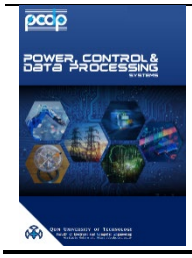
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Modified Metaheuristic Approach for Overcurrent Relay Coordination in Distribution Networks

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Jahandideh Shendi, Ahad [1]
Mohammadian, Leila [2*]
Ghanizadeh, Reza [3*]

[1] Department of Electrical Engineering, Shab.C., Islamic Azad University, Shabestar, Iran. eng.jahandideh64@gmail.com
[2] Department of Electrical Engineering, Shab.C., Islamic Azad University, Shabestar, Iran. le.mohammadian@gmail.com
[3] Department of Electrical Engineering, Ur.C., Islamic Azad University, Urmia, Iran. reza.ghanizadeh@iau.ac.ir

* ***Correspondence***
Address: Department of Electrical Engineering, Ur.C., Islamic Azad University, Urmia, Iran.

reza.ghanizadeh@iau.ac.ir
le.mohammadian@gmail.com

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ABSTRACT

Because conventional computational approaches falter under heavily constrained and nonlinear conditions, properly setting protective distribution relays remains an arduous task. While the metaheuristic algorithms have been applied to this problem, existing approaches typically optimize only time and current settings while assuming fixed relay characteristics, limiting the achievable coordination performance. This paper addresses this gap by proposing a unified Gravitational Search Algorithm (GSA) framework that simultaneously optimizes time multiplier settings, current settings, and relay characteristic selection from eight standard curves. By leveraging a combination of MATLAB for optimization and DIgSILENT for fault current estimation, this study evaluates its approach. The effectiveness of the technique is demonstrated through testing on both 30-bus and 9-bus distribution systems, where its performance is benchmarked against Informative Differential Evolution and Particle Swarm Optimization. Results demonstrate that the GSA-based approach achieves superior convergence and lower objective function values, with statistical analysis confirming its robustness and effectiveness in reducing relay operating times compared to the existing methods.

Keywords: Power distribution grids, the Gravitational Search Algorithm (GSA), overcurrent relay synchronization, and optimal system coordination.

1 Introduction

Safeguarding electrical grids demands meticulous calibration, as even slight inaccuracies in relay timing can compromise system stability. The lack of this coordination can potentially lead to partial or total blackouts in the network, resulting in irreparable damages. Faults in power systems lead to the occurrence of severe currents that can damage network equipment and jeopardize network security. In distribution networks, these faults can cause significant damages. Currently, the issue of enhancing the reliability of power supply to consumers in power departments has gained special significance. Matters such as interconnecting distribution networks at the 20 kV or 63 kV level have become notably important. Nowadays, distribution networks can no longer be assumed to be radial as in the past, necessitating a reconsideration of distribution network designs in light of their continuous interconnectivity [1].

Protective systems are essential components of any power system. In general, protective systems do not prevent damage to equipment but rather act after an error has occurred and damage has been inflicted. The primary goal of these systems is to prevent harm to personnel and to detect and isolate the minimum possible equipment damage in the shortest time possible after faults occur in the system. This is done in a way that ensures no interference in the operation of protective relays. Achieving this goal necessitates appropriate coordination among relays [2,3].

To determine ideal backup relay configurations, researchers have explored a wide array of optimization strategies. The use of optimization techniques in setting and coordinating backup relays was first introduced in [9]..Various methods for determining minimum breakpoint points in a network have been proposed in references [5,6]. Using a systemic topological analysis technique, the functional dependencies approach formulates relay setting limitations through a set of defined functional relationships, as noted in reference [7].

Robust optimization approaches constitute another major classification for managing backup relay coordination. Within this domain, researchers employ either sophisticated mathematical algorithms such as dual, two-phase, or simplex-based methods [9-17] or various intelligent computational techniques [18-34]. Intelligent methods are considered more suitable than mathematical optimization methods due to their flexibility and adaptability for a variety of problems. Because the inherent operating characteristics of overcurrent relays are nonlinear, their coordination must be modeled as a non-linear programming (NLP) problem. Depending on how IsetI_{set}Iset is defined, the formulation takes two distinct forms: treating IsetI_{set}Iset as a discrete parameter leads to a mixed-integer nonlinear program (MINLP), while holding it constant reduces the coordination model to a straightforward linear programming (LP) problem. To circumvent the computational hurdles inherent in nonlinear optimization, researchers frequently utilize linear programming to determine optimal relay coordination settings. This approach typically relies on established algorithms like the simplex [9, 10] or dual simplex methods [9, 12], often supplemented by the novel mathematical strategies discussed in [4]. Reference [9] employs a nonlinear programming method with continuous variables for I_{set} and TMS. However, because I_{set} is discrete in practice, the closest discrete number must be approximated, which could render the problem solution infeasible. In [10, 12], the set Iset is assumed to remain constant. Under this assumption, the overcurrent-relay coordination task can be reformulated as a linear programming (LP) optimization problem and subsequently addressed through different solution techniques. Given the potential for the resulting LP problem to become very large, reference [14] utilizes preliminary analysis to reduce optimization constraints, resolving the LP problem more swiftly. Reference [15] observes changes in network structure, solving the LP problem with fixed I_{set} . Reference [16] employs a nonlinear integer programming method for coordinating over current relays with continuous TMS and discrete I_{set} . Consequently, the over current relay coordination problem exhibits multiple local minima, conventional math-based optimization methods may lack the requisite effectiveness since they rely on initial assumptions and may converge to local minima. The rapid advancement of computational capabilities has encouraged the widespread application of intelligent optimization techniques for addressing nonlinear engineering problems. One such application is the optimal directional coordination of overcurrent relays. A variety of metaheuristic and evolutionary approaches have been investigated for this purpose. For example, Particle Swarm Optimization (PSO) was adopted in [23], while the Artificial Bee Colony (ABC) method was reported in [26]. The Cuckoo Search Algorithm was applied in [18, 19, 27], and the Imperialist Competitive Algorithm (ICA) was considered in [28]. Evolutionary optimization techniques were explored in [29, 30], whereas the Seeker algorithm was employed in [31]. In addition, the Genetic Algorithm (GA) was utilized for relay coordination in [21]. These studies demonstrate the broad use of intelligent optimization methods for solving the nonlinear overcurrent-relay coordination problem. Several other population-based optimization techniques have also been investigated for determining optimal coordination among directional overcurrent relays. These include Teaching-Learning-Based Optimization (TLBO), presented in [22], Harmony Search Algorithm (HSA), described in [35], and Biogeography-Based Optimization (BBO), applied in [36]. The Modified Electromagnetic Field Optimization (MEFO) method has likewise been introduced for this coordination task. Furthermore, [32] demonstrates the application of the Genetic Algorithm (GA) as an effective optimization approach for addressing complex optimization problems. To address this issue, in references [33-34], methods for solving coordination problems have been utilized. In reference [33], the problem of coordinating fault currents has been divided into two separate parts. To address the nonlinear component of the optimization

problem, a Genetic Algorithm (GA) is utilized to identify the appropriate fault-current setting parameters I_{set}. Using the obtained information, the objective function is evaluated by formulating a Linear Programming (LP) model to determine the corresponding Time Multiplier Setting (TMS) values. Due to operational conditions and various network events, network configurations are constantly changing. These variations in network configuration render the protective system non-selective. Relays must be capable of performing consistently in light of these changes to avoid inconsistencies. Reference [34] incorporates the effects of different network configurations into the mathematical formulation to account for this challenge. In reference [33], the Genetic Algorithm (GA) is combined with Nonlinear Programming (NLP) and employed. Due to its population-based search mechanism, the Genetic Algorithm (GA) is capable of exploring a wider region of the solution space. To leverage the advantages of both intelligent methods and nonlinear programming and simultaneously counteract their drawbacks, the Genetic Algorithm (GA) is utilized to determine initial estimates for temporal and flow variables (TMS, I_{set}) in the problem. Subsequently, these values are provided to the Nonlinear Programming (NLP) method to obtain final solutions.

