APPLICATION OF OPTIMIZATION TECHNIQUES TO SOLVE OVERCURRENT RELAY COORDINATION

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Publication 1

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ABSTRACT

Distribution systems continues to grow and becoming more complex with increasing operational challenges such as protection miscoordination. Initially, conventional methods were favoured to optimize protection coordination; however, the implementation process is laborious and time-consuming. Therefore, recent studies have adopted the utilisation of particle swarm optimization and genetic algorithms to solve overcurrent relay coordination problems and maximise system selectivity and operational speed. Particle swarm optimization and genetic algorithms are evolutionary algorithms that at times suffer from premature convergence due to poor selection of control parameters. Consequently, this thesis aims to present a comprehensive sensitivity analysis to evaluate the effect of the discrete control parameters on the performance of particle swarm optimizer and genetic algorithms, alternatively on the behaviour of overcurrent relays. The main objectives of this research work also include modelling and simulation of distribution system protection scheme, employment of evolutionary algorithms with control parameters that perform efficiently and effectively to maximise protection coordination between relays, optimize relay operating time and maintain the stipulate coordination time interval, and lastly, to outline future recommendations. The distribution network understudy was modelled and simulated on a real-time digital simulator to validate protection settings, and the verification of evolutionary algorithms performance was displayed on Matlab/Simulink. An extensive parametric sensitivity analysis was conducted to understand the impact of the individual control parameters and their respective influence on the performance of evolutionary algorithms. The findings indicate that particle swarm optimization is more sensitive to inertia weight and swarm size while the number of iterations has minimal effect. The results also depict that genetic algorithms' performance is mostly influenced by crossover probability, mutation probability, and population size. Sensitivity analysis results were verified by comparing the performance of particle swarm optimizer with genetic algorithms, which demonstrated that particle swarm optimization performs efficiently and robustly in solving the considered problem, especially in terms of convergence speed. Furthermore, overcurrent relays were more sensitive, selective, and the operational speed was reduced for particle swarm optimizer compared to other algorithms. The optimal protection coordination achieved using particle swarm optimization showed superiority of the algorithm, its ability to circumvent premature convergence, consistency, and efficiency.

Table of Contents

List of Figures

List of Tables

Acronyms and Abbreviations

AC	Alternating Current
CT	Current Transformer
CTI	Coordination Time Interval
DAPSO	Dynamic Adaptation Partible Swarm Optimization
ES	Evolutionary State
GA	Genetic Algorithms
IDMT	Inverse Definite Minimum Time
IEC	International Electrotechnical Committee
IED	Intelligent Electronic Devices
IEEE	Institute of Electrical and Electronic Engineers
MAPSO	Modified Adaptive Particle Swarm Optimization
MDE	Modified Differential Evolution
PSO	Particle Swarm Optimization
PSO-DE	Particle Swarm Optimization with Differential Evolution
PSO-LDIW	Particle Swarm Optimization with Linearly Decreasing Inertia Weight
PSO-RIW	Particle Swarm Optimization with Random Inertia Weight
PSO-CIW	Particle Swarm Optimization with Chaotic Inertia Weight
PSO-TVAC	Particle Swarm Optimization with Time-Varying Acceleration Coefficient
PSM	Plug Setting Multiplier
RMS	Root Mean Square
TMS	Time Multiplier Setting
VT	Voltage Transformer

CHAPTER 1

1 Introduction

This research work outlines the effective application of optimization techniques to coordinate overcurrent relays and the use of a real-time digital simulator (RTDS) for modelling, analysis, and protection of an electrical distribution system emanating from a 132 kV grid. There has been a significant focus on finding solutions to overcurrent relay coordination problems and premature convergence of evolutionary algorithms in terms of research and development. This research work details a comprehensive assessment of the effects of particle swarm optimization (PSO) and genetic algorithms (GA) control parameters on overcurrent relay selectivity, reliability, and speed. Thereafter, parameters that produce effective and efficient relay settings are utilised to model, analyse, and simulate an overcurrent protection scheme. In this chapter, background to the study is presented in section 1.1, significance of the research in section 1.2, research problem in section 1.3, research questions are provided in section 1.4, the objectives of the study are in section 1.5. Section 1.6 presents the research scope and limitations, contributions to current research are in section 1.7 and lastly, the dissertation structure in section 1.8.

1.1 Background to the study

Due to rising emphasis on substation automation, SCADA, and monitoring control, operational speed and protection coordination form the most important aspect and are prime factors in any protection system [1] – [7]. As the demand for electricity continues to rise, distribution systems are taking a strain and becoming more complex with increasing loads, voltages, and currents. Moreover, operational challenges such as a higher percentage of power network equipment damage and customer service disruptions caused by breakdowns and faults in the distribution feeders as overhead power systems are subjected to either partial or permanent faults [3], [6]. Although systems are designed to be as fault-free as possible, it is impractical to eliminate fault occurrence completely. However, system abnormalities must be catered to during engineering design stage, commissioning, and maintenance to circumvent enormous damage and guarantee the protection of expensive equipment [7], [8], [9]. Excessive current levels in distribution systems are due to system abnormalities. These high current levels can be utilized to characterize the presence of defects and aid to trigger protective device operation accordingly, which differ in design specifications and system complexity [10], [11]. If abnormal conditions occur in a network segment, a protective system is required to clear the fault speedily without affecting the healthy section and promptly segregate the faulty segment. Protection coordination is of paramount importance since the failure of protective device to operate under faulty conditions can damage some essential parts due to fire that may result from massive-short circuits; consequently, the system loses synchronism of the machinery and equipment [6], [12], [13], [14]. This necessitates the need to optimize overcurrent relay operating time and maximize selectivity.

For many years, power systems engineers and researchers relied on conventional optimization methods such as the simplex method, time grading margin, and dual simplex technique to perform relay coordination. The disadvantage of the methods is that the solution is based on iterative trial and error, and the process is laborious as well as time-consuming [6], [12]. Hence, many researchers [15], [16], [17], [18], [19] advocated the need for utilising evolutionary algorithms to mitigate setbacks presented by conventional optimization approaches. Evolutionary optimization techniques such as population-based incremental learning, particle swarm optimization (PSO), breeder genetic algorithms, and genetic algorithms (GA) have emerged as efficient and effective algorithms for handling complex optimization problems [15], [18], 19]. Nevertheless, setting evolutionary algorithms control parameters to attain optimum overcurrent relay settings is a long-standing issue [20]. Major concerns relating to premature convergence of algorithms include the poor selection of control parameters, which results in population locating to local solutions. This research work aims to model and simulate the distribution system overcurrent scheme and provide a simple sensitivity analysis approach for the proposed particle swarm optimization and genetic algorithms, comprehensive review, and comparison of algorithms with regard to convergence and fitness function values.

1.2 Significance of the research

Power system operation is a very crucial task since it is associated with nation's economic development and progression of technology. As a result, electric service companies invest economic and technical capitals to provide a reliable and safe electricity supply based on adequate equipment, reliable components, system protection, and modern devices. Under these considerations, not only reliable equipment needed in distribution systems but also a proper protection coordination and norms to withstand any kind of faults limiting its impact on the electrical distribution system. With this contextual, it is clear that essential service such as protection systems are mandatory in distribution systems. Although conventional techniques were favoured to determine protective device settings, optimization algorithms are becoming popular. The need for better optimization algorithms will continue to rise due to increasing complexity of problems on distribution systems. In early 2000s genetic algorithms were seemingly the preferred optimization technique for solving overcurrent coordination problem [21], [22]. Genetic algorithms are robust and reliable technique; however, it requires complex adjustments to each potential solution in order to accomplish better convergence. Not much studies state suitable genetic operators' values to avoid algorithm converging prematurely. The introduction of particle swarm optimization as an alternative to genetic algorithms for solving overcurrent relay coordination problems shown improvements due to it simple solution adjustments which are sufficient to employ the technique. This algorithm is often used in finding solutions to complex problem; however, to date, the tuning of control parameters to optimise protection coordination in distribution systems has not been sufficiently conducted. Therefore, this work aims to make a significant contribution in terms of tunning both particle swarm optimizer and genetic algorithms control parameters to optimize overcurrent relay settings and maximise selectivity.

1.3 Research problem

To demonstrate through simulations the efficiency and robustness of the proposed evolutionary algorithms. To simulate a distribution network model, implement an overcurrent protection scheme, and ensure proper protection coordination in the distribution system. Given the importance of electricity in economic growth and urbanisation, a continuous and reliable supply of electrical power is a necessity. Entities such as hospitals, airports, and prisons cannot afford power loss; thus, it is imperative to design distribution networks with two or more power sources to ensure a continuous supply of electrical power to customer loads. To protect distribution scheme equipment, mitigate customer service disruption, and reduce the severeness of abnormalities.

1.4 Research questions

The thesis objectives are guided by the following questions:

a) How do the proposed evolutionary algorithms perform in comparison with conventional techniques?
b) What control parameters mostly influence the performance of overcurrent relays?
c) What other approaches that can be implemented to further improve the proposed algorithms' results?
d) Is it possible to obtain selectivity for the distribution system with multiple similar power sources parameters?

1.5 Dissertation objectives

This research work addresses the following objectives:

- To model and simulate distribution system overcurrent protection scheme using RTDS software.
- Evaluate and investigate the effects of the selected evolutionary algorithms control parameters on the overcurrent relay selectivity, reliability, and speed.
- To employ an evolutionary algorithm with control parameters that perform efficiently and effectively to maximise protection coordination between relays.
- To validate the performance of the selected evolutionary algorithm by means of comparative study.
- Minimisation of relays' operating time and maintaining a coordination time interval of 0.4 seconds.
- To make future recommendations on studies that can be performed to supplement this research work.

1.6 Research scope and limitations

The research work identifies problems associated with protection coordination in the distribution system, reviews and implements some optimization techniques. The scope and limitations of this research are as follows:

- Only directional overcurrent protection relays are covered and addressed; distance and differential protection relays are not considered.
- Very inverse, extremely inverse, and definite time are not considered; the standard inverse characteristics are utilised.
- The main focus is on the implementation of optimization techniques, i.e., particle swarm optimizer, genetic algorithms, and dual simplex method.
- Parametric sensitivity analysis is conducted on the limited identified control parameters.
- The comparative study is limited to the proposed evolutionary algorithms and conventional coordination methods.
- Distribution network models are developed in real-time digital simulator and RSCAD simulator, and some of the standard models available in the software were utilised.

1.7 Contribution to current research

The contributions presented by this research work are as follows:

- The determination of poor performing control parameters based on the convergence speed and fitness function values which determines the robustness, efficiency, and superiority of the algorithm.
- Analysis of overcurrent relay response based on operational speed and system selectivity to evaluate whether protection coordination is accomplished.
- The modified adaptive particle swarm optimization (MAPSO) algorithm is proposed to enhance original particle swarm optimizer performance by making the control parameters adaptive.
- MAPSO is a constraint handling mechanism that enhances original particle swarm optimizer performance by making the control parameters adaptive and ensuring particles move towards feasible regions only.
- An evolutionary state-based inertia weight is proposed to balance exploration and exploitation search by enforcing the algorithm to retain feasible solutions only.
- A repulsion-based position update technique, as well as velocity reinitialization with respect to clamping-limit, is adopted to improve global exploration and increase robustness.

1.8 Outline of the dissertation

The research work is organised as follows:

Chapter 1: Introduction

This chapter provides a brief description of work undertaken, aims and objectives, contributions to current research, problem statement, research scope and limitations, dissertation questions, and importance of research. It introduces the background of overcurrent relay coordination, optimization techniques in particular evolutionary algorithms and linear programming methods, and the drawbacks encountered by conventional methods.

Chapter 2: Literature Review

The chapter presents an overview of relevant study in the power system protection field and introduces the concept of particle swarm optimization, genetic algorithms, and linear programming optimization methods. Furthermore, the research problem is clearly articulated. It outlines relevant research in the distribution network protection scheme and thus presents a context for and identifies research challenges related to the dissertation.

Chapter 3: Research Methodology

Research methodology provides methods adopted, processes followed, and software selection. It outlines a methodical approach employed in this work to accomplish research purposes detailed in the introduction. Also, it presents an overview of evolutionary algorithms, constraint handling techniques, and control logics designed in a real-time digital simulator draft interface.

Chapter 4: Distribution system model and RTDS simulations

In this chapter, the software simulation results of a simple distribution network are detailed and analysed. It contains model calculations and tables for coordination technique employed in the study. The inverse time overcurrent relay characteristics and operation outlined in theory are verified. The distribution system model is analysed, and overcurrent protection coordination is implemented, which showed proper coordination; however, the results obtained were not optimum. Hence, in the subsequent section, the application of optimization techniques to attain global optimal solution is discussed and implemented on the distribution system.

Chapter 5: Application of Optimization Techniques for Overcurrent Relay Coordination

This chapter presents the application of the proposed evolutionary algorithms, that is, genetic algorithms and particle swarm optimization. Also, the dual simplex technique is proposed for comparison purposes since its a deterministic method and solves a problem without any stochastic behaviour, convergence curves cannot be generated. The effects of particle swarm optimization and genetic algorithm control parameters on overcurrent relay performance were investigated to aid in determining parameters that perform inefficiently. A comparative study was conducted to verify parametric sensitivity analysis results and evaluate algorithms' performance in terms of convergence speed. Thereafter, protection scheme coordination was verified through real-time digital simulations and various faults occurred on different protection zones to ensure the distribution system was protected against asymmetrical faults. Overall, the chapter provides research experimental results in detail and discussions.

Chapter 6: Conclusion

The research work outcomes and main points are consolidated into a final summary and recommendations for future work are presented. A comprehensive understanding of the research problem is presented.

CHAPTER 2

2 Literature Review

2.1 Introduction

Due to accumulating loads, voltages, and short circuit duty, there arise concerns regarding protection reliability, selectivity, sensitivity, power quality, and control of the utility system [1]-[7], [23]. Consequently, distribution system protection has encountered challenges such as protection miscoordination resulting in researchers exploring solutions to coordination problem over the past few decades [13]. The implementation of a protection system is of fundamental importance to constantly monitor distribution network and ascertain maximum flow of electrical power without damaging equipment [12]. Generally, distribution systems can either be radial, loop, or network depending on the services required, location, and economics [24]. Radial networks consist of one power source and are not reliable as the occurrence of power failure may result in standstill of everything [24]. Therefore, there is an increasing necessity to design distribution systems with two or more power sources and safeguard optimal protection coordination.

Protection coordination is performed to maintain selectivity among protective devices subjected to fault possibilities, to ensure safe operation and system reliability [25]. In an efficient and properly coordinated system, abnormalities are eradicated within the smallest time possible, isolating the least faulty section only [6]. With protection relays, the main objective is to attain coordination between the upstream and downstream relays and breakers. The goal is to permit relay and circuit breaker adjacent to the fault to eradicate fault from the network before the backup relay could initiate the opening of its respective breaker [26]. There have been a substantial number of techniques proposed in literature, such as conventional methods and optimization techniques, that is, linear programming and evolutionary algorithms to find solutions to protection coordination.

2.2 Overview of electrical faults

A study in [27], claimed that the development of electrical power systems over the past 50 years caused electrical faults experienced in distribution systems to escalate. It was implicitly stated that larger networks consisting of generators, transformers, switchgears, transmission, and distribution circuits constitute a higher percentage of fault occurrence in some parts of the system [27]. However, transmission lines manifest the most significant possibility of faults occurrence due to great heights and exposure to atmospheric conditions [27]. As a result, there is no perfect power system; however, fault occurrence can be mitigated by enhancing system design, equipment quality, and maintenance. Fault presence on the system result in excessive currents that may damage expensive equipment. In most cases, the factors that contribute to fault occurrence include breaking down of a conductor, mechanical failure, deterioration of insulation, overheating, and voltage surge [28].

Electrical faults can be classified into two groups, namely, symmetrical and asymmetrical faults [28]. In [29], symmetrical faults are defined as balanced faults that affect all three phases, whereas asymmetrical faults are unbalanced faults that affect only one or two phases. Ref. [29] further claimed that for faults occurring on a transmission line farmost from the source results in higher magnitude of symmetrical short-circuit currents in comparison to other types of faults whereas, for short-comings that are very close to the source, the single phase-to-ground faults generates the highest magnitude of fault current and fault MVA [29]. With respect to overcurrent protection, asymmetrical faults such as phase-to-phase faults and phase-to-earth faults results in different range of fault current values. This influences the tripping time of all current-depending characteristics and coordination methods, especially the conventional or optimization methods [30].

2.3 Protection system functional characteristics

Schweitzer *et al.* [31] evaluated line protection reliability and redundancy. Analysing protection scheme selectivity, and sensitivity, speed is not covered in [31]. In [32], an analysis tool was used to evaluate protection system with respect to selectivity, sensitivity, speed, security, and dependability and presented a comparative study for scheme's performance. Protection scheme operational characteristics must satisfy stringent requirement of modern power schemes, which lack redundancy and operate near security limits [12], [13], [32]. The most important protection system characteristics are selectivity, reliability, sensitivity, and operational speed [11], [13], [31], [32].

a) **Reliability** has elements of dependability and security. Dependability means a system must trip when called upon, and security refers to the ability to prevent false trip signals [33], [34].
b) **Selectivity** refers to protection system's ability to detect abnormal conditions in the system and disconnect the faulty section only [11], [33].
c) **Sensitivity** refers to the capability of a distribution system to be sufficiently sensitive when a fault transpires within its protective zone. In this way, even the smallest fault can be discriminated against before causing significant irreparable damage [13], [32].
d) **Speed** of operation is the ability of the system to operate instantaneously after fault detection. The minimal operation of protective devices is essential in maintaining stability of the system and enhancing power quality [11], [32].

2.4 Protection system components

In order to control a protective device to react fast; and be reliable and selective under faulty conditions, protective relaying has been studied from literature to understand the basic relaying principles and component that form part of protection system. Ref. [35] of 2015 stated that protective relays provide the brains to detect abnormalities; however, these devices are unable to open and isolate the faulty section from the distribution systems. Thus, circuit breakers and other various types of circuit interrupters are essential to provide the muscle for fault isolation. Protective relays and circuit breakers work in conjunction to prompt removal of faulty parts or apparatus [35]. The protective relaying scheme includes instrumentation transformers, time delay relays, protective relays, auxiliary relays, trip circuits, and secondary circuits [28]. Each component plays a crucial part in the overall protection scheme operation. Some of the principal functions for protective relaying obtained from literature are stated below [28], [35], [36]:

- To promptly remove faulty elements when it begins to behave in an abnormally by triggering circuit breaker operation [28], [26].
- To discriminate and isolate the abnormally operating segment to circumvent further damage to the system [35].
- To minimize further damage to the defective part itself by disconnecting faulty section as quickly as possible [28].
- To improve system performance, system stability, reliability, and service continuity [28], [35].

2.4.1 Current transformers

According to [28], the primary function of the current transformer (CT) is to measure high alternating currents (AC) that cannot be sensed by normal ammeters. Additionally, instrument transformers provide possibilities of standardizing the relays and insulation to relays, measuring, and instruments from the primary high-voltage system [28]. In [33], CTs are defined as devices that step down large currents to lower values appropriate for relay operation and other instruments. These devices can allow current flow as high as 50 times the full load current for few seconds. In practice, the standard current transformer ratings are 1A or 5A [28], [33].

2.4.2 Voltage transformers

A further study in [11] stipulates that voltage transformers (VTs) are designed such that the windings' voltage drop is minimal, and the flux density in the core is below the saturation value to minimize the magnetization current. In this regard, the obtained magnetization impedance is practically constant over the required voltage range. Generally, the reduced secondary voltages of VTs are 110V or 120V with respective line-to-neutral values [6]. Majority of literature showed that most protective relays have nominal voltages of 120V line-to-line [6], [7], [13], [28], [35].

2.4.3 Circuit breaker

Circuit breakers are capable of making, breaking, and carrying currents under normal and abnormal conditions in distribution systems [33]. They segregate the faulty section from the system safely and reliably to mitigate further damages to equipment [37]. Ref. [33] stated that circuit breakers are unable to sense the presence of a fault in the system; hence, these devices work in conjunction with relays for timely disconnection of a faulty part or apparatus from the distribution systems.

2.4.4 Relays

It was repetitively indicated in previous sections that protective relays are devices that monitor circuit conditions and issue commands for opening of circuit under faulty circumstances. A significant number of literatures have reported on different types of relays used on distribution systems. Hewitson *et al.* [33], indicated the earlier analog relays had been gradually substituted with digital relays, and nowadays protection technologies are more focused towards the utilisation of digital relays. However, the electro-mechanical relays are still favoured in specific applications, with cost being one of the constituting factors [34]. Static analog relays are not commonly used on the distribution systems [33], [34].

