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New Hybrid Non-Dominated Sorting Differential Evolutionary Algorithm

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Abstract
This paper presents a new multi objective optimization algorithm with the aim of complete coverage, faster global convergence and higher solution quality. In this technique, the high-speed characteristic of particle swarm optimization (PSO) is combined with non-dominated differential evolutionary (NSDE) and an efficient multi objective optimization algorithm is created. This method posses high convergence characteristic in quite less execution times. Generating fewer populations to find the Pareto front also makes the proposed algorithm use less memory. For the purpose of performance evaluation, the algorithm is verified with four benchmarking functions on its global optimal search ability and compared with two recognized algorithm to assess its diversity. The capability of the suggested algorithm in solving practical engineering problems such as power system protection is also studied and the results are discussed in detail.

Keywords*: Hybrid algorithm, Multi objective obtimization, PSO, NSDE, Power system protection, Relay coordination, IFCL*

1. Introduction

Recently, optimization plays a significant role as a major branch of mathematics which is used in various sciences like power engineering, thus new investigations in this field are became more attractive for many researchers [1].

Solving nonlinear problems based on Heuristic approaches has led to many improvements in modern science. Many nonlinear problems according to their own structures work based on several parameters. Base on a fitness value which is given to each solution on the basis of a weighted sum of the objectives' values, choosing the proper algorithm is feasible [2-4].

Utilizing novel multi objective optimization approaches caused several progressions and remarkable achievements in various industrial branches [5-8]. But the main issue is that most of the multi objective methods like NSGA II, NSDE and so on, work on the basis of dominance concept and consequently their movements are toward the optimal solution. When they attain the optimum solution of one of the function's objectives, lead all the population nearby it, therefore searching for the other objectives executes in this specific zone [9-12]. Such techniques cause ignorance of the other zones' solutions which are improper for just this specific objective. The other drawback of these methods is low convergence speed.

The main goal of this investigation is to fix the above mentioned problems. In this study a couple of single objective optimization techniques including particle swarm optimization and cuckoo optimization algorithm are utilized together to perform as a multi objective optimization algorithm. The performance and efficiency of the presented investigation has been tested on power system protection.

2. The New Multi Objective Evolutionary Optimization Algorithm using PSO and NSDE

First by using single objective algorithm, a range is specified for each objective function which is going to be optimized. It guides the search to spend more time in that area. Then the best possible solution for all objective functions is achieved by using multi objective algorithm.

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2.1 Reference Range Determination for Objective Functions

In The first step is to determine an optional iterative factor corresponding to the calculated cost for each function.

$$f_k = [\alpha_1, \alpha_2, ..., \alpha_N]_{1\times N}$$

$$\alpha_1 + \alpha_2 + ... + \alpha_N < 1$$

Which N is the number of functions is going to be optimized, and $\alpha$is the iterative factor of each function.

Therefore in PSO algorithm, the optimization level of each function is α_i x Iter; where Iter is the total number of iterations.

The obtained population is then retrieved in Position set and a value called Cost is assigned to each population.

$$Position_i = [\beta_1, \beta_2, ..., \beta_M]_{1\times M}$$
$$Cost_i = [\gamma_1, \gamma_2, ..., \gamma_N]_{1\times N}$$

M is the number of variables.

At first step, a random initial population is created in sample space. But at next step, initial population is equal to Position set members of previous step with maximum Cost value (maximum profit).

$$FPosition_i = BPosition_{i-1}$$

Which FPosition is initial value of ith step ($i \geq 2$), and BPosition is population of (i-1)th step with best profit.

The global best of next steps is also equal to best population created at previous steps.

$$GlobalBPosition_i = BPosition_{i-1}$$

Where GlobalBPosition is global best of ith step and BPosition is best Position at (i-1)th step.

Then, the best obtained Position in mentioned steps is used as initial population of multi objective optimization algorithm.

$$pop = [BPosition_1, BPosition_2, ..., BPosition_N]_{1\times N}$$

This section, it is explained the results of research and at the same time is given the comprehensive discussion. Results can be presented in figures, graphs, tables and others that make the reader understand easily [2], [5]. The discussion can be made in several sub-chapters.

2.2. The Proposed Multi Objective Optimization Algorithm

Now the created population from the best of PSO populations is used as initial population for NSDE algorithm. In each step, DE algorithm guides the population of solutions towards an optimum using mutation and making a difference (Figure 1). Then created population is ranked using domain and ranking ideas. This iterative process continues until optimum solutions are achieved [13-27].

