Modified multi-objective PSO for coordination of directional overcurrent relays in interconnected networks

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Directional overcurrent relays are used to protect transmission lines against short circuits. Reducing the total operating time of relays has always been a challenge for protection engineers. For this purpose, various optimization algorithms have been introduced, some of which are based on multi-objective optimization. The objective functions of multi-objective algorithms must have the Pareto optimality property, which it's ignoring is one of the drawbacks of previous studies. In this paper, new objective functions are proposed for a multi-objective optimization problem. To solve the optimization problem, the Multi-object PSO (MOPSO)algorithm is applied with small but effective changes to get the fastest settings of relays. These changes include a leader selection method, a removal method of repository surplus members, and a new velocity vector for particles based on the value of the objective function in the previous iteration. The proposed algorithm is evaluated in IEEE 30-bus network and compared with the standard MOPSO. There is also a comparison with the recent outstanding papers. The proposed method, compared to the 15 algorithms of other papers, results in the lowest total operating time of relays with a 7% reduction.

keywords: *MOPSO, Optimization, Pareto-ranking, IEEE 30-bus network.*

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NOMENCLATURE

i, k	Relays indices
j	Fault location indices
R	Number of primary relays
B	Number of backup relays
t	Operating time of a relay
I_f	Fault current
$\mathbf{x}$	Decision variable, particle location
o	Number of objective functions
$g(\mathbf{x})$	Inequality constraint
m	Number of inequality constraint
$h(\mathbf{x})$	Equality constraint
q	Number of equality constraint
l	Particle indices
$\mathbf{v}$	Velocity vector
ω, c_1, c_2	Coefficients of velocity vector
$\mathbf{r}_1, \mathbf{r}_2$	Random vectors in the $[0, 1]$ interval
r	Number of repository elements
β	Selection pressure

1. INTRODUCTION

Protection systems are an integral part of power transmission networks. Protection of lines against short circuits is one of the first protection systems to be used for a long time. Directional overcurrent relays (DOCRs) have the task of performing this function in interconnected networks that must operate coordinated. The relays are coordinated from two perspectives: disconnecting the short-circuited line in the shortest possible time and carefully selecting the exact line to be disconnected. For this purpose, the settings of relays are found by defining an optimization problem. In the last decade, optimization problem solving methods, objective functions (OFs), how to meet the constraints and technical requirements of the power system have received a lot of attention and hundreds of papers have been published in this field. Meanwhile, evolutionary algorithms have opened up a special place for themselves.

Particle swarm optimization (PSO) is an evolutionary algorithm that can be considered as the fundamental algorithm among many others. Subsequent to the introduction of PSO in 1995 [1] and when the PSO discussion was still the matter of contention, researchers attempted to introduce its different types and application areas in several studies [2–4], including Quantum-behaved PSO, Bare Bones PSO, Chaos theory-based PSO, Fuzzy PSO, Opposition-based learning PSO, Nelder-Mead PSO, PSO with Time-Varying Acceleration Coefficients, PSO with Age-Group topology, etc. [5]. The authors suggest if the OF is smaller, the movement is accepted [6]. Standard PSO and linear programming (LP) are compared and it is concluded that PSO gives a better answer [7]. In this paper, in order to make a comparison possible, it is assumed that the current settings of the relays are known and the goal is to obtain the time settings of the relays. With this assumption, the optimization problem turns from a nonlinear problem to a simple linear problem. Combination of LP and PSO is also introduced for the relays coordination in interconnected networks [8]. In this technique, the Plug Setting (PS) of relays are determined by PSO and the Time Multiplier Setting (TMS) of relays are determined by the linear programming algorithm. The authors suggest that the movement of the particle in every dimension to be done step by step [9, 10]. Given that the velocity vector of standard PSO has inertia, cognitive and cooperation parts, the authors use them step by step to keep the particle in the interval [11]. The authors suppose a vector to the personal best position as the velocity vector when the constraints are not satisfied [12]. The PSO algorithm is compared with other methods, and it is reported that PSO has superior operation [13]. Since the settings of some relays are discrete, coordination of relays based on discrete settings is introduced [14]. Nelder-Mead PSO is used and PSO is reported as a fast algorithm with proper convergence [15, 16]. In [16], coordination for near and far end bus faults are performed. The different static topologies of the network are also optimized together. In this paper, the comparison of the convergence rates of the two methods is made based on the number of iterations instead of the number of function evaluation. The change in cognitive and cooperation coefficients during optimization is introduced [17]. The authors use PSO for coordination of relays in the presence of transient fault currents [18]. The optimization problem can be single-objective or multi-objective. multi-objective methods are applied when the goal is to optimize two or more OFs simultaneously. In such a case, minimizing of one function leads to increase in other functions essentially. The output of multi-objective methods is a curve known as Pareto-frontier in which the user can trade off between points. The authors propose an appropriate method for achieving Pareto-frontier using PSO, which is called MOPSO [19]. The relay are coordinated using the MOPSO/FDMT method in [20]. A multi-objective method (NSGA-II) based on Genetic Algorithm (GA) is used and compared with GA [21]. A developed multi-objective grey wolf optimizer (MOGWO) with fuzzy logic decision-making tool is introduced to optimize the coordination and is compared with grey wolf optimizer (GWO) [22].