Reference [37] proposes a hybrid optimization approach that integrates Biogeography-Based Optimization (BBO) with Differential Evolution (DE). The DE algorithm is effective in exploring the search space and determining a good global minimum location but may struggle in extracting solutions quickly. Accordingly, DE's strong global-search capability is combined with the solution-generation mechanism of BBO to address the relay coordination problem. A hybrid optimization framework based on Particle Swarm Optimization (PSO) and the Gravitational Search Algorithm (GSA) is presented in [38]. In [39], the coordination performance of overcurrent relays is investigated under two fault scenarios: faults occurring close to the primary relays and faults located at both near and remote positions. The problem of unintended relay operation within the coordination process is examined in [40]. Reference [41] introduces a new approach for simplifying the optimization model by reducing the number of constraints and determining the constraints that can prevent feasible overcurrent relay settings from being obtained. Furthermore, [42] presents an adaptive strategy for determining suitable overcurrent relay settings in power-system applications. This scheme adapts to changes in generation levels, new load variations, and network configuration changes, deriving relay settings considering these alterations. Reference [32] modifies the conventional objective function by incorporating an additional term to account for the nonlinear behavior of certain coordination constraints. In [43], a genetic-algorithm-based approach is introduced for determining the optimal settings and coordination of overcurrent relays in interconnected power networks. The coordination problem for overcurrent relays in distribution systems containing distributed generation is formulated in [29] as a continuous-variable nonlinear optimization model, which is subsequently solved using an evolutionary optimization technique. References [44] and [45] investigate the application of Fault Current Limiters (FCLs) to restrict and localize fault currents, thereby facilitating proper coordination among overcurrent protection relays.

A critical advancement in OCR coordination is the incorporation of relay characteristic selection as an optimization variable. Reference [49] introduced an intelligent approach for combined overcurrent and distance relay coordination that simultaneously optimizes relay settings and selects appropriate characteristic curves.

Recent years have witnessed the emergence of novel optimization paradigms and the consideration of new operational challenges. Gupta et al. [50] investigated the coordination of protective relays from a reliability perspective in distribution systems incorporating optimally allocated wind turbine generators. Their findings emphasized the need to account for renewable energy resources when developing effective relay coordination schemes. In another study, Abdelfattah et al. [52] proposed an artificial intelligence-driven approach for achieving optimal relay coordination while incorporating vehicle-to-grid (V2G) functionality, reflecting the increasing complexity of distribution systems resulting from the integration of electric vehicles.

Furthermore, Arslanoğlu et al. [53] examined the effectiveness of various advanced metaheuristic optimization techniques for coordinating directional overcurrent relays (OCRs) in distribution networks. The study provided a systematic comparison of several algorithms using consistent testing criteria to assess their relative performance. Rath et al. [54] applied grey wolf optimization (GWO) to distribution network OCR coordination, achieving competitive results with reduced computational effort. Li et al. [55] investigated OCR coordination in radial distribution systems characterized by the presence of inverter-interfaced distributed energy resources (DERs). To overcome the protection challenges caused by changing DER output and the reversal of fault-current direction, the authors developed a new coordination strategy that incorporates both the variable contribution of DER units and the bidirectional nature of fault currents. Alasali et al. [56] introduced a sophisticated voltage-relay configuration to enhance distance-relay coordination in power systems containing low-inertia regions. Their approach was designed to mitigate protection coordination difficulties associated with declining system inertia and the growing integration of renewable energy sources. In a separate study, Ashraf et al. [57] presented the Savannah Bengal Tiger Optimizer as an optimization technique for relay coordination in large-scale power networks involving hundreds of constraints. The reported results indicated that the proposed optimizer could achieve better solutions than conventional approaches when dealing with highly complex and constraint-intensive coordination problems.

Despite these substantial contributions, several research gaps remain. Existing GSA-based approaches [58,59] primarily optimize TMS and current settings while assuming fixed relay characteristics. The simultaneous optimization of TMS,

current settings, and relay characteristic selection within a unified GSA framework has not been addressed. Furthermore, most existing studies lack rigorous statistical validation of algorithm performance, with results often based on single optimization runs. This paper addresses these gaps by proposing a comprehensive GSA framework that simultaneously optimizes TMS, I_{set} and characteristic selection for each relay, supported by statistical analysis across multiple optimizations runs and test networks. The novelty of our work lies in:

1. A unified GSA framework that simultaneously optimizes TMS, I_{set}, and relay characteristic selection.
2. Implementation and validation on both 9-bus and 30-bus IEEE distribution networks.
3. Comprehensive comparison against multiple algorithms (PSO, IDE) with statistical validation.
4. Demonstration that characteristic selection significantly improves coordination performance compared to fixed-characteristic approaches.

2 Problem Statement

2.1 Preliminaries

In distribution and sub-transmission lines, over current relays are commonly utilized both as primary protection and backup protection mechanisms. However, in transmission lines, these relays are only utilized for backup protection purposes. A fundamental requirement of power-system protection is to disconnect only the faulted or smallest necessary portion of the network as rapidly as possible following a disturbance. At the same time, the protection scheme must maintain selectivity and prevent undesirable interactions between relay operations. Reliable protection also depends strongly on the proper implementation of backup protection, which ensures that a fault can still be cleared if the primary protection fails.

For overcurrent relays, the main adjustable parameters are the current pickup setting and the time multiplier setting (TMS). Appropriate values for these parameters should be obtained by considering several requirements simultaneously: minimizing the overall relay operating time, ensuring that every protected section is covered by both primary and backup protection, and maintaining the required coordination margin between successive relays. Consequently, optimal overcurrent relay coordination can be formulated as a constrained optimization problem involving multiple operating and coordination requirements.

2.2 Description of the Coordination Problem

The optimal coordination of overcurrent relays can be formulated as an optimization-based problem in which the protection requirements are represented through an appropriately designed objective function. The permissible ranges and coordination requirements associated with the decision variables are then incorporated as constraints. An optimization algorithm is finally applied to search for the parameter set that yields the minimum value of the defined objective function while satisfying all imposed constraints. Depending on the nature of the problem, various methods can be considered for its resolution.

2.2.1 Determination of Initial Network Information

Before commencing the optimization algorithm for coordinating over current relays, a set of initial information about the sample network is needed. The required data consist of the designated primary–backup relay relationships, together with the corresponding normal operating currents and fault-current paths associated with each relay.

A) Determining main and Backup Relay Pairs

When a fault develops within a power network, the protection device located nearest to the fault is expected to detect the abnormal condition and initiate the appropriate circuit-breaker operation to isolate the affected section. If the main relays or switches fail to operate for any reason, the fault must be cleared by the backup relays and switches on neighboring elements. Accordingly, evaluating relay operating times requires establishing the protection relationships within the network by determining which backup relay is associated with each primary relay. In this way, the corresponding primary–backup relay pairs can be defined for the coordination analysis. Taking the grid model depicted in Figure 1 as a reference, the coordination between primary and secondary relays is formulated in the subsequent expression:

$$(primary\,.backup): (i\,.j_1).(i\,.j_2).\ldots.(i\,.j_m) \quad \text{Eq 1}$$

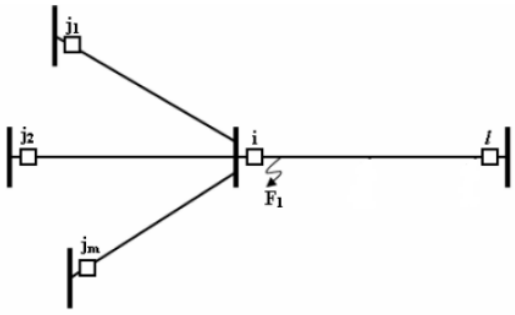


Figure 1: depicts the configuration of the relay pairs, consisting of a primary and a backup unit [34].

B) Utilization of load shedding and short-circuit program

Establishing the lowest pickup threshold alongside the anticipated fault currents across protective devices typically relies on running fault analysis and load curtailment routines during overcurrent relay coordination. Typically, the minimum setting current for relays is set to a factor of 2.1 for relays in the same direction as the line current, and for relays that do not sense the line current due to the presence of

directional elements or, in other words, are not in the same direction as the line current, it is considered to be equal to the line current. Therefore, to adjust the setting current of the relays, the load shedding program is utilized to calculate the desired values. Network short-circuit analysis is likewise employed to quantify the resulting current flows across both primary unit i and its corresponding backup device during a symmetrical three-phase disturbance at location F1, depicted in Figure 1.

