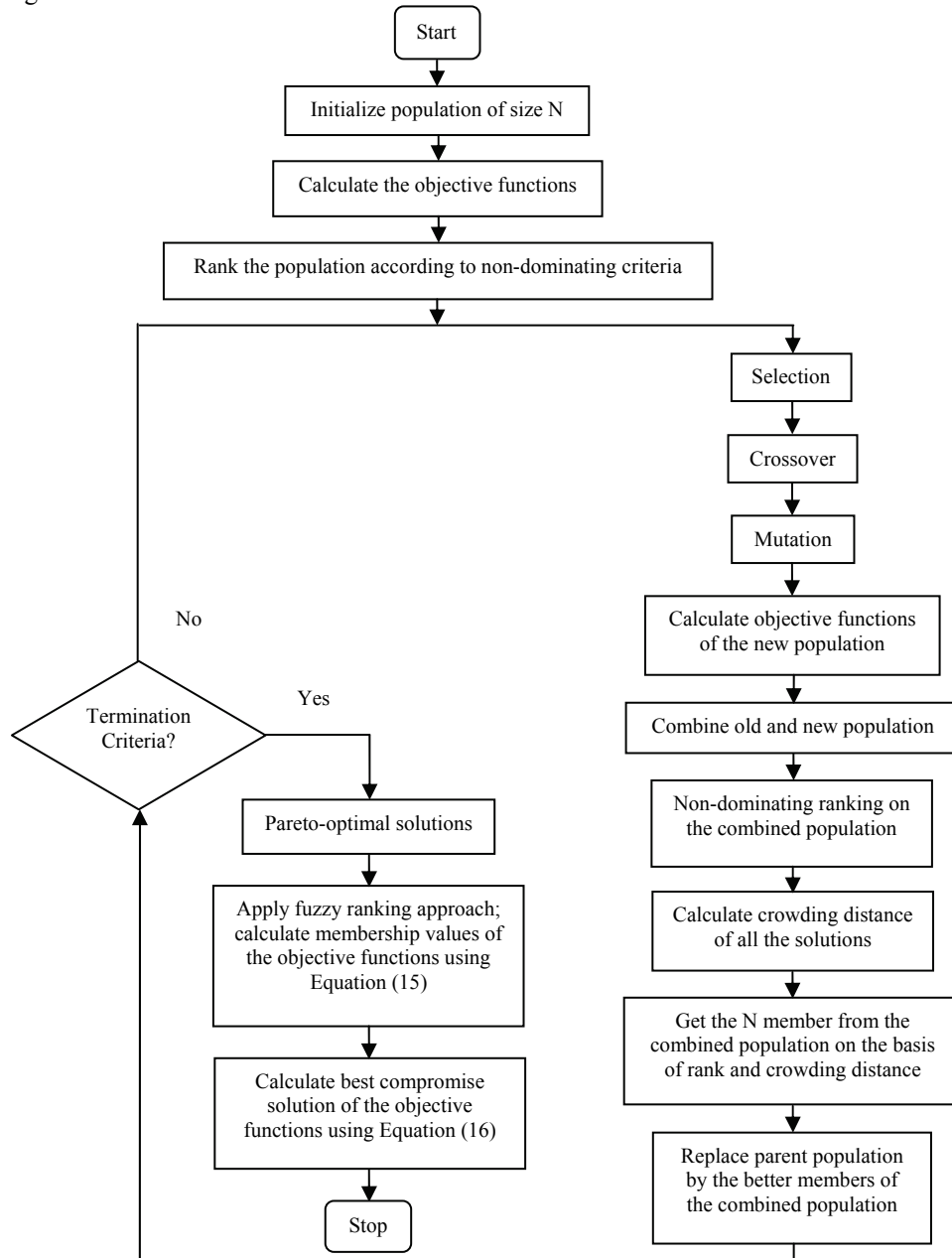


Fig. 1. Flow chart of proposed NSGA-II algorithm

Step 1: Set up NSGA-II parameters like particle size, number of generations, crossover probability, mutation probability distribution indices for crossover and mutation.