In [38], protective relays are referred to as devices that detect and energize the trip coil to separate the faulty part of the system under the requirements of reliability, selectivity, operational speed, and sensitivity. Therefore, relays constitute the critical fragment of the protection system. The operation of relays is triggered by voltage and current measurements obtained from instrumentation transformers [34], [38]. These devices issue a trip command to open breaker contacts when the current in relay coil exceeds the predetermined threshold [38].

2.5 Primary and backup protection

Protection system incorporates a series of devices whose objective is to safeguard personnel and expensive power systems equipment from system abnormalities [6]. Excessive fault currents lead to equipment damage and are also hazardous to personnel. Consequently, there must be a primary protection and a backup scheme with appropriate grading margin, that is, operating time must be longer for point furthest from the fault position [24]. According to [39], there are two relay types based on their location in the distribution system; the one which is closer to the fault and that reacts first is referred to as main relay and the other which is used as a backup relay. The main reasons that contribute to primary protection defects are a failure in circuit breaker, failure in tripping mechanism, failure in tripping voltage, failure in protective relay, and loss of supply to the relay [6], [27], [39]. Backup protection operates when these catastrophes occur in distribution systems, and if these devices are not properly coordinated, maloperation occurs as a result [39].

2.6 Protection scheme

With overcurrent protection being the most favoured method of protection due to its simplicity and lower cost on the distribution level, there are other types of protection that can be implemented on distribution systems [6]. Other forms of protection under consideration include differential protection, transformer protection, and busbar protection [11], [30].

2.6.1 Overcurrent protection

Excessive current levels in electrical network are due to abnormal conditions on the scheme. These high current levels can be utilised to signal the presence of a fault and aid to trigger the operation of protective devices, which depends on design complexity and precision required [11]. There are many types of overcurrent protection devices, such as moulded-case circuit breakers, thermomagnetic switches, fuses, and overcurrent relays [11], [34]. The moulded-case circuit breakers and thermomagnetic switches consist of basic operational arrangements and are primarily utilised to protect low-voltage equipment [13], [34]. Similarly, fuses are protection devices that are typically used to protect low-voltage lines and transformers [6], [11]. Overcurrent relays are commonly used to protect power systems from excessive currents. According to [30], overcurrent protection in comparison with differential and distance protection systems is cost-effective and thus preferred on a distribution level.

2.6.6.1 Time overcurrent relay

Protection is one of the crucial aspects when designing any type of electrical power systems. Hence, it is of paramount importance to use a proper type of protection. The overcurrent relays are selected based on parameters, characteristics, and requirements [37]. The relay detects the fault in the electric circuit by constantly metering the electrical qualities which vary under faulty and normal conditions [34]. Electrical qualities that may be changed when abnormalities transpire are current, frequency, voltage, and phase angle [36]. The variation in one or more of these parameters may signal fault presence, fault type, and location. Once the fault is detected, the relay operates and issue the trip signal to the trip coil of the circuit breaker to open and isolate the defective part from the network [40]. Overcurrent relays can be categorised into three groups: instantaneous, definite time, and inverse time overcurrent relays [26].

a) Instantaneous overcurrent relay

As the name suggests, this relay operates instantaneously when the current in coil exceeds the pre-set value [41]. Majumder *et al.* [42] indicated that the operating time of this relay is continuous, there is no intentional time delay, operation criterion is constant, and it operates in 0.1 seconds or less. The relay settings are configured such that for costumer loads farmost from the power source, the relay operates with a low current value, and current levels gradually increases when approaching the source [41]. Thus, the relay with the lowest setting functions first and isolates the load at the point closer to the fault. The major downside of this type of protection is having little selectivity at high values of short circuit current [11].

b) Definite time overcurrent relay

Definite time overcurrent relay works after a certain period when the current reaches the predetermined value [42]. The relay settings are varied to handle various current levels by utilising different operational times. The main attribute of this relay is that the protection is more selective, which means it only discriminates the faulty part. The drawback of this type of overcurrent relay is slower operating time for defects near the power source that have high magnitude of fault currents [42]. Therefore, for a long radial feeder with a large number of protective zones, its use may be prohibitive.

c) Inverse time overcurrent relay

In an inverse relay, the operating time is inversely proportional to the fault current. This means an increase in fault current results in a reduced operational speed [42]. Inverse-time relays are also known as inverse definite minimum time (IDMT) overcurrent relays. The unique attribute of the IDMT relay is that it can be configured over a great variety of relay operating time and currents [43]. The characteristics of an IDMT relay are dependent on standard type chosen for operation of relays. These standards can be ANSI, user-defined, IEEE, or IAC [41]. The relay determines the time of operation by means of characteristic curves and their respective parameters. According to IEC 60255-151:2009, the inverse time overcurrent relays have the IDMT characteristics denoted by equation (2.1) [41].

$$T_{op} = \frac{C}{PSM^{\alpha}-1} \times TMS \tag{2.1}$$

Where T_{op} the time of operation, C is the constant for relay characteristic, α the constant demonstrating inverse time type ($\alpha > 0$), TMS is the time multiplier setting, and PSM is the plug setting multiplier. The grading of a protection system can be obtained by using correct TMS values. According to [26], the range of TMS usually is 0 to 1.0 in steps of 0.1 [26]. Nevertheless, at times it changes in steps of 0.05. In order to understand relays' characteristics curves, Ref. [26], provided different types of inverse characteristics curves. Different types of curves were attained by changing α and C values. Table 2-1 below illustrates values for α and C corresponding to each curve.

Table 2-1 Different types of Inverse characteristics curves

Relay Characteristic Type	α	C
Standard inverse	0.02	0.14
Very inverse	1	13.5
Extremely inverse	2	80
Long-time standby earth fault	120	1

In 2019, Sugumar *et al.* [44] stated that if the electric supply resistance remains constant and the fault current varies substantially as moved aloof from the relay, it is beneficial to use IDMT overcurrent protection to attain high-speed protection over an outsized section of the protected circuit. However, if the electric supply resistance is considerably bigger than the electric feeder resistance, then the IDMT relay's characteristic is incapable of being exploited, and definite time overcurrent relay may be used [44].

2.6.2 Differential protection

Although overcurrent protection is most favoured in distribution systems, most literature proved that overcurrent relays are not too sensitive as they cannot differentiate between minor defects and heavy load conditions. In such instances, differential relays are preferred [28], [37]. The differential protection is the technique that only operates when the phasor difference of two or more comparable electric qualities surpasses the pre-set values [28]. The principle is based on the direct application of Kirchhoff's first law [45]. Thus, current differential protection functions on the results of a comparison between phase angle and current magnitudes entering and leaving the circuit [45].

2.6.3 Transformer protection

Currently, the transformer differential protection is common in microprocessor-based relays, which execute current compensation, signal processing, filtering, and calculation of restraint and differential currents [46]. The overcurrent protection presented above is unable to provide thermal protection of transformers; hence, there is an increasing need to design a distribution system with transformer protection [34]. In [47], the operational challenges encountered on transformer protection were addressed. Amongst others, transformer protection fails to preserve security during the saturation of CTs for peripheral defects while sustaining sensitivity to detect low magnitude internal faults [47]. Current transformer saturation decreases the CTs secondary current output and leads to false differential current seen by the relay [47].

2.6.4 Busbar protection

The faults that affect busbars are rare, according to [48], they contribute 6% to 7% of the total faults in a power system, but their effects are quite severe. Conventional approaches for protecting busbars incorporates percentage differential protection, overcurrent-based differential protection, high-impedance differential protection, and overcurrent-based interlock schemes [49]. A study in [25], showed there were limitations experienced with usage of backup overcurrent relays, dedicated busbar protection using numerical overcurrent relays with instantaneous protection and blocking logic was used to give a cost-effective and reliable result [25].

2.7 Optimization techniques

Nowadays, power systems engineers have adopted the utilisation of optimization techniques to eliminate the necessity of finding set of breakpoints [15], [16], [17], [18], [19]. The use of analytic and conventional methods can be time-consuming and laborious, particularly for sophisticated and extensive distribution systems. Optimization techniques are classified into two groups, i.e., mathematical-based, and artificial intelligence-based optimization techniques [50], [51]. Urdaneta *et al.* [51] proposed the first mathematical-based optimization method for solving time inverse overcurrent relay coordination problem, the paper highlighted that this method includes simplex, dual simplex, and big-M methods. It was proved experimental that radial networks tend to yield optimal solution whereas, meshed networks lead to big constraint matrix due to larger combination of relay coordination pairs and number of relays in the system [51]. Mathematical based optimization presents limitations such as the tendency of getting trapped in local minima for non-convex problems and time-consuming [52] consequently, researchers have explored the use of artificial intelligence-based optimization algorithm to obtain global solutions for overcurrent relay coordination problem [50], [52], [53]. Ref. [53] utilised artificial intelligence-based technique to solve optimization problem, it was found that larger number of selectivity constraints for meshed networks results in an infeasible solution [53]. Currently, evolutionary and heuristic computation-based techniques such as differential evolution [20], ant colony optimization [39], particle swarm optimization [54], genetic algorithms [55], and teaching learning-based optimization [56] are employed to solve the protection coordination problems.

2.7.1 Linear programming techniques

The linear programming technique main attributes are simplicity, fast, and easy to implement [39], [57]. This method is usually implemented to circumvent non-linear programming complexity nonetheless, the result attained by this approach is not global solution [57]. The overcurrent relay coordination problem is considered as a linear optimization problem when PSMs are fixed to an appropriate value within the range, and only the TMSs are optimized [58]. In 2010, Bedekar *et al.* [59] undertook a comprehensive study investigating optimization techniques that yield optimum coordination, it was found that the dual simplex technique which operates on the duality of the problem outperforms all the variants of the genetic algorithms and simplex method. It gave optimal solutions in the least iterations, where the number of calculations per iteration was also less than other methods [59]. Additionally, it does not require the introduction of artificial variables; therefore, computational memory was lessen compared to two-phase simplex, big-M, and revised simplex techniques [60].

A further study in [24] implemented a dual simplex method and genetic algorithms on a radial system to solve the overcurrent relay coordination problem [24]. The TMSs optimal solutions were suitably attained and verified through both algorithms [27]. The significant observations made during this study was that the genetic algorithms effectively search through a large search space and are useful when less information is known [24]. Nonetheless, the genetic algorithm consumed more time since it handles extensive data, and dual simplex methods are convenient in the sensitivity analysis [24]. Most conventional optimum methods have shown limitations with regards to the number of constraints to be considered for in the problem [41].

2.7.2 Meta-heuristic and hybrid optimization techniques

Since the solution attained from linear programming methods is not close to global optimum solution, meta-heuristic optimization methods have been established to attain a global optimum solution in reasonable computational effort [61]. In [62], a comparative study of different meta-heuristic optimization methods was presented. Similarly, the effectiveness of the differential evolution algorithm was verified [62]. References [63], [64] solved the overcurrent relay coordination problem using PSO algorithm. This approach checks the fitness of the newly calculated value with the earlier one and update particle solution only when the new solution is improved [63], [64]. The authors in [65] used a hybrid PSO algorithm for optimum coordination of overcurrent relay.

Ref. [66] utilizes genetic algorithms to coordinate distance relays with overcurrent relays. It was also presumed that distinct characteristic curves may be chosen for proper coordination while setting PMSs at predetermined values [66]. In [67] and [68], a genetic algorithm was used to obtain optimal solutions for relay settings. A study in [69] defined genetic algorithms as search methods that emulate a population's evolution and explore global search space of a considered problem to obtain global solutions [70].

Through the literature survey, scholars have exploited several optimization algorithms to accomplish optimum coordination of relays in distribution system by using varies fitness functions. These fitness functions are dependent on primary relay operational time. The near-end fault approach [71], [72], near-end and far-end fault approach [58], [71], [72] were executed to coordinate relay. For near-end fault approach, the obtained optimization was not optimal which resulted in protection relay miscoordination [70].

2.7.2.1 Particle swarm optimization technique

For many years, power systems engineers and researchers relied on conventional techniques to perform overcurrent relay coordination. The disadvantage of the methods is that the solution is based on iterative trial and error, and the process is laborious as well as time-consuming [6], [12]. Hence, many researchers advocated the need for utilising evolutionary algorithm to mitigate setbacks presented by conventional optimization methods [13], [14], [15], [16]. In PSO, each particle fly through the hyperdimensional design space at a random velocity initially, and its current location in the i-th dimension is signified by $s_i^{(k)}$ where k the iteration number, and i the individual particle. Each particle memorises its best position and its own experience denoted by $pbest_i^{(k)}$, and the overall algorithms' experience is denoted by $gbest^{(k)}$. At each iteration the particle velocity $v_i^{(k)}$ is altered with current velocity and position from personal best solution and the global best solution. Consequently, the $v_i^{(k)}$ and $s_i^{(k)}$changes according to the following equations [73], [74]:

$$v_i^{(k+1)} = v_i^{(k)} + c_1 rand_1^{(k)} \left(pbest_i^{(k)} - s_i^{(k)}\right) + c_2 rand_2^{(k)} \left(gbest^{(k)}\ s_i^{(k)}\right)\ ; i = 1\ to\ N \quad (2.2)$$

$$s_i^{(k+1)} = s_i^{(k)} + v_i^{(k+1)}\ ; i = 1\ to\ N \quad (2.3)$$

Where N the swarm size, $rand_1^{(k)}$and $rand_2^{(k)}$are two randomly generated numbers every k iteration with a range between 0 and 1 [73]. Acceleration coefficient c_1 and c_2 also referred to as the cognitive and social parameters respectively, are positive constants. In [75], the particle velocity update equation is classified into three terms namely, first term represents particles' momentum which incorporates the impacts of previous velocity on current velocity, the second part is associated with cognitive component which signifies the pull of particles' velocity towards its own personal best (pbest) while the third term represents the global best (gbest) or social interaction between particles [75]. After the calculation of particles' new position and velocity, $pbest_i^{(k)}$ and $gbest^{(k)}$ are updated with the following equations [75]:

$$pbest_i^{(k)} = \begin{cases} s_i^{(k)},\ if\ f\left(s_i^{(k)}\right) < f(pbest_i^{(k)}) \\ pbest_i^{(k)},\ if\ f(s_i^{(k)}) \geq f(pbest_i^{(k)}) \end{cases} \tag{2.4}$$

$$gbest^{(k)} = \begin{cases} s_i^{(k)},\ if\ f\left(s_i^{(k)}\right) < f gbest^{(k)}) \\ gbest^{(k)},\ if\ f(s_i^{(k)}) \geq f(gbest^{(k)}) \end{cases} \tag{2.5}$$

Where f is the fitness function of the algorithm. Typically, the particles' velocity value is fixed to the range $[-v_{max}, v_{max}]$ to mitigate the possibility of particles flying out of the search space [73]. Setting higher value for v_{max} results in particles fly past optimum solution, whereas smaller value leads to particles not exploring sufficiently search space thence particle gets trapped in local optimal solution [73], [74].

1. Inertia weight

Due to limitation presented by v_{max}, Shi and Eberhart [76] proposed the addition of weight term on velocity update equation to sharpen particles' searching ability by stabilising local search and global search [76]. The inertia weight (w) is scaling factor associated with the iteration velocity during the last time step and aids to improve convergence rate of PSO algorithm. According to the modification proposed in [76], inertia weight is incorporated into equation (2.2) as follows:

$$v_i^{(k+1)} = wv_i^{(k)} + c_1 rand_1^{(k)}\left(pbest_i^{(k)} - s_i^{(k)}\right) + c_2 rand_2^{(k)}\left(gbest^{(k)} - s_i^{(k)}\right) \tag{2.6}$$

A larger inertia weight value facilitates exploration whereas smaller value promotes exploitation which increases local search capability of PSO algorithm. Earlier study conducted in [76] showed substantial improvement in PSO performance when inertia weight is set between 0.9 to 1.2. Recently, studies have adopted the use of linearly decreasing inertia weight which was first implemented in [77], the w value was kept between 0.9 to 0.4 of which yield in improved PSO performance. The following weighting function is used in linearly decreasing inertia weight.

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} \times iter \tag{2.7}$$

Where w_{max} is the maximum inertia weight, w_{min} the minimum inertia weight, $iter$ is the current iteration, and $iter_{max}$ is the maximum number of iterations. In [73] authors, undertook a comprehensive study and applied inertia weight ranging between 0.8 – 1.2, it was found that larger inertia value promotes global search, whereas smaller inertia value promotes local search [73].

2. Acceleration constants c_1 and c_2

The two constants, c_1 and c_2 are associated with velocity of flying particles to the most optimist position and its own best location, these constants control the length and time taken to reach optimum solution by each particle. Shi and Eberhart [73] set both acceleration coefficients to 2 and seen improvement in algorithm performance whereas when altered particle fly to infeasible solutions. For bigger acceleration coefficient values, the particle fly past optimal solution region and for smaller values, particle fails to reach target regions due to being trapped in unfeasible region before travelling toward optimal solution [73], [76]. This is undesired since these parameters plays an essential role in PSO algorithm efficiency and effectiveness. Therefore, acceleration coefficients have been set to 2 since the beginning of PSO method [73], [76].

3. Number of iterations

A study conducted in [78] proved experimental that larger maximum number of iterations $iter_{max}$ increases computational time and it was seen the selected value have a direct effect on the probability of algorithm locating global optimal solution [78]. Moreover, premature convergence may occur due to poor choice of maximum number of iterations. Too little iteration number decreases the likelihood of the algorithm attaining global optimum solution whereas bigger maximum number of iterations improves convergence rate at the cost of computational effort [78], [79].

4. Size of population

Normally, swarm size, N, is chosen based on the dimensionality and complexity of the optimization problem. Its plays an essential role in PSO algorithm performance and have an impact on population diversity as it regulates the number of particles in the hyperdimensional search space [73], [74], [76]. Ref. [80] stated that swarm size chosen between 5 and 10 particles is a good estimation, however the utilisation of swarm ranging between 10 to 50 particles is common in solving optimization problems [80]. When larger population size is selected, particles tend to discover more search space and PSO algorithm performs proficiently, but at the expense computational time [73], [80].

2.7.2.2 Genetic algorithm

Genetic algorithms searches solution space of a function by using survival of the fittest strategy, as opposed to PSO algorithm that is inspired by social behaviour of animals and births [15], [16], [18], [81]. The GA solution initialises randomly to generate new population by means of genetic operators such as mutation, selection, and crossover [15], [17]. Roulette wheel selection method allocates selection probability to each chromosome based on its fitness function value [81], [82], [83]. The randomly generated numbers are compared to the cumulative probability to determine the selection of new population. This technique has drawback of converging prematurely to local optima due to the dominance of individuals that constantly succeeds in the competition and are chosen as a parent [81],

[83]. The probability $P_i(t+1)$ for each chromosome i is define in equation (2.8), where $f_i(t)$ is the fitness of chromosome i, and n denote population size [82], [83].

$$P_i(t+1) = \frac{f_i(t)}{\frac{1}{n}\sum_{j=1}^{n} f_j(t)} \tag{2.8}$$

Due to limitations presented by roulette wheel method on genetic algorithms, extensions such a ranking method, scaling technique, and tournament selection were introduced to allow minimisation and negativity [82], [83], [84]. In ranking-based selection approach, the probability for each chromosome P_i is assigned based on the succession of individual solution i when all solutions are mapped by fitness function to allow minimization. Chromosomes with higher fitness values have a great probability of appearing in the next generation. A number generated randomly between zero and one constitutes to the reproduction of new population n_{keep} of feasible solutions. The probability of individual P_i is determined as follows [83], [84]:

$$p_i = \frac{n_{keep} - i + 1}{\sum_{i=1}^{n_{keep}} i} \tag{2.9}$$

a) Crossover or Recombination

Subsequently, the fitness comparable selection approach has been employed to make fitness biased reproduction of the preceding generation, the crossover and mutation probabilities come into play [82], [83]. Crossover takes two individuals from the reproduced population pairs and apply recombination. Simple or single-point recombination creates a random number r from a uniform distribution and create two new individuals ($x_i{}'$ and y_i') according to the following equations [85]:

$$x_i{}' = \begin{cases} x_i & if\ i < r \\ y_i & otherwise \end{cases} \tag{2.10}$$

$$y_i' = \begin{cases} y_i & if\ i < r \\ x_i & otherwise \end{cases} \tag{2.11}$$

Crossover introduces new locality for supplementary execution within the hyperplanes, which are not signified by either parent arrangement [84], [85]. Therefore, the likelihood of obtaining greater performing offspring is considerably increased. High crossover probability results in the introduction of new structures into the population rapidly, whereas extremely high crossover probability causes discarding of structures quickly before selection generates enhancements [79]. If crossover probability is too small, the search stagnates due to low exploration rate [79].

b) Mutation

Mutation introduces heterogeneity into the population by expanding the search area that the GA algorithm evaluates and preventing GA algorithm from converging too fast before exploring the entire search space [83], [84]. Increasing mutation probability results in algorithm searching outside the current region of variable space which may impair the population by distorting existing good solutions.