Characteristics of overcurrent relays

Both the time multiplier setting (TMS) and pickup current threshold serve as governing parameters that dictate an overcurrent protection device's tripping duration within its mathematical formulation. The primary goal of coordinating directional overcurrent relays is to optimize current and time settings across all relays, ensuring minimal operating time during network faults. A cornerstone of overcurrent protection selectivity under contingency states involves formulating analytical models that couple fault current magnitudes with device tripping durations to assess response delays across the network. For overcurrent relays, manufacturers typically provide modelling in the form of various inverse time characteristic curves, following ANSI/IEEE or IEC 255-3 standards. These include definite time, normal inverse, very inverse, and other characteristic types. Trip latency in IDMT protective devices accelerates dynamically in response to surging current magnitudes, exhibiting a non-linear decay profile defined by the chosen standard curve. These relays have longer operating times for currents near the threshold and shorter times as the current magnitude rises. They are commonly employed in systems where short-circuit currents increase as the fault location nears the bus bar. The performance characteristics of these relays are often presented on logarithmic scales. For instance, Figure 2 illustrates an example of such characteristics, and Figure 2 compares performance curves for various characteristic types under different TMS settings.

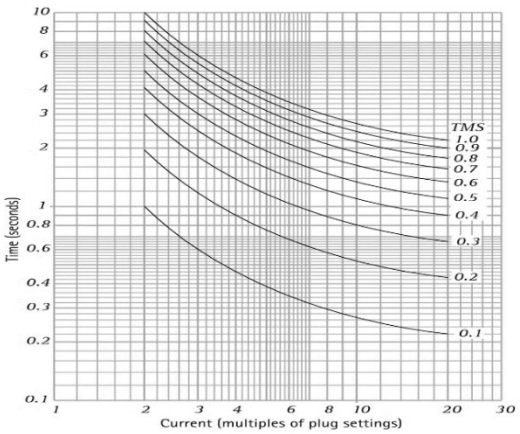


Figure 2: Trip duration profiles across distinct time dial values evaluated for IDMT protection units.

Formulating the synchronized protection strategy for overcurrent units is treated herein as a nonlinear optimization challenge. Due to the presence of two variables in the relay characteristic formulation, the problem has been transformed into a non-linear form. There are various relationships for modelling the characteristics of Overcurrent Relays, with this paper employing the most common relationship known as the Varley model (following Eq 1) for modelling and calculating the operation time of Overcurrent Relays.

$$t_i = TMS_i * \left(\frac{K}{(\frac{I_{sc_i}}{I_{set_i}})^{\alpha} - 1} + L \right) \quad \text{Eq 2}$$

t_i: Operation time of relay i-th.

TMS_i: Time dial setting multiplier of relay i th.

I_{set_i}: Current setting of relay i th (Pick-Up current).

I_{sc_i}: Fault current traversed by relay branch (the measured current value in fault conditions).

K and L and α: Constant coefficients based on the relay specifications (according to Table 1).

This model is applicable for various types of overcurrent relays, including electromagnetic, static, and digital relays. Today, digital relays offer numerous capabilities. One of these capabilities is the ability to input and select relay characteristic curves, which enhances the accuracy and speed of relay operation, particularly improving the performance of the protective system significantly. In this paper, digital relays are assumed.

3 Proposed Method

3.1 Objective Function

The optimization framework detailed in (2) [39] is structured around discovering suitable pickup and time-multiplier configurations, thereby enabling relays proximate to a disturbance to disconnect damaged line segments with minimal latency.

$$OF = min \sum_{i}^{n} w_i \, t_i \quad \text{Eq 2}$$

In this formulation, nnn denotes the total number of primary relays in the network, whereas tit_iti represents the tripping time of the iiith relay under fault conditions. The weighting factor wiw_iwi expresses the likelihood of a fault on the corresponding line and is generally assigned a value of one.

As observed from (1):

$$t_i = f\left(TMS_i . I_{set_i}\right) \quad \text{Eq 3}$$

Both the pickup threshold Iseti and time multiplier parameter TMSi serve as the primary decision variables dictating the nonlinear cost function in overcurrent protection coordination. Even without considering system constraints, solving this optimization problem remains complex. Therefore, the coordination problem's objective function is accompanied by specific constraints, which will be discussed in detail below.

3.1.1 Constraints of the Coordination Problem for Over Current Relays

Optimization frameworks for overcurrent relay selectivity enforce dual restriction categories: device-level boundaries encompassing permissible trip durations alongside current and time-dial thresholds and discrimination criteria designed to maintain reliable margins between primary and auxiliary protection stages.

A) Constraints on minimum and maximum time settings of relays

The time settings of relays have a range of both minimum and maximum values, as expressed in (4):

$$TMS_i^{min} \le TMS_i \le TMS_i^{max} \quad \text{Eq 4}$$

where TSM_irepresents the time setting of i-th relay. It is essential to note that these constraints should be applied before commencing the optimization algorithm. TMS is considered a continuous variable that varies between a minimum of 0.025 seconds to a maximum of 1.2 seconds [33].

B) Constraints on minimum and maximum current settings of relays

Operating as a discrete parameter, the pickup threshold of the i-th device (I_{set_i}) is demarcated by two opposing operational boundaries: peak continuous load demand at the lower end and the least detectable fault current within the remote backup zone at the upper limit. These physical and design bounds are imposed via the ensuing inequalities:

$$I_{set_i}^{min} \le I_{set_i} \le I_{set_i}^{max} \quad \text{Eq 5}$$

$$I_{load_i}^{max} \le I_{set_i} \le I_{fault_i}^{min} \quad \text{Eq 6}$$

To prevent unwarranted tripping during peak continuous operation while preserving sensitivity to the weakest fault levels, the lower boundary of the pickup threshold I_{set} is determined by selecting the supreme value between two governing network criteria [34]:

. The minimum current setting on the relay's time delay unit, which adds excess current.

Scaling the peak operational current across the device by a security margin typically selected within the 1.1–1.31 interval guarantees that inadvertent trip signals remain inhibited across all severe steady-state loading scenarios.

Similarly, the smallest value between the following two quantities will be selected as the maximum current setting value for the relay adjustment:

- The minimum fault current on the bus bar where the relay is installed.
- The maximum current setting on the relay's time delay unit, adding excess current.

$$\max(I_{load_i}^{max}, I_{set_i}^{min}) \le I_{set_i} \le \min(I_{fault_i}^{min}, I_{set_i}^{max}) \quad \text{Eq 7}$$

Pre-execution initialization routines enforce strict boundary limits on both the pickup threshold (IsetI) and the time dial parameter (TMS), while specialized computational algorithms are implemented to handle the quantized characteristics inherent to overcurrent trip calibrations.

C) Relay operation time range

Trip duration in overcurrent devices is governed by the discrepancy between the detected disturbance amplitude and the pre-set pickup value; evaluating this latency relies on standard manufacturer curves or explicit mathematical formulations, bounded by the mathematical relations presented in (8):

$$t_i^{min} \le t_i \le t_i^{max}.\ i = 1. \ldots . m \quad \text{Eq 8}$$

where t_i^{min} and t_i^{max} represent the minimum and maximum operation times of relay i th, respectively [31].

D) Discrimination margin boundaries governing primary and auxiliary protection pairs

The relays present in power systems may malfunction for various reasons. Therefore, each relay must be supported by other relays so that in case of their failure, the backup relays can ensure proper operation. Consequently, for a reliable protection system, utilizing backup protection for network main relays is essential. Hence, main protection and backup protection must operate in harmony. Preserving scheme selectivity requires primary units to initiate fault clearing faster than their designated secondary counterparts. In other words, in such a protection system, backup protection inherently operates slower than the main protection, meaning that backup protection functions after a coordination time interval (CTI). CTI, the value of this time delay, is related to the type of relay (electromechanical or microprocessor-based), type of switches (speed of power switch operation), measuring instruments, and other system parameters. Numerical and digital protection units compress this grading buffer down to 0.1–0.2 s, contrasting with the prolonged 0.3–0.4 s latency traditionally demanded by induction-disc electromechanical architectures [24].

