A Hybrid Optimization Algorithm (IA-PSO) for Optimal Coordination of Directional Overcurrent Relays in Meshed Power Systems

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Abstract: This paper presents a hybrid optimization approach for the optimal coordination of Inverse Definite Minimum Time (IDMT) directional overcurrent relays in meshed power systems, namely Immune Algorithm and Particle Swarm Optimization (IA-PSO) algorithm. The algorithm is employed by coupling the immune information processing mechanism with the particle swarm optimization algorithm in order to achieve a better global solution with less computational effort. In protection coordination problem, the objective function to be minimized is the sum of the operating time of all main relays. The optimization problem is subject to a number of constraints which are mainly focused on the operation of the backup relay, which should operate if a primary relay fails to respond to the fault near to it, Time Dial Setting (TDS), Plug Setting (PS) and the minimum operating time of a relay. The proposed optimization algorithm aims to minimize the total operating time of each protection relay. Two systems are used as case study to check the efficiency of the optimization algorithm which are IEEE 4-bus and IEEE 6-bus models. Results are obtained and presented for IA and PS and IA-PSO algorithms. The obtained results for the studied cases are compared with those results obtained when using other optimization algorithms which are Teaching Learning-Based Optimization (TLBO), Chaotic Differential Evolution Algorithm (CDEA) and Modified Differential Evolution Algorithm (MDEA). From analysing the obtained results, it has been concluded that IA-PSO algorithm provides the most optimum solution with the best convergence rate.

Key-Words: Meshed Power Systems, Directional Overcurrent Protection Relays, Optimal Coordination, Immune Algorithm, Particle Swarm Optimization, Hybrid Optimization Algorithms.

Nomenclature

IDMT	Inverse Definite Minimum Time
T	Relay total operating time
I_F	Fault current
TDS	Time Dial Setting
PS	Plug Setting
CT	Current transformer
$CT_{pr\text{-}rating}$	Primary rating of *CT*
I_{relay}	Current seen by the relay
OF	Objective function
TDS_{min}	Minimum value for *TDS*
TDS_{max}	Maximum value for *TDS*
T^{min}	Minimum value of relay operating time
T^{max}	Maximum value of relay operating time
CTI	Coordination Time Interval
$T_{pri\text{-}cl\text{-}in}$	Operating time to clear near end fault
$T_{pri\text{-}far\text{-}bus}$	Operating time to clear far end fault
$T_{primary}$	Operating time of primary relay
T_{backup}	Operating time of backup relay
N_{cl} and N_{far}	Number of relays installed at both ends of the primary line

1 Introduction

Due to the rapid development of huge industrial systems, stability and security issues of power systems have recently acquired more attention. The basic function of protection systems is to detect and remove the faulty parts as fast and selectively as possible. Therefore, various relays with different operating principles are used to detect system abnormalities and execute appropriate actions in order to rapidly isolate faulty components from a healthy system. Each protection relay needs to be coordinated with the relays protecting adjacent equipment. Hence, relays should not only be correctly operated, but also properly coordinated with each other by finding optimum relay settings. This gives importance to the problem of relays coordination.

Directional overcurrent relay is a good technical and economic choice for protection of transmission and distribution power systems [1]. Such a relay with inverse time characteristics consists of an instantaneous unit and a time overcurrent unit.

The overcurrent unit has two parameters to be defined which are PS and TDS. The use of computers in the power systems application of relay coordination has relieved protection engineers from huge mathematical calculations. Conventionally, classical protection philosophy and parameter optimization techniques are reported in literature for relay coordination studies. In conventional classical protection approach, the looped transmission and distribution system are treated as radial in relay coordination studies.

Relays at remote end are set first and corresponding backup relays are set thereafter from the coordination protection point of view. In this way, all possible paths are taken into account for optimal setting of relay parameters.

Coordination of overcurrent relays requires the accurate selection of optimum settings. Out of both, only the values of TDS can be optimized while solving the coordination problem with the help of optimization algorithms. In protection coordination problem, the total operating time of all main relays is minimized. Constraints of the problem are considered in the secondary relay which should operate if the main relay fails to respond to the fault near to it, TDS and PS and minimum operating time of the relay.

Table I represents the different optimization algorithms which were developed by researchers to provide optimum solution for relay settings and coordination in order to achieve optimum protection.

TABLE I
Literature for optimisation algorithm

Ref.	Optimization Algorithm
[2]	Evolutionary Algorithm (EA)
[3]	Differential Evolution Algorithm (DEA)
[4]	Modified Differential Evolution Algorithm
[5]	Self-Adaptive Differential Evolutionary
[6]	Particle Swarm Optimization (PSO)
[7-8]	Modified Particle Swarm Optimization
[9]	Evolutionary Particle Swarm Optimization
[10]	Box-Muller Harmony Search
[11]	Zero-one Integer Programming
[12]	Covariance Matrix Adaptation Evolution Strategy
[13]	Seeker Algorithm
[14]	Teaching Learning Based Optimization
[15]	Chaotic Differential Evolution Algorithm
[16]	Informative Differential Evolution Algorithm
[17]	Firefly Optimization Algorithm
[18]	Krill Herd Algorithm
[19]	Non-dominated Sorting Genetic Algorithm
[20]	Biogeography Based Optimization