As a result, lower mutation rate is recommended [84], [86]. Uniform mutation randomly selects one variable j and make it equal to a uniform random number $U(a_i, b_i)$ where a_i and b_i are lower and upper bound, respectively [86].

$$x_i' = \begin{cases} U(a_i, b_i) & if\ i < j \\ x_i & otherwise \end{cases} \tag{2.12}$$

c) Population size

The group of chromosomes known as population affects the performance and efficiency of GA algorithms. It was stated in [84] that smaller population size leads to poor performance of the algorithm due to insufficient sample size for hyperplane exploration. Larger population discourages premature convergence by allowing more particles to cover the search space, however at the cost of computational efforts [84]. According to [87] anywhere between 10~50 is a good selection, however in other work anywhere between 25~250 yield effective and efficient solutions to optimization problem [87].

2.8 Other alternative algorithms

Apart from linear programming, meta-heuristic, and hybrid optimization strategies, other studies propose the use of analytical methods [50], [89], [90]. As a first instance [50], proposed utilisation of curve-fitting techniques which involves mathematical modelling of time inverse relay characteristics to attain TMS and operating time of overcurrent relay. The method begins with a functional form such as polynomial functions with possibility of estimating the published relay curves [50], [89]. Subsequently, functional coefficients are executed by means of computer which best fits the curves. Although curve-fitting methods are the simplest approaches for obtaining relay settings, they have significant drawbacks, that is, imprecisely results for current settings less than 1.3 times the pickup current and are appropriate for manual handwork, however, are not suitable for computer application [50], [89]. Developmental studies that utilise this technique up to 1989 are accessible at IEEE Committee report [90].

Reference [91] and [92] conducted an extensive research on the use of graph theory in solving protection coordination problems. Datta *et al.* [89] stated that graph theory approach provides the best alternative settings, not optimal solutions. In [93], this technique was successfully applied for the formation of relative sequence matrix, which was utilised to determine the least breakpoint relays, primary, and backup relay pairs. Another method was presented in [94] to reduce complexity, it provides the minimum number of breakpoints, and the whole multi-loop network becomes a radial system. Graph theory methods are fairly convenient in solving overcurrent protection coordination for interconnected distribution networks [94]. However, computational time for achieving proper optimal relay coordination are exponential functions of network dimensions, and much unutilized intermediate data is generated [50], [93], [94].

Ref. [95] of 2013 proposed an analytic method to solve overcurrent relay coordination problems by using numerical iterations. With this approach, it was stated that global solutions are attainable regardless of an initial solution. Nonetheless, analytic approach-based methods for obtaining the solution to overcurrent relay coordination problems may be complicated for highly meshed complex networks. In [96], a numerical iterative approach, assuming TMS and PSM values was proposed for the overcurrent relay coordination problems. However, no mathematical formulation was proposed to guarantee convergence of the considered method. Based on the findings from the literature, it can be concluded that analytic approaches are not suitable for large systems; hence, the optimization-based technique is popular in obtaining an optimal solution to overcurrent relay coordination problems.

The authors in reference [97] implemented a fuzzy-based relay consisting of an inference system and neural network learning module to afford best protection settings that consider changes in the operational circumstances. The disadvantage of the proposed methods regarding practical application is the absence of analysis involving system operation stability and the contemplation of fault eliminating time. Another drawback is the lack of simulations to assure accurate operation of the protection system under different conditions [97]. The fuzzy method was used for modelling overcurrent relays operating curves in [98] and overcurrent relays operating time was calculated using the neural networks approach.

Lastly, adaptive method was proposed in [99] to handle miscoordination of primary and backup relay pairs of overcurrent relays. The main factors that result in protection miscoordination are changing load, generation, and topology [99]. Improper relay coordination may cause severe damage to the system during fault occurrence [99], [100]. References [101], [102] described an adaptive protection coordination scheme as a system where relays must respond fast to changes in conditions of the system and adapt to new system settings in accordance with new predominant conditions such as topological and operative changes. This method plays an essential part in enhancing selectivity and sensitivity of the protection scheme in the distribution networks with distributed generators [52].

2.9 Conclusion

This chapter presented a comprehensive review of past and current research work on distribution systems protection. The concept of the PSO algorithm and genetic algorithms was introduced, and their control parameters were studied to understand how they impact the performance of evolutionary algorithms. Basic overview of distribution system protection was clearly articulated to understand the background of the study. Furthermore, a discussion was provided to review other alternative algorithm and their respective drawbacks.

CHAPTER 3

3 Research Methodology

This chapter presents a detailed design process utilized in accomplishing the objectives of this study, as stated in Chapter 1. Fundamental theory to substantiate selected parameters is also outlined with reference to other researchers' work. This study was conducted on an existing distribution network layout. The models were constructed on the RSCAD draft interface and appropriate approaches were deployed to solve overcurrent relay coordination problems.

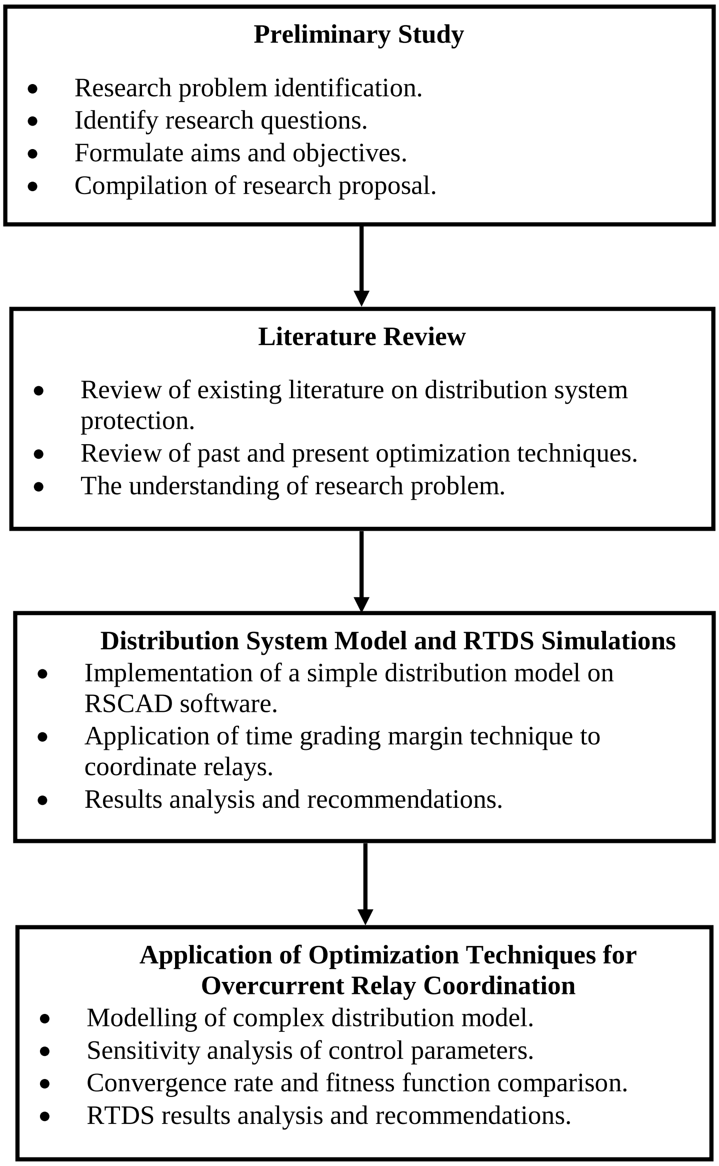

Figure 3-1: Research methodology block diagram

Figure 3-1 depicts the methodology block diagram employed in this work. It incorporates a preliminary study which is the early stage of the research development and includes the identification of research problem, contributions to current research, aims and objectives, significance of research and research questions. Also, it contains a review of various literature on distribution system protection and optimization techniques utilized in the past and present, as well as methodologies used to coordinate protection schemes. A simple distribution model was developed on RSCAD software to understand the concept of overcurrent protection coordination using the time grading margin method. Thereafter, optimization techniques were applied on a more complex system where sensitivity analysis was conducted, and the comparison of convergence rate and fitness function was performed.

3.1 Software selection

To achieve research objectives as stated in Chapter 1, it is of paramount importance to select software with desirable features to permit modelling of electrical distribution network, the simulation of various faults, and execute protection coordination. The software tools considered for availability and suitability were RTDS, PSCAD, and Matlab/Simulink [103]. Power system computer-aided design (PSCAD) is a time-domain simulator tool principally used for transient studies in power systems [104], [103]. Its primary purpose is the simulation of power systems with respect to time domain and frequency. Also, it is utilized in power electronics and power systems studies, harmonic research, commutation starting, and transient torque analysis [104]. On the other hand, Matlab provides an excellent platform for implementing evolutionary algorithms, plotting graphs and data, solving linear programming problems, and optimization of linear and non-linear functions [104]. Both software tools are known as offline simulation packages or non real-time simulators [103], [104]. Based on the suitable features and availability, Matlab was used in this work for overcurrent relay coordination.

RTDS is a parallel processing computation facility used for designing, developing, and testing power systems protection [6]. It comprises both hardware and software for digital simulation of transient electro-magnetic programs, and it is classified into two categories, i.e., digital real-time simulation and hardware-in-loop real-time simulation [105]. The software package comprises RSCAD which is a user-friendly graphical user interface and model library that allows construction and power analysis by the user. With a digital real-time simulation, the system modelled inside the simulator does not include external interfacing, whereas, in the hardware-in-loop (HIL) simulation, certain parts of the digital simulation are substituted with actual physical components [6], [105]. A study in [103] proved that the operation of a digital real-time test is the same as the HIL test. The authors replaced a virtual relay with a physical SEL 351S overcurrent relay on an eight-bus power system, and faults occurred on different protection zones to observe system behaviour [103]. A further study in [105] substantiates the effectiveness of HIL simulation by testing electrical machines and presents an experimental design for a hardware-in-loop test [105]. Due to convenient features and availability for the successful execution of this work, RTDS is thus selected to accomplish research purposes.

3.2 Real-time simulation component control logics

In this subsection, different control logic models developed in the RSCAD for conducting software-in-loop simulation are discussed. The control logics presented comprise circuit breaker logic, fault logic, instrument transformers, and relay logic.

3.2.1 Circuit breaker logic

In [106] and [107], a circuit breaker was defined as a protective device that interrupts abnormal circuit conditions by detaching defective components when excessive currents flow in its protective zone, hence, forestalling further damage in the system [106]. It comprises breaker contacts, trip coil, latching mechanism, and auxiliary contacts that work in conjunction with overcurrent relays to open and close the circuit breaker [33]. In practice, the overcurrent relay receives information, which it analyses and sends a trip command to open and close the circuit breaker. The presence of abnormalities in the system triggers relay contacts to energize the breaker trip coil; as soon as the trip coil gains enough energy, it releases a signal to unlatch and open breaker main contacts under the control of the tripping spring. The trip coil is then de-energized by the opening of the breaker auxiliary contacts [33], [106], [107].

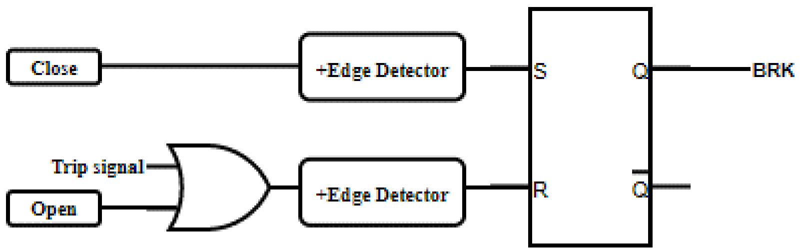

Figure 3-2: Circuit breaker logic diagram

The circuit breaker model in a real-time digital simulator was controlled by using a single logic input. The model was designed to respond to close and open commands using an SR flip-flop component, as shown in Figure 3-2 above. Initially, the breaker (BRK) was closed, which is represented by a binary output of 1 and can be manually opened using an 'open' push button on the runtime interface. As soon as the relay initiates a signal to the breaker logic, the binary output becomes 0, and the main contacts open, which can be manually closed using a 'close' push button on the runtime interface. The logic similarly encompasses edge detectors to detect the rising edge. The control logic is invaluable in the providing a progressively proficient way of testing rather than switching between the draft and runtime interface to execute changes on the system.

3.2.2 Fault control logic

The protection of the distribution system against asymmetrical faults (i.e., single line and double line) is a necessity. Moreover, the capability to regulate fault type, fault selectivity, and the application of fault during runtime is indispensable. In this regard, a fault logic circuit was designed in the draft model to permit users to implement these changes on the runtime interface. The fault logic allows the initiation of fault by means of a push-button, selection, and adjustment between different combinations of line-to-ground faults via dial switch. The dial switch can be adjusted from 1 to 7 to select the fault type.

3.2.3 Instrument transformers

Including instrument transformers in the model makes it conceivable to assess their effect on the performance of the distribution scheme. Alternatively, the secondary current and voltage signals can be directed straight to the protection equipment using the appropriate ratios. In this case, the signals were sent directly to an overcurrent relay. In the draft interface, the current transformer and voltage transformer models are not attached to any other component since they do not contribute to the simulation and are only used to provide secondary signals for interfacing with the overcurrent relay. The current transformer model entails the primary currents which are equivalent to the circuit breaker currents as an input and the corresponding CT ratio. By contrast, the voltage transformer model, also known as a potential transformer (PT), requires PT ratio, input RMS voltage, and the name of the corresponding bus. For purposes of this research, transducers for use on the control system processor are selected.

3.2.4 Overcurrent relay

Overcurrent relays constitute the imperative portion of the protection scheme; consequently, their functionality plays a crucial role as a decision-making element on the distribution system. The relay detects, evaluates fault, and decides whether it is large enough to jeopardize the system with the help of instrument transformers' voltage and current measurements. Overcurrent relays are triggered by voltage and current signals of which in this research project are configured to give off 110 V in the potential transformer and emit 1 A or less in the current transformer. If abnormal conditions arise and exceed the predetermined current and voltage values, the relay triggers the operation of the circuit breaker to open breaker contacts.

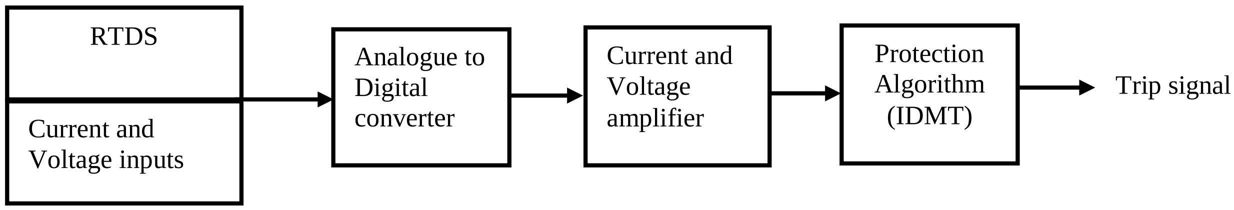

Figure 3-3: Overcurrent relay functional block diagram

Figure 3-3 depicts an overcurrent relay functional block diagram with multiple features that are appropriate for constituting protection purpose on the distribution network with the (51/67P) overcurrent relay element (PTOC) activated. The relay consists of six inputs that are fed by secondary currents and voltages from instrument transformers. The pickup current is computed, and comparator functions to compare the amount of current in the relay coil with the predetermined value. If the phase current is bigger than the predefined value, the comparator output triggers the info and start signal to be activated, and then after some time delay, the trip signal becomes active. The digital amplifier amplifies digital signals at the simulator output into magnitudes which correspond to instruments' secondary parameters within the RTDS model. These currents are fed to the relays from the amplifier which institute a trip command when all the tripping requirements are achieved.

3.3 Protection set-up

At first, suitable sizing and choice of current and voltage transformers were performed. The CT ratios were chosen based on full load currents. Protection zones were then classified on the distribution scheme and overcurrent relays were configured for each zone. The pickup currents were calculated based on the selected plug setting values and set as elucidated in the subsequent section. With theoretical support from literature, the suitable characteristic curve chosen for all overcurrent relays was the IEC standard inverse curve. Time multiplier settings selection determines appropriate protection coordination between protective devices [108], [109] and mainly depends on factors such as chosen IDMT type, downstream breaker operational time, and maximum fault current. For downstream breakers, the TMS values were set to a lowest value, simulations were then executed, and protection coordination study was performed for all overcurrent relays starting from breakers near costumer loads up to the breaker closer to the power source.

a) Current setting

According to [110], the pickup current setting can be selected between 50% to 200% and in steps of 25%. Ref. [26] indicated that this current setting is utilised for inverse overcurrent relays which sense phase-to-phase faults. For earth leakage faults, the setting is a bit different. It can be anything between 10% to 70% in steps of 10% [26]. Current setting can be defined as the adjustment of tappings on the relay coil to obtain the desired relay pickup current. The more current setting the relay has, the greater current the relay needs to send the trip command [26], [110], [111]. In this work, a current setting of 125% was selected.

b) Pick-up current

Pick-up current is the threshold current value, and it is detected with the current level sensation principle which must be surpassed for the relay to operate [112]. References [10] and [113] presented two common approaches to compute the pickup current. The first method stipulates that the pickup current is twice the maximum load current, or it must be one-third of the minimum fault current at the nearest busbar [10]. Second method proposes that pickup current must be selected between 125% of the maximum load current and 2/3 times of minimum fault current [113]. From these findings, the equation for calculating the pickup current was formulated as shown below. Overcurrent relay trip settings are computed with pickup current and TMS parameters. With TMS ranging from 0 to 1 in steps of 0.1, at times it varies in steps of 0.05, as stated in chapter 2 [118].

$$Pickup\ current = rated\ CT\ secondary\ current \times current\ setting \tag{3.1}$$

c) Plug setting multiplier (PSM)

Plug setting multiplier is referred to as the ratio of fault current in the relay coil to pick-up current [6].

$$PSM = \frac{Fault\ current\ in\ relay\ coil}{pickup\ current} \tag{3.2}$$

3.4 Optimization problem modelling

With modern engineering and science development, optimization problems in various areas are increasingly challenging [115]. Solving optimization problems requires problem formulation of the model under study, which will result in a fitness function whose parameters must be minimised or maximised [116]. In [111], the optimization problem was developed as a constrained optimization and solved by means of various optimization techniques. Optimal relay coordination was achieved by minimising the sum of all primary relay operating time using TMSs and PSMs [111]. This authenticates that relay coordination is mainly dependent on TMS and pickup current. Additionally, relay coordination problem for evolutionary algorithms can be represented as follows [62]:

- Linear
- Non-Linear
- Mixed integer non-linear problem

From the IEC characteristic equation (2.1) of the overcurrent relay discussed in Chapter 2, PSM^{α} is the variable that primarily governs the problem type. If the PSM^{α} value is continuous, the optimization problem becomes non-linear problem; for a fixed PSM^{α} value, the coordination problem is developed as a linear problem [62]. When PSM^{α} is taken as discrete variables, the coordination problem becomes a mixed-integer nonlinear programming which is even difficult to solve [38]. Whereas in genetic algorithms, the random generation of the initial population increases the likelihood of particles to converge into global solution and overcomes the limitations of conventional rule-based approaches to solve coordination problem [12].

In this study, the value of PSM was predetermined based on the guidelines reviewed in Chapter 2 and only TMS will be optimised. Accordingly, the relay settings from equation (2.1) become:

$$T_{op} = TMS \times K \tag{3.3}$$

Where: $K = \frac{C}{PSM^{\alpha}-1}$ (3.4)

It can be seen from the equation that K is a constant and the relationship between relay operating time and TMS is linear. Therefore, the overcurrent relay problem was developed as a linear problem.

3.4.1 Fitness function

With many different forms of objective functions available for optimization problem formulation, in this study, the utilised objective function was minimised such that the relays' operating time is reduced when a fault occurs on its primary protection zone. Overcurrent relays must remove faults as promptly without any constraints violation to mitigate the thermal and mechanical stress on distribution system equipment. Many publications have adopted the use of primary relay operating time as a fitness function for the optimization problem, while other authors integrate supplementary expressions besides constraints in the objective function. Further elaboration on different methods exploited by researchers for constraints handling is presented in the subsequent section. Ref. [54] highlighted that for a given overcurrent relay, if its main time of operation is minimised, then its operational time when operating as a backup relay is similarly optimised [54]. In other words, the main relays' operating time and those of the backup relays are not conflicting when considered as distinct fitness, and thus a decrease in one result in the reduction of the other. Authors in [55] and [117] incorporated TMS, pickup current setting, and CTI in the fitness function. Whereas in [72], the backup relay operating is comprised as part of the objective function.