Step 2: Read line data, bus data and costs for each generator.

Selection of control variables embedded in the individuals is a first step while applying evolutionary computation algorithm. Generator real power redispatch is a control variable in this work. Hence the control variables are generated randomly satisfying their practical operation constraints (6).

Step 3: For each chromosome of population, run Newton Raphson power flow to calculate the objective function 1, 2, 3 using Equation (1), (2) and (3) respectively.

Step 4: Non-domination sorting of population is carried out and then tournament selection is applied to select the best individuals based on crowding distance.

Step 5: Crossover and Mutation operators are carried out to generate offspring (Q_t) and the new vectors obtained must satisfy the limits if not set it to the appropriate extreme.

Step 6: Calculate the value of each objective function of Q_t and merge the parent and offspring population to preserve elites.

Step 7: Again perform non-dominated sorting on the combined population based on crowding distance measure and obtain the best new parent population (P_{t+1}) of size N out of $2N$ population, so this would be the parents for next generation and this process is carried out till a maximum number of generations are reached.

Step 8: Obtain Pareto front of optimal solutions.

Step 9: Apply fuzzy ranking method, determine membership values of objective functions 1, 2 and 3 using Equation (15).

Step 10: Determine the best compromise solution of objective functions 1, 2 and 3 using Equation (16).

8. Simulation results

The simulation studies are performed on system having 2.27 GHz Intel 5 processor with 2 GB of RAM in MATLAB environment. The proposed Fuzzy ranking based NSGA-II approach is applied to minimize three competing objectives of generation cost, transmission line overload and real power loss for different contingency cases in IEEE 30 and IEEE 118 bus systems. N-1 contingency analysis is carried out under base load conditions to identify the harmful contingencies. To demonstrate the effectiveness of the proposed approach, three different harmful contingency cases are considered.

For the studies, the following parameters are used.

Particle size: 40, No. of generation: 100, Crossover probability: 0.9, Mutation probability: 0.1, Distribution index for cross over: 20, Distribution index formulation: 20.

The results of three cases are compared with other evolutionary algorithms. The transmission line limits for IEEE 30 bus system is taken from [22]. The transmission line limits for IEEE 118 bus system is taken from [23].

8.1. IEEE 30 bus system

This system consists of 6 generator buses, 24 load buses and 41 transmission lines with total load of 283.4 MW and 126.2 MVAR. Two cases are considered for illustration purpose. The amount power flow, power violation and overload factors in the identified overloaded lines before generation rescheduling are summarized in Table 1.

Table 1. Summary of contingency analysis for IEEE 30 bus system

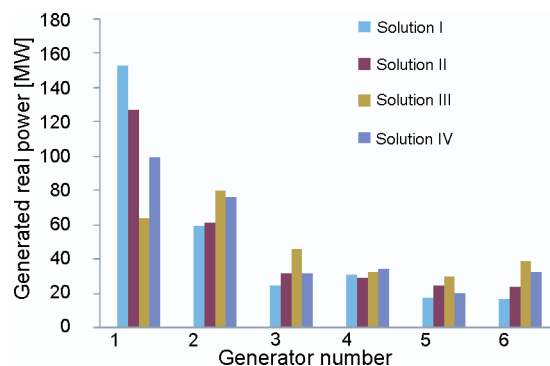
Case	Outage line	Line overloaded	Line limit (MVA)	Actual power flow (MVA)	Overload factor	Total power violation (MVA)	Power loss (MW)
A	1-2	1-3	130	307.01	2.3616	426.70	60.63
		3-4	130	279.60	2.1508		
		4-6	90	175.55	1.9506		
		6-8	32	46.51	1.4536		
B	2-5	1-2	130	165.44	1.2726	160.26	32.82
		2-4	65	74.67	1.1487		
		2-6	65	102.96	1.5840		
		4-6	90	123.68	1.3742		
		5-7	70	110.10	1.5729		
		6-8	32	35.42	1.1067		

The outages of the line 1-2 and 2-5 are the most critical one which have resulted in overloading of other lines. As a consequence of line 1-2 outage, lines 1-3, 3-4, 4-6 & 6-8 get overloaded. Lines 1-2, 2-4, 2-6, 4-6, 5-7 & 6-8 get overloaded due to the outage of line 2-5.