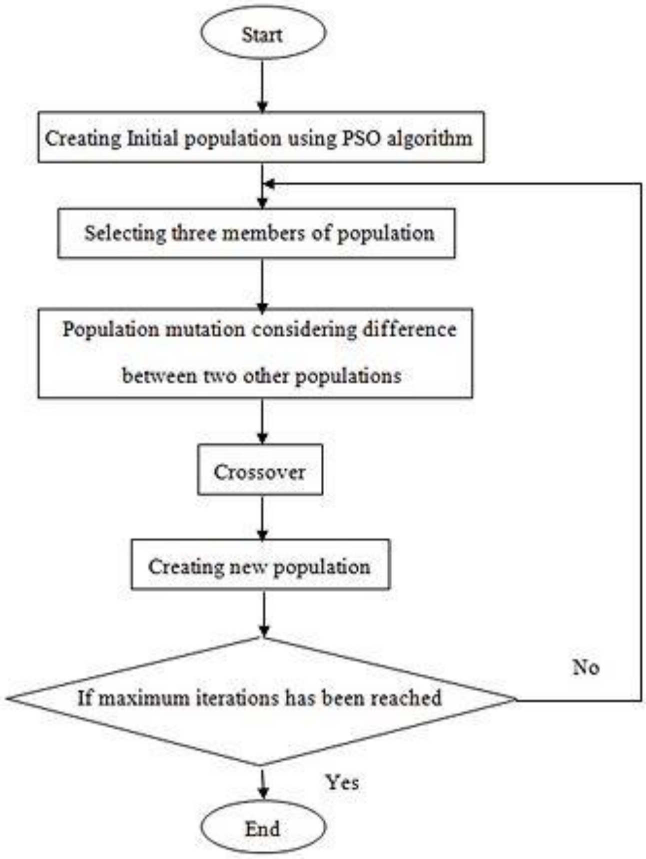


Figure 1. The proposed improved DE algorithm

2.3. A Benchmark Study of Proposed Algorithm

In this section, the efficiency of proposed multi-objective Pareto optimization algorithm is investigated on a set of standard benchmark problems [28]. For this purpose, the ZDT family of functions was selected, because they are the most recognized test functions for benchmarking the performance of multi-objective Pareto optimization methods. Computer specifications to run all optimization procedure are Core i5, CPU 3.00 GHz, 8 GB memory (RAM), Windows 8 operating system. Some of ZDT functions, Fonseca and Fleming functions, CTP1 function (two variables) and Tset function 4 which have been summarized in Table 1, contain two objectives. Considering Table 1, on each of the test problems and for same population size, suggested algorithm dramatically outperformed both NSDE and NSGA II in terms of run time.

The algorithm performance is also judged by the location of solutions compared to the optimal Pareto front. The closer solutions to the real Pareto optimum frontier mean the better performance of the algorithm. The Figure 2 shows the new algorithm provides a better match to real Pareto front. Considering Figure 2, NSGA-II is far away from the true Pareto front for all test functions and NSDE for two test functions.

2.4. Application of Proposed Algorithm in Solving Practical Engineering Problems

Optimization techniques have important application in the power systems protection. For the object of achieving a reliable protective system, the operating time of protective devices must be minimized. This is a single objective optimization problem [29]. But the continuous changes in power flow patterns and short circuit levels due to the power system topology variation, cause miss-coordination between protective devices. In these situations, traditional protection devices may fail to detect fault conditions. This is where the multi objective optimization techniques must be called to address these issues.

Table 1. Benchmark functions

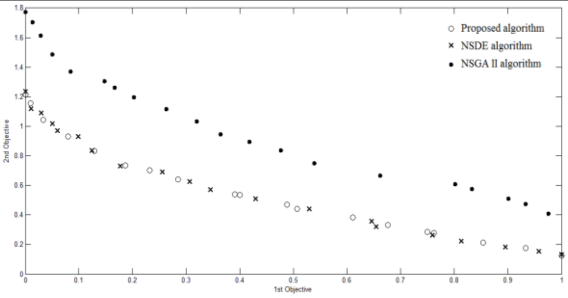
Problem	Formulation	Run time (s) for 100 iteration and 20 population		
		Proposed algorithm	NSDE algorithm	NSGA II algorithm
ZDT1	$f_1(x)=x_1$ $f_2(x)=g(x)\left[1-\sqrt{\frac{x_1}{g(x)}}\right]$ $g(x)=1+9\frac{(\sum_{i=2}^{n}x_i)}{(n-1)}$	4.8017	7.3181	7.2924
ZDT2	$f_1(x)=x_1$ $f_2(x)=g(x)\left[1-\left(\frac{x_1}{g(x)}\right)^2\right]$ $g(x)=1+9\frac{(\sum_{i=2}^{n}x_i)}{(n-1)}$	5.0288	6.9858	7.9016
ZDT3	$f_1(x)=x_1$ $f_2(x)=g(x)\left[1-\sqrt{\frac{x_1}{g(x)}}-\frac{x_1}{g(x)}\sin(10\pi x_1)\right]$ $g(x)=1+9\frac{(\sum_{i=2}^{n}x_i)}{(n-1)}$	4.7893	6.9667	7.1350
ZDT6	$f_1(x)=1-\exp(-4x_1)\sin^6(4\pi x_1)$ $f_2(x)=g(x)\left[1-\left(\frac{f_1(x)}{g(x)}\right)^2\right]$ $g(x)=1+9\left[\frac{(\sum_{i=2}^{n}x_i)}{(n-1)}\right]^{0.25}$	4.9802	6.8195	7.5947
Test Function 4	$f_1(x,y)=x^2-y$ $f_2(x,y)=-0.5x-y-1$ s.t. $g_1(x,y)=6.5-\frac{x}{6}-y\geq 0$ $g_2(x,y)=7.5-0.5x-y\geq 0$ $g_3(x,y)=30-5x-y\geq 0$	5.0531	5.2052	6.4149
Fonseca and Fleming function (n = 20)	$f_1(x,y)=1-\exp(-\sum_{i=1}^{n}(x_i-\frac{1}{\sqrt{n}})^2$ $f_2(x,y)=1-\exp(-\sum_{i=1}^{n}(x_i+\frac{1}{\sqrt{n}})^2$	5.9184	6.0439	7.6279
CTP1 function (2	$f_1(x,y)=x$ $f_2(x,y)=(1+y)\exp(-\frac{x}{1+y})$	6.0231	6.1712	7.1431