To solve coordination problems with respect to time multiplier setting, the relay standard characteristics demonstrated in equations (2.1) and (3.3) are used in this work. For a predetermined pickup current setting values of all overcurrent relays, the fitness function which optimizes the primary relay operating time is given by:

$$min \sum_{i=1}^{n} K_i \times TMS_i \tag{3.5}$$

Where n is the number of relays, and K_i is the coefficient of the i-th relay given by equation (3.4). It can be noted that due to the specific characteristics of the mathematical formulation of the optimization problem, the solution is independent of the coefficient of the i-th variables, as long as they are positive real numbers. Accordingly, equation (3.5) is reduced to:

$$min \sum_{i=1}^{n} TMS_i \tag{3.6}$$

This fitness function is subjected to the following constraints:

$$0.01 \leq TMS \geq 1.0 \tag{3.7}$$

$$0.1 \leq I_{pickup} \geq 1.0 \tag{3.8}$$

$$\Delta t \geq 0 \tag{3.9}$$

3.4.2 PSO Constraint handling mechanism

To avoid premature convergence and computational time presented by reinitialization of particles' initial position approach implemented in [85], Ref. [118] proposed the application of a penalty on infeasible solutions which resulted in PSO avoiding premature convergence [118]. Richardson *et al.* [82] introduced two terms in the penalty function, i.e., the amount at which constraint was violated and the number of constraint violations [82]. According to this modification, the PSO cost function is calculated as:

$$F_i(x) = \begin{cases} f_i(x), & if\ feasible\ solution \\ f_i(x) + \beta_1 \left(\sum_{i=1}^{d} h\right) + \beta_2\left(\sum_{i=1}^{d} y\right), & If\ infeasible\ solution \end{cases} \tag{3.10}$$

Where $F_i(x)$ the penalty function, $f_i(x)$ the original cost function, $\beta_1$and β_2 are penalty factors, $\sum_{i=1}^{d} y$ is the sum of the amount d violated constraints, and $\sum_{i=1}^{d} h$ is the sum of d violated constraints. The penalty factors $\beta_1$and β_2 are both set at 10^3. This strategy penalises infeasible solutions by keeping track of constraint violations. The flowchart in Figure 3-4 depicts the PSO operation utilised in this research work [82].

3.4.3 GA constraint handling approach

Parsopoulos *et al.* [119] proposed the utilization of penalty factor to account for the sum of violated constraints and this technique is referred to as a non-stationary multistage assignment penalty function mechanism. In [117], a strategy for managing constraint violation was not employed; as a result, overcurrent relays' operating time was minimised, but relays were not selective. Ref. [120] presents an improved constraint handling approach that incorporates a term that examines the number of constraints violated and increase a fitness value by a factor to penalise infeasible solution. The same strategy was adopted in this work, stationary penalty function, p, penalises infeasible solution. Too big penalty function value results in the algorithm not recovering after being penalised; hence, the value must be within average [121]. All constraints are converted into inequality as illustrated:

$$p - \epsilon \leq 0 \tag{3.11}$$

$$p_1 = W_1 \sum(-\Delta t_{mb}) \tag{3.12}$$

$$p_2 = W_2 \sum(TMS - 1) \tag{3.13}$$

$$p_3 = W_3 \sum(0.05 - TMS) \tag{3.14}$$

Where ϵ is the small tolerance value, W_1 controls the weighting of miscoordination penalty, W_2 controls the weighing of the upper bound penalty, and W_3 controls the weighting of the lower bound penalty [121]. The equations presented below shows the objective function with the penalty factor incorporated. The n_{th} penalty function p_n is added to the n_{th} constraint function h_n only if constraint violation occurs [87].

$$J = J + \max(0, p_n) \tag{3.15}$$

$$p_n = \begin{cases} \sum_{n=1}^{3} -h_n \; if \; h_n < 0 \\ 0 \quad\quad otherwise \end{cases} \tag{3.16}$$

The occurrence of constraints violation results in addition of penalty function to the fitness function. During the optimization process, overcurrent relay parameters were treated as continuous, thereafter, as discrete toward the end of the process, resulting in poor coordination [72]. To address this miscoordination, authors [72] proposed that algorithms' trial solutions must be rounded off to the upper value prior to a fitness evaluation. In this work, the same proposed approach was employed. Figure 3-5 depicts the flowchart used in this work to find main operating time, backup operating time, and change in primary and backup pairs.

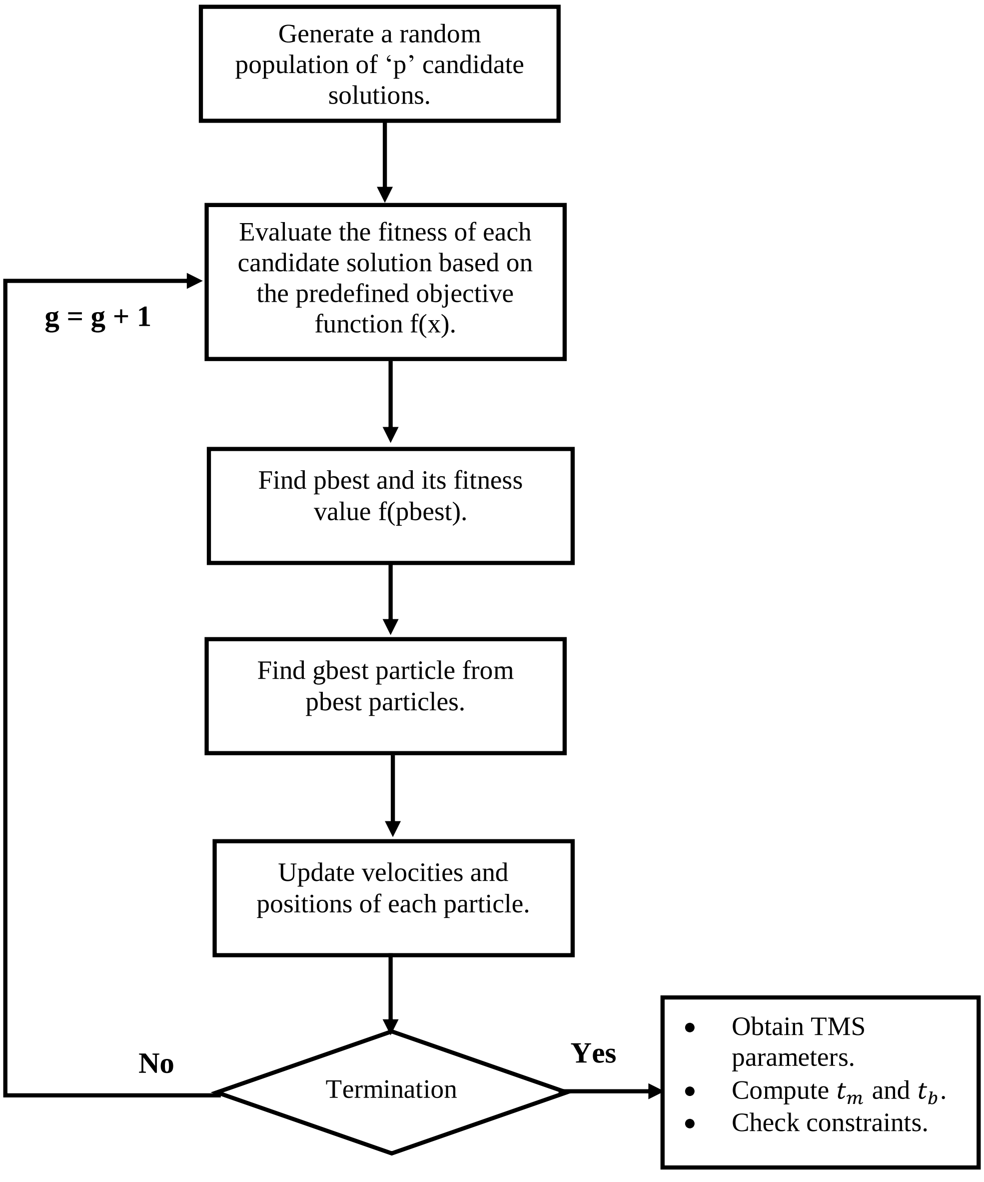

Figure 3-4: Flow chart demonstrating the application of PSO for relay coordination

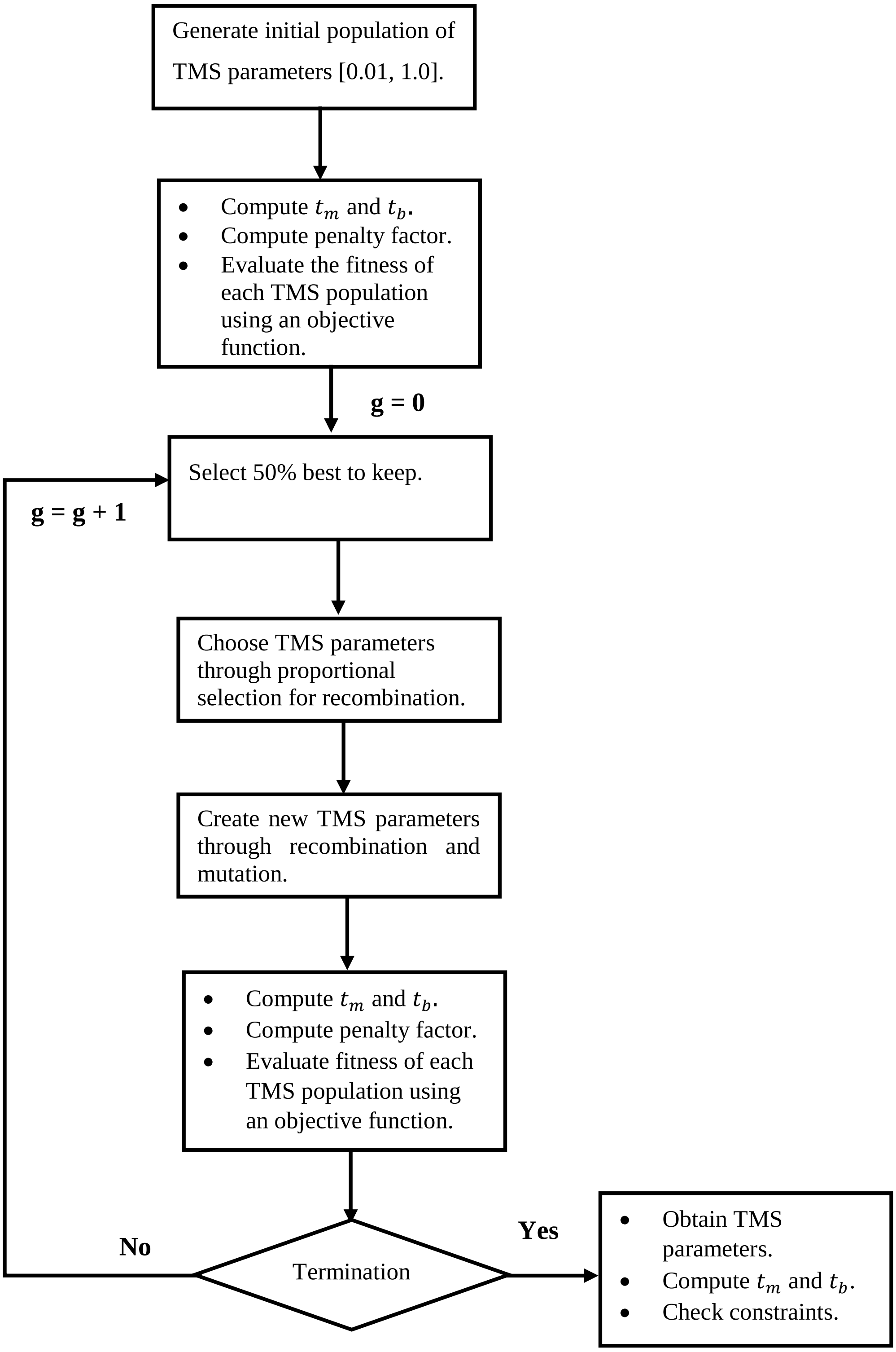

Figure 3-5: Flow chart demonstrating the application of GA for relay coordination

3.4.4 Dual simplex modelling

This optimization technique was developed and modified by Lemke to solve linear programming problems and is favoured due to its desirable characteristics of obtaining optimal solutions through a smaller number of iterations [106]. It begins with an infeasible solution and after a few iterative computations, a feasible and optimal solution can be obtained. With overcurrent relays, tap settings and full load currents must be determined to assist in the determination of time multiplier settings protecting the distribution system [106], [122]. Overcurrent relay coordination problem in meshed power network can be developed as an optimization problem which minimises the summation of relay operating time using the equation depicted in (3.5) above. Suppose that the overcurrent relay's plug setting and TMS values are known, the operating time can be computed for a specified short-coming current by means of the mathematical expression shown in equation (3.3) above. A similar manner was adopted in this work, with current settings, fault currents, and plug setting predetermined; a dual simplex table was formed. Due to the complexity of the distribution system, the optimization problem was then solved using Matlab software to mitigate human error and time consumption.

The algorithm of the dual simplex technique utilised to solve the minimisation problem is presented below [106], [122]:

1. Start.
2. Convert the problem into a minimization problem.
3. Convert all the constraints into ≥ type.
4. Rewrite the functions into standard form by adding surplus variables which are basic variables.
5. Form the Dual Simplex table.
6. Find $C_j - \sum(C_j \times a_{ij})$.
   6.1 If any $C_j - \sum(C_j \times a_{ij})$ element becomes non-negative, go to step 10.
   6.2 If all the elements in this row become positive and if all the elements in the RHS column are non-negative, go to step 9.
   6.3 If at least one element in RHS is negative, go to step 7.
7. Identify the key column, key row, and pivot element, thereafter, form a dual simplex table.
8. Go to step 6.
9. Print results.
10. Stop.

3.5 Design process

The design process undertaken in this study are as follows:

- Modelling of a simple distribution network on RSCAD.
- Utilization of time grading margin for overcurrent relay coordination.
- Complex system modelling and execution of optimization techniques on Matlab/Simulink.
- Investigating the effects of particle swarm optimization and genetic algorithms control parameters on overcurrent relay performance.
- Convergence rate and fitness function analysis.
- Application of optimization techniques on overcurrent relays.
- Sensitivity, selectivity, and speed analysis.

3.6 Conclusion

In this chapter, overcurrent relay parameters and RTDS components' control logics are detailed to provide a better understanding to the analysis of faults. Also, protection set-up was outlined which briefly explained protection coordination for a simple distribution network by means of time grading margin. A comparative study was conducted to explore available software simulator tools. Dual simplex method, GA and PSO algorithms were discussed, and the design process followed was presented through the use of flowcharts and expressions. It can be concluded that this chapter clearly outlined methodologies adopted to achieve research work objectives. The application of such methodologies is deployed in subsequent chapters.

CHAPTER 4

4 Distribution system model and RTDS simulations

4.1. Introduction

This chapter aims to illustrate the overcurrent protection coordination of a simple distribution system model by means of the conventional time grading method. The system is modelled and simulated under abnormal conditions using the RTDS software. The software tool is further utilized to set-up overcurrent relay settings and coordinates them with the associated relays. For this study, the focus was on calculating the pickup current settings and time multiplier setting of overcurrent relays. This chapter is thus organised as follows; Firstly, the distribution model under study is presented in Section 4.2. Thereafter, the measured system parameters during simulations are evaluated in Section 4.3. Section 4.4 provides a real-time digital simulation results for both primary and backup protection.

4.2. System description

To accurately understand overcurrent protection coordination problem of a complex distribution system, a simple model needs to be studied. The proposed model which includes two input sources, three step-down transformers, and two customer loads, was developed in a study in [123]. This system represents a commonly implemented distribution network configuration and is utilized in this study for testing protection coordination. The majority of distribution systems in South Africa are of a radial nature, and the occurrence of planned and unplanned outages results in customers losing electricity [124]. Consequently, the implementation of distribution systems with two or more power sources is of paramount importance for improving system reliability. Figure 4-1 shows a single-line diagram of the modelled distribution system with specifications obtainable from 132/11 kV substation [125]. The two input voltages have identical characteristics and have a three-phase AC supply with an RMS voltage of 132 kV at 60 Hz, which is further stepped down to 11 kV and subsequently distributed to a single busbar with two outgoing feeders. The first feeder supplies customer load with a voltage of 11 kV at 1 MVA, whereas the second feeder comprises a transformer that further decreases the voltage from 11kV to 6.6 kV for end-users.

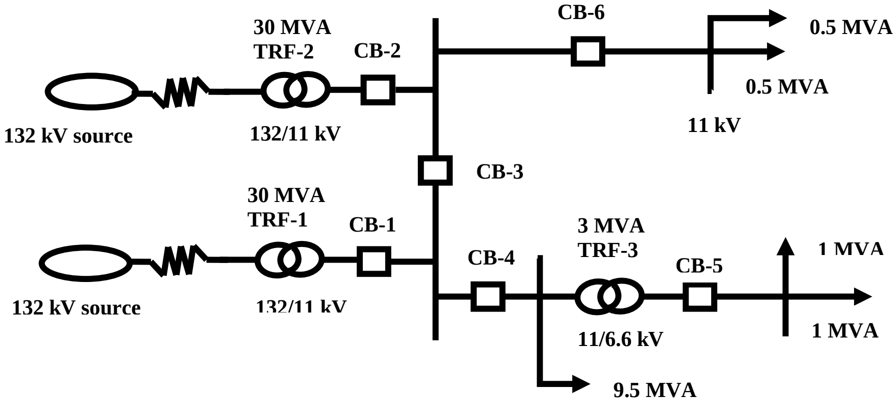

Figure 4-1: Distribution system model [123]

Setting and coordinating relays subjected to different system conditions is of essential importance to speedily isolate the defective part in distribution schemes [126]. The process of overcurrent protection coordination includes selecting the accurate size of current and voltage transformers [114]. In this case, instrument transformers are modelled as ideal, which means the non-linear magnetization characteristic of the transformer core has not been considered. Additionally, CT and VT ratios which are selected based on primary currents and voltages of the transformers, are configured with an overcurrent relay to ensure appropriate protection coordination. The ANSI/IEEE C57.13-1978 CT ratio standard tables utilized are available in [127]. As seen in Figure 4-1, the system consists of six primary protection zones indicated by circuit breakers named CB-1, CB-2, CB-3, CB-4, CB-5, and CB-6. Each protection zone is subjected to a fault for testing system selectivity, sensitivity, speed, and reliability. The summary of network specifications can be found in Appendix A - Table A.1.

4.3. Measured system parameters

In this section, the simulation results of the distribution model under study are presented. With all distribution model equipment settings calculated and set, the network is executed on the RSCAD simulator to determine full load conditions. Shown in Table 4-1 are measured line currents and voltages that transit from the current and potential transformer for input signals to the overcurrent relays.

Table 4-1: Measured voltage and current during simulations

	$V_{primary}(kV)$	$V_{secondary}(V)$		$I_{primary}$(A)	CT ratio	$I_{secondary}$(A)
PT1	10.98	108.0	**CT1**	103.90	200:1	0.5157
PT2	10.98	108.0	**CT2**	102.60	200:1	0.5089
PT3	10.98	108.0	**CT3**	51.38	100:1	0.4980
PT4	10.98	107.9	**CT4**	155.20	200:1	0.7699
PT5	6.56	103.6	**CT5**	258.50	300:1	0.8588
PT6	10.98	107.9	**CT6**	51.23	100:1	0.4963

Figure 4-2 illustrates overcurrent relay RMS currents detected from the current transformers' secondary windings. It can be seen that under a no defect scenario, the normal voltages and currents circulate through the VTs and CTs. The current is distributed to customer loads and there is no disturbance in the system. Shown in Figure 4-3 are distribution system RMS voltages as seen from the VTs primary windings.