A. Related works

Generally, IEEE 8, 9, 14, 15, and 30 bus networks are used by authors to evaluate and prove ideas for relays coordination. The distribution part of IEEE 30-bus network is always used as a large-scale network, which has different versions based on the number of distributed generation (DG). Some papers work on this network with two DGs, which the common feature of them is the use of identical fault currents [23]. This common feature makes it fair to compare algorithms. Five single-objective algorithms are compared in [24]: GA, PSO, Differential Evolution (DE), Harmony Search (HS) and Seeker Optimization Algorithm (SOA). It is reported that DE algorithm has better results. The authors compare three algorithms in [25]: Gravitational Search Algorithm (GSA), Sequential Quadratic Programming (SQP) and hybrid GSA-SQP. They report that the hybrid GSA-SQP algorithm has better performance. Three techniques are compared in [26]: Invasive Weed Optimization (IWO), Improved IWO (IIWO) and hybrid-IIWO. Hybrid-IIWO technique has the best performance. The authors also use a modified water cycle algorithm (MWCA) [27] and a modified electromagnetic field optimization (EFO) algorithm for optimal coordination [28]. Therefore, at least 15 algorithms have been used to coordinate the relays in the distribution part of IEEE 30-bus network with two DGs.

B. Motivation

Standard evolutionary computation algorithms are not inherently suitable for optimal relay coordination because these problems have a high number of constraints and decision variables.

Despite the strengths of PSO, it has some disadvantages that include suffering from the partial optimism, which causes the less accuracy of the particles movement direction, and being unable to work out the problems of scattering properly [29].

In multi-objective optimization, objective functions should be selected in such a way that the parto-optimality property be established between them, which is generally disregarded.

C. Contributions

This paper uses MOPSO for optimization. Small but effective changes are applied to this algorithm to minimize total operating time of relays. These changes include a method of selecting the leader, a method of removing surplus repository members, a new velocity vector for particle based on the value of the OF in the previous iteration, and introduction of effective OFs in accordance with the requirements of multi-objective methods.

The rest of this paper is structured as follows. Section 2 explains the problem formulation of DOCRs coordination. Section 3 illustrates a brief review of multi-objective optimization methods. Section 4 explains the proposed method. Section 5 presents the results obtained by the proposed method on test network and gives a comparison between different algorithms. Finally, the main conclusions are given in Section 7.

2. PROBLEM FORMULATION

A. Objective function

The relay coordination is accomplished in the form of an optimization problem. The decision variables are TMS and PS. The objective function is the total operating time of the primary relays and their backups, which is defined according to the following relationship [26]:

$$\text{Objective Function} = \sum_{i=1}^{R}(t_{ij}^{p} + \sum_{k=1}^{B} t_{kj}^{b}) \tag{1}$$

Where, t_{ij}^{p} and t_{kj}^{b} are the operating time of i^{th} primary relay and k^{th} backup relay for j^{th} fault.

The operating time of inverse definite minimum time relays with standard inverse curve is as follows: [30]:

$$t_{ij} = \frac{0.14 \times TMS_i}{(\frac{I_{f_i}}{PS_i \times CT_{ratio}})^{0.02} - 1} \tag{2}$$

Where, I_{f_i} is the measured fault current in location i.

B. Constraints

Three categories of constraints must be met in the coordination of relays; coordination constraints, operating time and relay settings constraints.

B.1. Coordination constraint

To maintain selectivity property in the protection system, there must be a coordination time interval (CTI) between the tripping of the primary relay and its backups. In case of improper operatin of primary relay, the backup relay trips. The coordination constraint between the primary-backup relay pairs is defined as follows:

$$t_{kj}^{b} - t_{ij}^{p} \geq CTI \tag{3}$$

The value of CTI varies from 0.20 s to 0.50 s [31].

B.2. Operating time constraint

In order to maintain the transient stability of the network, the relays must remove the fault before a certain time. Also, to prevent undesirable tripping, the operating time should not be less than a specified time. These constraints are defined as follows:

$$t_i^{\min} \leq t_{ij} \leq t_i^{\max} \tag{4}$$

Where, $t_i^{\min}$ and $t_i^{\max}$ are the minimum and maximum allowable operating times in turn.