variables)

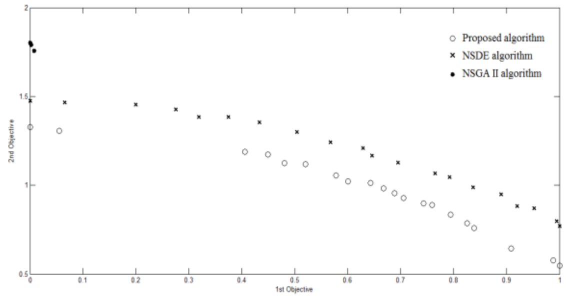
s.t

$$g_1(x,y) = \frac{f_2(x,y)}{0.858\exp(-0.541 f_1(x,y)} \geq 1$$

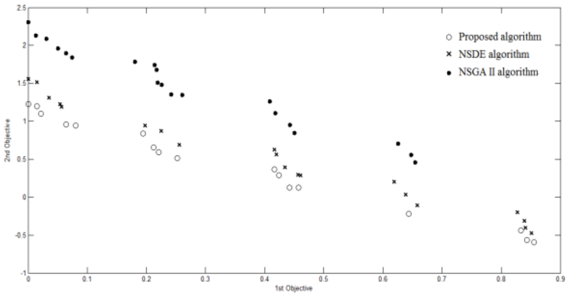
$$g_2(x,y) = \frac{f_2(x,y)}{0.728\exp(-0.295 f_1(x,y)} \geq 1$$



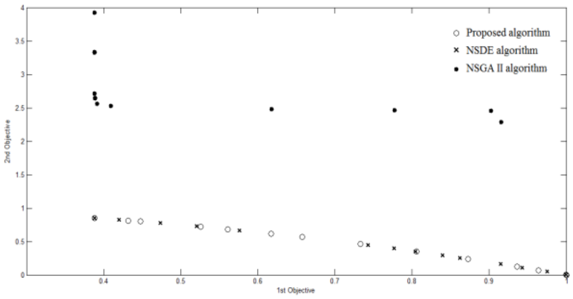
ZDT1



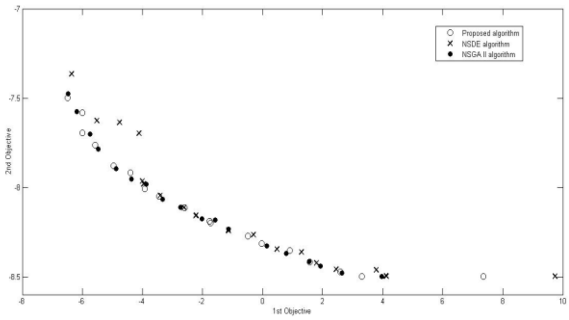
ZDT2



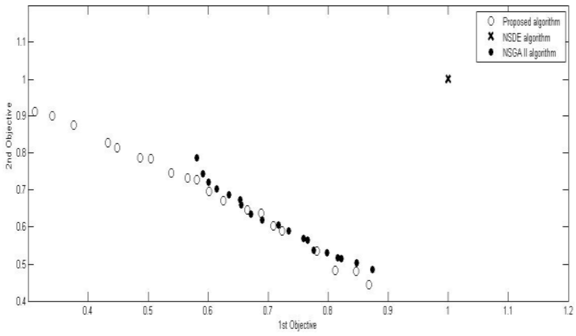
ZDT3



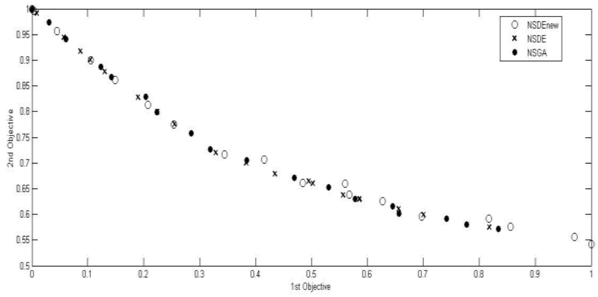
ZDT6



Test function 4



Fonseca and Fleming function



CTP1 function (2 variables)

Figure 2. Optimal Pareto front for four benchmarks with population size 100 using NSGA II and new proposed algorithm

Several studies have been done around these topics up to now and different multi objective optimization algorithms used in order to find better solutions [30-33]. But the disadvantage of these algorithms such as NSGA II is that they do not cover entire space. So there are possibilities of solutions elimination which are optimum for just one objective function and acceptable for other objective functions. Another problem is the low convergence speed of these algorithms. If the online protection be considered, the high convergence speed becomes more important.