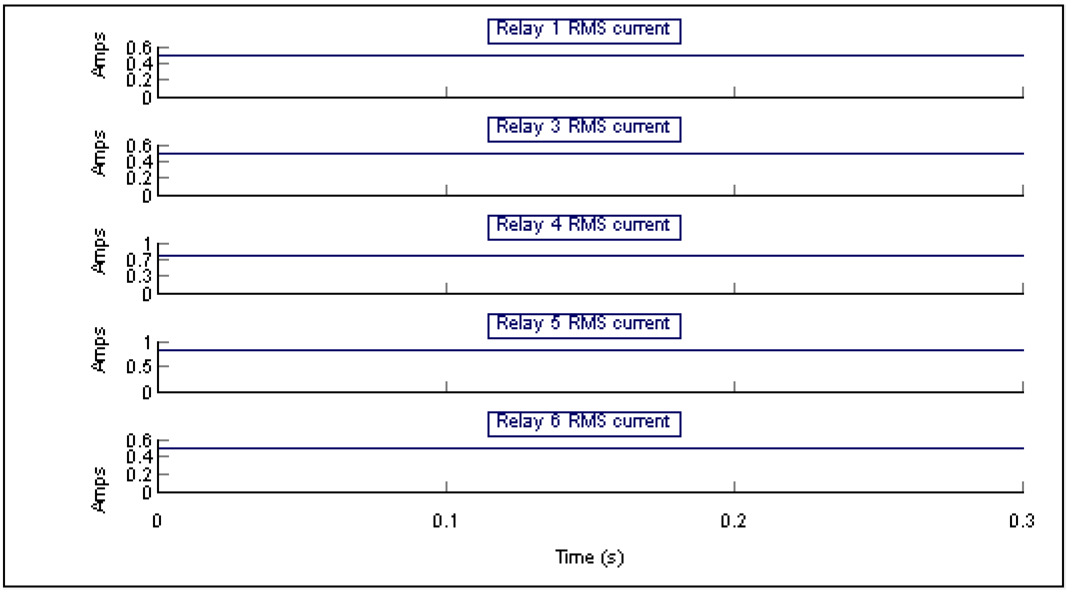

Figure 4-2: Relays' RMS currents

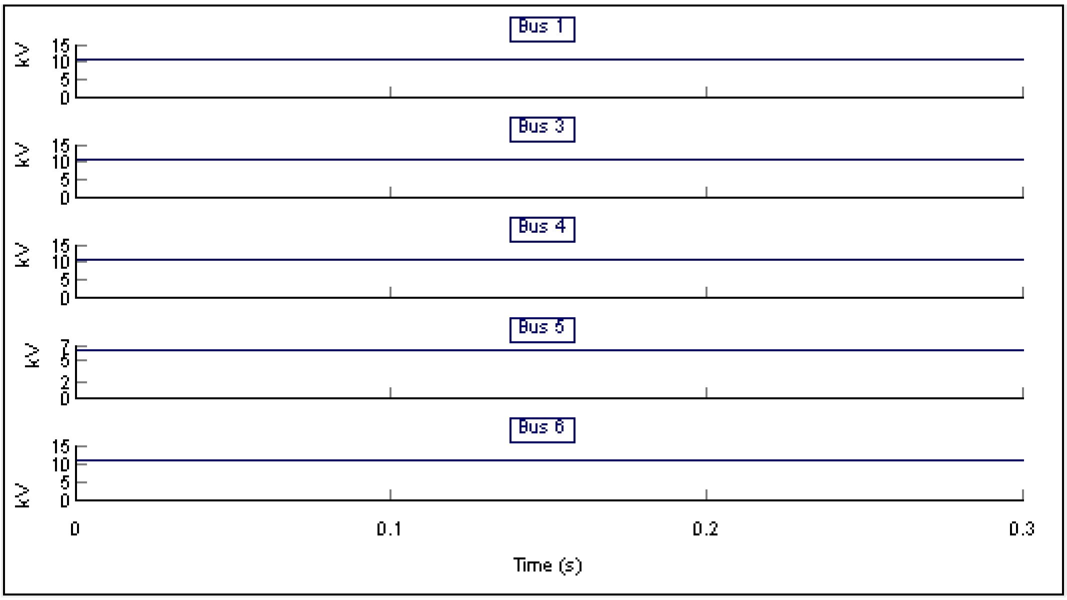

Figure 4-3: System RMS voltages

System set-up includes the configuration of a multi-functional overcurrent relay to make use of IEC standard inverse characteristics. Although other operating curve characteristics such as very inverse and extreme inverse are available, standard inverse tends to be more favoured on distribution level due to their convenient operating time, as elaborated in the literature reviewed in chapter 2. The aim of overcurrent relays is to give sufficient time for the breaker and relay closet to the fault to isolate the defective element from the network prior to the operation of adjacent backup relay and breaker. This is achievable by calculating the relay time of operation properly of which in this case is done by means of a conventional time grading approach.

4.3.1. Time grading margin method

The selection of appropriate time grading margin is a necessity to maximise protection selectivity [33]. In [128], time grading is defined as the time interval permissible between the operation of two neighbouring relays to attain correct discrimination between them [128]. Poor protection coordination which results from improper or insufficient grading margin selection, causes more than one relay to operate for a fault. This leads to difficulties in distinguishing fault location and result in costumer being without electricity unnecessarily. In numerical protective relays, the grading margin can be selected as low as 0.2 seconds since there is no overrun [11], whereas in conventional relays, the time interval ranges from 0.3 to 0.5 seconds [26]. Accordingly, the most significant factors that need to be taken into consideration to ensure adequate grading margin in distribution systems are as follows [128], [129]:

- Circuit breaker interrupting time (0.1 s).
- Relay timing errors as defined in IEC 60255 (7.5% of operating time) [41].
- Current transformer errors (0.1 s).
- Relay overshoot time (0.05 s).
- Safety margin (typically 0.1 s).

The grading margin is chosen as 0.4 seconds by taking the sum of the above factors. It should be noted that the assumptions are based on the factors described above and historical studies of the time grading margin. Chong *et al.* [129] stated that for 132 kV and lower voltage circuit breakers, fault current interrupting time should be chosen as 0.1 seconds unless otherwise specified by the CB manufacturer [129]. Additionally, IEC 60255 stipulates a relay index error that governs the maximum relay timing error for a specific category of relay technology utilized in an application [129]. For instance, the allowable timing error of an electromechanical relay is 7.5% of operational time may surpass stipulated time grading margin, which increase the likelihood of relay failing to grade properly [128]. The occurrence of the CT errors constitutes relay timing errors; hence if not accounted for, it may lead to an insufficient grading margin in the system [128], [129].

In contrast, as seen in Figure 4-1, the distribution model under study consists of six protective relays denoted by CB-1 to CB-6. The time of operation for each relay was calculated using IEC characteristic equations, standard inverse to be precise. With two unknown variables on the equation, certain assumptions were made; for instance, the time dial setting was chosen to be the minimum of 0.025 seconds. The pickup currents were calculated using equation (3.1), and the single line-to-ground fault was applied on different feeders to attain fault currents. Then the plug setting multiplier was calculated by means of equation (3.2). Thereafter, the main relay time of operation was determined. The time of operation for backup relay is equivalent to the summation of the grading margin and the primary relay time of operation. In this way, the overcurrent relay response time was documented for the corresponding fault current. The plot of fault current against relays' time of operation was generated, as shown in Figure 4-4 below. It is observable from the curves that fault current is inversely proportional to the time of operation, meaning the IDMT overcurrent relay characteristics are satisfied.

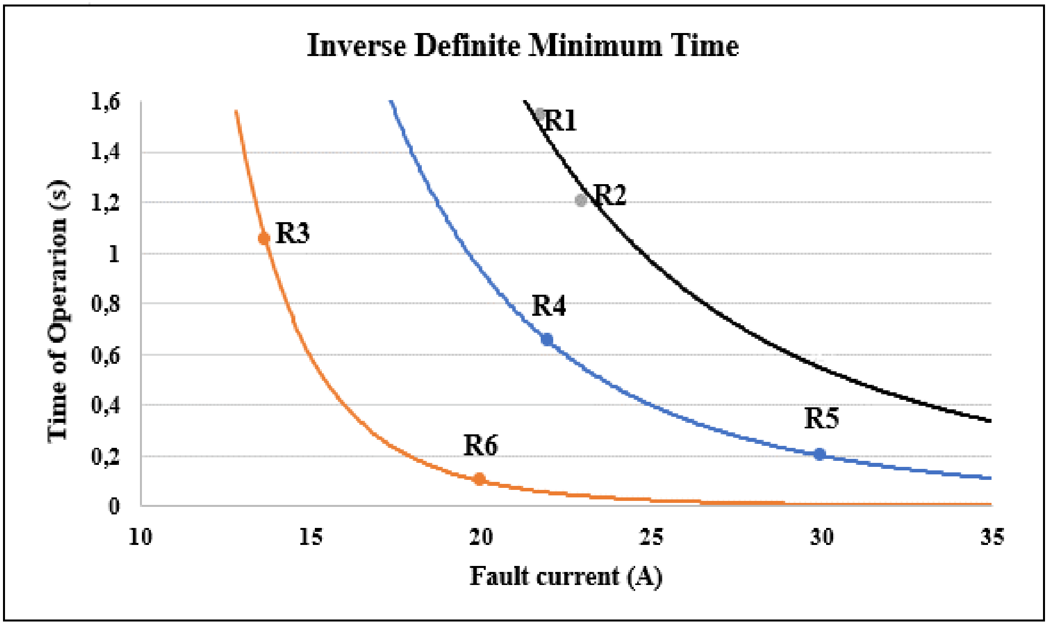

Figure 4-4: Overcurrent relay coordination

The orange curve demonstrates protection coordination between relay 6 and relay 3. When a fault occurs on customer load 2, the respective protective relay (R6) must operate and send a trip command to the circuit breaker for separation of the faulty part while keeping healthy fragment of the system intact. However, in case of relay R6 malfunctioning, the downstream relay (R3) must operate. The same topology applies to the blue and black curves. If a fault transpires on feeder 5 and the corresponding relay (R5) fails to work, backup relay (R4) must be triggered to remove the fault. In rarer circumstances where both relay 5 and relay 4 fails to eradicate system abnormalities, R3 must operate. From these curves, it can be seen that proper protection coordination of overcurrent relays is accomplished. The practical display of simulation results of the distribution system under study is presented in the next section.

4.4. Real-time simulation results:

4.4.1. No-fault condition

During the normal operating condition, the nominal voltage and nominal current flow into the system and there is no trip signal, see Figure 4-5. With CB-1, CB-3, CB-4, CB-5, and CB-6 used to test no-fault conditions, all breakers remain closed as there are no abnormalities detected in the system. The current and voltage measured by the current transformer and voltage transformer are perfectly sinusoidal. The currents are drawn continuously from the power source to the costumer load in the different feeders.

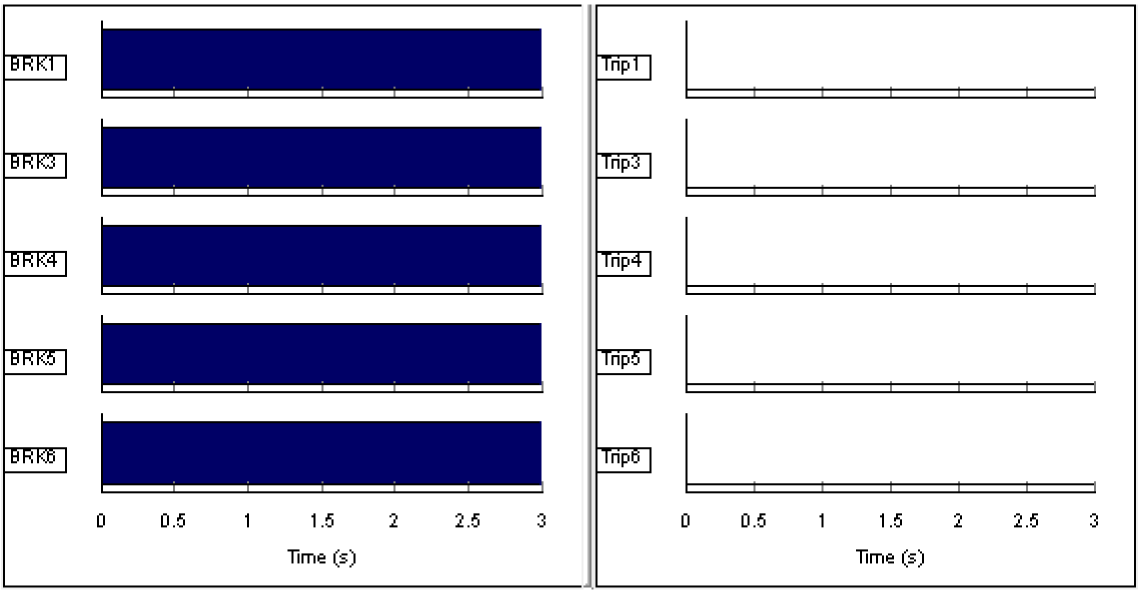

Figure 4-5: Normal operational condition

Although distribution networks are designed to be as fault-free as possible by ensuring proper equipment installation and periodic maintenance, it is not practical to design a system to eliminate fault occurrence completely. However, system abnormalities must be catered to during the design stages to circumvent enormous damage in the system. It must be designed such that the duration of defects and the number of customers affected is minimised. More so, it must guarantee the protection of expensive power systems equipment and the elimination of safety hazards speedily. Faults that prolong on a network can damage essential parts due to fire that may occur from massive, short circuits; consequently, the system loses synchronism of the system machinery and equipment. Therefore, this research study incorporates such conditions and ensures that the distribution system is protected against asymmetrical faults. In the next subsection, the fault transpires on different protection zones to verify protection coordination.

4.4.2. Fault at protection zone 1

The 11 kV single busbar line is subjected to a single line-to-ground fault denoted by LGFLT 1 and the system behaviour under this abnormal condition is demonstrated in Figure 4-6. It is observable from the figure that relay 3 detects the abnormal condition first and sends a trip command to discriminate faulty section, and as a result, breaker 3 opens at 1.6793 seconds. Since protective relay 3 protects the busbar line, it is configured to function as a non-directional relay. Non-directional relay operates irrespective of the current flow direction; hence, the pickup current and TMS is 0.6225 A and 0.4770, respectively. From the software simulation, the measured operating time of relay 3 is 1.0584 seconds with negligible percentage error. On the other hand, relay 1 operates 1.5391 seconds later. For both overcurrent relays, the theoretical relay operating time is approximately equivalent to the relays' operating time attained from the plots.

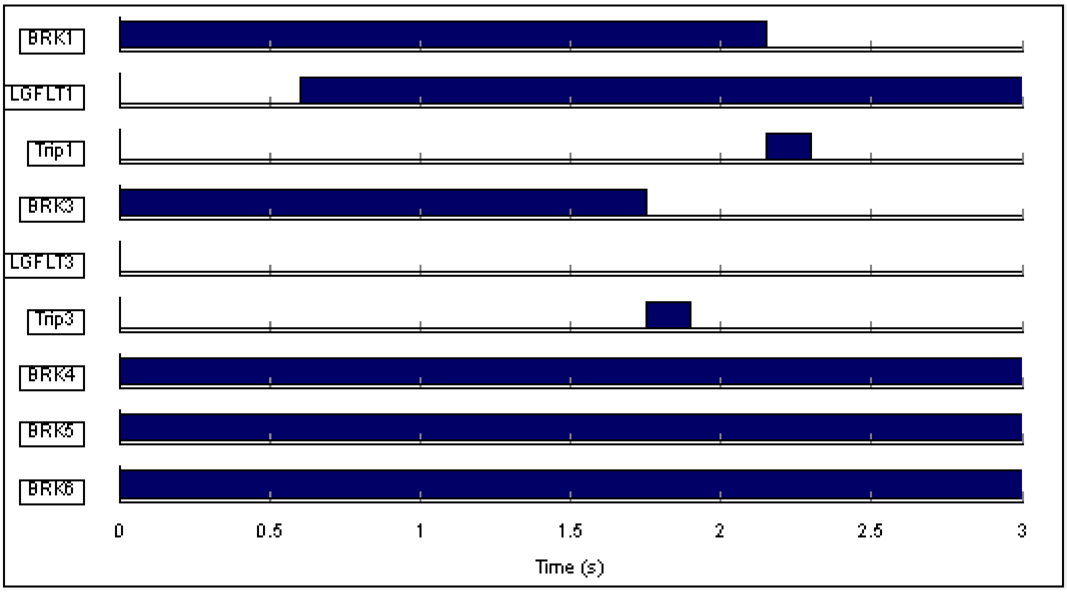

Figure 4-6: Fault occurring on the 11 kV busbar

As discussed earlier, selectivity is the ability of a protection scheme to eradicate a fault as soon as possible with the smallest interruption of the system equipment by striving for high-speed tripping on all feeders while safeguarding high levels of dependability and security [33]. This mechanism is represented in figure 4-6 above, only the relays closest to the fault operated, and the healthy part remained functional. The circuit breakers denoted by BRK4, BRK5, and BRK6 remained closed and intact. This substantiates that selectivity, as well as stability, is achieved in the distribution systems. Additionally, the relays were sensitive enough to discern the presence of abnormalities. The advantageous design of a distribution scheme with two power sources is also demonstrated. As seen, a partial power outage transpired when the first power source was subjected to the fault. The second source continued to supply customer load; this further proves that basic protection requirements are fulfilled and the system reliability.

4.4.3. Analysis with fault at location 4

Figure 4-7 illustrates system analysis with fault transpiring at protection zone 4. A single line-to-ground fault denoted by LGFLT4 occurs at approximately 0.6209 seconds. The current in the relay coil increases from 0.7699 A to 25.02 A, exceeding the predetermined value. Therefore, an overcurrent relay sends a trip command to open the circuit breaker; subsequently, it opens at 1.2801 seconds. With a TMS value of 0.3122 and the pickup current of 0.9624 A, the operating time is computed to be 0.6492 seconds. However, the measured operating time during simulation is 0.6592 seconds; this results in a percentage error of 1.54%. Accordingly, it can be deduced that the theoretical operating time of relay 4 is approximately equivalent to the operating time attained from simulations.

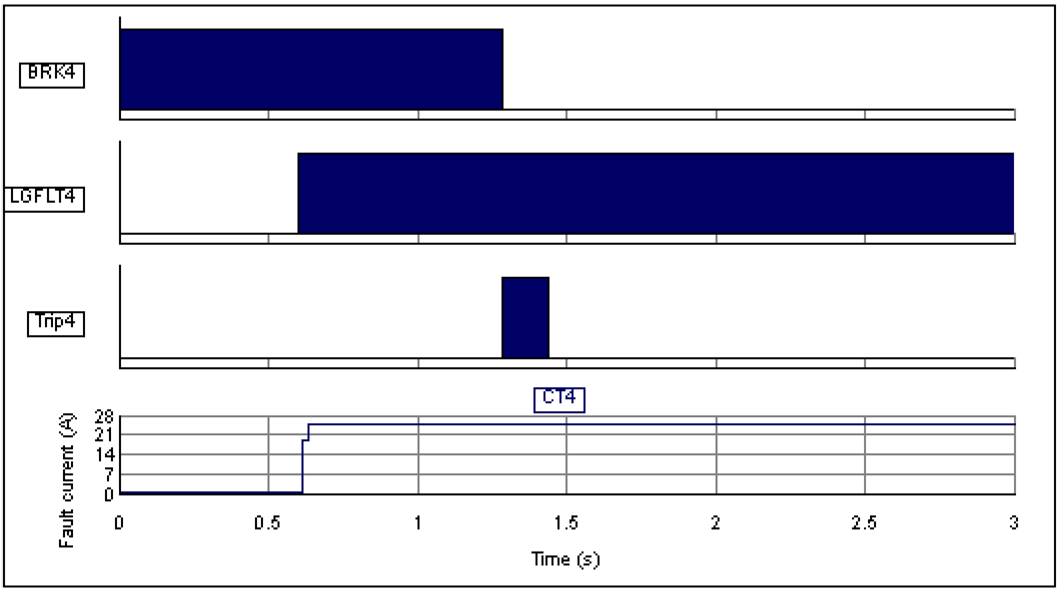

Figure 4-7: Relay 4 operating for a fault occurring at zone 4

4.4.4. Analysis with fault at zone 5

With all relay 5 parameters and TMS value computed and set, the fault occurs on feeder 5 and the relay operating time determined and verified with the runtime graphs. Figure 4-8 below demonstrates a 6.6 kV distribution feeder with a CT secondary current of 0.8588 A; thus, the relay 5 pickup current value is computed to be 1.0737 A. The CT ratio is 300:1 and the fault current seen in the relay coil is 30.97 A. Taking the TMS value of 0.125, the relay operating time is computed to be 0.2492 seconds, while Figure 4-8 gives the operating time of 0.2498 seconds. It can be seen from the figure that the circuit breaker denoted by BRK6 and other components of which are not shown in the graph remained operational and intact.

Moreover, it can be noted that in this section, only the primary protection is tested, and the outcome is as expected. Only the overcurrent relays closest to the fault operated and prompt removal of the faulty equipment. According to [107], it is impossible to obtain selectivity for all the possible system configurations with multiple similar equivalent sources. The author further states that due to the similarity of currents seen by relays, it is impossible to attain selectivity for the system simultaneously. However, this is proven otherwise; the system under study consists of two sources with equivalent parameters and selectivity is accomplished perfectly without obscurity. Therefore, the goal of the primary relay of which is to protect the system against abnormalities occurring within its primary zone is proficient.