B.3. Relay settings constraints

Current and time settings of the relays impose some constraints into the optimization problem. These constraints are considered according to the following three inequalities:

$$TMS_i^{\min} \leq TMS_i \leq TMS_i^{\max} \tag{5}$$

$$PS_i^{\min} \leq PS_i \leq PS_i^{\max} \tag{6}$$

$$Ip_i^{\min} \leq Ip_i \leq Ip_i^{\max} \tag{7}$$

Where, $TMS_i^{\min}$ and $TMS_i^{\max}$ indicate the lower and upper limits of TMS respectively, $PS_i^{\min}$ and $PS_i^{\max}$ represent the lower and upper limits of PS in turn, $Ip_i^{\min}$ and $Ip_i^{\max}$ are the lower and upper pickup current limits, respectively.

3. BRIEF REVIEW OF MULTI-OBJECTIVE OPTIMIZATION

A. Definitions

A multi-objective optimization problem is generally defined as follows:

$$\begin{cases} \text{minimize } \mathbf{f}(\mathbf{x}) = [f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_o(\mathbf{x})], \\ \mathbf{x} = [x_1, x_2, \ldots, x_n] \\ g_i(\mathbf{x}) \geq 0, \quad i = 1, 2, \ldots, m \\ h_i(\mathbf{x}) = 0, \quad i = 1, 2, \ldots, q \end{cases} \tag{8}$$

Pareto optimality is a situation that cannot be modified so as to make any one objective function better off without making at least one objective function worse off. Therefore, a situation is called Pareto optimal if it is not Pareto dominated. The rule of domination is defined as follows: Vector $\mathbf{u} = [u_1, u_2, \ldots, u_k]$ dominates vector $\mathbf{v} = [v_1, v_2, \ldots, v_k]$ and is denoted by $\mathbf{u} \preceq \mathbf{v}$ if and only if:

$$(\forall i,\ u_i \leq v_i) \wedge (\exists i,\ u_i < v_i) \tag{9}$$

Pareto-frontier is the set of all Pareto optimal allocations and is the goal of solving the multi-objective optimization problems. Nondominated decision variables are stored in a repository. One member of the repository is chosen as the leader in each iteration. The leader is selected from a low-density zone using the roulette wheel algorithm. Also, If the number of repository members exceeds a predefined limit, surplus members will be removed which is done from a high-density zone using the roulette wheel algorithm again.

B. Multi-object PSO

In this paper, MOPSO is used. The particles motion rule is as follows:

$$\mathbf{v}^{l+1} = \omega.\mathbf{v}^{l} + c_1.\mathbf{r}_1.(\mathbf{pbest} - \mathbf{x}^{l}) + c_2.\mathbf{r}_2.(\mathbf{leader} - \mathbf{x}^{l}) \tag{10}$$

$$\mathbf{x}^{l+1} = \mathbf{x}^{l} + \mathbf{v}^{l+1} \tag{11}$$

Where, $\mathbf{v}^{l+1}$ and $\mathbf{v}^{l}$ are the current and previous velocity vectors, respectively. $\mathbf{r}_1$ and $\mathbf{r}_2$ are random vectors in the $[0, 1]$ interval. ω, c_1, c_2 are the coefficients of inertia, cognitive, and cooperation parts, respectively. $\mathbf{x}^{l+1}$ and $\mathbf{x}^{l}$ indicate the next and the current location in turn. The ω is damped linearly during the algorithm implementation:

$$\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{\text{iteration}_{\max}} \times \text{iteration} \tag{12}$$

Where, $\omega_{\max}$ and $\omega_{\min}$ are the upper and lower limits of ω.

4. PROPOSED METHOD

To coordinate the relays in the optimal approach, the following two important facts should be considered:

- **Method of constraints handling:** Evolutionary algorithms are designed for unconstrained problems. To meet the constraints, one can either define the single-objective optimization problem and use the penalty function method,in which the coefficient of penalty function is determined by trial-and-error, or use the Pareto ranking method. In the second method, the objective functions must be defined properly to consider the principle of Pareto optimality. Applying improper objective functions is a drawback of some papers.

- **Local optimum points:** The relays optimum coordination problem has many local optimum points due to the high number of constraints and decision variables. The algorithm should not be trapped at these points.

In this paper, four simple but very effective suggestions are provided to consider the above. These suggestions include:

1. Appropriate objective functions

2. Targeted method of the leader selection

3. Targeted removal method of repository surplus members

4. Effective velocity vector for PSO

These suggestions are explained below:

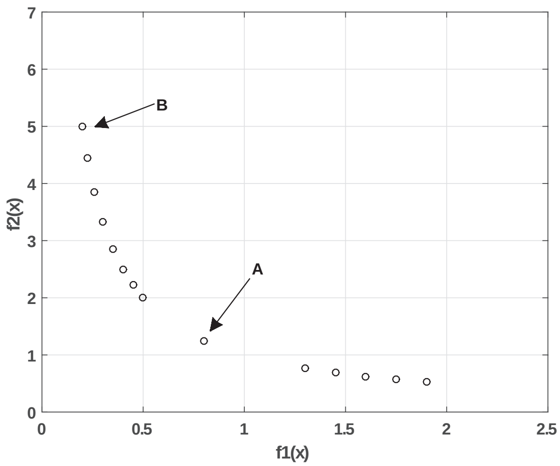

Fig. 1. Sample Pareto-frontier to show proposed leader selection method.