8.1.1. Case A & Case B

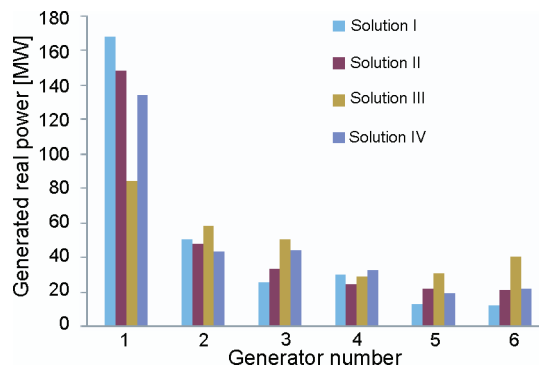
In case A, four lines get overloaded with a total power violation of 426.70 MVA and real power loss of 60.63 MW. In case B, six lines get overloaded with a total power violation of 160.26 MVA and real power loss of 32.82 MW.

Fig. 2. Control variable setting for corrective action – case A



The control variable setting to minimize the generation cost, transmission line overload and real power loss for case A and case B is shown in Figures 2 and 3 respectively.

Fig. 3. Control variable setting for corrective action – case B



The five intermediate solutions with their membership value out of the obtained non-dominated solution set using proposed method for case A and case B is shown in Tables 2, 3 respectively.

Table 2. Pareto optimal intermediate solutions based on fuzzy ranking for case A

Generation cost (\$/h)	Overload index	Real power loss (MW)	μ_1	μ_2	μ_3	μ_{\min}
870.03	0.00	9.11	0.7086	1.0000	0.6549	0.6549
841.43	260.16	15.30	0.9890	0.6569	0.1335	0.1335
841.70	165.74	14.89	0.9863	0.7814	0.1679	0.1679
872.41	0.00	8.83	0.6852	1.0000	0.6790	0.6790
844.14	72.83	14.13	0.9624	0.9039	0.2321	0.2321

Table 3. Pareto optimal intermediate solutions based on fuzzy ranking for case B

Generation cost (\$/h)	Overload index	Real power loss (MW)	μ_1	μ_2	μ_3	μ_{\min}
834.22	2.03	13.21	0.9464	0.9805	0.2800	0.2800
877.34	0.00	8.96	0.5306	1.0000	0.7753	0.5306
832.01	17.39	13.92	0.9677	0.8326	0.1974	0.1974
833.60	5.76	13.35	0.9524	0.9445	0.2641	0.2641
861.84	0.00	9.92	0.6800	1.0000	0.6634	0.6634

The best compromise solutions are determined depending upon their highest rank i.e. the solution which minimizes all the three objectives simultaneously. The best solutions are shown in bold in Table 2 and 3 and have a rank of 0.6790 and 0.6634 which means that all the three objectives are satisfied at least 67.90% and 66.34%. The Pareto optimal solution for both cases is shown in Table 4.