The high convergence rate of this algorithm can be used in operations required low optimization time such as online power system protection. In this section, to prove capability of proposed technique, this algorithm is applied to optimal placement and capacity problem of inductive fault current limiters considering optimal overcurrent relay coordination, and the results are discussed in detail.

3. Problem Definition

First, combination of IFCLs at different locations is needed to be compared to determine the optimal placements. It is also required to minimize the number of IFCLs to be installed, because the IFCL cost increase with rise in the number of them. So, several scenarios are defined with different numbers and locations of IFCLs.

The first object function equation to calculate the cost of inductive fault current limiter is given as follows [34]. This equation is used to calculate the minimum FCL impedance.

$$Cost_{IFCL} = \begin{cases} 11\times 10^{7} \times \left(3.95 - 3.2377\, e^{-0.045X}\right) & X \geq 6.5 \quad \Omega \\ 413\times 10^{5} \times \left(5.1 - 5.1e^{-0.025X}\right) & X \geq 6.5 \quad \Omega \end{cases}$$

The placement of IFCLs can also have an effect on the relay coordination by changing the short circuit levels, therefore a new coordination of relays is also required after the placement of IFCLs.

To clarify the miss-coordination problem, the second object function equation is stated in the following form [35]:

$$OF_1 = \alpha_1 \times \sum (t_i)^2 + \beta_1 \times \sum \left(\Delta t_{mb} - \beta_2 \times \left(\Delta t_{mb} - \left|\Delta t_{mb}\right|\right)\right)^2$$
$$\Delta t_{mb} = t_b - t_m - CTI$$

Which Δt_{mb} , is the discrimination between main and backup relays (miss-coordination has occurred between bth and mth relays if Δt_{mb} be negative.). The t_i , is operating time of ith relay. The t_m , is operating times of the main relays. The t_b , is operating times of the backup relays. The CTI , is coordination time interval. The α_1 , β_1 and β_2 are weighting factors.

The above objective function should be minimized subject to various constraints. These constraints are relay setting constraints and backup-primary relay coordination time interval. The coordination constraints are:

$$TDS_i^{\min} \leq TDS_i \leq TDS_i^{\max}$$
$$t_{bi} - t_{mi} \geq \Delta t_{mb}^{\min}$$

The operating times of overcurrent relay is a function of fault location and short-circuit current level. All relay operating times can be calculated based on their pickup current and from the following equation:

$$t = \left[\frac{0.14}{M^{c} - 1}\right] \times TDS$$
$$M = \frac{I_f^{\max}}{I_{peakup}}$$

Where M is the ratio of relay current to the relay setting. I_{peakup}, is relay setting and I_f^{max}, is maximum short circuit current.

4. Results and Discussion

The proposed method is implemented and tested on IEEE 8-bus system which shown in Figure 3. This system consists of 14 overcurrent relays.

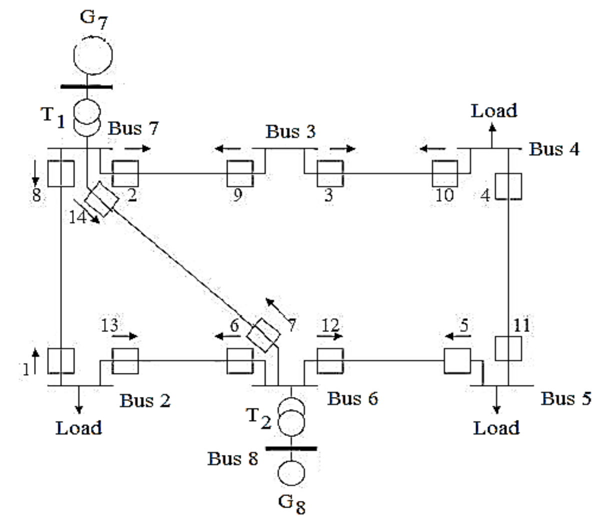


Figure 3. 8-bus test system without DGs

Two DGs with 10 MVA capacities are connected to bus 4 and bus 5. Systems with and without DGs installed are compared to demonstrate how the presence of these sources influences the over current relay coordination. Figure 4 presents changes in the system topology that caused six constraints to be violated, when the network settings are considered for the overcurrent relays.