For disturbances situated adjacent to the primary breaker, the required trip discrimination relative to the designated backup unit obeys:

$$t_j - t_i \ge CTI \ \cdot \begin{matrix} i = 1. \ldots . m \\ j = j_1. \ldots . j_m \end{matrix} \quad \text{Eq 9}$$

Where:

For disturbance F1, ti denotes the trip delay exhibited by the designated primary device.

Under proximal fault F1, tj designates the response latency associated with the secondary protection unit.

For each device i supported by an auxiliary pool of size m, ensuring comprehensive selective grading throughout the interconnected network imposes the following governing inequality on all primary–secondary pairs:

$$t_{backup} - t_{primary} \ge CTI \quad \text{Eq 10}$$

E) Formulation of coordination problem

Formulating the DOCR coordination task as a constrained optimization problem seeks to minimize a targeted fitness metric while simultaneously satisfying physical curve limits alongside selectivity, sensitivity, and operational dependability requirements, defined as follows:

$$\min_{x.y \in X} f(x.y.p) \quad \text{Eq 11}$$

Subject to Constraints:

$$t = g(x.y) \quad (Relay\ characteristic) \quad \text{Eq 12}$$

$$h(x) \leq 0 \quad (Coordination\ constraints) \quad \text{Eq 13}$$

$$TMS_{min} \leq TMS \leq TMS_{max} \quad \text{Eq 14}$$

$$I_{set,min} \leq I_{set} \leq I_{set,max} \quad \text{Eq 15}$$

$$t_{min} \leq t \leq t_{max} \quad \text{Eq 16}$$

Here, (x,y) evaluates the formulation's cost metric across decision vector components x and y, whose values are drawn from the admissible calibration domain X; meanwhile, p delineates the evaluated disturbance scenarios and t captures the resulting breaker tripping latency.

In the optimization model mentioned, Eq 13 denotes selectable constraints to enable a choice between primary and backup protection. The optimization space is bounded by pickup reach criteria in (14)–(15) and permissible clearing speed envelopes in (16), both essential for dependable in-zone fault clearing. Within this constrained domain, the coordination formulation drives the primary objective minimizing aggregate protective device latencies toward optimality.

The following discussion delineates the operational framework of the Gravitational Search Algorithm, emphasizing its algorithmic deployment in settling the optimal directional overcurrent relay calibration problem explored herein.

As innovation cycles continue to intensify, the formulation and solution of engineering optimization tasks have correspondingly grown in sophistication and computational difficulty. Therefore, considering the importance of time and accuracy, conventional classical optimization methods are no longer capable of solving these high-dimensional problems. Instead of exhaustive search, metaheuristic algorithms are employed. These metaheuristic algorithms offer time-saving capabilities and can bypass local optima through specific measures to converge towards an optimal solution. These metaheuristic algorithms are based on random search, and their main drawback lies in their inherent randomness, without any guarantee of reaching an optimal solution. The solutions obtained from metaheuristic algorithms are generally acceptable but not necessarily mathematically optimal. Closely approaching the true global extremum, these candidate answers align with what [47] designates as engineering optima.

3.2 Gravitational Search Algorithm (GSA)

The Gravitational Search Algorithm (GSA), introduced in 2009 [48], is a metaheuristic optimization technique based on gravitational laws and motion within a discrete-time artificial system. The problem's defined range serves as the system environment. According to gravitational law, each mass interacts with others through gravitational force, enabling information exchange. This mechanism is leveraged in optimization by representing potential solutions as positions in space, with their similarity to other solutions quantified as distances. The masses are assigned based on the objective function values.

The GSA operates through two main phases:

- Initialization Phase: Establishing a discrete-time artificial system within the problem environment, positioning objects, applying governing laws, and adjusting parameters.
- Optimization Phase: Progressing through time, updating object positions and parameters, and continuing until a stopping criterion is met.

3.2.1 Formation, Law Establishment, and Parameter Adjustment

Initially, the problem space is defined as a multi-dimensional coordinate system where each point represents a potential solution. The search agents, or objects, within this space are characterized by four attributes:

- Position: Represents a specific solution in the problem space.
- Active Gravitational Mass: Determines the gravitational force the object exerts on others.
- Inactive Gravitational Mass: Dictates the object's susceptibility to the gravitational pull of other objects.
- Inertial Mass: Influences the object's resistance to changes in motion.

The values of these masses are assigned based on the solution quality or compatibility of each object.

Once the system is established, the governing laws are defined. It is assumed that the behavior of objects is governed solely by the laws of gravity and motion, modelled after their natural counterparts:

Law of Gravity: Each object exerts an attractive force on all other objects in the system. According to the interaction model illustrated in Fig. 4, the attractive gravitational intensity scales with the product of the active and passive gravitational masses across interacting agents, decaying with their spatial separation. In terms of dynamic kinematics, an agent updates its instantaneous velocity through a linear combination of its prior momentum (damped by a scaling factor) and its current acceleration, where the latter corresponds directly to the cumulative gravitational pull normalized by the body's inertial mass. Within an N-body search population, every individual agent occupies discrete spatial coordinates that correspond directly to a potential candidate solution.As per Eq 17, the position of the i-th object in dimension d is denoted by x_i^d, and m represents the dimension of the problem.

$$X_i = \left(x_i^1 . \cdots . x_i^d . \cdots . x_i^m\right) \quad for\ i = 1.2. \cdots . N \quad \text{Eq 17}$$

In this system, at time i, a force $F_{ij}^d(t)$is exerted by object j in the direction of dimension d. The value of this force is

calculated according to Eq 18. M_{aj} and M_{pj}represent the active gravitational mass of object j and the passive gravitational mass of object i, respectively. G(t) is the gravitational constant at time *t*, and R_{ij} is the distance between objects *i* and *j*. To determine the distance between objects, Eq 19 utilizes the Euclidean distance (norm 2). Additionally, ε is a very small number in this equation. p represents the power of the distance, which is a real number greater than one. This value is usually considered to be equal to one.

$$F_{ij}^{d}(t) = G(t)\frac{M_{pi}(t) \times M_{aj}(t)}{R_{ij}(t)^{p} + \varepsilon}\left(x_{j}^{d}(t) - x_{i}^{d}(t)\right) for\ i = 1.2.\cdots.N \quad \text{Eq 18}$$

$$R_{ij}(t) = \left\|X_{i}(t).X_{j}(t)\right\|_{2} \quad \text{Eq 19}$$

Let $F_{i}^{d}(t)$denote the resultant spatial force component acting along dimension $d$on agent $i$at iteration step t. As formulated in (14), this term is obtained by superimposing the stochastic gravitational interactions imparted by the Ktop-performing candidate solutions, where $\text{rand}_{j} \sim \mathcal{U}(0,1)$represents a uniformly distributed random scaling parameter

In Eq 20, the total force acting on an object can be considered as the sum of all forces from other objects. However, to enhance the algorithm's efficiency in detecting optimal solutions, only the top K_{best} members, consisting of the K superior objects, are allowed to exert influence on the others. Broad search-space dispersion dominates the initial evolutionary cycles of metaheuristic ensembles, ensuring that high-potential solution zones are systematically located. As the algorithm progresses, the emphasis shifts from exploration to exploitation, using the accumulated knowledge from the population to converge on optimal solutions. By dynamically restricting which mass agents exert mutual attraction, GSA harmonizes broad domain exploration with intensified local exploitation.