In this research work, a hybrid optimization technique namely IA-PSO is proposed to select the optimal values of relay settings and present a solution for the coordination problem between primary and backup relays. In this paper, IA, PSO and IA-PSO algorithms are applied to IEEE 4-bus and IEEE 6-bus systems which are modelled and simulated to verify the efficiency of the proposed hybrid algorithm. Moreover, the obtained results when using these three algorithms are compared with the published results obtained for TLBO, CDEA and MDEA algorithms. When compared with the other algorithms, IA-PSO algorithm shows faster convergence and provides an improvement in minimizing the total operating time (T) of each protection relay in the two studied cases.

2 Optimal Relay Coordination Problem

The operating time of IDMT relay is inversely proportional to the fault current. Hence, overcurrent relay will operate fast after sensing a high current. However, IDMT relays are categorized into standard inverse, very inverse and extremely inverse types. Relay characteristics depend on the type of standards selected for its operation. These standards can be ANSI, IEEE, IEC or user defined. Typically, there are overcurrent relays for protection against inter phase faults and phase to earth faults on the line.

The tripping time of the relay follows a time over current delayed curve, in which the time delay depends upon the current. The two decisive factors are *TDS* and *PS*. The operating time of the relay is closely related to *TDS*, *PS* and the fault current (I_F). The total operating time is given by a non-linear mathematical equation [3], [11-15] with respect to the coordination time constraint between backup and primary relays:

$$T = \frac{\alpha \times TDS}{\left(\frac{I_F}{PS \times CT_{pr-rating}}\right)^{\beta} - \gamma} \tag{1}$$

α, β and γ are constants. According to IEEE standards [21], the values of these constants are given by 0.14, 0.02 and 1.0, respectively. I_F is the fault current at *CT* primary terminal where the fault occurs while $CT_{pr-rating}$ is the primary rating of *CT*.

The ratio between I_F and $CT_{pr-rating}$ gives the current seen by the relay denoted by I_{relay}.

$$I_{relay} = \frac{I_F}{CT_{pr-rating}} \tag{2}$$

2.1 Objective Function

As in Figure 1, a close-in fault (or near end fault) is a fault that occurs close to the relay and a far-bus fault (or far end fault) is a fault that occurs at the other end of the line.

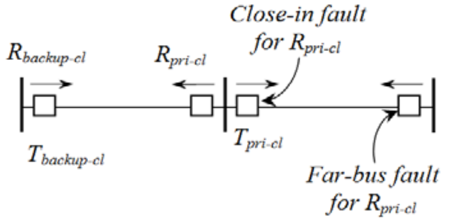


Fig. 1. Close-in and far-bus faults for primary relay.

In coordination studies, the summation of the operating time of all the primary relays to clear a near or far end fault can be considered as an objective function that is to be minimized. Therefore, the objective function (OF) can be expressed as follows, as given in [4], [14-15]:

$$Minimize\ OF = \sum_{i=1}^{N_{cl}} T^i_{pri-cl-in} + \sum_{j=1}^{N_{far}} T^j_{pri-far-bus} \tag{3}$$

where,

$$T^i_{pri-cl-in} = \frac{0.14 \times TDS^i}{\left(\dfrac{I^i_F}{PS^i \times CT^i_{pr-rating}}\right)^{0.02} - 1} \tag{4}$$

$$T^j_{pri-far-bus} = \frac{0.14 \times TDS^j}{\left(\dfrac{I^j_F}{PS^j \times CT^j_{pr-rating}}\right)^{0.02} - 1} \tag{5}$$

2.2 Constraints

Three constraints are considered for the minimization problem. The first constraint is *TDS* of the relay which is the time delay before the relay operates whenever the fault current becomes equal to or greater than the *PS* setting [12-17].

$$TDS^i_{\min} \le TDS^i \le TDS^i_{\max} \tag{6}$$

i varies between 1 and N_{cl}. TDS^i_{min} and TDS^i_{max} are the minimum and maximum limits of *TDS* which are 0.05 and 1.10 sec, respectively. The second constraint concerning *PS* takes the form:

$$PS^i_{\min} \le PS^i \le PS^i_{\max} \tag{7}$$

i varies between 1 and N_{far}. PS^i_{min} and PS^i_{max} are the minimum and maximum values of *PS* which are 1.25 and 1.50, respectively. Relay operating time is related to the fault current which can be seen by the relay and the pickup current setting. Relay operating time is based on the type of the relay and it can be determined by standard characteristic curves of the relay or analytic formula. Hence, the relay operating time is defined by:

$$T_i^{\min} \le T_i \le T_i^{\max} \tag{8}$$

T^{min} and T^{max} are the minimum and maximum values for the relay operating time which are 0.05 and 1.00, respectively.

The coordination time interval between the primary and the backup relays must be verified during the optimization procedure. In this paper, the chronometric coordination between the primary and the backup relays is used as equation (9):

$$T_{backup} - T_{primary} \ge CTI \tag{9}$$

T_{backup} and $T_{primary}$ are the operating time of the backup and primary relay, respectively and *CTI* is the minimum coordination time interval.