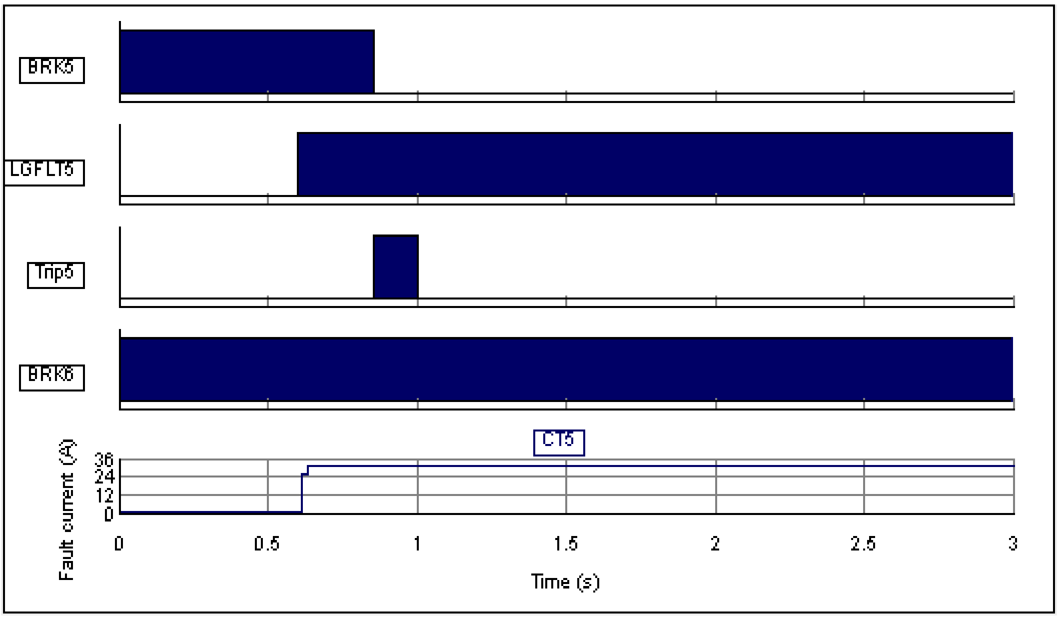

Figure 4-8: Relay 5 operating for a fault occurring at feeder 4

4.4.5. Protection coordination results

With protection relays, the main objective is to attain proper coordination between the upstream and downstream relays and breakers. The purpose is to permit relay and breaker near to the fault to eradicate shortcomings from the scheme before the operation of backup relay and breaker [6]. If the primary breaker from fault zone fails to work, the relay closer to the source must initiate the opening of its breaker. As previously state, the main reasons that constitute to primary protection defect are failure in circuit breaker, failure in tripping mechanism, failure in tripping voltage, failure in protective relay, and loss of supply to the relay. Hence, designing distribution systems with proper relay coordination is crucial not only for system protection but also for personnel safety. The system under study is coordinated by means of the design method stated in the aforementioned section.

Figure 4-9 below displays the failure of relay 2 to operate when a fault transpires in its protection zone. To test system protection coordination, the relays are effectuated to malfunction by disabling the trip signal that governs the circuit breaker to open for a fault on its protection zone. Simulation studies are conducted by allowing fault occurrence and observing the upstream relays' behaviour. Subsequent is the simulation result of relay 2 maloperation; the relay is blocked from issuing the trip signal to the governing breaker. From the figure, it is observable that fault 2 occurred at 0.6209 seconds and relay 2 failed to clear the fault on the protection zone 2. As expected, circuit breaker 3 opens at 1.0584 seconds and isolates the faulted apparatus to eliminate further damage to the distribution system. The operation of the backup relay confirms proper protection coordination between relay 2 and relay 3 in the system.

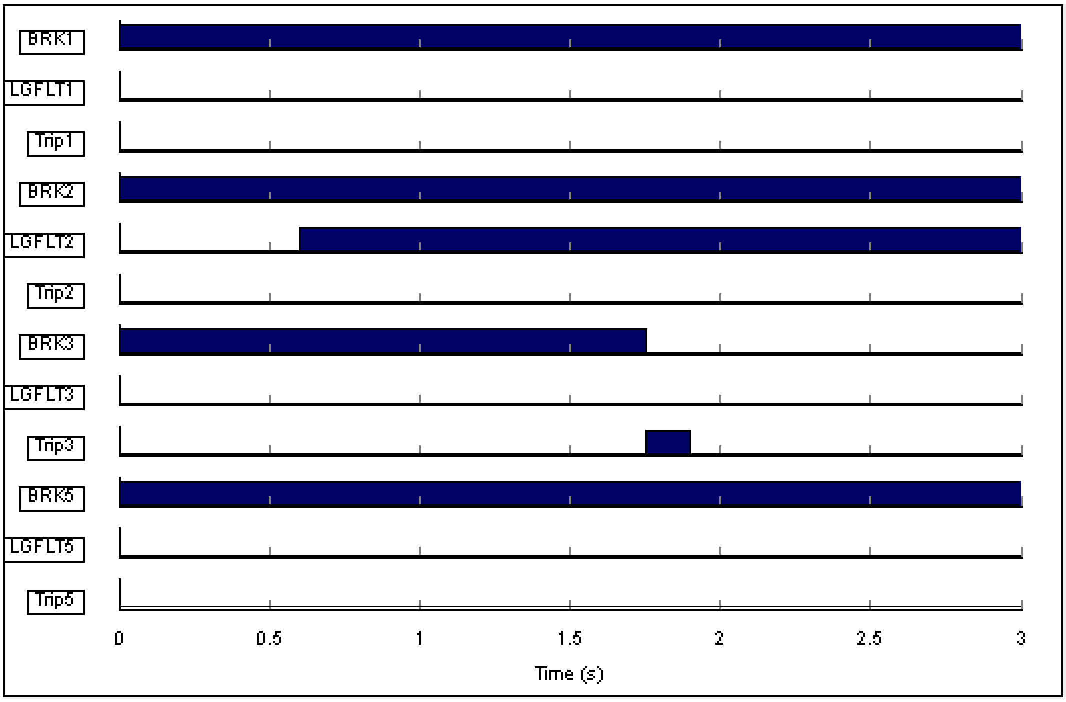

Figure 4-9: Relay 2 failing to operate

4.4.5.1. Testing protection coordination of relay 6 and 3

Figure 4-10 demonstrates the verification of 11 kV upstream circuit breaker which opens in response to the fault transpiring at protection zone 6. Relays 2, 3 and 6 are coordinated such that if the breaker closest to the fault fails to operate, the relays closer to the power source must operate. With downstream relay 6 defective, the upstream relay 2 and relay 3 opened as shown below.

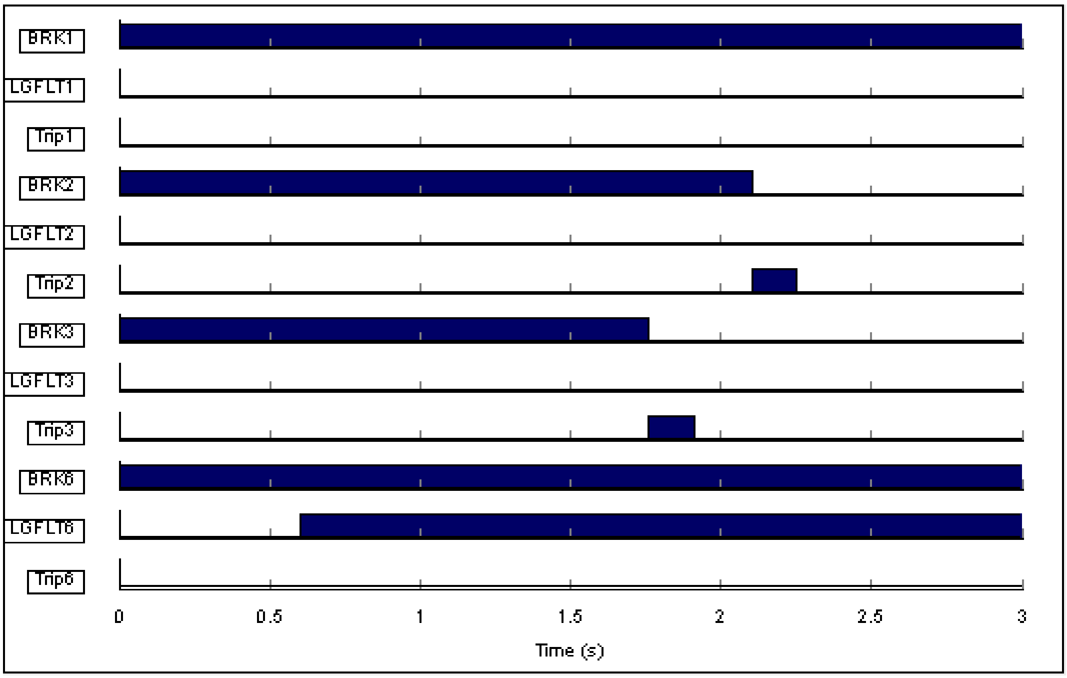

Figure 4-10: Relay 6 failing to operate

4.4.5.2. Testing of protection coordination of relay 5 and 4

In this section, relay 5 and relay 4 are incapacitated to substantiate coordination amongst them. A fault transpires at protection zone 5, followed by observations of whether the upstream circuit breaker clears the fault. Depicted in Figure 4-11 are the plots attained when relay 5 and relay 4 fails to isolate faulty section. Breaker 3 opens at 1.0584, which is approximately 0.4 seconds later than the time circuit breaker 4 should have opened and about 0.8 seconds later than the time breaker 5 should have operated.

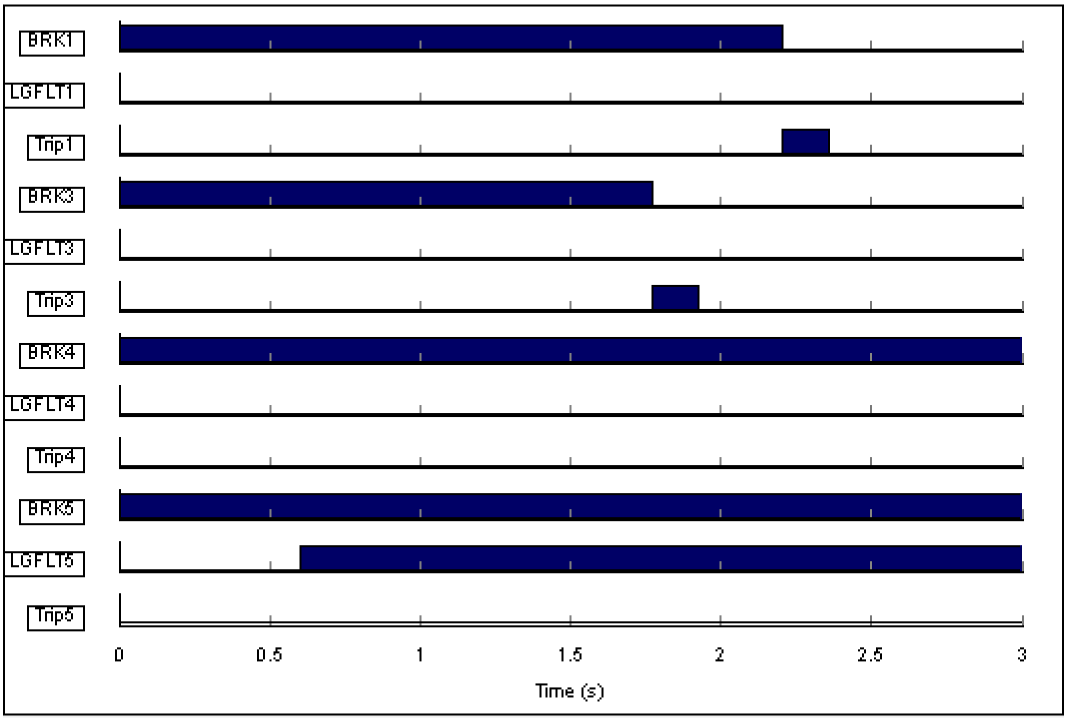

Figure 4-11: Relay 4 and relay 5 fail to operate

4.5. Conclusion

In this chapter, the software simulation results of a simple distribution system were presented and analysed. With the help of control logic circuits and other essential protection components, the system was successfully executed. The inverse time overcurrent relay characteristics and operation outlined in theory were verified. The plots were generated to demonstrate systems' response when a fault occurs on different protection zones. Protection coordination was performed by means of a conventional time grading method and tested to ensure the system is protected in case of primary protection failure. The system was properly coordinated; however, the results were not the optimum solution; hence, in the next section, the application of optimization techniques to obtain a global optimal solution is discussed and implemented on the distribution system.

CHAPTER 5

5 Application of Optimization Techniques for Overcurrent Relay Coordination

In the previous chapter, protection coordination of overcurrent relays performed by means of conventional time grading method revealed that the computed time multiplier parameters were highly dependent on an initial guess, particularly the initial time dial setting, and the addition of grading value have the most influence on the system behaviour. A number of different grading margin values were considered, where it was observed that insufficient grading margin selection caused more than one relay to operate for a fault - leading to difficulties in determining fault location and unnecessary loss of supply to some customers. Many researchers advocated the need for utilising evolutionary algorithms to mitigate setbacks presented by conventional optimization methods. Evolutionary algorithms offer a possibility for optimal relay coordination due to their random nature and ability to perform a parallel search for a number of potential solutions [51], [73], [76].

In this chapter, the application of the proposed algorithms in solving optimization problems is studied and distribution network simulation results are detailed and analysed. Also, the effect of multiple power sources on protection system characteristics is investigated through the comparison of a radial network to the system that consists of two power sources. In theory, protection system must detect and isolate abnormal conditions as quickly as possible to maintain stability and reliability on distribution systems. Consequently, it can be stated that the goal is to assure system selectivity with maximum sensitivity and speed. However, it was observed that these parameters are not independent, as two of them are more likely to decrease when the other one increases.

To address the issue of overcurrent relay coordination, which is considered a highly constrained optimization problem, evolutionary algorithms and linear programming methods were employed for time multiplier settings computation. Protection coordination problem comprises a fitness function that optimizes relay operating time and aids in the determination of overcurrent relay parameters. Analyses of the optimization problem at hand were performed through the comparison of fitness values, convergence rate, primary and backup relay operating times provided by each algorithm. Derived optimal operational time for overcurrent relay was compared with regards to calculated values and simulated data.

The evaluation mechanism, by which algorithms are compared is as follows:

- The algorithm that succeeded in obtaining the best fitness value is preferred, whereas any algorithm that yields poor performance due to premature convergence is not further considered.

- The algorithm that determines the best global solution with the fewest iterations is preferred over the other.
- Secondary to the speed of convergence is the efficiency and robustness of the algorithm – this is characterised by the lower number of iterations and diversity maintenance.

5.1 Optimization problem

In this problem, the objective is to minimise time multiplier setting values to accomplish optimum protection coordination in the distribution system. Distribution network layout developed in [130] is modified and utilised in this study, as shown in Figure 5-1. The linear programming and evolutionary algorithms were applied on the 132 kV network which comprises two power sources, overcurrent relays, circuit breakers, and step-down power transformers. To begin with, all model overcurrent relays were configured to utilise IEC 60255–151:2009 standard inverse characteristics [41], primary and backup pairs for coordination were identified, and determination of fault currents and pickup current settings was performed. Thereafter, the optimization problem was modelled as a linear problem and the stationary penalty factor was used to penalise infeasible solutions. In the course of optimization process, time multiplier parameters were treated as continuous, subsequently, as discrete, towards the end of which resulted in poor coordination. To address this miscoordination, authors in [107] proposed that algorithms' trial solutions must be rounded off to the upper value prior to fitness value evaluation. In this work, a similar approach is utilised. The design variables are fault points F-1 to F-11 and the circuit breakers denoted by CB-1 to CB-11.

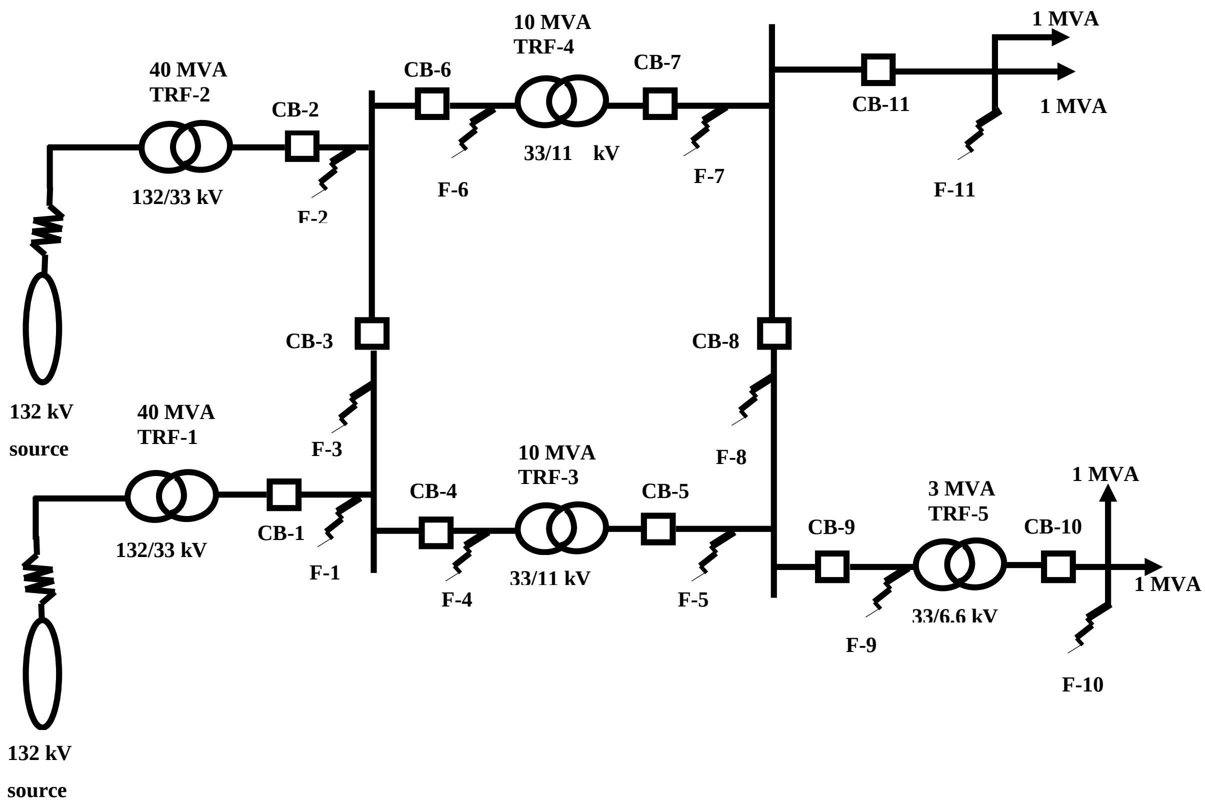

Figure 5-1: 132 kV Protection system under study [130]

5.2 Optimization problem setup

The proposed methods, that is, particle swarm optimization, dual simplex and genetic algorithms were implemented to the above-mentioned system. Dual simplex method is a widely used linear programming-based technique that utilises the duality of the problem to minimise the objective function. Since dual simplex is a deterministic approach, i.e., the method solves an optimization problem without stochastic behaviour, convergence curves cannot be generated, and thus optimum solutions will be utilised for comparison purposes. The PSO optimization problem was configured with the number of iterations set at 1000 and the swarm size set at 100, whereas GA was formulated with the population size of 100 and number of generations set at 1000, both algorithms were initiated and employed through Matlab functions. The maximum velocity and inertia weight was set at 50 and 0.9, respectively. GA algorithm was permissible to mutate at the rate of 0.01 and utilise a single-point crossover. These algorithms' parameters are selected based on the sensitivity analysis conducted in the subsequent section.

5.2.1 Dual simplex method

The challenge of relay coordination in the distribution network can collective be referred to as a linear programming optimization problem where the employment of a dual simplex technique may minimise the time of operation for relays adjacent to the fault. Given that all positive coefficients exist in the fitness function and also the right-hand side contains positive variables, the dual simplex technique becomes suitable for a minimization problem [32]. This technique reoptimizes a problem after the addition of constraint or other parameters altered to attain optimal feasible solution. In [106], the minimum discrimination time for each relay was 0.1 seconds, whereas authors in [32] and [131] both considered as 0.2 seconds and the coordination time interval chosen as 0.2 seconds. Both approaches yield appropriate coordination for fault at any point in the distribution network. Consider the distribution network depicted in Figure 5-1, with only relay-1, relay-2, relay-3, and relay-4 considered for demonstration purposes. The minimum time of operation for each relay is chosen as 0.2 seconds and the coordination time interval is set at 0.4 seconds. The maximum fault currents at F-1, F-2, F-3, and F-4 are 1.24kA, 1.23kV, 0.35kV, and 1.37kV separately, with the current transformer ratios being set at 100:1, 100:1, 50:1, and 100:1 for relay 1, 2, 3, and 4 respectively. The PSM and K values are computed using equations (2.2) and (3.5), and are tabulated as shown in Table 5-1. Let X_1, X_2, X_3, X_4 be TMS of relay-1, relay-2, relay-3, and relay-4 separately. The coordination problem can be formulated as:

$$\text{Min Z} = 2.021X_1 + 2.019X_2 + 1.682X_3 + 1.534X_4$$

Subject to: $2.221X_1 - 2.019X_2 \geq 0.4$

$$2.219X_2 - 1.682X_3 \geq 0.4$$

$$1.882X_3 - 1.534X_4 \geq 0.4$$

$$2.021X_1 \geq 0.2$$

$$2.019X_2 \geq 0.2$$

$$1.682X_3 \geq 0.2$$

$$1.534X_4 \geq 0.2$$

Table 5-1: PSM and K values

Fault point and current		**Relays**			
		Relay-1	Relay-2	Relay-3	Relay-4
F-1 1.24kA	*PSM*	28.49	-	-	-
	K	2.021	-	-	-
F-2 1.23kA	*PSM*	28.49	28.54	-	-
	K	2.021	2.019	-	-
F-3 0.35kA	*PSM*	-	28.54	54.48	-
	K	-	2.019	1.682	-
F-4 1.37kA	*PSM*	-	-	54.48	78.74
	K	-	-	1.682	1.534

As stated in the aforementioned sections, the lower and upper constraints of time multiplier setting for all the relays are set at 0.01 and 1, respectively. Matlab/Simulink program was developed to solve overcurrent relay coordination problems. Its code yields an optimum solution after several iterations and the obtained TMS values are presented in the subsequent section.