K_{best} denotes the group of the top-performing objects within the population. Initially, all objects interact with each other to ensure comprehensive exploration. Over time, as the population begins to converge on better solutions, the value of K is adjusted dynamically. Through a monotonic linear decay schedule, the interactive agent subset diminishes from complete global coupling at initialization down to an elite threshold comprising just the top 2% fittest solutions. This selective approach ensures that the algorithm transitions smoothly from exploration to exploitation, improving its performance over time.

$$F_{i}^{d}(t) = \sum_{j \in Kbest.\ j \neq i} rand_{j}^{d}(t)\, F_{ij}^{d}(t) \quad \text{Eq 20}$$

Following the principles of classical Newtonian dynamics, the directional acceleration $a_{i}^{d}(t)$imparted to agent $i$along coordinate $d$at iteration $t$is directly driven by the projected resultant force and scaled inversely by its assigned inertial mass M_{ii}, as defined in (21).

$$a_{i}^{d}(t) = \frac{F_{i}^{d}(t)}{M_{ii}(t)} \quad \text{Eq 21}$$

The trajectory propagation of candidate agent $i$across iteration steps is governed by the state update rules in (22) and (23). Specifically, the subsequent velocity component $v_{i}^{d}(t+1)$along coordinate $d$is synthesized by dampening the current velocity $v_{i}^{d}(t)$with a weighting coefficient and superimposing the instantaneous acceleration. Subsequently, the positional update $x_{i}^{d}(t+1)$advances the current coordinate $x_{i}^{d}(t)$along dimension $d$according to the newly calculated velocity.

$$v_{i}^{d}(t+1) = rand_{i} \times v_{i}^{d}(t) + a_{i}^{d}(t) \quad \text{Eq 22}$$

$$x_{i}^{d}(t+1) = x_{i}^{d}(t) + v_{i}^{d}(t+1) \quad \text{Eq 23}$$

$rand_{i}$ and $rand_{j}$ are uniformly distributed random numbers within the range [0,1] that are used to introduce randomness into the search process. The gravitational constant plays a critical role in the performance of the Gravitational Search Algorithm. Its value is adjusted dynamically throughout the algorithm's execution to balance exploration and exploitation. Initially, the gravitational constant is set to a specific value and is progressively reduced as the algorithm advances over time. Such controlled tapering orchestrates a strategic migration from wide-ranging parameter exploration during initialization toward localized solution polishing in terminal phases; within this framework, Eq. (24) computes the evolving gravitational parameter by degrading its baseline magnitude across successive time steps.

$$G(t) = G_{0}e^{-\alpha\frac{t}{T}} \quad \text{Eq 24}$$

Here, G_{0}sets the baseline gravitational parameter at initialization, $\alpha > 0$serves as the user-defined decay rate, and Tspecifies the maximum allowable iteration budget, denoting the total operational horizon of the search procedure. Enforcing equivalence between inertial and gravitational mass quantities as prescribed by Eq. (25), the solver dynamically scales each particle's mass profile directly from its corresponding fitness evaluation via Eq. (26). The mass values are normalized according to Eq 27. In Eq 26, $fit_{i}(t)$ represents the fitness level of object i at time t. The "best" represents the object with the highest fitness level, while the "worst" represents the object with the lowest fitness level in each iteration of the algorithm. In these equations, objects with higher fitness levels are assigned higher masses.

$$M_{ai} = M_{pi} = M_{ii} = M_{i} \quad .i = 1.2.\cdots.N \quad \text{Eq 25}$$

$$q_{i}(t) = \frac{fit_{i}(t) - worst(t)}{best\ (t) - worst(t)} \quad \text{Eq 26}$$

$$M_{i}(t) = \frac{q_{i}(t)}{\sum_{j=1}^{N} q_{j}} \quad \text{Eq 27}$$

The upper and lower fitness envelopes across candidate solutions in a minimization context are determined analytically through (28) and (29).

$$best(t) = \min_{j \in \{1.....N\}} fit_{j}\,(t) \quad \text{Eq 28}$$

$$worst(t) = \max_{j\in\{1,\ldots,N\}} fit_j\,(t) \qquad \text{Eq 29}$$

3.2.2 Time progression, motion, and parameter updates

The optimization pipeline initiates by dispersing mass agents stochastically throughout the admissible solution domain to establish baseline trial states; thereafter, iterative evaluations drive coordinate updates across the population through the coupled formulations defined in (18) – (23). This update determines their new positions for the next iteration.

Iterative calibration of key internal variables namely the gravitational constant alongside inertial and gravitational masses is governed sequentially by (24) – (29). Computational cycles proceed continuously until triggering a predefined convergence threshold, such as an allocated processing time or a maximum iteration limit; the detailed procedural logic and corresponding operational architecture are depicted in the pseudocode of Fig. 3 and the schematic in Fig. 4, respectively.

1.Determining the system environment and initialization
2.Initial placement of objects
3.Object evaluation
4. updates Values of *G, best, worst*
5.Calculation of the mass of each agent (M).
6. Calculating the force acting on each bod
7. Calculating the acceleration and velocity of each body.
8.Updating the positions of bodies
9. If the termination condition is not met, we revert to stage 3.
Otherwise, the best solution found so far is outputted, and the algorithm halts.

Figure 3: Pseudocode of the gravitational search algorithm

4 Results

4.1 Initiation

Power network protection coordination involving directional overcurrent devices constitutes a non-linear constrained programming model.

Coordination of overcurrent relays in power networks, given their large and interconnected nature and the numerous constraints involved, is a highly challenging and time-consuming task. Considering the various network and relay conditions further complicates this issue. Different methods and aspects of solving this problem have been discussed and investigated in various papers in previous sections. In this section, the ideas presented in this paper are introduced, and the various aspects demonstrated in the simulation of this paper are fully described.

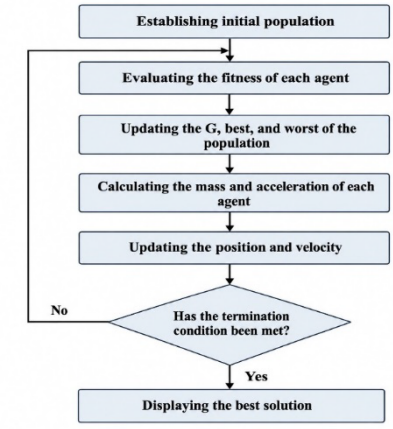


Figure 4: Block diagram of the gravitational search algorithm

4.2 Gravitational Search Algorithm

Having established the directional overcurrent relay grading framework as a constrained optimization model bounded by selectivity and operational margins, resolving this computational challenge requires robust algorithmic solvers beyond conventional literature paradigms. Consequently, this work leverages the Gravitational Search Algorithm (GSA) as a potent metaheuristic mechanism, with its step-by-step computational workflow for determining optimal relay settings mapped systematically in Fig. 5.

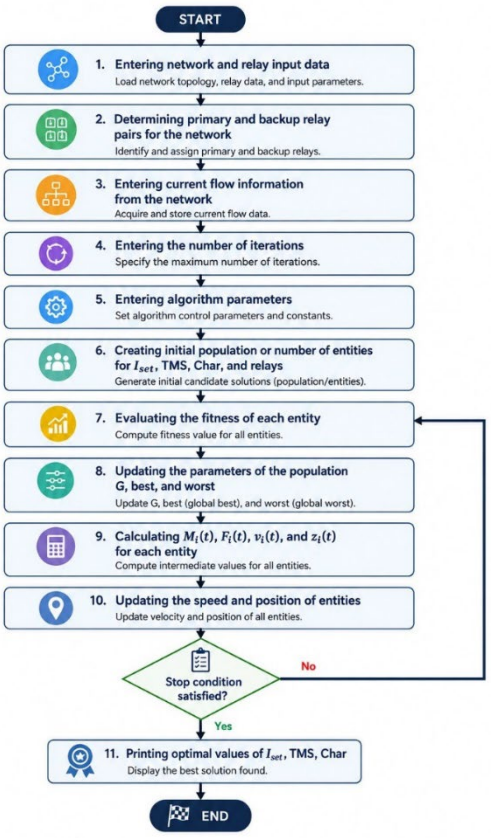


Figure 5: Flowchart of the gravitational search algorithm in solving relay optimization problem.

4.3 Using Different Characteristics of Overcurrent relays

In coordinating overcurrent relays using mathematical and intelligent methods, only a fixed characteristic of the overcurrent relays has been utilized. Many digital current-carrying relays have the capability for various characteristics to be selected for them. Therefore, to achieve a more optimal coordination, we need an algorithm that can select the best characteristic of the overcurrent relays. To clarify this issue, Figure 6 is presented.