Table 4. Pareto optimal solution for both case A and case B

Pareto-optimal solution	Cases	Generation cost (\$/h)	Overload index	Real power loss (MW)
Solution I (Best generation cost)	A	840.31	758.24	16.89
	B	828.66	97.82	15.62
Solution II (Best overload index)	A	850.51	0	12.37
	B	838.39	0	12.65
Solution III (Best real power loss)	A	942.30	0	5.02
	B	932.35	0	7.03
Solution IV (Best compromise solution)	A	872.41	0	8.83
	B	861.84	0	9.92

From Table 4, it is clear that; overload is managed by changing rescheduling of generators active power for both cases. If the operator wants to alleviate the line overload completely, he will choose solution II. If the operator wants to reduce the power loss, he will choose solution III. However, if the operator allows some overload and takes solution I. To satisfy solutions I, II and III, the operator will choose solution IV which gives best compromise solution with alleviation of overload and compromised generation cost of 872.41 \$/h and 861.84 \$/h for Case A and Case B respectively. The computation time for Case A and Case B is 31.62 seconds and 29.89 seconds respectively for 100 generations. The Pareto-front of generation cost, overload index and real power loss, generation cost versus overload index and generation cost versus real power loss for case A is shown in figure 4, 5 and 6 respectively.

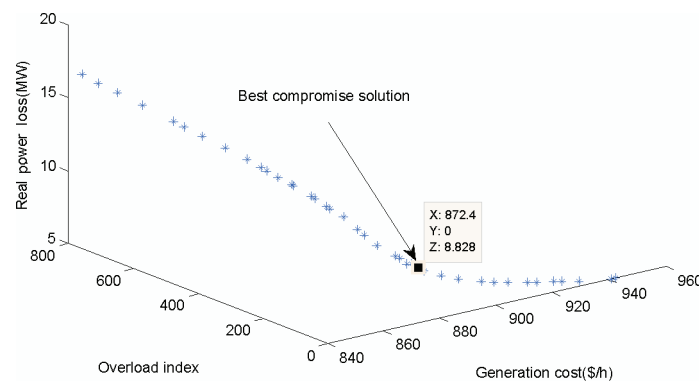


Fig. 4. Pareto-front of generation cost, overload index and real power loss – case A

Table 5. Control variables for best overload index for case A

Method	OI	Generated real power (MW)					
		1	2	5	8	11	13
Proposed method	0	127.35	60.59	31.35	28.96	24.46	23.06
PSO	0	127.32	56.20	36.12	25.08	22.07	28.89
DE	0	129.33	73.59	32.38	31.46	15.88	13.25

The Pareto-front of generation cost, overload index and real power loss for case B is shown in Figure 7. Table 5 shows the control variables for best overload index compared with simple PSO and DE for case A. Table 6 shows the control variables for best overload index compared with simple PSO and DE for case B.