For electromechanical relays, *CTI* varies between 0.30 and 0.40 sec, while for numerical relays *CTI* varies between 0.10 and 0.20 sec [13-14]. The value of T_{backup} and $T_{primary}$ can be determined by equations (10) and (11) respectively.

$$T^i_{backup} = \frac{0.14 \times TDS^x}{\left(\dfrac{I^i_F}{PS^x \times CT^i_{pr-rating}}\right)^{0.02} - 1} \tag{10}$$

$$T^i_{primary} = \frac{0.14 \times TDS^y}{\left(\dfrac{I^i_F}{PS^y \times CT^i_{pr-rating}}\right)^{0.02} - 1} \tag{11}$$

3 Hybrid Immune Algorithm and Particle Swarm Optimization (IA-PSO) Technique

3.1 Overview of Immune Algorithm (IA) [26]

Immune Algorithm (IA) has been widely used to solve optimization problems by applying the same principle of operation of the human immune system. According to [22-23], the capability of IA method for pattern recognition and memorization provides a more efficient way to solve discrete optimization problems as compared to Genetic Algorithm (GA).

The cost function and limit constraints are represented as antigen inputs, while the solution process is simulated by antibody production in the feasible space through a genetic operation mechanism. The calculation of affinity between antibodies is embedded within the algorithm to determine the promotion/suppression of antibody production [26].

An IA based decision making procedure [24-26] is proposed in this study. The population of memory cells is a collection of the antibodies (feasible solutions) accessible towards optimality, which is the key factor to achieve fast convergence for global optimization [24-25]. In this paper, a genetic coding structure of IA is adopted and the diversity and affinity of antibodies are calculated during the decision making process to find the optimal solution [26].

The data structure of genes can be depicted as shown in Figure 2. For a feeder with N possible strategies of phase arrangement involving M object nodes, it will generate N antibodies having M genes in the antibody pool. The gene *node (i)* consists of a sequence of alternating sign-less integer numbers representing the candidate connection schemes of n branches connecting node i [24-26].

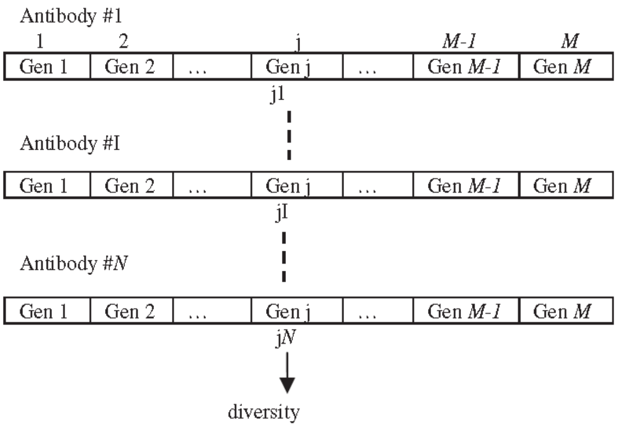


Fig. 2. Data structure of gens with corresponding information entropy.

The diversity of feasible strategies in the population is measured between the antibodies. This will be increased to prevent local optimization during the searching process of optimal solution. For each evolving generation, the new antibodies are generated to strengthen the diversity of antibody population in the memory cell [24-26]. With the data structure of genes in Figure 2, the entropy E_j of the j^{th} gene ($j = 1, 2, ... , M$) is defined as follows:

$$E_j = -\sum_{i=1}^{N\infty} P_{ij} . \log P_{ij} \tag{12}$$

N is the quantity of antibodies and P_{ij} is the probability that the j^{th} allele comes out at the j^{th} gene. If all alleles at the j^{th} gene are the same, the entropy of the j^{th} becomes zero. The diversity of all genes is calculated as the mean value of informative entropy as follows [26]:

$$E = \frac{1}{M} \sum_{j=1}^{M} E_j \tag{13}$$

If the affinity of some antibodies is the same during immune process, it will influence the searching efficiency of optimization for the planning of phase arrangement. In this paper, as in [24-26], two types of affinity are calculated for the proposed method. One type is the affinity between antibodies which is defined as:

$$\left(Ab\right)_{ij} = \frac{1}{1+E(2)} \tag{14}$$

E (2) is the information entropy of these two antibodies. It should be noted that the genes of the i^{th} antibody and the j^{th} antibody will be the same when E(2) is equal to zero. The affinity between the i^{th} and j^{th} antibody, $(Ab)_{ij}$, will be within the range [0, 1]. The other type of the affinity is the one between antibody and antigen (i.e. the objective function) [26].

$$\left(Ag\right)_i = \frac{1}{1+OPT_i} \tag{15}$$

OPT_i is the total cost representing the connection between the antigen and antibody i. The antigen with the maximum affinity $(Ag)_i$ will be the optimal phase arrangement within the feasible space. The process to solve the cost function for optimal solution is simulated by the interaction of antibody and antigen in IA [26]. During evolution of genes, the candidates of solution with high affinity are selected and included in the memory cells, which is then used to generate new candidate solution.