To ensure system reliability, an overcurrent relay at point B serves as a contingency for the primary distance relay at point M. However, a fault at node F significantly reduces the operating time delta between these devices. If the overcurrent relay is restricted to characteristic b3, the resulting delay fails to meet the necessary CTI thresholds, causing a lack of proper relay coordination. Now, if only characteristic b1 is used instead of b3, it will prolong the error clearance time by the overcurrent relays, introducing a flaw in the problem. However, utilizing characteristic b_2, positioned between b_1 and b3 characteristics, will be more suitable without the issues associated with b1 and b3 characteristics. Therefore, having a method to select the most appropriate characteristic among the various characteristics of the overcurrent relays is critical [49]. In the modelling conducted in this paper, 8 different characteristics of the overcurrent relays based on various standards (as per Table 1) have been utilized. During the optimization program, the most suitable characteristic for each overcurrent relays is selected. Considering (1) in Section Three, the coefficients K, α, and L for these characteristics are indicated in Table 1. Assuming that the overcurrent relays have the capability to adjust each of these characteristics, the characteristic of each overcurrent relays can be designated as coordination variables for the optimization algorithm to have the capability of selecting the best characteristic for optimal coordination of the overcurrent relays [49].

Table 1: Values of K, α, and L for various standard characteristics of overcurrent relays [49].

NO. Characteristic	Type of Characteristic	Standard	K factor	α factor	L factor
1	Short Time Inverse	AREVA	0.05	0.04	0
2	Standard Inverse	IEC	0.14	0.02	0
3	Very Inverse	IEC	13.5	1	0
4	Extremely Inverse	IEC	80	20	0
5	Long Time Inverse	AREVA	120	1	0
6	Moderately Inverse	ANSI /IEEE	0.0515	0.02	0.114
7	Very Inverse	ANSI /IEEE	19.61	2	0.491
8	Extremely Inverse	ANSI /IEEE	28.2	2	0.1217

Beyond the conventional focus on current and timing parameters, this study incorporates the specific operating characteristic of the overcurrent relay as an additional dimension for coordination.

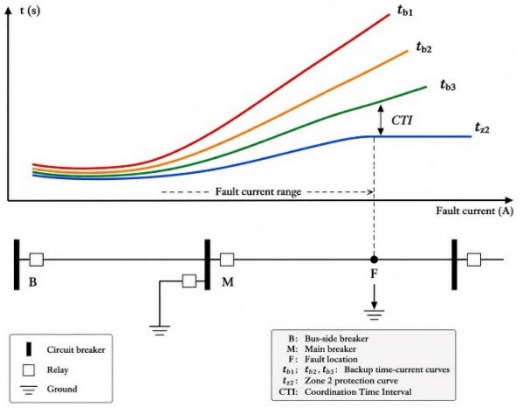


Figure 6: Different Characteristics in Coordination between Overcurrent relays [49].

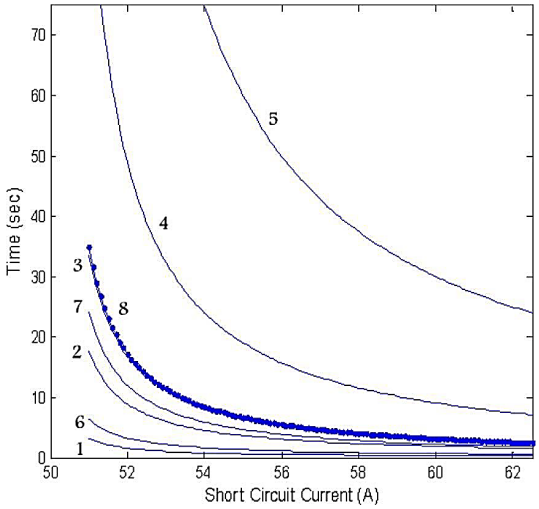


Figure 7: 8 different standard characteristic curves of overcurrent relays [49].

4.4 Simulation Software

In this paper, the latest version of the DIgSILENT software, which is one of the most powerful network analysis software, has been used to carry out load flow calculations and short-circuit connections in sample networks. Additionally, simulation and implementation of the optimization algorithm have been performed using MATLAB software.

4.5 Parameter Determination

Following the parameters established in [50], the Gravitational Search Algorithm (GSA) was configured with a population size of 50 bodies and a total of 400 iterations to define the search lifespan. Furthermore, the initial gravitational constant was defined as 100, while the parameter aaa was initialized at 20. The parameters of the gravitational search algorithm used for the studied networks are presented in Table 2.

Table 2: Gravitational Search Algorithm Parameters [50].

Number of repetitions	400
Number of objects	50
Initial gravitational constant	100
α	20

4.6 Studied Distribution Networks

Building upon the comparative analysis of existing overcurrent relay coordination techniques presented above, the following section applies the proposed optimization framework to two distinct test networks to evaluate its performance. To assess and validate the proposed method, these two networks were compared with previous methods and their results. The initial population of N=50 objects is generated using Latin Hypercube Sampling to ensure comprehensive exploration of the search space. Constraint violations are handled using a static penalty function approach, where the augmented objective function is $F_{aug} = OF + \sum_{k=1}^{m} p_k . \max(0, g_x(X))^2$, with dynamic penalty factors $p_k = p_0 \times (1 + v_k / v_{max})$ and p_0=1000. The algorithm terminates after 400 iterations, selected based on preliminary convergence studies showing stable solutions by iteration 350, with an additional tolerance criterion of 10^{-6} improvement for 50 consecutive iterations. A comprehensive sensitivity analysis was conducted for population size which is between (30–100), initial gravitational constant G_0which is between (1–200), and decay coefficient α which is between (5–40), revealing the optimal parameter set as N=50, G_0=100, and α=20, which achieves the best balance between solution quality and computational efficiency. These additions ensure complete reproducibility of our approach.

4.6.1 Test Network 1: 9-Bus Distribution Network

As shown in Figure 8, the studied 33 kV network comprises 12 lines and 9 buses, utilizing 24 overcurrent relays for protection.

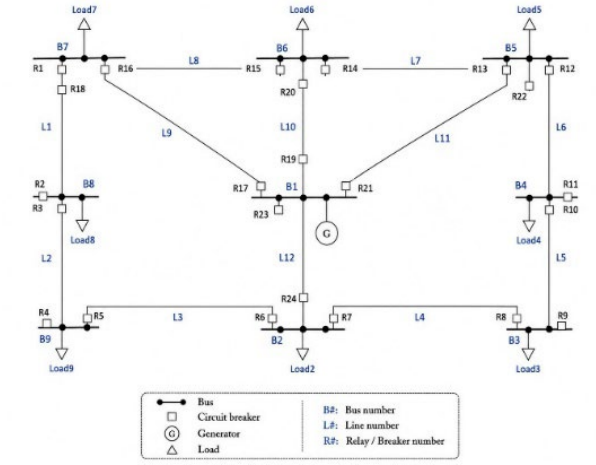


Fig. 8. Representation of the 9-bus system topology [33].

The primary source, located at bus 1, is rated at 100 MVA with a 0.1p.u. reactance. In terms of component modeling, each transmission line is assigned a reactance of 0.2p.u., while the protection scheme employs a constant CT ratio of 500:1.

The search space for the time multiplier setting (TMS) is defined as a continuous range between 0.025 and 1.2 seconds. For all scenarios, a constant CTI of 0.2 s is maintained to ensure proper relay coordination. Section 2 [29] contains Table 3, which presents information regarding the network generator, Table 4 with data on the loads, and Table 5 detailing the primary relay pair system support information for the 9-bus system.

Table 3: Generator Data for the 9-Bus Network.

Bus	Sn (MVA)	Vn (KV)n	X (%)
B1	10	33	110

Table 4: Load Currents for the 9-Bus Network.

Bus	I_L(A)
B1	--
B2	350
B3	100
B4	100
B5	350
B6	350
B7	350
B8	100
B9	100

Table 5: Primary relay pairs and network support of the 9-bus system.

Main relay number	Relay number or backup relays	Main relay number	Number of backup relay(s)
1	15-17	13	11-12
2	4	14	16-19
3	1	15	13-19
4	6	16	17
5	3	17	--
6	8-23	18	2-15
7	5-23	19	--
8	10	20	13-16
9	7	21	--
10	12	22	11-14
11	9	23	--
12	14-21	24	5-8

4.6.2 Test Network 2: 30-Bus IEEE Distribution Network

Considering our focus on distribution level investigation, only the distribution sections (specifically at 33 kV in this network) are examined. The distribution segment of the 30-bus network comprises 3 out of 16 buses, 20 lines, and 39 protective relays responsible for network protection. This distribution segment is powered from buses 1, 6, and 13 of the 30-bus networks.