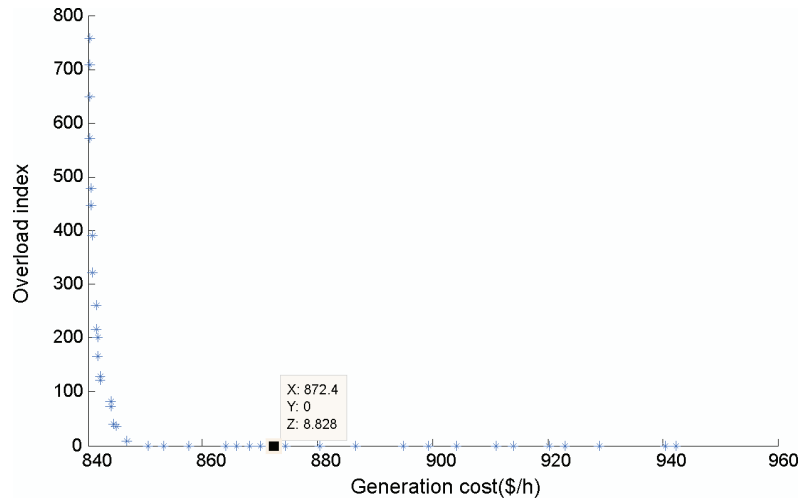


Fig. 5. Pareto-front of generation cost versus overload index – case A

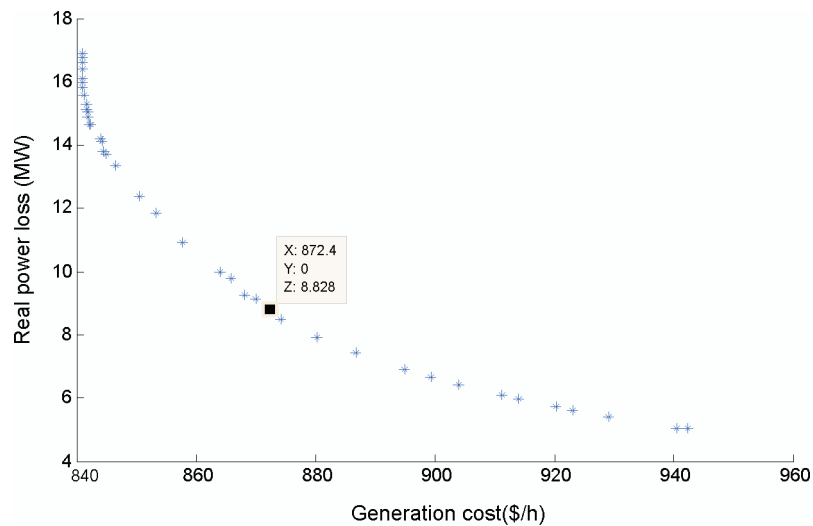


Fig. 6. Pareto-front of generation cost versus real power loss – case A

In both case A and case B, the proposed method relieves the overloaded lines reported in Table 1 by generation rescheduling alone with a minimum generation cost of 850.51 \$/h and 838.39 \$/h when compared to simple PSO and DE based approaches which have the cost of 859.44 \$/h, 845.02 \$/h and 851.45 \$/h, 841.52 \$/h respectively.

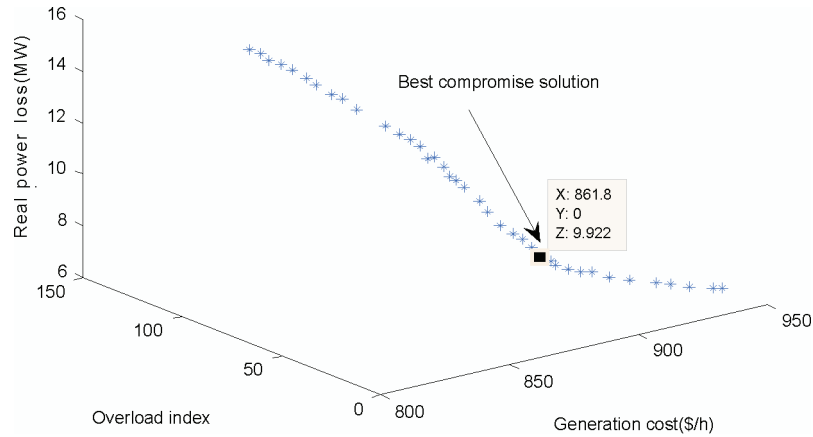


Fig. 7. Pareto-front of generation cost, overload index and real power loss – case B

Table 6. Control variables for best overload index for case B

Method	OI	Generated real power (MW)					
		1	2	5	8	11	13
Proposed method	0	148.51	47.63	33.11	24.31	21.53	20.95
PSO	0	139.03	51.97	33.65	23.32	20.66	26.92
DE	0	141.22	51.26	33.23	23.02	20.42	26.59

In line 1-2 outage under base load case, GA based approach reported in [24] was not completely minimize the severity index even if rescheduling of generators active power and generator bus voltage magnitude and still has the severity index of 2.473 when compared to proposed NSGA-II approach. The power loss is reduced from 60.63 MW to 12.37, 12.29 and 12.49 using proposed, PSO and DE approaches respectively. In case B, among the six overloaded lines, the overload factor of the most overloaded line 2-6 is 1.5840 and that after rescheduling is reduced to 0.9596, 0.9429 and 0.9498 using proposed, PSO and DE approaches respectively. Similarly, the power loss is reduced from 32.82 MW to 12.65, 12.15 and 12.34.