The computation procedure is therefore executed as follows [26]:

Step 1: Recognition of antigens,
Step 2: Production of initial antibody population,
Step 3: Calculation of affinity,
Step 4: Evaluation and selection,
Step 5: Crossover and mutation,
Step 6: Decision on optimal strategy.

During this process, the antibody having high affinities with the antigen will be added to the new memory cell, which will be maintained after applying the operation of crossover, mutation and selection for the population. The search process of optimization continues until no further improvement in relative affinity can be obtained and thus the antibody with the highest affinity in the memory cell will be the optimal strategy for the solution [26].

3.2 Overview of Particle Swarm Optimization (PSO) Algorithm [26]

Particle Swarm Optimization (PSO) is a population-based evolutionary technique which has a number of key advantages over other optimization techniques. PSO finds the optimal solution using a population of particles. Each particle represents a candidate solution to the problem. PSO is basically developed through simulation of bird flocking in two dimensional spaces [27]. Attractive features of the PSO include ease of implementation, the fact that no gradient information is required and its application can be extended in neural network training and minimizing function. The PSO is presented by [26-32] as follows:

Step 1: Each individual particle has the following properties: a current position in search space x_i, a current velocity V_i, and a personal best position X_{pbest},

Step 2: The personal best position X_{pbest}, corresponds to the position in search space, where particle i presents the smallest error as determined by the objective function f, assuming a minimization task,

Step 3: The global best position denoted by X_{gbest}, represents the position yielding the lowest error among all the X_{pbest}'s.

Consider a swarm of P particles; with each particle's position representing possible solution point in the design problem space. For each particle, the authors in [29-31] proposed that its position x_i is updated in the following manner:

$$V_i(t+1) = W + V_i(t) + c_1 \times r_1 . \left[P_{best}(t) - x_i(t)\right] + c_2 \times r_2 . \left[G_{best}(t) - x_i(t)\right] \quad (16)$$

and,

$$x_i(t+1) = x_i(t) + V_i(t+1) \quad (17)$$

Subscript t indicates a time increment, $X_{pbest}(t)$ represents the best ever position of particle i at time t, and $X_{gbest}(t)$ represents the global best position in the swarm at time t. r_1 and r_2 represent uniform random numbers between 0 and 1.

To allow the product $c_1 \times r_1$ or $c_2 \times r_2$ to have a mean value of 1, c_1 and c_2 are assumed constant values typically in the range of 2 to 4. Authors in [27] proposed that the cognitive and social scaling parameters c_1 and c_2 can be selected such that $c_1 = c_2 = 2$. The factor w is the inertia weight.

For large W, the search becomes more global, while for smaller one, the search becomes more local. The coefficients c_1 and c_2 are learning factors, which help particles to accelerate towards better areas of the solution space [31-32].

3.3 Overview of IA-PSO Algorithm [26]

During calculations, it is important to avoid PSO sinking into a local optimized solution. The characteristics of a particle are calculated by the basic PSO method as mentioned above, in which each particle undergoes vaccination and immunization. Each PSO particle corresponds to an antibody of IA, and each element of particle is equal to each gene of the antibody. The adaptive degrees of particles can be improved by vaccination. The higher the adaptive degree of a particle, the better is the particle.

Hence, to avoid trapping in a local optimal solution and ensure the search capability of a near global optimal solution, mutation is employed as it can play an important role in IA-PSO. The process of IA-PSO can be described as follows [33-36]:

Step 1: An initial particle swarm is randomly generated for which there is a random initial solution and speed.

Step 2: The next position (X'_{id}) of a particle can be calculated according to the current position (X_{id}) of that particle, original speed (V_{id}) of the particle, experienced best position (P_{id}) of the particle and experienced best position (P_{gd}) of particle swarm. The speed of particle is calculated according to equation (16). The new solution is then calculated according to equation (17),

Step 3: After particles have arrived at new positions, each particle is compared with its experienced best position, P_{id}. If the new particle is improved, P_{id} will be replaced by the new improved particle. Similarly, each particle is compared with the experienced best position P_{gd} of particle swarm, if the new particle is better; P_{gd} will be replaced by it,

Step 4: The optimized particle swarm is inoculated,

Step 5: Immune vaccination, for this there are three main parts: picking-up vaccine, vaccination, and immune selection. Some characteristic information picked-up from a person's pre-knowledge about the problem to be solved, are regarded as bacteria used to change a certain integrant of the particle, aimed at guiding the search process. However, the post-vaccinal particle must be checked by immune selection, which is capable of suppressing the degradation phenomena. If the fitness of the post-vaccinal particle is smaller than the original one, the original one will be preserved; otherwise, the post-vaccinal particle will be regarded as the new particle and replace the original particle. Therefore, the optimized particle swarm is undergoes immunization and hence, a new particle swarm is generated,

Step 6: The newly generated particle at Step 5 above is returned to Step 2 and calculations are repeated until the optimal solution is found or the maximum iterative number is reached.