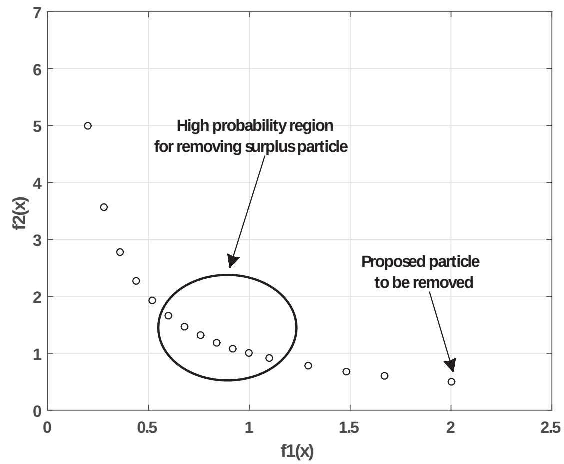

Fig. 2. Sample Pareto-frontier to show proposed surplus elimination method.

A. Objective functions

Appropriate objective functions pave the way for the optimum answer. In this paper, the multi-objective optimization method is used. As a result, there is no need to adjust the penalty function coefficient to address the selectivity constraint. The objective functions are as follows:

$$\begin{cases} f_1(\mathbf{x}) = \sum_{i=1}^{m} \max(1 - \frac{t_{kj}^b - t_{ij}^p - CTI}{CTI}, 0) \\ f_2(\mathbf{x}) = \sum_{i=1}^{R} (t_{ij}^p + \sum_{k=1}^{B} t_{kj}^b) \end{cases} \tag{13}$$

The first objective function which is introduced and used in this paper has the following properties:

1. Maintains Pareto optimally between objective functions. That is, increasing one function reduces another function.
2. Once the Pareto-frontier is identified, there is no need to trade off between points; The point with the lowest value for the $f_1(\mathbf{x})$ function is selected as the answer.
3. Its value is proportional to deviation from the coordination constraint.

B. Leader selection

As explained in sections 3, in conventional MOPSO, the leader is selected from a low-density zone using the roulette wheel algorithm. Considering selected OFs, for the algorithm to be led to the lower penalty function, it is proposed to select the leader from the particles at the beginning of the Pareto-frontier interval. In other words, the leader is chosen from the particles that have the lower penalty. Figure 1 shows a sample Pareto-frontier. According to the new method, the B particle with the minimum penalty has more chances than the A particle to be the leader. Although, the A particle is located in the empty zone.

For this purpose, particles of the repository are first arranged according to the penalty function value in an ascending order. Then, the following probability function is used to determine the probability of selection in the roulette wheel algorithm:

$$P(i) = \frac{i^{-\beta}}{\sum_{i=1}^{r} i^{-\beta}} \tag{14}$$

Where, $P(i)$ is the selection probability function of the ith element of the repository, β indicates the selection pressure, and r represents the number of repository elements. The smaller β is chosen, the probability of particle selection increases from the beginning of the Pareto-frontier interval.

In conventional MOPSO, the leader may be selected in an iteration from the beginning of the Pareto-frontier interval and in the next iteration from the end of the Pareto-frontier interval. Consequently, the direction of the velocity vector toward the leader varies in different iterations which causes a fluctuation in the movement of particles. As a result, the convergence to the global optimum point is reduced. Because of leader selection method explained, this problem is eliminated and leader selection fluctuations are prevented.

C. Removing surplus members of repository

Generally in MOPSO, the number of repository members is limited to a certain number. For the algorithm to be led to a lower penalty, it is suggested to eliminate surplus members of the repository from the particles at the end of the Pareto-frontier interval. Figure 2 shows a sample Pareto-frontier. Conventionally, a particle from the marked zone which is located in crowded zone is removed. According to the new method, the particle with the maximum penalty is eliminated.

For this purpose, the particles of the repository are first arranged according to the value of penalty functions in an ascending order. Then extra members are selected from the particles that have high penalty function. This eliminates the possibility of removing members with low penalty functions.