8.2. IEEE 118 Bus System

This system consists of 54 generator buses and 186 transmission lines with total load of 4242 MW and 1438 MVAR. One case is considered for illustration purpose. The amount power flow, power violation and overload factors in the identified overloaded lines before generation rescheduling are summarized in Table 7.

8.2.1. Case C

In case C, the five lines get overloaded with a total power violation of 77.63 MVA and real power loss of 197.03 MW. The control variable setting to minimize the generation cost, line overload and real power loss is shown in Figure 8.

Table 7. Summary of contingency analysis for IEEE 118 bus system

Case	Outage line	Line overloaded	Line limit (MVA)	Actual power flow (MVA)	Overload factor	Total power violation (MVA)	Power loss (MW)
C	8-5	12-14	100	107.20	1.0720	77.63	197.03
		13-15	100	103.07	1.0307		
		12-16	130	143.65	1.1050		
		15-17	200	223.48	1.1174		
		16-17	130	160.22	1.2325		

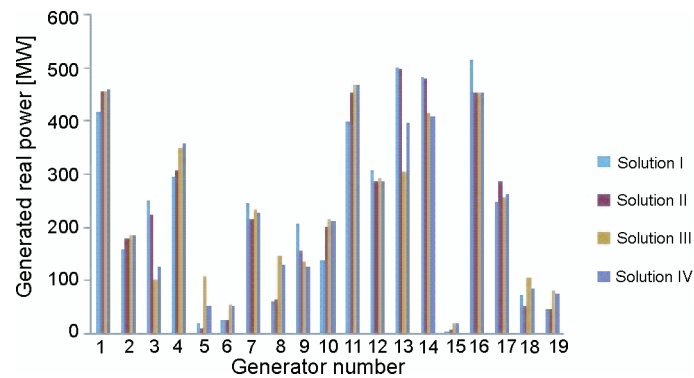


Fig. 8. Control variable setting for corrective action – case C

The five intermediate solutions with their membership value out of the obtained non-dominated solution set using proposed method is shown in Table 8. The best solutions are shown in bold in Table 8. The Pareto optimal results obtained from the proposed fuzzy ranking based NSGA-II approach is presented in Table 9. When only cost minimization is considered, the minimum value obtained is 133959.86 \$/h, when only overload alleviation is considered, minimum value obtained is 0 and when only power loss minimization is considered, minimum value obtained is 129.56 MW.

Table 8. Pareto optimal intermediate solutions based on fuzzy ranking for case C

Generation cost (\$/h)	Overload index	Real power loss (MW)	μ_1	μ_2	μ_3	μ_{\min}
134277.92	17.05	148.53	0.9855	0.2214	0.0877	0.0877
140312.12	0.00	135.31	0.6837	1.0000	0.7233	0.6837
145521.15	0.00	131.56	0.4233	1.0000	0.9037	0.4233
134489.73	6.31	146.96	0.9749	0.7121	0.1633	0.1633
134297.62	21.51	148.29	0.9845	0.0178	0.0995	0.0178

Table 9. Pareto optimal solution for case C

Pareto-optimal solution	Generation cost (\$/h)	OI	Real power loss (MW)
Solution I (best generation cost)	133959.86	1.49	153.76
Solution II (best overload index)	133999.04	0	149.46
Solution III (best real power loss)	153985.33	0.53	129.56
Solution IV (best compromise solution)	140312.12	0	135.31