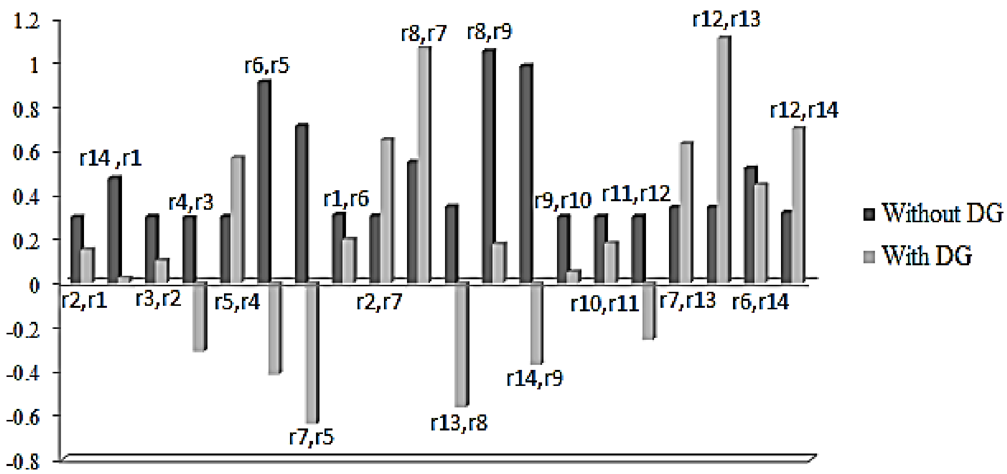


Figure 4. The discrimination between main and backup relays operating time

The suggested technique is applied to determine the best locations and number of the IFCLs for the proposed network with DGs. Simulation results show the optimum number of IFCLs is 2 and the optimal location of X(1) and X(2) would be on lines 1-2 and 2-6 respectively.

The solutions spreading for the considered distribution network with the purpose of minimizing both objective functions 1 & 2 using new method, NSDE and NSGA II are respectively shown in Figures 5, 6, 7.

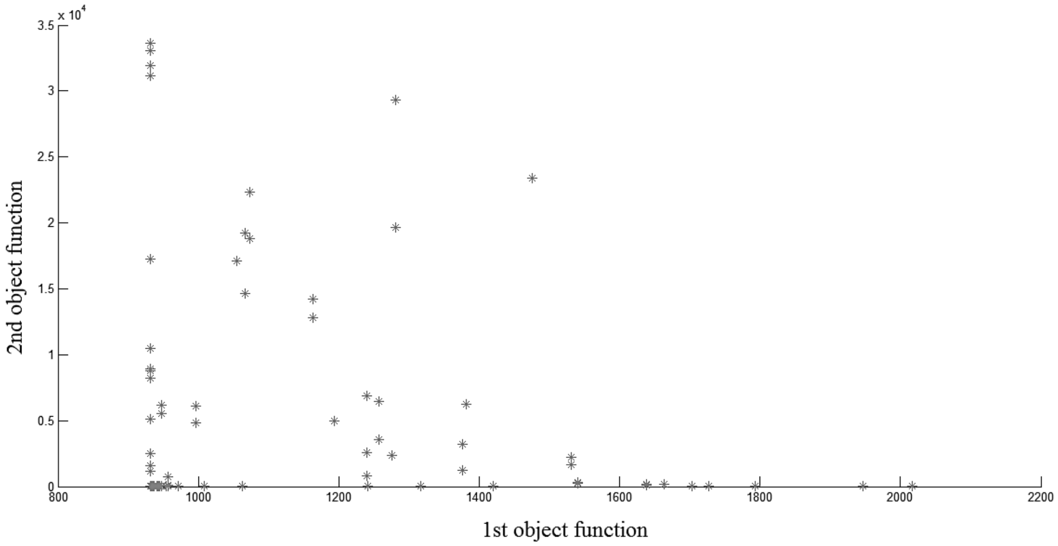


Figure 5. The solutions spreading over the last 50 iterations (Purposed algorithm)

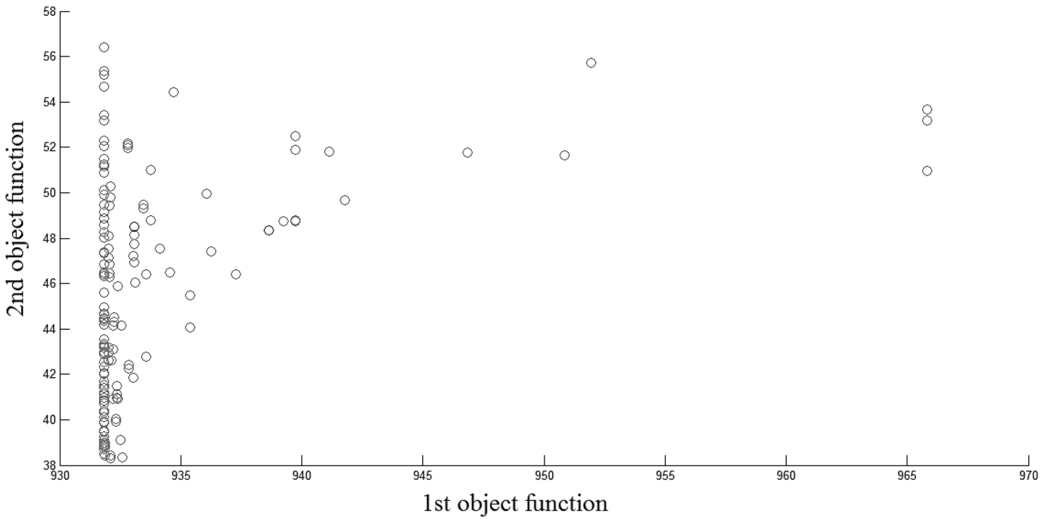


Figure 6. The solutions spreading over the last 50 iterations (NSDE)