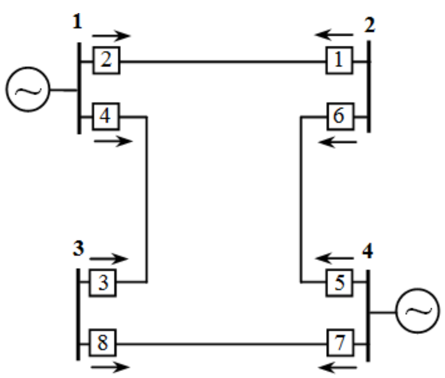
4 Case Study

The optimization algorithms IA, PSO and IA-PSO are validated and tested on two systems, namely IEEE 4-bus and IEEE 6-bus models as shown in Figures 3.a and 3.b, respectively.

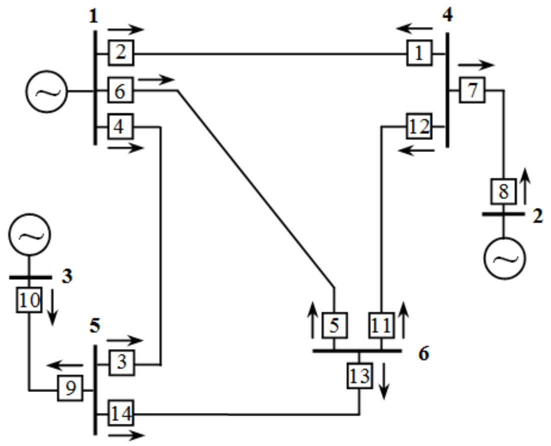
The first case study consists of two power generators, four lines and eight IDMT directional overcurrent relays. The objective of the optimization problem in this case is to coordinate the settings of eight relays. Accordingly, there are 16 decision variables which are TDS^1 to TDS^8 and PS^1 to PS^8.

The second case study consists of three power generators, seven lines and fourteen IDMT directional overcurrent relays. The objective of the optimization problem in this case is to coordinate the settings of fourteen relays. Accordingly, there are 28 decision variables which are TDS^1 to TDS^{14} and PS^1 to PS^{14}.

CTI is selected to take the value of 0.30 sec in each of the studied cases.



(a)



(b)

Fig. 3. Case study systems:
(a) IEEE 4-bus, (b) IEEE 6-bus.

For each case study, the values used for I_F and CT_{pr_rating} are listed in Tables II and III such that the data related to $T^i_{Pri\text{-}far\text{-}bus}$ and $T^j_{Pri\text{-}far\text{-}bus}$ are shown in Table II, while the data related to T^x_{backup} and $T^y_{primary}$ are shown in Table III [15].

TABLE II
I_F and $CT_{pr\text{-}rating}$ for $T^i_{pri\_cl\_in}$ and $T^j_{pri\_far\_bus}$ in case study:
(a) IEEE 4-bus, (b) IEEE 6-bus.

(a)

$T^i_{pri\_cl\_in}$			$T^j_{pri\_far\_bus}$		
TDS^i	I^i_F	$CT^i_{pr\text{-}rating}$	TDS^j	I^j_F	$CT^j_{pr\text{-}rating}$
TDS^1	20.32	0.4800	TDS^2	23.75	0.4800
TDS^2	88.85	0.4800	TDS^1	12.48	0.4800
TDS^3	13.60	1.1789	TDS^4	31.92	1.1789
TDS^4	116.81	1.1789	TDS^3	10.38	1.1789
TDS^5	116.70	1.5259	TDS^6	12.07	1.5259
TDS^6	16.67	1.5259	TDS^5	31.92	1.5259
TDS^7	71.70	1.2018	TDS^8	11.00	1.2018
TDS^8	19.27	1.2018	TDS^7	18.91	1.2018

(b)

$T^i_{pri\_cl\_in}$			$T^j_{pri\_far\_bus}$		
TDS^i	I^i_F	$CT^i_{pr\text{-}rating}$	TDS^j	I^j_F	$CT^j_{pr\text{-}rating}$
TDS^1	2.5311	0.2585	TDS^2	5.9495	0.2585
TDS^2	2.7376	0.2585	TDS^1	5.3752	0.2585
TDS^3	2.9723	0.4863	TDS^4	6.6641	0.4863
TDS^4	4.1477	0.4863	TDS^3	4.5897	0.4863
TDS^5	1.9545	0.7138	TDS^6	6.2345	0.7138
TDS^6	2.7678	0.7138	TDS^5	4.2573	0.7138
TDS^7	3.8423	1.7460	TDS^1	6.3694	1.7460
TDS^8	5.6180	1.7460	TDS^2	4.1783	1.7460
TDS^9	4.6538	1.0424	TDS^3	3.8700	1.0424
TDS^{10}	3.5261	1.0424	TDS^4	5.2696	1.0424
TDS^{11}	2.5840	0.7729	TDS^5	6.1144	0.7729
TDS^{12}	3.8006	0.7729	TDS^6	3.9005	0.7729
TDS^{13}	2.4143	0.5879	TDS^1	2.9011	0.5879
TDS^{14}	5.3541	0.5879	TDS^2	4.3350	0.5879

TABLE III
I_F and $CT_{pr\text{-}rating}$ for $T^x{}_{backup}$ and $T^y{}_{primary}$ in case study: (a) IEEE 4-bus, (b) IEEE 6-bus.