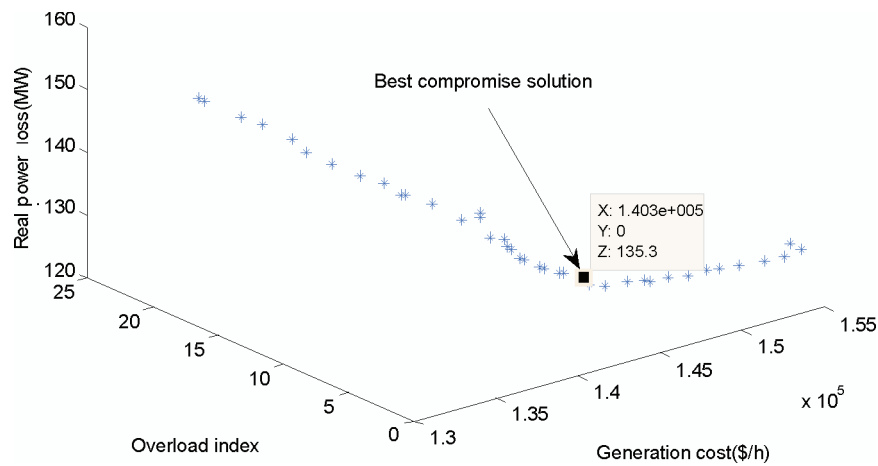


Fig. 9. Pareto-front of generation cost, overload index and real power loss – case C

Table 10. Control variables for best overload index for case C

Generator bus number	Generated real power (MW)			Generator bus number	Generated real power (MW)		
	Proposed method	PSO	DE		Proposed method	PSO	DE
10	455.23	417.05	464.79	65	453.69	457.96	229.47
12	179.33	172.20	175.49	66	286.57	339.90	319.04
25	222.88	104.91	278.59	69	499.47	821.16	806.79
26	306.23	294.86	200.44	80	480.79	306.13	447.97
31	8.73	9.35	5.00	87	5.06	10.18	8.48
46	24.99	22.96	30.05	89	452.69	538.41	663.08
49	213.64	232.83	200.00	100	285.98	254.38	140.22
54	62.03	107.58	57.94	103	51.52	10.00	10.00
59	155.71	223.39	112.22	111	45.65	33.68	75.52
61	201.25	50.00	194.73				

The results simulated from Table 9 reveals that the best compromise solution of multi-objective problem is solution IV with the highest rank of 0.6837. The best compromise solution obtained is quite satisfactory and has the generation cost and real power loss of 140312.12 \$/hr and 135.31 MW respectively. The computation time is 58.88 seconds for 100 generations. The Pareto-front of generation cost, overload index and real power loss is shown in Figure 9. Table 10 shows the control variables for best overload index compared with simple PSO and DE.

In case C, the proposed method relieves the overloaded lines reported in Table 7 with a minimum generation cost of 133999.04 \$/h when compared to simple PSO and DE based approaches which have the cost of 138884.50 \$/h and 138549.90 \$/h respectively. The power loss is reduced from 197.03 MW to 149.46, 164.93 and 177.83 using proposed, PSO and DE approaches respectively.

9. Conclusion

This paper has proposed a fuzzy ranking based non-dominated sorting genetic algorithm-II for overload management by generation rescheduling in a contingent power network. The Fuzzy ranking method is used to find the best compromise solution from Pareto-optimal front. The proposed method has been tested and examined on the standard IEEE-30 and IEEE 118 bus systems. Line overloads are simulated due to unexpected line outage under base load conditions for considered cases. In Case A, Case B and Case C, the proposed method has relieved the overloaded lines with a minimum generation cost of 850.51 \$/h, 838.39 \$/h and 133999.04 \$/h when compared to simple PSO and DE based approaches. The proposed fuzzy based NSGA-II algorithm is capable to handle different competing objectives and provides a set of non-dominated pareto-optimal solutions. This helps the system operator to choose a suitable optimum solution among the different possibilities according to the system requirement. However, single objective optimization algorithms such as simple PSO and DE does not give any choice for the operator.

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