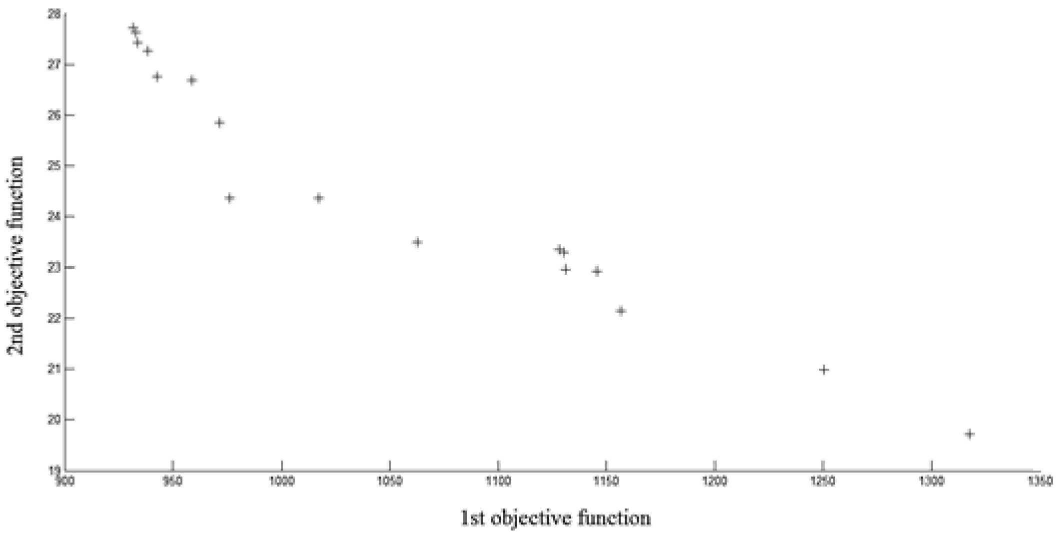


Figure 7. The solutions spreading over the last 50 iterations (NSGA II)

Table 2 shows the comparison between obtained results considering the number of function calls (table). To compare the speed of three mentioned methods in finding optimum solutions, the trend in the solutions is presented trough curves shown in Figure 8.

Table 2. Comparison between the numbers of function calls in three mentioned technique

Algorithm	Iterations	Population size	Number of function calls
Proposed Algorithm	150	50	6181
NSDE	150	50	7552
NSGA II	150	50	8451

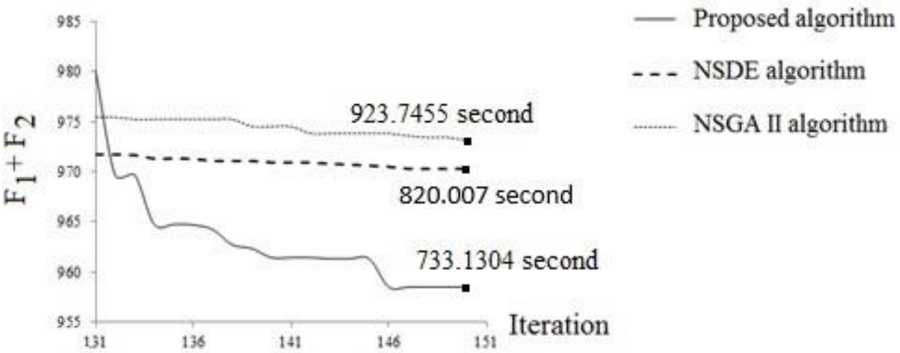


Figure 8. Rate of convergence to the optimum over the last 50 iterations

Considering Figure 9, the lower relay time delay setting is achieved by suggested algorithm. Figure 10 also demonstrates the calculated discrimination between main and backup relays operating time through proposed method is lower.