(a)

$T^x{}_{backup}$			$T^y{}_{pimary}$		
Relay No.	I_F^i	$CT^i{}_{pr\text{-}rating}$	*Relay No.*	I_F^j	$CT^j{}_{pr\text{-}rating}$
5	20.32	1.5259	1	20.32	0.4800
5	12.48	1.5259	1	12.48	0.4800
7	13.61	1.2018	3	13.61	1.1789
7	10.38	1.2018	3	10.38	1.1789
1	116.81	0.4800	4	116.81	1.1789
2	12.07	0.4800	6	12.07	1.5259
2	16.67	0.4800	6	16.67	1.5259
4	11.00	1.1789	8	11.00	1.2018
4	19.27	1.1789	8	19.27	1.2018

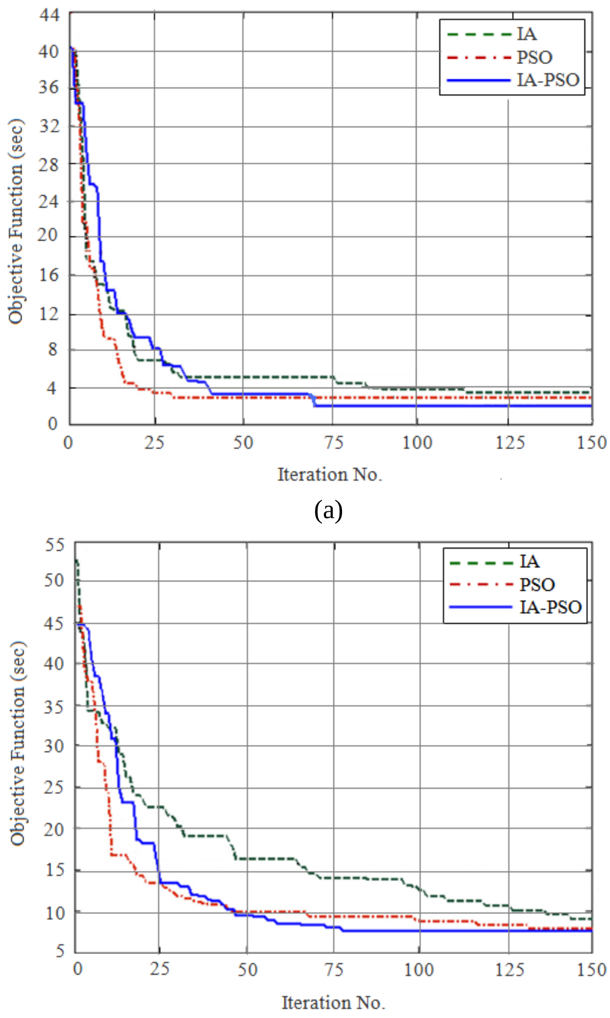
(b)

$T^x{}_{backup}$			$T^y{}_{primary}$		
Relay No.	I_F^i	$CT^i{}_{pr\text{-}rating}$	*Relay No.*	I_F^j	$CT^j{}_{pr\text{-}rating}$
8	4.0909	1.7460	1	5.3752	0.2585
11	1.2886	0.7729	1	5.3752	0.2585
8	2.9323	1.7460	1	2.5311	0.2585
3	0.6213	0.4863	2	2.7376	0.2585
3	1.6658	0.4863	2	5.9495	0.2585
10	0.0923	1.0424	3	4.5897	0.4863
10	2.5610	1.0424	3	2.9723	0.4863
13	1.4995	0.5879	3	4.5897	0.4863
1	0.8869	0.2585	4	4.1477	0.4863
1	1.5243	0.2585	4	6.6641	0.4863
12	2.5444	0.7729	5	4.2573	0.7138
12	1.4549	0.7729	5	1.9545	0.7138
14	1.7142	0.5879	5	4.2573	0.7138
3	1.4658	0.4863	6	6.2345	0.7138
3	1.1231	0.4863	6	6.2345	0.7138
11	2.1436	0.7729	7	4.1783	1.7460
2	2.0355	0.2585	7	4.1783	1.7460
11	1.9712	0.7729	7	3.8423	1.7460
2	1.8718	0.2585	7	3.8423	1.7460
13	1.8321	0.5879	9	5.2696	1.0424
4	3.4386	0.4863	9	5.2696	1.0424
13	1.6180	0.5879	9	4.6538	1.0424
4	3.0368	0.4863	9	4.6538	1.0424
14	2.0871	0.5879	11	3.9005	0.7729
6	1.8138	0.7138	11	3.9005	0.7729
14	1.4744	0.5879	11	2.5840	0.7729
6	1.1099	0.7138	11	2.5840	0.7729
8	3.3286	1.7460	12	3.8006	0.7729
2	0.4734	0.2585	12	3.8006	0.7729
8	4.5736	1.7460	12	6.1144	0.7729
2	1.5432	0.2585	12	6.1144	0.7729
12	2.7269	0.7729	13	4.3350	0.5879
6	1.6085	0.7138	13	4.3350	0.5879
12	1.8360	0.7729	13	2.4143	0.5879
10	2.0260	1.0424	14	2.9011	0.5879
4	0.8757	0.4863	14	2.9011	0.5879
10	2.7784	1.0424	14	5.3541	0.5879
4	2.5823	0.4863	14	5.3541	0.5879

Further details on the values of the parameters used for each of the three algorithms are mentioned in the Appendix.