D. Modification on velocity vector

Optimal coordination of the DOCRs in the interconnected network has many local optimum points, since the number of decision variables and constraints are very high. To increase the speed of convergence and the escape rate from the local optimum points, it is proposed to update the position of the particles according to the following Pseudo-Code:

$$\begin{cases} \text{if } f_2(\mathbf{x}^l) < f_2(\mathbf{x}^{l-1}) \text{ then } \mathbf{v}^{l+1} = \omega.\mathbf{v}^l \\ \text{Else use (10)} \end{cases} \tag{15}$$

Consider Fig. 3 for more explanations. In this figure, point A and B are $\mathbf{x}^{l-1}$ and $\mathbf{x}^l$ simultaneously and the vector from A to B is $\mathbf{v}^l$. Dashed arrows are the three parts of conventional velocity vector according to (10). This vector leads the particle

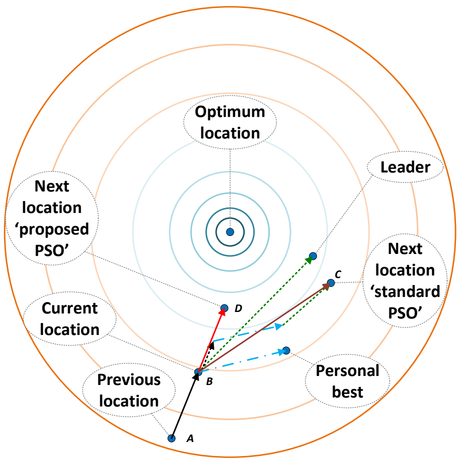

Fig. 3. Proposed velocity vector for PSO.

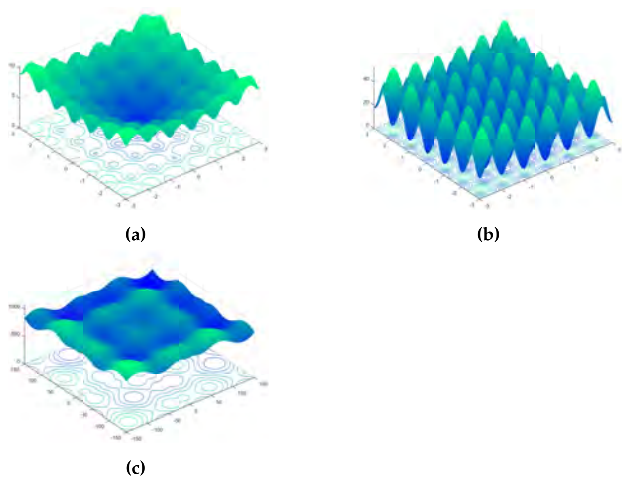

Fig. 4. Benchmark functions: (a) Ackley, (b) Rastrigin, (c) Schwefel.

to move from B to C. The vector from B to D is the vector based on the proposed method, which equals $\mathbf{v}^{l+1} = \omega.\mathbf{v}^{l}$. Point D is closer to the optimum point than point C, which means that the proposed vector improves the movement of particles. In the most cases, as mentioned above, the proposed method increases the convergence and the escape rate from the local optimum points.

The proposed method is evaluated on three benchmark functions that have many local optimum points. The description of these functions are presented in Table 1. Figure 4 depicts the surface profile of these benchmark functions for two decision variables.

The performance of the PSO algorithm was evaluated on these functions to count and compare the number of trappings in local optimum points. Figure 5 illustrates the average number of times that local optimum point is obtained when the evaluation was accomplished for 100 times. The results show that the proposed method effectively decreases the number of trappings in local optimum points.

Table 1. Benchmark functions.

Name	Description
Ackley	$f(x) = -20e^{-0.2\sqrt{\frac{1}{n_x}\sum_{j=1}^{n_x} x_j^2}} - e^{\frac{1}{n_x}\sum_{j=1}^{n_x}\cos(2\pi x_j)} + 20$
Rastrigin	$f(x) = \sum_{i=1}^{n_x}(x_i^2 - 10\cos(2\pi x_i) + 10)$
Schwefel	$f(x) = \sum_{i=1}^{n_x} x_i \sin(\sqrt{\lvert x_i \rvert}) + 418.989 \times 2$

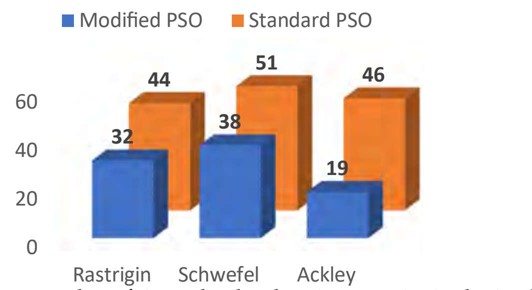

Fig. 5. Average number of times that local optimum point is obtained.