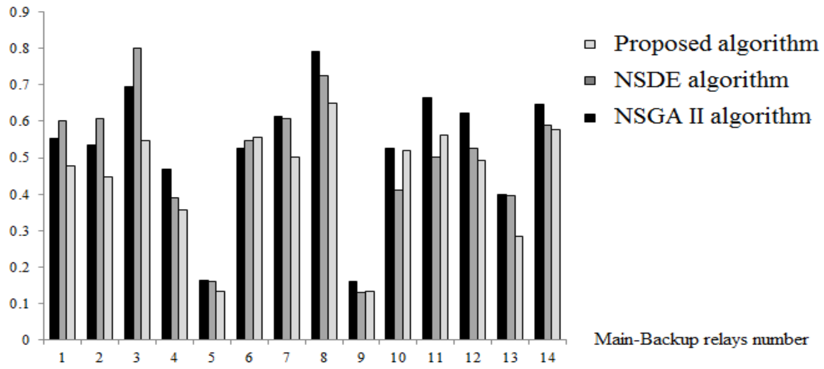


Figure 9. Relay time delay setting

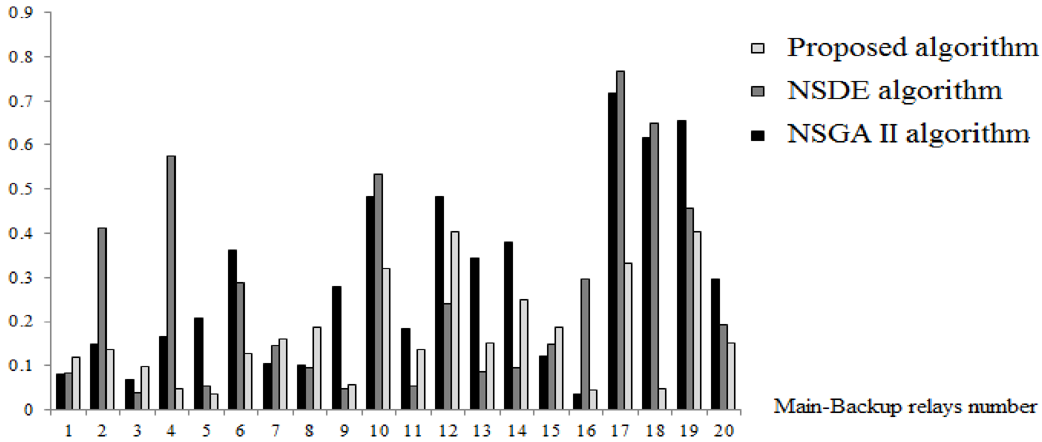


Figure 10. The discrimination between main and backup relays operating time

The obtained results demonstrate that the suggested approach presents a better performance in terms of relays coordination with respect to NSDE and NSGA II algorithms under equal iterations.

5. Conclusion

In this paper, two single objective optimization methods, particle swarm optimization and cuckoo optimization algorithm were used together in the form of a multi objective optimization algorithm. In proposed method, determination of initial limited area for each objective function, and moving all functions toward global optimum, caused the range of solutions covered the entire space and not limited to a specific area. In this technique, the members of rank 2 (or upper) had been also moved quickly toward lower ranked points. This caused faster convergence to the optimum solution. For the purpose of performance evaluation, the proposed multi-objective Pareto optimization algorithm had been investigated on a set of standard benchmark problems. From the results of these test functions, it had seen that the proposed algorithm remarkably outperformed a known algorithm (NSGA II), in terms of better matching to optimum Pareto front, run time and solutions diversity.

The capability of this algorithm in solving complex engineering problems such as power system protection had been also studied. The results indicated that the fast convergence and high speed characteristic of suggested approach can be used in online applications require fast decision-making such as online power system protection.

References

[1] Kotinis M. A particle swarm optimizer for constrained multi-objective engineering design problems. *Engineering Optimization*. 2010; 42: 907–926.

[2] Xue B, Zhang M, Browne WN. Particle swarm optimization for feature selection in classification: A multi-objective approach. *IEEE Transactions on Cybernetics*. 2013; 43: 1656–1671.

[3] Xue B, Cervante L, Shang L, Browne WN, Zhang M. A multi-objective particle swarm optimisation for filter-based feature selection in classification problems. *Connection Science*. 2012; 24: 91–116.

[4] Yun R, Yu CS. Improved NSGAII with a new distribution and its application in multi-objective reservoir operation. *Applied Mechanics and Materials*. 2011; 90-93: 279–286.

[5] Bernardon DP, Garcia VJ, Ferreira ASQ, Canha LN. Multicriteria distribution network reconfiguration considering subtransmission analysis. *IEEE Trans. Power Deliv*. 2010; 25: 2684–2691.

[6] Amanulla B, Chakrabarti S, Singh SN. Reconfiguration of power distribution systems considering reliability and power loss. *IEEE Trans. Power Deliv*. 2012; 27: 918–926.

[7] Matcha, Murali, Sharath Kumar Papani, and Vijetha Killamsetti. "Adaptive Relaying of Radial Distribution System with Distributed Generation". *International Journal of Electrical and Computer Engineering (IJECE)*. 2013; 3(3): 407-414.

[8] KR, Aejaz Ahmed, Mohd ZA Ansari, and Mohamed Jalaluddin. "Simulation Analysis of a Power System Protection using Artificial Neural Network". *International Journal of Electrical and Computer Engineering (IJECE).* 2012; 3(1): 78-82.

[9] Liu Y, Collette M. Improving surrogate-assisted variable fidelity multi-objective optimization using a clustering algorithm. *Applied Soft Computing*. 2014; 24: 482–493.

[10] Zhao W, Sameer A, Abbass HA. MOCCA-II: A multi-objective co-operative co-evolutionary algorithm. *Applied Soft Computing*. 2014; 23: 407–416.

[11] Zhao X, Liu Z, Yang X. A multi-swarm cooperative multistage perturbation guiding particle swarm optimizer. *Applied Soft Computing*. 2014; 22: 77–93.

[12] Xu G, Yang Y, Liu B, Xu Y, Wu A. An efficient hybrid multi-objective particle swarm optimization with a multi-objective dichotomy line search. *Journal of Computational and Applied Mathematics*. 2014; 280: 310–326.