5 Simulation Results and Comparison

The convergence characteristics for applying each of the three optimization algorithms (IA, PSO and IA-PSO) for the two cases of IEEE 4-bus and 6-bus systems are presented in Figures 4.a and 4.b, respectively. It is clear that IA-PSO algorithm provides the fastest convergence rate when compared with that observed when using IA and PSO algorithms.



(b)

Fig. 4. Convergence characteristics of IA, PSO and IA-PSO in case study: (a) IEEE 4-bus, (b) IEEE 6-bus.

5.1 Optimal Relay Settings

The new optimal relays settings (*TDS* and *PS*) for each relay in the two studied cases are obtained using IA, PSO and IA-PSO algorithms and presented in Table IV.

TABLE IV
Optimal relays settings: (a) IEEE 4-bus, (b) IEEE 6-bus.

(a)

Relay No.		*IA*	*PSO*	*IA-PSO*
1	*TDS*	0.0511	0.0528	0.0560
	PS	1.2922	1.3533	1.4583
2	*TDS*	0.2148	0.2235	0.2415
	PS	1.4243	1.5999	1.7156
3	*TDS*	0.0504	0.0529	0.0561
	PS	1.2645	1.3263	1.4309
4	*TDS*	0.1536	0.1602	0.1732
	PS	1.5267	1.5913	1.6174
5	*TDS*	0.1279	0.1339	0.1441
	PS	1.5893	1.5914	1.6172
6	*TDS*	0.0503	0.0526	0.0563
	PS	1.6961	1.3276	1.4309
7	*TDS*	0.1346	0.1411	0.1543
	PS	1.5765	1.4922	1.7178
8	*TDS*	0.0506	0.0543	0.0566
	PS	1.3569	1.3276	1.4305

(b)

Relay No.		*IA*	*PSO*	*IA-PSO*
1	*TDS*	0.1534	0.2602	0.4064
	PS	0.9833	0.5864	0.4722
2	*TDS*	0.2836	0.4739	0.7506
	PS	0.9776	0.5764	0.4709
3	*TDS*	0.1469	0.2406	0.3872
	PS	0.8219	0.5102	0.4119
4	*TDS*	0.1522	0.2711	0.4031
	PS	0.9844	0.5349	0.4726
5	*TDS*	0.0754	0.1268	0.2005
	PS	0.8215	0.4891	0.4118
6	*TDS*	0.0754	0.1264	0.2011
	PS	0.9065	0.5411	0.4437
7	*TDS*	0.0754	0.1265	0.2003
	PS	0.8212	0.4892	0.4109
8	*TDS*	0.0744	0.1265	0.2133
	PS	0.8208	0.4886	0.4108
9	*TDS*	0.0758	0.1268	0.2006
	PS	0.8215	0.4854	0.4124
10	*TDS*	0.0854	0.1424	0.2265
	PS	0.9868	0.5877	0.4724
11	*TDS*	0.0984	0.1647	0.2610
	PS	0.9819	0.5872	0.4618
12	*TDS*	0.0781	0.1401	0.2039
	PS	0.9853	0.5459	0.4739
13	*TDS*	0.0772	0.1265	0.2002
	PS	0.9624	0.5715	0.4642
14	*TDS*	0.1078	0.1779	0.2837
	PS	0.9842	0.5864	0.3731

5.2 Optimal *CTI*

Optimal *CTI*, between the backup and primary overcurrent relays, is calculated using the obtained optimum values of *TDS* and *PS* for each of the two studied cases when using MDEA, TLBO, IA, PSO and IA-PSO optimization algorithms, as shown in Table V.

From Table V, it is observed that IA-PSO optimization algorithm generally gives minimum *CTI* values when compared with those obtained when using other optimization algorithms.

TABLE V
Optimal *CTI* value: (a) IEEE 4-bus, (b) IEEE 6-bus.

(a)

Relay No.		***MDEA* [4]**	***TLBO* [14]**	***IA***	***PSO***	***IA-PSO***
1	4	0.300	0.539	**0.438**	**0.384**	**0.304**
2	6	0.348	0.649	**0.538**	**0.372**	**0.312**
2	6	0.299	0.600	**0.523**	**0.376**	**0.318**
4	8	0.397	0.510	**0.436**	**0.309**	**0.313**
4	8	0.299	0.432	**0.348**	**0.408**	**0.324**
5	1	0.299	0.300	**0.312**	**0.338**	**0.329**
5	1	0.400	0.356	**0.311**	**0.492**	**0.322**
7	3	0.299	0.355	**0.503**	**0.357**	**0.309**
7	3	0.349	0.382	**0.322**	**0.313**	**0.317**