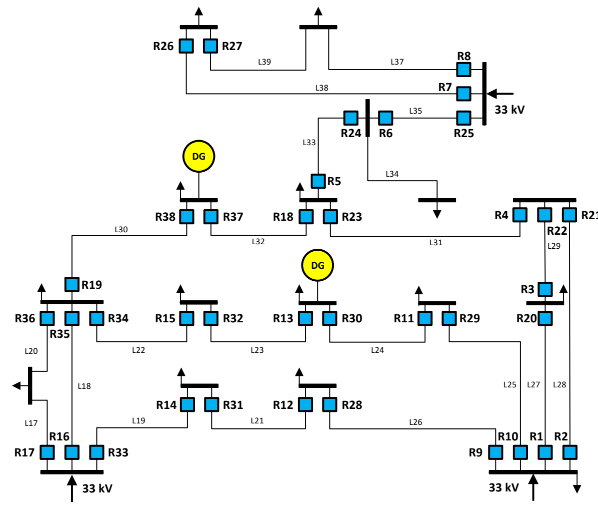

Fig. 6. Distribution part of IEEE 30 bus network.

5. RESULTS AND DISCUSSIONS

The proposed method is applied to IEEE 30-bus test network to evaluate its performance in a large case with DG penetration. The optimization problem has 72 decision variables and 214 constraints. The generators, transmission lines, and transformers information are given in [32]. As Fig. 6 shows, the network consists of 19 lines and three 33 kV inputs. Thirty eight DOCRs are used to protect the lines. The short-circuit currents are given in Table 2 [23]. Two DGs are installed at buses 10 and 15. The transient reactance and capacity of DGs are 0.15 p.u. and 10 MVA, respectively. The TMS_i^{min} and TMS_i^{max} boundaries are 0.1 and 1.1, respectively. The PS_i^{min} and PS_i^{max} boundaries are 1.5 and 6, respectively. The CTI is set to 0.3 s as in [22]. The CT Ratio for relays is 1000:5.

The following two algorithms are assessed for proving the superiority of the proposed method in coordination of DOCRs.

- Case #1: Conventional MOPSO.
- Case #2: Modified MOPSO.

The optimum settings for this network using the new approach are presented in Table 3. The relays settings and operating times are within the limits with no miscoordination, which indicate that the solution is indeed feasible. Fig. 7 shows the Pareto frontier. The point on the vertical axis is selected as the

Table 2. Fault currents of primary-backup relay pairs

p [1]	b [2]	I_p [3]	I_b [4]	p	b	I_p	I_b
1	21	7665.3	698.8	19	15	5445.2	1527.3
1	28	7665.3	1552	19	16	5445.2	3128.3
1	29	7665.3	1380.6	19	17	5445.2	801.3
2	20	7985.7	1053.9	20	22	3481.5	3481.5
2	29	7985.7	1375.2	21	3	5411.8	3243.6
2	28	7985.7	1545.8	21	23	5411.8	2193.5
3	1	4086.7	4086.7	22	2	4333	2147
4	2	5411.2	2138.8	22	23	4333	2204.6
4	3	5411.2	3272.5	23	24	3689.7	1724.2
5	4	4960.8	3001.3	23	37	3689.7	1968.5
5	37	4960.8	1961	24	25	2695	2695
6	5	2416	2416	26	8	1026.8	1026.8
7	6	5669	1790.9	27	7	1472.3	1472.3
8	6	5607.7	1774.8	28	31	2036.8	2036.8
9	20	7212.6	1103.5	29	30	2518.9	2518.9
9	21	7212.6	721.2	30	32	2998.8	2149
9	29	7212.6	1379	31	33	3263.6	3263.6
10	20	7339.3	1095.8	32	34	2930.4	2930.4
10	21	7339.3	716.1	33	35	6456.2	1954.5
10	28	7339.3	1538	33	36	6456.2	500.6
11	10	3457.1	3457.1	34	16	5796.6	3123.9
12	9	5034.9	5034.9	34	17	5796.6	800.1
13	11	3727.3	2875	34	38	5796.6	1886.8
14	12	2906.5	2906.5	35	15	4222	1533.2
15	13	2660.5	2660.5	35	17	4222	794
16	14	6185.6	1668.1	35	38	4222	1896.7
16	36	6185.6	490.9	36	15	6420.2	1509.7
17	14	7492.9	1641.1	36	16	6420.2	3052.4
17	35	7492.9	1885.4	36	38	6420.2	1867.7
18	4	4719.4	3002.1	37	19	3788.9	2940.9
18	24	4719.4	1717.7	38	18	3133.2	2292.2

[1] Primary relay
[2] Backup relay
[3] Fault current of primary relay
[4] Fault current of backup relay

Table 3. Optimal relay settings

R# [1]	TMS	PS	R#	TMS	PS	R#	TMS	PS
1	0.376	1.500	14	0.100	3.742	27	0.100	1.500
2	0.267	1.500	15	0.100	3.106	28	0.108	4.003
3	0.237	1.895	16	0.152	4.876	29	0.240	1.500
4	0.100	5.922	17	0.100	1.857	30	0.123	5.671
5	0.100	5.133	18	0.100	5.026	31	0.136	4.324
6	0.155	1.500	19	0.100	5.998	32	0.100	5.958
7	0.100	2.859	20	0.100	2.997	33	0.218	3.686
8	0.100	2.294	21	0.145	1.500	34	0.139	5.962
9	0.342	1.500	22	0.232	1.746	35	0.100	4.832
10	0.403	1.500	23	0.109	4.890	36	0.100	1.500
11	0.271	1.820	24	0.220	1.501	37	0.100	4.415
12	0.121	5.177	25	0.216	2.973	38	0.100	4.378
13	0.125	4.363	26	0.100	1.500			