5.2.2 Evolutionary algorithms control parameters sensitivity analysis

With respect to overcurrent protection characteristics, algorithms' control parameters that maintain selectivity and optimize the speed of operation are preferred. Whereas any control parameter that yields two infeasible solutions, the one with a better fitness function value is favoured. Matlab/Simulink is utilised for modelling, computation, and demonstration of analysis. Convergence curves are computed to demonstrate PSO and GA algorithms control parameters performance under various conditions.

5.2.2.1 PSO sensitivity analysis

In this sensitivity analysis study, PSO algorithm control parameters are considered through constraining particles to feasible areas. Irrespective of optimization problem nature, some of the control parameters' values and choices have a major influence on PSO algorithm efficiency, and other control parameters have minimal or no effect [82]-[84], [132]. As discussed in the aforementioned section, the basic PSO parameters are swarm size, velocity components, number of iterations, acceleration coefficients, velocity clamping, and inertia weight. To examine PSO performance, only swarm size, number of iterations, and inertia weight are considered in this work.

a) Swarm size

Swarm size sensitivity analysis conducted employs a range between 10 and 500 particles, acceleration coefficient is set at 2, maximum velocity and inertia weight is set at 50 and 0.9, respectively. The optimization problem is formulated with an iteration of 1000 and it is imperative to note that all other control parameters are kept constant throughout the simulation. The effects of swarm size (N) on PSO algorithm performance are demonstrated in Figure 5-2. It is noticeable that the incremental change of swarm size causes PSO to perform more effectively and efficiently; Nevertheless, more computational time is required to achieve the global optimum solution. Another observation of interest in Figure 5-2 is that population size at 250 and 500 displays similar sensitivity, whereas performance slightly diverges for smaller sizes, i.e., 10 and 100. Due to a highly constrained optimization problem, where particles change based on their experience and the history of the whole swarm, the obtained results were expected. Additionally, larger variation between the enhancement for changing individual position and global best position either resulted in convergence at local optimum in lieu of global optimum or unnecessary wandering by individuals. An increase in swarm size, rises the probability of particles settling to global minima and surpassing a definite threshold of which results to equivalent performance. Although the smaller swarm succeeded in obtaining global minima, the positioning of particles with different sizes varies.

A research paper [73] focusing on this section with swarm size range between 20 and 160 particles reported that swarm sizes have minimum influence on the PSO algorithm performance [73]. However, it was observable that the performance of smaller sizes slightly differs from larger swarm sizes. A further study in [80], detailed sensitivity analysis with swarm size set between 25 and 500 particles, the study outcome proposed that the selection of swarm size must be made based on the number of variables [80].

The effects of swarm size on the overcurrent relay selectivity are investigated and verified. The convergence curve demonstrated that population size at 250 and 500 converges to the fitness of values of 3.39 seconds and 2.97 seconds, respectively. Consequently, time multiplier parameters at 500 particles are slightly smaller than swarm size set at 250, which means the sum of the relay operating time (i.e., speed of operation) is optimized and the system is more selective with maximum sensitivity. When abnormalities occur, it is detected by both primary and backup protection. The primary protection operates first as it consists of smaller operating time compared to backup protection. For smaller swarm sizes set at 10 and 100 particles, the function converges to fitness values of 5.06 seconds and 4.45 seconds, separately. The behaviour demonstrates that overcurrent relays are taking too long to operate at 10 particles which violates one of the protection principles to isolate faults speedily. This implies that protection coordination is not accomplished, some of the overcurrent relays exceed coordination time interval (i.e., CTI $\geq$ 0.4). With swarm size set at 100, satisfactory optimum protection coordination is achieved in the distribution system. Also, selectivity is achieved, with only faulty equipment isolated promptly from the system within stipulated CTI.

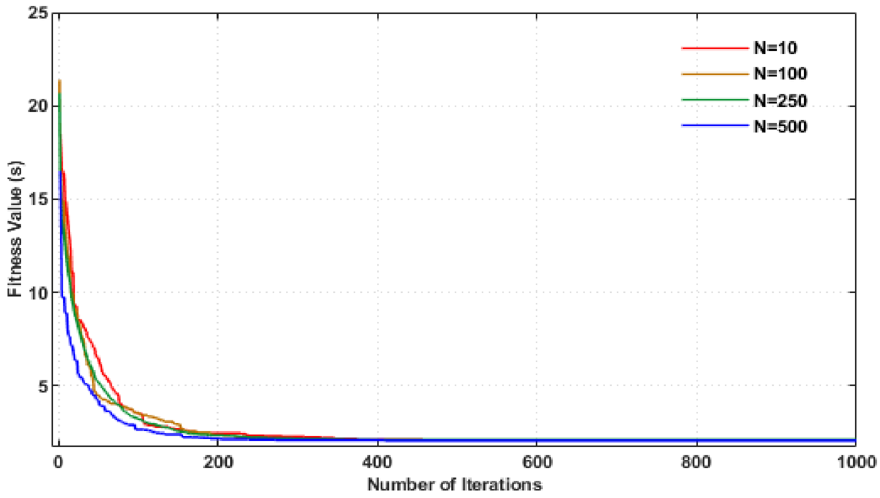

Figure 5-2: Effects of swarm size on PSO performance

b) Number of iterations

Ref. [78] suggested the utilisation of iterations range between 10 – 50 for moderate complex problems and 200 – 400 for most complex problems [78]. In this sensitivity analysis, the number of iterations is set at 100, 500, and 1000 iterations, acceleration coefficient is set at 2, maximum velocity and inertia weight is set at 50 and 0.9, respectively. Figure 5-3 depicts the primary relays' operating time. It is clear that the operating time attained by means of varying iterations is similar in all relays. Thus, increasing the number of iterations have inconsiderable impact in the performance of PSO and leads to unnecessary increase in computational demand at times. Furthermore, the protection system remains selectivity throughout the iterations variation and the speed of operation is minimised. Overcurrent relay response display that increasing number of iterations fails to improve the efficiency of PSO since the algorithm only controls search duration and not particle traverse in search space. This study outcome indicates that the number of iterations is dependent on problem nature and the extent of complexity as a smaller value lessens the likelihood of attaining the global solution, while larger values rise computational efforts.

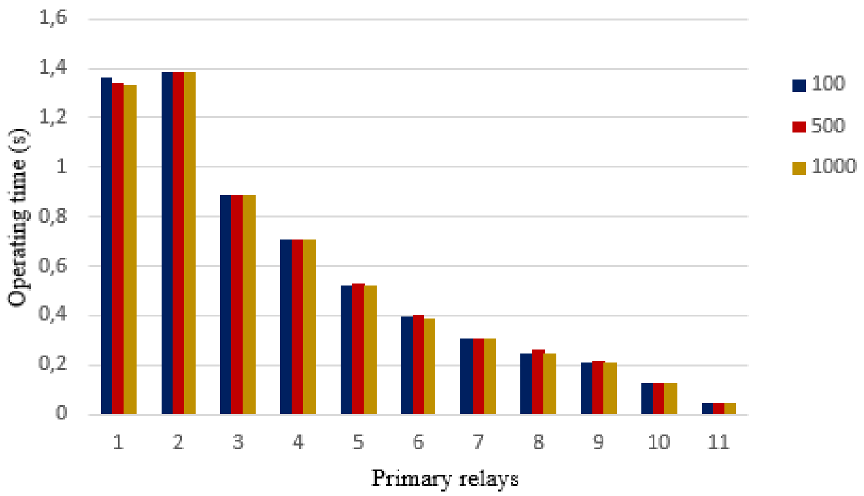

Figure 5-3: Primary relay operating time

c) Inertia weight

Xin *et al.* [78] proved experimentally that inertia weight ranging from 0.4 – 0.9 yields excellent results with improved efficiency and performance of PSO [78]. The linearly decreasing approach allows particles to explore broader search space in beginning and neighbouring areas in subsequent stages with reduced speed. It offers a substantial probability of reaching an optimum solution quickly [132]. Authors in [73] undertook a comprehensive study and applied inertia weight ranging between 0.8 – 1.2, and it was found that a larger inertia value promotes global search, whereas a smaller inertia value improves local search [73]. The ultimate goal of inertia weight is the reduction of velocities or iterations and sharpen the exploration and exploitation ability of particles. Based on the aforementioned research work, three different ranges of inertia weight (i.e., W1 = 0.0 – 1.0, W2 = 0.8 – 1.2, and W3 = 0.9 – 0.4) are implemented. Swarm size is set at 100 particles, and 1000 iterations are utilised. To circumvent the effect initial population, 10 simulation runs are taken, acceleration coefficient parameters are set at 2, minimum and maximum velocity are 0 and 50, respectively. Figure 5-4 depicts PSO sensitivity to various inertia weight values. At W1 = 0.0 – 1.0, PSO converges prematurely due to the decreased search abilities and particles getting trapped in local minimum.

With respect to overcurrent protection, no significant improvement in relay coordination is achieved. Likewise, the overall operating time increased, which means circuit breaker response time is longer. This is undesirable as shortcomings that persevere longer in the system can damage some essential parts due to fire that may occur from massive-short circuits; consequently, the system loses synchronism of the equipment and machinery. Larger inertia weight values, W2 = 0.8 – 1.2, failed to achieve proper protection coordination between relays and performed inefficiently. Thus, it violates protection principles which are selectivity and speed of operation. As claimed by [78], [133], and [134], a linearly decreasing inertia weight (W3 = 0.9 – 0.4) achieves better convergence by balancing global and local searches. All overcurrent relays preserve selectivity and protection coordination is accomplished in the distribution network. As seen in Figure 5-4, W3 the swarm converges more accurately and efficiently with fewer iterations than W1 and W2. The decreasing inertia weight process allows all particles to shift from exploratory mode to exploitative mode, which produces an excellent optimization solution.

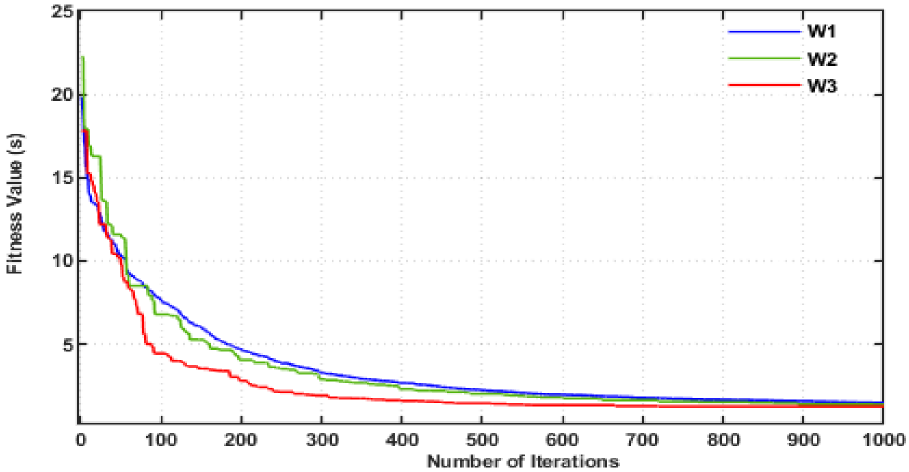

Figure 5-4: Inertia weight sensitivity analysis

5.2.2.2 GA sensitivity analysis

Setting genetic algorithms control parameters to obtain optimal solutions is a long-standing problem. Normally, control parameters are selected by the user with no guideline of what values might yield a better solution. Hence, a sensitivity analysis approach and verification with an experimental system is performed to establish suitable values of parameters and study the conceivable consequence of genetic operators and their impact on the performance of overcurrent relays. This study is inclusive of parametric analysis of genetic operators such as crossover probability, population size, and mutation probability. The goal is to evaluate the behaviour and determine optimal parameters for GA which optimizes the time multiplier settings of overcurrent relays.

a) Population size

Population size is another contention that influences the categorization performance of the GA algorithms. In 2007, Lobo *et al.* [87] undertook a performance study considering known control parameters with respect to evolutionary algorithms [87]. It was found that greater population size increments parallelism which helps in finding solutions for complex optimization problems; however, it requires more valuations per generation, leading to an unacceptably slow convergence rate. Bakirli *et al.* [88] employed a range from 25 to 250 and claimed that the more population size increases, the fitness values also increase, similarly more computational effort is required [88]. A sensitivity analysis is conducted with population size ranging between 10 – 500, number of generations is set at 1000, mutation rate of 0.01, and single-point crossover. As anticipated, the results depict that by increasing population size, GA performs robustly and efficiently at the expense of computation time, which agrees with Bakirli *et al.* [88]. In Figure 5-5, it is noticeable that larger population size (N = 500) succeeded in converging to the global minima with fewest iteration number and hence managed to perform more efficiently than smaller population size (N = 10). Also, incremental changes in population size influences both exploitation, and exploration which influences GA outcome greatly. With respect to protection coordination, overcurrent relays managed to operate promptly when population size is set at 500 and at N = 10 relays took too long to operate with coordination time interval longer than the stipulated value. This results in protection miscoordination and loss of selectivity as well as system reliability. When the population size is set at 100, efficient performance is achieved with a properly optimized speed of operation and coordination time interval is within the desired range.

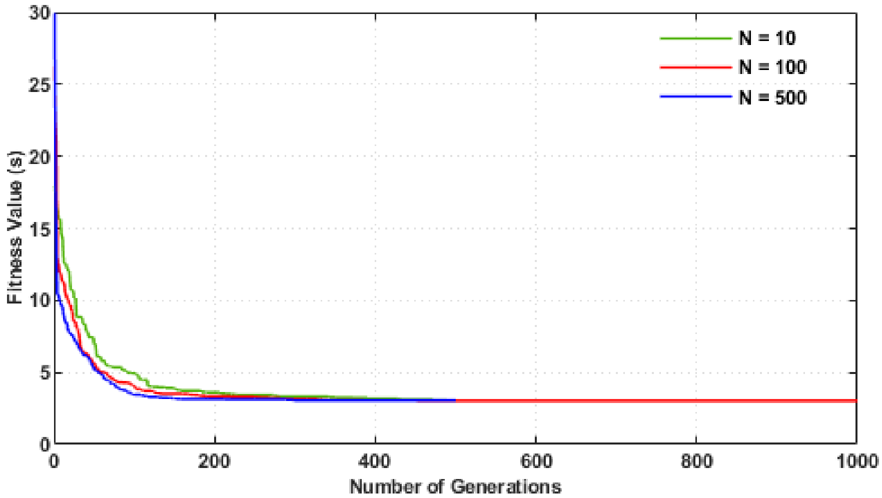

Figure 5-5: Effect of population size on GA performance

b) Crossover and mutation probability

Rojas *et al*. [21] claimed that a number of crossover points (one, two, or uniform) have minimal effect on the performance of GA, while crossover probability, mutation rate, and population size have a significant influence [21]. Authors in [135] employed a combination of crossover and mutation probability [20% mutation, 80% crossover] and [10% mutation, 90% crossover], and it was found that the combination of mutation and crossover probability yields the best outcomes however, mutation probability must be set at narrow range to avoid premature convergence, and too high mutation facilitates random search [135]. A further study in [88] displayed the superiority of crossover values ranging from 0.3 – 0.9, it was proven experimentally that bigger crossover probability (0.9) causes important individuals with better fitness values to get lost in the search space. This sensitivity study employs a single-point crossover range from 0.3 – 0.9, mutation rate range between 0.01 – 0.3, population size set at 100, and the maximum number of generations set at 1000.

From Table 5-2, it is clear that the fitness value increases proportionally with the crossover and mutation probability, as expected. During crossover rate incremental simulations, the mutation probability was kept constant at the value of 2%. The dynamic performance of the considered crossover rate is depicted in Figure 5-6 and the considered crossover ranges are presented in Table 5-2. Increasing the crossover rate caused an increase in the fitness value, which means overcurrent relays took long to operate and the coordination time interval is exceeded on some relays.

In the second case, sensitivity analysis is conducted with four different mutation probability range from 0.02 – 0.3 and a constant single-point crossover probability of 30%. As depicted in Figure 5-7, the parameter affects fitness value similarly to crossover probability substantially. The incremental changes in mutation rate increase the fitness value and help to circumvent local optima through the prevention of chromosome from being too identical to one another. This fulfils the purpose of mutation in genetic algorithms which is to preserve and introduce diversity. Overall, overcurrent relays speed of operation is more optimized at 2% mutation rate, which means the relays are more selective and speedily when required to operate.

Table 5-2: Comparison of time multiplier settings

Time Multiplier Setting	**Crossover Rate**							**Mutation Rate**			
	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.02	0.1	0.2	0.3
TMS 1	0.33	0.49	0.57	0.75	0.77	0.79	0.83	0.35	0.45	0.36	0.42
TMS 2	0.34	0.45	0.51	0.73	0.69	0.75	0.79	0.22	0.37	0.33	0.39
TMS 3	0.29	0.43	0.47	0.69	0.65	0.65	0.66	0.18	0.17	0.29	0.33
TMS 4	0.23	0.36	0.43	0.51	0.62	0.59	0.63	0.14	0.19	0.25	0.35
TMS 5	0.21	0.28	0.37	0.30	0.51	0.57	0.57	0.21	0.23	0.19	0.30
TMS 6	0.19	0.19	0.33	0.25	0.43	0.49	0.50	0.17	0.13	0.19	0.29
TMS 7	0.17	0.17	0.20	0.19	0.31	0.43	0.45	0.15	0.11	0.17	0.21
TMS 8	0.18	0.15	0.18	0.17	0.23	0.31	0.31	0.09	0.06	0.22	0.17
TMS 9	0.15	0.11	0.15	0.15	0.17	0.25	0.29	0.02	0.12	0.15	0.19
TMS 10	0.08	0.07	0.13	0.08	0.11	0.13	0.21	0.11	0.07	0.07	0.13
TMS 11	0.13	0.02	0.07	0.13	0.02	0.02	0.13	0.02	0.02	0.02	0.02
$\sum \boldsymbol{TMS}$	2.30	2.72	3.41	3.95	4.51	4.98	5.37	1.66	1.92	2.25	2.80

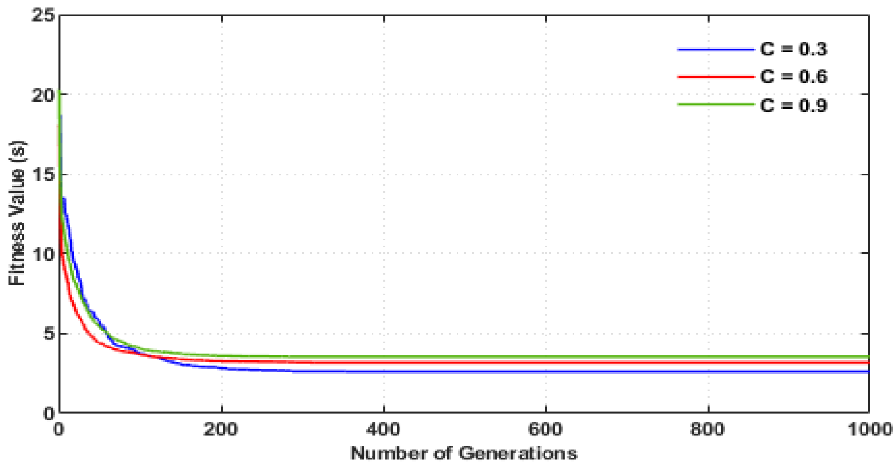

Figure 5-6: Crossover probability on GA performance

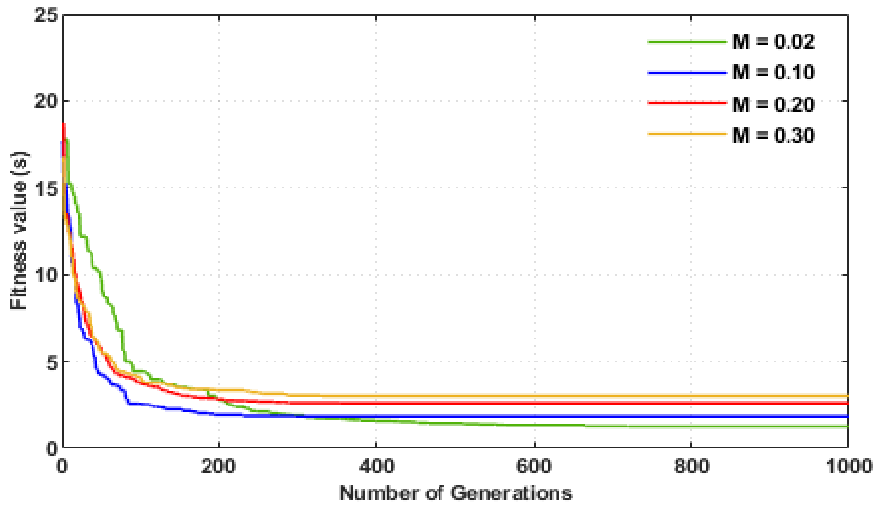

Figure 5-7: Mutation sensitivity analysis

The flow charts seen on Chapter 3 details the procedure followed in the application of evolutionary algorithms to solve overcurrent relay coordination problem. Table 5-3 presents the algorithms selected parameters based on sensitivity analysis conducted in the abovementioned section. From the figure, it can be seen that the number of generations is set at 1000 to provide adequate time for the population to explore search space. Also, a larger number of iterations is used to reach optimal solution to ensure proper inertia weight at each iteration.