[13] Singh, Himmat, and Laxmi Srivastava. Modified Differential Evolution algorithm for multi-objective VAR management. *International Journal of Electrical Power & Energy Systems*. 2014; 55: 731-740.

[14] Ali, Musrrat, Patrick Siarry, and Millie Pant. An efficient differential evolution based algorithm for solving multi-objective optimization problems. *European journal of operational research*. 2012; 217: 404-416.

[15] Yildiz, Ali R. Hybrid Taguchi-differential evolution algorithm for optimization of multi-pass turning operations. *Applied Soft Computing*. 2013; 13: 1433-1439.

[16] Wang, Ligang et al. Multi-objective optimization of coal-fired power plants using differential evolution. *Applied Energy*. 2014; 115: 254-264.

[17] Bonilla-Petriciolet, Adrián, Shivom Sharma, and Gade Pandu Rangaiah. Phase Equilibrium Data Reconciliation Using Multi-Objective Differential Evolution with Tabu List. *Multi-Objective Optimization in Chemical Engineering: Developments and Applications*. 2013; 46: 267-292.

[18] Yildiz, Ali R. A new hybrid differential evolution algorithm for the selection of optimal machining parameters in milling operations. *Applied Soft Computing*. 2013; 13: 1561-1566.

[19] Li, Yan-Fu, Giovanni Sansavini, and Enrico Zio. Non-dominated sorting binary differential evolution for the multi-objective optimization of cascading failures protection in complex networks. *Reliability Engineering & System Safety*. 2013; 111: 195-205.

[20] Zhang, Huifeng et al. Daily hydrothermal scheduling with economic emission using simulated annealing technique based multi-objective cultural differential evolution approach. *Energy*. 2013; 50: 24-37.

[21] Goudos, Sotirios K et al. A Multi-Objective Approach to Subarrayed Linear Antenna Arrays Design Based on Memetic Differential Evolution. *IEEE Transactions on Antennas and Propagation*. 2013; 61: 3042-3052.

[22] Preetha Roselyn J, D Devaraj and Subhransu Sekhar Dash. Multi Objective Differential Evolution approach for voltage stability constrained reactive power planning problem. *International Journal of Electrical Power & Energy Systems*. 2014; 59: 155-165.

[23] Lai, Johnny CY et al. Hypoglycaemia detection using fuzzy inference system with multi-objective double wavelet mutation Differential Evolution. *Applied Soft Computing*. 2013; 13: 2803-2811.

[24] Zhang, Huifeng et al. Short term hydrothermal scheduling using multi-objective differential evolution with three chaotic sequences. *International Journal of Electrical Power & Energy Systems.* 2013; 47: 85-99.

[25] Guo, Jun et al. A novel multi-objective shuffled complex differential evolution algorithm with application to hydrological model parameter optimization. *Water resources management*. 2013; 27: 2923-2946.

[26] Xu, Bin et al. Optimization of p-xylene oxidation reaction process based on self-adaptive multi-objective differential evolution. *Chemometrics and Intelligent Laboratory Systems*. 2013; 127: 55-62.

[27] Zhang, Huifeng et al. An efficient multi-objective adaptive differential evolution with chaotic neuron network and its application on long-term hydropower operation with considering ecological environment problem. *International Journal of Electrical Power & Energy Systems*. 2013; 45: 60-70.
[28] Chase N, Rademacher M, E Goodman E. A Benchmark Study of Multi objective Optimization Methods.
[29] Thangaraj R, Pant M, Deep K. Optimal coordination of over-current relays using modified differential evolution algorithms. *Engineering Applications of Artificial Intelligence*. 2010; 23: 820–829.
[30] Amorim EA, Hashimoto SHM, Lima FGM, Mantovani JRS. Multi Objective Evolutionary Algorithm Applied to the Optimal Power Flow Problem. *Latin America Transactions, IEEE (Revista IEEE America Latina)*. 2010; 8: 236 – 244.
[31] Abido MA. Multi objective evolutionary algorithms for electric power dispatch problem. *IEEE Transactions on Evolutionary Computation*. 2006; 10: 315 – 329.
[32] Mendoza F, Bernal-Agustin JL, Dominguez-Navarro JA. NSGA and SPEA Applied to Multi objective Design of Power Distribution Systems. *IEEE Transactions on Power Systems*. 2006; 21: 1938-1945.
[33] Zhihuan L, Yinhong L, Xianzhong D. Non-dominated sorting genetic algorithm-II for robust multi-objective optimal reactive power dispatch. *Generation, Transmission & Distribution, IET*. 2010; 4: 1000 – 1008.
[34] Razavi F, Askarian Abyaneh H, Al-Dabbagh M, Mohammadi R, Torkaman H. A new comprehensive genetic algorithm method for optimal overcurrent relays coordination. *Electric Power Systems Research*. 2008; 78: 713–720.
[35] Mirzakhani A, Taghikhani M. Retrieval system protection coordination of distribution networks after the installation of distributed generation resources with an intelligent algorithm. *Tech J Engin & App Sci*. 2013: 3333-3345.