(b)

Relay No.		***MDEA* [4]**	***TLBO* [14]**	***IA***	***PSO***	***IA-PSO***
8	1	0.288107	2.18859	**0.9532**	**0.6123**	**0.3439**
11	1	4.029328	1.534819	**0.9242**	**0.4267**	**0.2362**
8	1	0.80684	3.249765	**1.2657**	**0.9043**	**0.3002**
3	2	1669.695	2.201281	**1.1544**	**0.6539**	**0.3531**
3	2	0.199929	0.438233	**0.3369**	**0.32567**	**0.3004**
10	3	-0.18123	0.418234	**0.3187**	**0.3156**	**0.3057**
10	3	0.378005	1.236218	**0.8239**	**0.3447**	**0.3054**
13	3	0.300372	0.30791	**1.0543**	**0.3257**	**0.3003**
1	4	0.458382	0.843753	**0.5564**	**0.3355**	**0.3009**
1	4	0.199845	0.517069	**0.3653**	**0.3387**	**0.3129**
12	5	0.225775	0.937599	**0.6249**	**0.3012**	**0.3455**
12	5	0.839275	1.525362	**1.0658**	**0.4259**	**0.3324**
14	5	0.519282	1.180526	**0.7862**	**0.3294**	**0.3753**
3	6	0.578187	0.551088	**0.3675**	**0.3139**	**0.3435**
3	6	0.347919	0.30015	**0.3045**	**0.3034**	**0.3325**
11	7	0.200146	1.373804	**0.9156**	**0.3754**	**0.3212**
2	7	0.238046	0.982896	**0.6550**	**0.3134**	**0.3564**
11	7	0.237149	1.472532	**0.8814**	**0.4223**	**0.3247**
2	7	0.200045	1.019525	**0.6795**	**0.3142**	**0.3038**

5.3 Comparing Results

Table VI presents the minimum values of the objective function which are obtained when using IA, PSO and IA-PSO algorithms for each case study. It also shows the published results of the minimum objective function values for other optimization algorithms for each system [4, 14, 15].

TABLE VI
OF Comparison for case study:
(a) IEEE 4-bus, (b) IEEE 6-bus.

(a)

Algorithm	*OF (sec)*
TLBO [14]	5.5890
MDEA [4]	3.6674
CDEA [15]	3.6774
IA	**3.6758**
PSO	**3.6524**
IA-PSO	**3.1239**

(b)

Algorithm	*OF (sec)*
TLBO [14]	23.7878
CDEA [15]	10.6272
MDEA [4]	10.3514
IA	**9.3468**
PSO	**8.1245**
IA-PSO	**7.6722**

From Table VI, though IA and PSO algorithms provide better results than TLBO, CDEA and MDEA, still IA-PSO algorithm offers the best performance and provides the minimum objective function when compared with the other optimization algorithms. This proves the validity of the proposed algorithm in relays coordination.

6 Conclusions

In this paper, three optimization algorithms, namely IA, PSO, and IA-PSO, were presented to solve the coordination problem of IDMT directional overcurrent relays. The proposed optimization algorithms were validated and tested on IEEE 4-bus and IEEE 6-bus meshed power system models.

Though the three algorithms showed better results than those obtained in literature for other optimization algorithms, such as TLBO, CDEA and MDEA, robustness and feasibility of IA-PSO algorithm were clearly observed in the obtained results.

Based on the obtained simulation results, IA-PSO in particular proved its superiority in providing the minimum operating time T of relays at a fast convergence rate as well as securing minimum *CTI* between primary and backup relays. This was achieved through finding the optimum *TDS* and *PS* values of each relay. The advantages encountered when using IA-PSO are attributed to its hybrid nature which combines the immune information processing mechanism and the particle swarm optimization algorithm to achieve better and fast solution. Therefore, it is recommended to use the proposed IA-PSO as an efficient hybrid optimization algorithm in the coordination of directional overcurrent relays.

Future work will consider developing the proposed algorithm to be capable of dealing with more complicated cases of optimal coordination of overcurrent relays. These cases may include conflicting objective functions and various systems topologies of large power systems that may be equipped with FACTS devices, Fault Current Limiter (FCL) or renewable energy resources.

7 Appendix

7.1 IA Algorithm

Replacement rate = 0.15,
Cloning rate = 0.20,
Mutation rate = 0.15,
Suppression threshold = 10^{-6},
Percentile amount of clones to be re-selected = 0.80,
Pruning threshold = 1.10,
Population size = 100,
Maximum number of generation = 150.

7.2 PSO Algorithm

$c_1 = 0.50$, $c_2 = 1.50$, $W = 0.70$,
Population size = 100,
Maximum number of generation = 150.

7.3 IA-PSO Algorithm

$c_1 = 0.20$, $c_2 = 1.40$, $W = 0.90$,
Replacement rate = 0.15,
Cloning rate = 0.20,
Mutation rate = 0.15,
Suppression threshold = 10^{-6},
Percentile amount of clones to be re-selected = 0.50,
Pruning threshold = 1.00,
Population size = 100,
Maximum number of generation = 150.

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