[1] Relay number

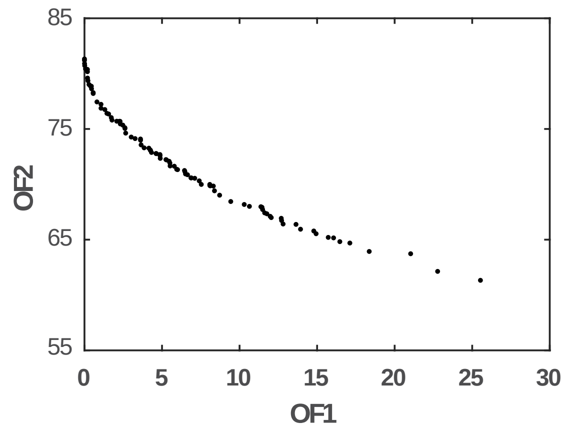

Fig. 7. Pareto frontier.

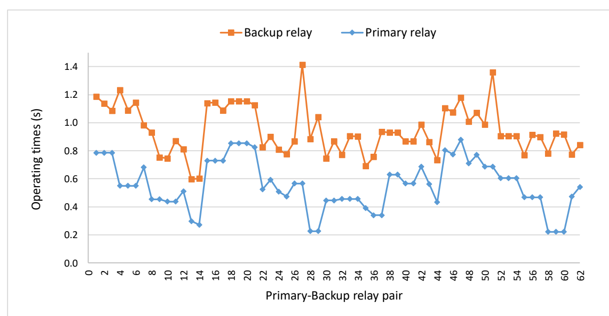

Fig. 8. Operating time of primary–backup relay pairs

final answer, according to the scenario described in Section A. The operating time of the primary–backup relays and discrimination time using the proposed method is listed in Table 4 and represented graphically in Fig. 8. The results obtained by different optimization techniques are given in Table 5. Fig. 9 shows the comparison between recent outstanding algorithms. Table 5 shows that the proposed method gives the least total operating time of primary relays (21.39 s) and the least total operating time of backup relays (58.7 s). In addition, the proposed method gives the least total discrimination time (24.28 s) without any miscoordination between relay pairs.

6. STATISTICAL EVALUATION

The proposed algorithm was run 30 times to evaluate its robustness statistically. Statistical analysis of OF and operating times of primary and backup relays in terms of mean, minimum, maximum, standard deviation, and 95% confidence interval are presented in Table 6.

For OF the best result is 80.09 s, and the worst is 85.6 s. The standard deviation is 1.66, which is small enough and indicating high robustness of the proposed algorithm. With 95% confidence the population mean is between 82 and 83.2, based on 30 samples.

For primary and backup relays operating times the best result are 0.221 s and 0.958 s, and the worst are 0.88 s and 1.414 s respectively. The standard deviation is 0.17 for both times. With

Table 4. Primary and backup operating times and CTIs

p [1]	b [2]	t_p [3]	t_b [4]	CTI	p	b	t_p	t_b	CTI
1	21	0.79	1.19	0.10	19	15	0.46	0.77	0.02
1	28	0.79	1.14	0.05	19	16	0.46	0.90	0.15
1	29	0.79	1.09	0.00	19	17	0.46	0.90	0.15
2	20	0.55	1.23	0.38	20	22	0.39	0.69	0.00
2	29	0.55	1.09	0.24	21	3	0.34	0.76	0.12
2	28	0.55	1.14	0.29	21	23	0.34	0.94	0.30
3	1	0.68	0.98	0.00	22	2	0.63	0.93	0.00
4	2	0.45	0.93	0.18	22	23	0.63	0.93	0.00
4	3	0.45	0.75	0.00	23	24	0.57	0.87	0.00
5	4	0.44	0.75	0.01	23	37	0.57	0.87	0.00
5	37	0.44	0.87	0.13	24	25	0.69	0.99	0.00
6	5	0.51	0.81	0.00	26	8	0.56	0.86	0.00
7	6	0.30	0.60	0.00	27	7	0.43	0.73	0.00
8	6	0.27	0.60	0.03	28	31	0.80	1.10	0.00
9	20	0.73	1.14	0.11	29	30	0.77	1.07	0.00
9	21	0.73	1.14	0.11	30	32	0.88	1.18	0.00
9	29	0.73	1.09	0.06	31	33	0.71	1.01	0.00
10	20	0.85	1.15	0.00	32	34	0.77	1.07	0.00
10	21	0.85	1.15	0.00	33	35	0.69	0.99	0.00
10	28	0.85	1.15	0.00	33	36	0.69	1.36	0.37
11	10	0.82	1.12	0.00	34	16	0.60	0.90	0.00
12	9	0.53	0.83	0.00	34	17	0.60	0.90	0.00
13	11	0.59	0.90	0.01	34	38	0.60	0.90	0.00
14	12	0.51	0.81	0.00	35	15	0.47	0.77	0.00
15	13	0.47	0.78	0.00	35	17	0.47	0.91	0.15
16	14	0.57	0.87	0.00	35	38	0.47	0.90	0.13
16	36	0.57	1.41	0.55	36	15	0.22	0.78	0.26
17	14	0.23	0.88	0.36	36	16	0.22	0.92	0.40
17	35	0.23	1.04	0.51	36	38	0.22	0.92	0.40
18	4	0.45	0.75	0.00	37	19	0.47	0.77	0.00
18	24	0.45	0.87	0.12	38	18	0.54	0.84	0.00