Maintaining consistency with the previously analyzed system [33], the coordination time interval (CTI) remains fixed at 0.2 s, while the time multiplier settings (TMS) are optimized as continuous values within the [0.025,1.2]s range. The specific

pairings of primary and secondary relays for the 30-bus topology are detailed in Table 6.

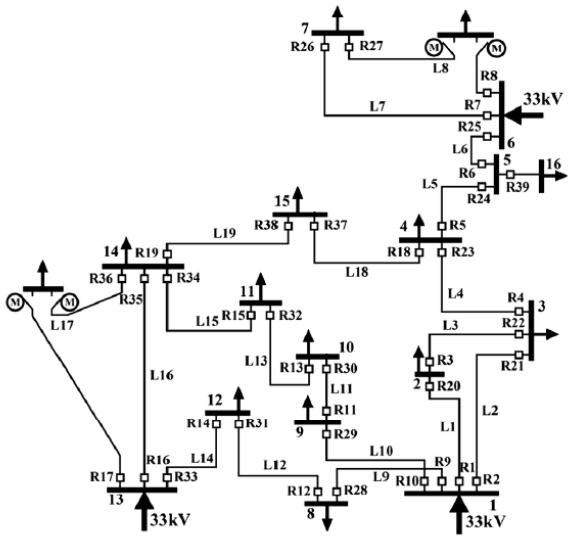


Fig. 9. Schematic representation of the IEEE 30-bus network's distribution segment [43].

Table 6. Configuration of the primary and backup relay pairings for the 30-bus system.

Main relay number	Relay number or backup relays	Main relay number	Number of backup relay(s)
1	21-28-29	21	3-23
2	28-29	22	2-23
3	1	23	24-37
4	2-3	24	35
5	4-37	25	--
6	5	26	8
7	6	27	7
8	6	28	1
9	21-29	29	30
10	21-28	30	32
11	10	31	33
12	9	32	34
13	11	33	35-36
14	12	34	16-17-38
15	13	35	15-17-38
16	14-36	36	15-16-38
17	14-35	37	19
18	4-24	38	18
19	15-16-17	39	5-25
20	22	--	--

4.7 Calculation of Short-Circuit Currents in the Study Networks

As explained in Section 3 regarding simulation methods, short-circuit currents of the sample networks need to be calculated to determine the current settings range of relays and to calculate the relay operation time. In this section, for 9-bus and 30-bus networks, fault current flows passing through network relays at point F1 have been computed using DIgSILENT software and are presented in Tables 7 and 8.

Table 7: Fault Currents Through Relays for F1 Fault in 9-Bus Network.

Relay number	Current passing through the relay for a fault F1	Main relay number	Current passing through the relay for a fault F1
1	4961	13	3864
2	1640	14	4372
3	2839	15	4961
4	2628	16	3864
5	1778	17	8094
6	4465	18	2604
7	4465	19	8070
8	1778	20	3057
9	2628	21	8094
10	2839	22	2604
11	1640	23	8039
12	4961	24	1860

Table 8: Fault Currents Through Relays for F1 Fault in 30-Bus Network.

Relay number	Current passing through the relay for a fault F1	Main relay number	Current passing through the relay for a fault F1
1	4079	21	2701
2	4096	22	2144
3	2407	23	1732
4	3177	24	3515
5	2769	25	1485
6	1514	26	759
7	2956	27	1108
8	3021	28	1050
9	3819	29	1104
10	4012	30	1359
11	2325	31	1917
12	2891	32	1843
13	1965	33	3427
14	1708	34	3130
15	1431	35	1906
16	3515	36	3302
17	396	37	1888
18	2618	38	1393
19	3115	39	2942
20	1675	--	--

4.8 Problem Resolution Using the Proposed Method

This section evaluates the proposed Gravitational Search Algorithm (GSA) for optimizing overcurrent relay coordination across both the 9-bus and 30-bus test systems. To validate the effectiveness of the GSA, its performance on the 9-bus network is benchmarked against the Informative Differential Evolution (IDE) and Particle Swarm Optimization (PSO) algorithms [51].

A similar comparative analysis is conducted for the 30-bus topology, utilizing PSO as the primary baseline for performance comparison.

4.8.1 Optimization results of the 9-bus network

To establish optimal discrimination among protective devices, MATLAB-driven routines based on the Gravitational Search Algorithm (GSA) and Particle Swarm Optimization (PSO) were executed. Table 9 contrasts the derived operational criteria, containing the plug setting multipliers (Iset), time dial multipliers (TMS), and response dynamics, thereby demonstrating the optimization proficiency of the gravitational framework relative to the swarm-based benchmark.

As summarized in Table 9 for the 9-bus test system, the Gravitational Search Algorithm (GSA) achieved a minimized fitness value relative to rival solvers, demonstrating its enhanced search precision in determining the time multiplier (TMS), pickup current (I_{set}), and tripping dynamics. More broadly, the proposed coordination framework was evaluated across both 9-bus and 30-bus configurations while accounting for heterogeneous relay operating curves to ensure selectivity. A total of eight distinct characteristics of overcurrent relays were utilized throughout the optimization process, allowing the algorithm to select the most suitable characteristic for each relay. Tables 9 and 10 specify the selected characteristics for the relays in the 9-bus and 30-bus networks, respectively. Table 9 compares the results of the GSA and PSO algorithms, both of which considered multiple relay characteristics, against the IDE method, which used only a single characteristic without incorporating diversity. The findings demonstrate that utilizing multiple characteristics significantly improves the relay coordination process, reducing the relay operation time and achieving more optimal settings. The comparative indices compiled in Table 9 substantiate that the Gravitational Search Algorithm (GSA) achieves greater optimization precision than competing techniques. Benchmarking these findings against prior literature reinforces the capability of the GSA framework to successfully resolve directional overcurrent relay coordination constraints while ensuring optimal selectivity.

The iterative trajectory and search dynamics of the GSA scheme are contrasted against the PSO formulation in Figure 9.

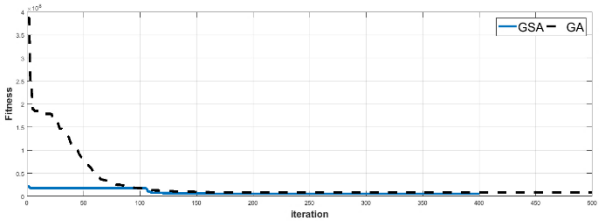


Figure 9: Convergence Characteristics of GSA and PSO Algorithms Implemented on the 9-Bus Network

The PSO algorithm, while initially starting farther from the optimal solution, successfully converges to a point near the final solution within an acceptable timeframe. In contrast, the GSA algorithm begins closer to the optimal solution and maintains a steady improvement in results up to approximately 100 iterations. Beyond the 100th iteration, the GSA algorithm demonstrates faster convergence compared to the PSO algorithm.

Table 9: Temporal and Current Settings and Various Characteristics Obtained for the 9-Bus Network