[1] Primary relay
[2] Backup relay
[3] Operating time of primary relay
[4] Operating time of backup relay

Table 5. Comparison between different methods.

Method	$\sum t_{ij}^{p}$ [1]	$\sum t_{kj}^{b}$ [2]	OF [3]
PSO [24]	58.64	94.08	152.72
WCA [27]	31.26	94.32	125.59
GSA-SQP [25]	26.82	69.18	96.01
Hybrid-IIWO [26]	24.75	65.38	90.14
MOGWO [22]	22.74	60.55	83.3
Conventional MOPSO (Case #1)	22.92	63.58	86.49
Modified MOPSO (Case #2)	21.39	58.7	80.09

[1] Total operating time of primary relays
[2] Total operating time of backup relays
[3] Objective Function

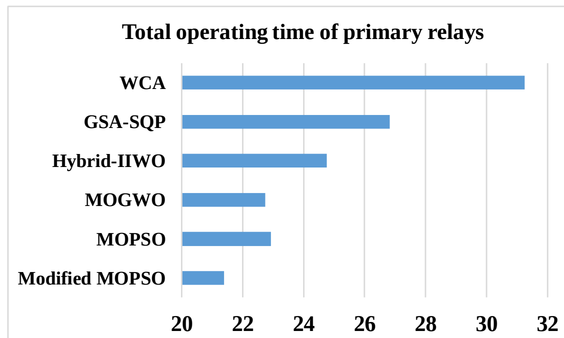

Fig. 9. Comparison between algorithms.

Table 6. Statistical evaluation.

	OF [1]	t_p [2]	t_b [3]
Mean	82.626	0.560	0.947
Minimum	80.09	0.221	0.598
Maximum	85.6	0.880	1.414
SD [4]	1.660	0.176	0.172
95% CI [5]	82.626±0.594	0.560±0.0567	0.947±0.0428

[1] Objective function
[2] Operating time of primary relays
[3] Operating time of backup relays
[4] Standard deviation
[5] Confidence interval

95% confidence the population mean is between 0.504 and 0.617 for primary relays operating time. In the same way, with 95% confidence the population mean is between 0.904 and 0.99 for backup relays operating time.

These advantages are mainly due to the selected objective functions and the increased escape rate from the local optimum points with the proposed velocity vector. This table shows the excellent performance of the Modified MOPSO.

7. CONCLUSION

Previously, numerus algorithms have been implemented in the forms of single-objective and multi-objective methods for coordination of DOCRs in interconnected networks. They have been developed to eliminate miscoordination and reduce the total operating time of relays. In the problem of relays optimum coordination, many local optimum points exist due to the high number of constraints and decision variables. It is tough to achieve the global optimum point in the single-objective method, because the coefficient of penalty function is chosen in a trial-and-error method. Proper objective functions have not been chosen in several papers that have used multi-objective methods; therefore, a rational scenario has not been provided for selection of the answer from Pareto-frontier.

In this paper, a multi-objective optimization algorithm based on modifications in MOPSO was proposed. Two appropriate objective functions in accordance with the requirements of multi-objective methods were proposed. In addition, a method for selecting the leader and a method for removing surplus members from the repository were proposed. A new velocity vector was also proposed for MOPSO to avoid local optimum points. These techniques have made the algorithm effective in coordination optimizing of directional overcurrent relays. With the standard MOPSO and the proposed algorithm, the problem of relays optimum coordination in IEEE 30 bus network was solved. It was shown that the proposed algorithm achieves less total operating times than standard MOPSO. In addition, the obtained result reduced the total operating time of the relays by 7.1% compared to the state-of-the-art paper. The proposed algorithm performed better than the previous 15 methods.

The lowest total operating time of the primary relays and the lowest total operating time of the backup relays compared to the related papers are obtained by the proposed method.

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