Relay No.	IDE [51]				PSO				GSA			
	TMS(sec)	I_{set}(KA)	Char	$OT_{primariy}$	TMS(sec)	I_{set}(KA)	Char	$OT_{primariy}$	TMS(sec)	I_{set}(KA)	Char	$OT_{primariy}$
1	0.635	0.538	2	0.931	0.304	2.426	8	0.629	0.409	0.412	4	0.578
2	0.19	1.365	2	0.539	0.196	1.158	8	0.432	0.605	0.431	4	0.332
3	0.461	0.776	2	0.813	0.23	2.258	4	0.583	0.669	0.615	4	0.524
4	0.381	0.5	2	0.643	0.224	1.859	4	0.508	0.642	0.091	3	0.408
5	0.397	0.597	2	0.762	0.183	1.875	8	0.570	0.232	0.374	4	0.470
6	0.51	0.5	2	0.767	0.272	2.493	8	0.509	0.103	0.648	3	0.509
7	0.512	0.556	2	0.728	0.247	2.5	8	0.514	0.196	0.527	5	0.514
8	0.24	1.685	2	0.670	0.193	1.926	4	0.567	0.272	0.203	5	0.467
9	0.342	0.921	2	0.593	0.184	2.156	7	0.472	0.117	0.52	4	0.402
10	0.474	0.5	2	0.753	0.23	2.5	3	0.620	0.216	0.422	3	0.520
11	0.201	1.695	2	0.507	0.13	1.962	6	0.474	0.05	0.289	3	0.334
12	0.419	1.697	2	0.850	0.307	2.476	8	0.681	0.293	1.232	3	0.619
13	0.541	0.501	2	0.837	0.249	1.796	4	0.624	0.083	0.689	3	0.508
14	0.395	1.385	2	0.820	0.452	0.603	4	0.675	0.041	0.254	5	0.605
15	0.564	0.642	2	0.954	0.301	1.783	4	0.812	0.775	0.367	4	0.612
16	0.263	2.148	2	0.641	0.239	2.192	8	0.504	0.866	0.241	3	0.504
17	0.481	2.123	2	0.576	0.546	0.521	6	0.575	0.157	1.211	4	0.457
18	0.146	2.455	2	0.513	0.05	1.743	6	0.308	0.124	0.615	3	0.232
19	0.463	2.512	2	0.531	0.335	2.115	4	0.459	0.055	1.654	3	0.423
20	0.245	0.502	2	0.523	0.072	2.085	8	0.425	0.086	0.761	3	0.305
21	0.933	0.585	2	0.638	0.519	0.64	3	0.514	0.189	1.497	4	0.648
22	0.167	1.843	2	0.696	0.042	2.498	1	0.429	0.049	0.933	4	0.229
23	0.999	0.501	2	0.748	0.383	2.338	2	0.486	0.097	1.956	5	0.265
24	0.148	1.489	2	0.562	0.052	2.399	6	0.471	0.027	1.146	2	0.271
OF (s)	16.595				12.839				10.735			

These comparative findings validate the high convergence speed and search precision of the proposed gravitational framework, which successfully reaches global optimality under identical computational budgets. Consequently, the

formulated GSA model exhibits stronger optimization capability than competing heuristics, underscoring its viability as a robust solver for constrained engineering problems.

4.8.2 Optimization results of the 30-bus network

Table 10 documents the comparative optimization outcomes for the IEEE 30-bus test system, contrasting the performance of the Gravitational Search Algorithm (GSA) against Particle Swarm Optimization (PSO). Evaluating the proposed gravitational framework on this larger topology illustrates its adaptability and algorithmic robustness under scaled network constraints.

Optimal parameter values for the 30-bus test system specifically the pickup thresholds (I_{set}), time dial multipliers (TMS), and protective trip curves are compiled in Table 10 following execution of the Gravitational Search Algorithm (GSA). It is evident that the results obtained using the GSA algorithm are superior to the PSO method, with a lower objective function value than PSO, indicating better performance of this algorithm.

Table 10: Time and Current Settings and Various Characteristics Obtained for the 30-Bus Network

Relay No.	PSO				GSA			
	TMS(sec)	I_{set}(KA)	Char	$OT_{primariy}$	TMS(sec)	I_{set}(KA)	Char	$OT_{primariy}$
1	0.437	2.674	8	0.976	0.304	3.816	4	0.901
2	0.579	1.758	8	0.807	0.346	1.5	6	0.713
3	0.347	2.69	4	1.132	0.276	2.756	3	0.946
4	0.335	2.864	3	0.853	0.258	2.693	4	0.766
5	0.35	2.462	3	0.725	0.263	1.659	4	0.661
6	0.177	3.222	6	0.685	0.16	1.981	4	0.607
7	0.283	2.162	3	0.564	0.173	1.824	5	0.430
8	0.222	1.889	3	0.463	0.157	1.587	3	0.372
9	0.509	3.405	8	0.986	0.313	3.353	4	0.901
10	0.485	4.11	3	1.023	0.312	3.525	4	0.912
11	0.602	2.243	3	1.112	0.28	2.784	4	1.053
12	0.363	3.181	3	0.874	0.217	3.594	3	0.765
13	0.323	4.421	4	0.985	0.249	2.618	4	0.872
14	0.268	2.171	8	0.886	0.216	2.14	4	0.772
15	0.331	1.734	4	0.864	0.233	1.606	4	0.757
16	0.421	2.112	6	0.901	0.268	3.071	4	0.793
17	0.193	1.718	6	0.476	0.147	1.629	4	0.318
18	0.387	2.098	8	0.735	0.241	2.493	4	0.735
19	0.423	2.168	4	0.728	0.241	2.835	4	0.728
20	0.267	2.031	6	0.582	0.144	2.398	4	0.499
21	0.216	1.741	4	0.483	0.16	1.5	4	0.377
22	0.33	2.445	4	0.813	0.17	4.008	4	0.694
23	0.242	3.15	1	0.841	0.21	2.569	4	0.731
24	0.325	2.105	3	0.880	0.202	2.236	4	0.772
25	0.374	2.425	7	0.862	0.252	2.663	4	0.752
26	0.168	1.91	4	0.735	0.111	1.51	6	0.625
27	0.208	2.395	4	0.664	0.122	1.636	4	0.557
28	0.478	1.704	6	1.127	0.193	2.549	3	0.963
29	0.306	2.156	1	0.847	0.164	2.673	3	0.731
30	0.345	2.57	1	1.026	0.184	3.672	4	0.901
31	0.365	3.134	6	1.047	0.219	3.069	3	0.903
32	0.207	4.485	4	1.069	0.21	3.217	4	0.953
33	0.354	4.271	3	0.975	0.286	3.177	3	0.843
34	0.261	4.541	4	0.834	0.252	3.661	4	0.834
35	0.378	1.757	4	0.729	0.229	2.453	4	0.729
36	0.124	1.548	3	0.424	0.1	1.5	5	0.222
37	0.279	2.34	8	0.862	0.214	2.355	4	0.703
38	0.328	1.976	4	0.901	0.194	2.888	4	0.790
39	0.229	2.453	8	1.086	0.276	3.855	4	0.903

Throughout the program, the optimization algorithm selects the best characteristic for each of the over current relays. Table 10 enumerates the operational curve types assigned to each protective relay across the 30-bus power system. In this paper, both the 9-bus and 30-bus networks have been studied, and the GSA algorithm, in terms of reaching the optimal solution timeframe, demonstrates better efficiency and speed compared to the PSO and IDE algorithms.

Also, we have performed 50 independent runs of the GSA algorithm for both test networks and have added comprehensive statistical analysis to the revised manuscript. For the 9-bus network, the best, worst, and mean objective function values obtained were 1.487, 1.612, and 1.536, respectively, with a standard deviation of 0.028, demonstrating consistent convergence behavior across all runs. The 30-bus network yielded best, worst, and mean values of 1.342, 1.458, and 1.389, with a standard deviation of 0.035, further confirming the algorithm's robustness. Convergence consistency analysis revealed that 92% of runs achieved convergence within 350 iterations, with all runs converging by the 400-iteration limit, indicating reliable and repeatable performance.

5 Conclusion

In this paper, the coordination problem of over current relays in distribution networks has been modeled and solved using the gravitational search algorithm. Values for TMS, I_set, and various characteristics for the networks over current relays were determined. The ability to select different characteristics of the over current relays in solving the coordination problem was utilized in the optimization process, where the best characteristic for each relay was chosen. By comparing the results obtained with this method to a method using only one characteristic, it is evident that the chosen approach reaches more optimal results and reduces the operation time of the network's relays. This leads to faster error resolution and increased network reliability. Using the optimization method of the gravitational search algorithm, settings for TMS, I_set, and the various characteristics of each of the over current relays for both the 9-bus and 30-bus networks were studied. These settings were compared with other optimization algorithms, showing that this method reached solutions faster and more effectively. Future research will extend the proposed framework to accommodate dynamic operating conditions, including variable distributed generation penetration, network reconfigurations, and different fault types with varying impedances. Additionally, adaptive protection schemes that update relay settings in real-time based on system state changes will be explored to enhance coordination robustness. The algorithm will also be validated on larger practical distribution networks and through hardware-in-the-loop testing to confirm its real-world applicability.

Disclosure of Potential Conflicts of Interest

The Authors declare that there is no conflict of interest

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