Table 5-3: The parameters of evolutionary algorithms (GA and PSO)

GA Parameters	PSO Parameters
Generation: 1000	Iterations: 1000
Population: 100	Swarm size: 100
Selection: Proportional	Velocities: $V_{max} = 50$ $V_{min} = 0$
Crossover: Single Point	Inertia weight: $w_{max} = 0.9$ $w_{min} = 0.4$
Simple (with extrapolation)	Acceleration Coeff.: $c_1 = 2$ $c_2 = 2$
Uniform Mutation	
Mutation rate = 0.01	

5.3 Comparison of convergence rate and fitness function

Optimization performance can only be appreciated after a certain number of iterations. In this research work, the simulation is made of 1000 iterations which is enough to appreciate any improvement of the algorithm. Figure 5-8 depicts the convergence characteristics of GA and PSO obtained from Matlab. It can be seen that GA and PSO converges to the fitness value of 3.554 seconds and 3.175 seconds, respectively. These fitness values clearly shows that PSO algorithm convergence rate is slightly faster than GA, that is, in Figure 5-8, the red curve (represents PSO) is quicker to reach its optimal solution than the blue curve (represents GA). Furthermore, it is good to observe that GA curves are smoother because the curve has fewer changes during convergence. With respect to the coordination problem at hand, the optimal solution is initially unknown thus, the dual simplex method is utilised to measure the performance of the evolutionary algorithms. Hence, for all time multiplier values, GA and PSO algorithm yield the best performance compared to dual simplex.

It can be deduced from the results that GA algorithm has the ability to exploit search space much more efficient at the beginning of the search. The fitness value drops rapidly from the initial value of 20.20 seconds to 6 seconds, where it starts to settle. It settles between 5.20 and 3.80 seconds for about 68 iterations. The algorithm maintains diversity and converges steadily until it reaches a fitness value that is within 5% of the final value (3.38 seconds) in 285 iterations. Final fitness value of 3.554 seconds was reached in 975 iterations. The PSO algorithm begins at a fitness value of 18 seconds and reaches a fitness value of 4 seconds in 79 iterations. It reaches the fitness value within 5% of the final fitness value after 250 iterations and slowly converges until it reaches the final fitness value of 3.175 seconds in 971 iterations. This shows the efficiency of the proposed optimization algorithm. The claim made in the empirical study [73] is precise with regards to algorithm behaviour, i.e., finding the best fitness value, as PSO algorithm was able to attain the global optimal solution even with 100 particles.

During simulations, it was observed that GA consumes more time since it handles large amount of data. This technique successfully searches through a large and complex search space and it is more efficient when less data is known. In one version [131], dual simplex method and GA were implemented on a radial network and TMS values for overcurrent relay were determined. The obtained solution depicted that dual simplex technique was more sensitive than GA. In another study [20], the dual simplex algorithm utilized for optimum relay coordination problem outperformed GA technique. The comparative study conducted with respect to GA implies that PSO produces better optimum solutions than GA [136]. A further study in [137] implemented a dual simplex method and PSO algorithm for radial and parallel feeder systems. In both cases, the particle swarm optimization algorithm yields good satisfactory results than the linear programming technique.

Among other factors, swarm size and inertia weight possess a direct impact on the performance of PSO algorithm, as seen in the sensitivity analysis study. It was observed during simulations that increasing swarm size increases the likelihood of PSO algorithm settling to global optimal or local minima near it. While, when a smaller value was selected, premature convergence occurred. However, the disadvantage of a large swarm size is the increased computational effort [79]. It was claimed in a study [138], where sensitivity analysis for the number of iterations was conducted, that number of iterations have negligible influence on the performance of PSO algorithm. In this work, when a larger swarm size was chosen, the particles tend to cover more space in the search area. The quality of results enhanced with additional particles in the design search space. Hence, it can be deduced that PSO algorithm certainly depends on these parameters.

To achieve an optimum solution for overcurrent relay coordination, GA parameters such as crossover percentage, population size, and mutation probability were varied. A smaller population size (below 1000) was chosen while other parameters remained constant. This resulted in premature convergence and concise computation time. With the crossover rate being the main factor determining the population size of the parent particles, when the crossover probability was set low, the network could not reproduce sufficient offsprings. When a higher rate was set, the building blocks could not add up and accumulated on a single chromosome. Therefore, a moderate rate is recommended for better results. It was suggested by authors in [70] that a constant mutation rate between 5% and 20% shall be considered for the overcurrent relay coordination problem. This range yields an improved solution than a very low or high rate for the mutation process. It was also experimented that the mutation rate is inversely proportional to population size.

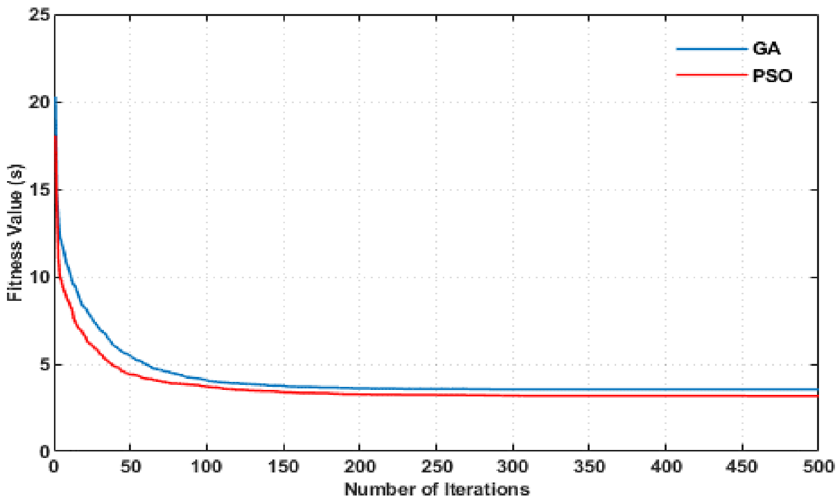

Figure 5-8: Comparison of fitness value for GA and PSO

Table 5-4 shows TMS parameters for optimization techniques. Interestingly the data obtained is between 0.01 ~1.0, of which are the stipulated TMS values. Due to the factors discussed above, PSO provides TMS parameters for overcurrent relays that are slightly smaller than GA parameters.

Table 5-4: Parameters for overcurrent relay coordination techniques

	GA	PSO	Dual Simplex
TMS 1	0.72	0.66	0.75
TMS 2	0.69	0.57	0.73
TMS 3	0.57	0.50	0.69
TMS 4	0.45	0.46	0.51
TMS 5	0.30	0.28	0.30
TMS 6	0.22	0.21	0.25
TMS 7	0.18	0.17	0.19
TMS 8	0.15	0.13	0.17
TMS 9	0.13	0.11	0.15
TMS 10	0.09	0.07	0.09
TMS 11	0.05	0.02	0.13
$\sum \boldsymbol{TMS}$	3.55	3.18	3.96

Although PSO algorithm managed to perform efficiently and effectively, further modifications can be performed to improve PSO performance such that the operational speed and TMS values are further reduced. Sensitivity analysis results revealed that PSO is sensitive and dependent on its initial settings; particularly, inertia weight has the most influence on its performance. Different ranges of inertia weight were utilised and considered for sensitivity analysis, where it was seen that some parameters were unsuccessful in traversing particles leading to premature convergence. A significant number of researchers advocated the necessity of using larger inertia weight in the beginning, thereafter, slowly decreasing to minimal value [73], [76]. Nonetheless, the time-based inertia weight variation may not lead to global optimal solution hence, a self-adapting weight may be effective [73]. PSO algorithm is a population-based and stochastic inspired optimization method that at times suffers from premature convergence which results in algorithm ineffectiveness. Therefore, it is of paramount importance to introduce modifications to the algorithm such that the convergence speed is improved and circumvent premature convergence. An adaptive strategy that modifies cognitive and social parameters, as well as inertia weight through observing current position and modifying control parameters, is employed in this work. A modified adaptive particle swarm optimization (MAPSO) previously proposed in [139], [140], [141], [142] and [143] is modified and altered to best suit the overcurrent coordination problem. The algorithm introduces an evolutionary state as a novel scheme to adapt control parameters such that relay operating time is reduced and the limitations presented by the original PSO are addressed through keeping track of particles' current position with respect to its global best solution and personal best solution [142]. The three contributions presented by MAPSO are described below:

a) MAPSO is a constraint handling mechanism that enhances original PSO performance by making the control parameters adaptive and ensuring particles move towards feasible regions only.

b) An evolutionary state-based inertia weight is proposed to balance exploration and exploitation search by enforcing the algorithm to retain feasible solutions only.

c) A repulsion-based position update technique, as well as velocity reinitialization with respect to clamping-limit, is adopted to enhance global exploration and increase robustness.

5.4 Modified Adaptive Particle Swarm Optimization (MAPSO)

The modified adaptive particle swarm optimization (MAPSO) aims to attain distinctive inertia weight and acceleration coefficient values. MAPSO is a self-adaptive technique that uses feedback parameters produced by the fitness function of the individual particle. In [141], a chaotic-based non-linear inertia weight was proposed to provide balance between exploration and exploitation by reducing or increasing the search step [141]. However, the algorithm presented issues such as poor convergence, instability, and lack of feasible solutions. Another study in [142] proposed the use of evolutionary state-based inertia weight to balance exploration and exploitation. An evolutionary estate (ES) which is the mechanism used to self-automate the algorithm based on the environment as follows [142]:

$$ES_i^k = \frac{f(pbest_i^k) - f(gbest^k)}{f(x_i^k)} \tag{5.1}$$

Where ES_i^k is the evolutionary estate, i the individual particle, k the iteration number, $f\left(pbest_i^k\right)$ the personal best solution fitness function, $f(gbest^k)$ is the global best fitness solution across the whole swarm, and $f(x_i^k)$ the fitness value of each particle current feasible solution [142]. Higher ES_i^k value indicates the most recent feasible solution of an individual particle is near its personal best solution $\left(pbest_i^k\right)$ and the global best solution$(gbest^k)$ at far end, this occurs when $f\left(x_i^k\right) = f\left(pbest_i^k\right)$ [141], [142]. Smaller value of ES_i^k means either the most recent feasible solution of the individual particle is at the far end for both personal best and global best solutions or the personal best solution is near the global best. When $f\left(pbest_i^k\right) = f(gbest^k)$, evolutional estate ES_i^k become zero [141], [143]. This strategy yields optimum global solution and improves convergence thus, it is adopted in this research work to self-adapt inertia weight and evaluate the fitness function of each particle.

5.4.1 Inertia weight

Yang *et al.* [144] proposed a PSO algorithm with dynamic adaptation (DAPSO) that consists of two feedback parameters namely, aggregation factor which compares all particle performance with the best performing particle in the current iteration, and speed factor which evaluate the particles' personal best solution were utilised to adapt inertia weight w_i^k. Accordingly, inertia weight w_i^k was adapted using the following equation (5.2); where h_i^k is the speed factor, s the aggregation factor, w_s the initial inertia weight, α and β are system parameters with a range of [0,1]. This approach suffers from explosive divergence resulting in particles leaving the feasible region and never return, thus the algorithm is unstable and inefficient [144].

$$w_i^k = w_s - \alpha\left(1 - h_i^k\right) + \beta s \tag{5.2}$$

Another study [145] proposed a self-regulating inertia weight that controls each particle by increasing inertia weight value for the best performing particle while decreasing for all other particles. This arrangement transpires from an idea that the best performing particle contains higher fitness value in its direction, hence, accelerates fast whereas other all particles should proceed with a linearly decreasing inertia weight strategy. The self-regulating formula is given in equation (5.3), where w_i^k the inertia weight for i-th particle in the k-th iteration, η is a constant to control acceleration rate, w_{max} and w_{min} are maximum and minimum inertia weight. Harrison *et al.* [146] in 2018 demonstrated that a self-regulating inertia weight approach can only lead to convergence behaviour when a certain threshold is known and is problem dependent, thus suggesting the use of particles' fitness values in adapting inertia weight [146].

$$w_i^k = \begin{cases} w_i^{k-1} + \eta\Delta w & for\ the\ best\ particle \\ w_i^{k-1} - \Delta w & for\ all\ other\ particles \end{cases} \tag{5.3}$$

$$\Delta w = \frac{w_{max} - w_{min}}{k} \tag{5.4}$$

$$w_i^k = w_{min} + (w_{max} - w_{min})\left(\frac{\sum_{i=1}^{N} S_i^k}{N}\right) \tag{5.5}$$

Equation (5.5) depicts adapting strategy based on particle success. This approach was proposed in [147] to evaluate particles' behaviour such that the particle that improves its fitness at k iteration succeeds whereas, failure in enhancing fitness results in local minima solution [147]. N refers to swarm size and S_i^k a constant that is set to 1 if particle succeeds and 0 if unsuccessful. An increase in success percentage increases the inertia weight and decrease with decreasing success percentage. Other researchers [148] used non-linear function of decreasing inertia weight like the scheme developed in [149] which does not require known iteration number. It's a new technique for updating inertia weight such that particles that obtain better solutions are considered for more exploitation capability. The scheme demonstrated a substantial improvement in the performance with regards to convergence speed and efficiency compared to dynamic adaptive particle swarm optimization DAPSO [149]. Although the above-mentioned variants improved the original PSO performance, the models become more complex due to the introduction of new parameters. Also, some adaptive variants are designed to solve unconstrained problems and suffer from premature convergence. Therefore, this research proposes a constraint handling mechanism that improves original PSO performance by making the algorithm control parameters adaptive while ensuring the model is simple. In the proposed method, the evolutionary state ES_i^k behaviours like inertia weight w_i^k hence, the performance of inertia weight is considered equivalent to evolutionary state [142].

5.4.2 Acceleration coefficients

The movement of particles per iteration is controlled by acceleration coefficients, that is, both cognitive c_1^k and social c_2^k parameters. Typically, c_1^k and c_2^k are set at a constant value of 2.0 for the original PSO algorithm [150] however, experimental results depicted that the employment of alternative configuration may yield better performance. It was proven that assigning different acceleration coefficient values results in improved performance and faster convergence [151]. Carlisle and Dozier [152] claimed that choosing larger cognitive parameter c_1^k than a social parameter c_2^k may lead to superior performance but with constraint $c_1^k + c_2^k \leq 4$. It was suggested in [151] that both cognitive and social parameters can be set as linearly decreasing values, but no improvement in performance was reported. Ratnaweera *et al*. [153] implemented PSO with time-varying acceleration coefficients (PSO-TVAC) such that c_2^k increases linearly over time while c_1^k decreases. The strategy aims to improve convergence by attracting more particles towards the global best solution. In [142], acceleration coefficients are influenced by evolutionary state instead of being time-based as follows [142]:

$$c_1^k = \begin{cases} \left(\frac{(c_{max}-c_{min})\times(iter_{max}-k)}{iter_{max}}\right) + c_{min} & if\ 0 \leq ES_i^k \leq 0.5 \\ c_{max} - \left(\frac{(c_{max}-c_{min})\times(iter_{max}-k)}{iter_{max}}\right) & if\ 0.5 \leq ES_i^k \leq 1.0 \end{cases} \tag{5.6}$$

$$c_2^k = \begin{cases} c_{max} - \left(\frac{(c_{max}-c_{min})\times(iter_{max}-k)}{iter_{max}}\right) & if\ 0 \leq ES_i^k \leq 0.5 \\ \left(\frac{(c_{max}-c_{min})\times(iter_{max}-k)}{iter_{max}}\right) + c_{min} & if\ 0.5 \leq ES_i^k \leq 1.0 \end{cases} \tag{5.7}$$

$0 \leq ES_i^k \leq 0.5$ is regarded as a low evolutionary state in which the particle explores more global search at the beginning and towards the end, local search is encouraged [142]. Larger evolutionary state $0.5 \leq ES_i^k \leq 1.0$ promotes exploitation in the beginning by permitting particles to converge towards the swarms' best solution and progressively, more global exploration is encouraged towards the end [142]. The two constants c_{min} and c_{max} are set at 0 and 2.0, respectively. The same approach is adopted in this work to allow self-adapting acceleration coefficients to feasible regions.

5.4.3 Velocity update and reinitialization

Pasupuleti and Battiti [154] introduced gregarious particle swarm optimization (G-PSO) which does not take into consideration particles' previous velocity for determining new velocity [154]. The G-PSO population moves toward the global best position and once a particle gets trapped close to the global best solution, that particle reinitialises with a random velocity [154]. Consequently, the algorithm continues exploring the local search while the original PSO proceeds by circumventing them. In [155], an adaptive parameter setting of particle swarm optimization based on velocity information (APSO-VI) was proposed, the algorithm uses current velocities of the particle to adapt inertia weight with the goal of getting velocity near to the ideal velocity [155]. The idea of a decreasing velocity in the APSO-VI algorithm was introduced earlier in [156] to adapt inertia weight in a conversant particle swarm such that exploitation and exploration are regulated [156]. Authors in [142] proposed the reinitialization of velocity with regards to velocity clamping limit as given in the subsequent equation.

$$v_d^{k+1} = \begin{cases} rand \times v_{max}^d & if\ v_d^{k+1} = 0\ and\ rand \leq 0.5 \\ rand \times \left(-v_{max}^d\right) & if\ v_d^{k+1} = 0\ and\ rand > 0.5 \end{cases} \tag{5.8}$$

The expression reinitialises a single component since other parameters in the velocity vector might contain a good structure which would allow the particle to move towards the global best solution with v_d^{k+1} referring to a certain dimension d of the velocity vector, v_{max}^d the velocity clamping limit of dimension d, and $rand$ randomly produced from a uniform distribution ranging [0,1] [142]. For velocity update, the authors in [142] also proposed repulsion-based particle velocity update that improves global exploration capabilities and increases robustness by introducing repulsion between particles. It utilises an evolutionary state to adapt the equation based on the proximity of the most recent feasible solution and the modified velocity-update equation is as follows [142]:

$$v_i^{k+1} = ES_i^k v_i^k + c_1 rand_1^k\left(pbest_i^k - s_i^k\right) + c_2 rand_2^k\left(gbest^k - s_i^k\right) - ES_i^k\left(gbest^k - pbest_i^k\right) \tag{5.9}$$

Particle repulsion occurs based on two aspects, that is, the difference between the global best solution $gbest^k$ and personal best solution $pbest_i^k$, and the evolutionary state ES_i^k value [142]. Higher evolutionary state ES_i^k leads to low particle repulsion while lower evolutionary state ES_i^k results in higher repulsion experienced by particle [142]. The use of repulsion-based velocity-update was adopted in this work with MAPSO algorithm pseudocode presented in Appendix B.

5.4.4 Sensitivity analysis

Shi and Eberhart [76] set both acceleration coefficients to 2 and seen improvement in the algorithm performance whereas when altered the particle fly to infeasible solutions. As depicted in Figure 5-9, the acceleration coefficient combination ($c_1 = 2$ and $c_2 = 2$) managed to perform better and efficiently which agrees with [76]. It can be seen that $c_1 = 2$ and $c_2 = 2$ combination converges fast whereas $c_1 = 2.5$ and $c_2 = 1.0$ convergence rate was slow which resulted in more iterations required to explore search space. For $c_1 = 2.5$ and $c_2 = 1.0$ combination, the particle fails to reach target regions due to being trapped in infeasible region before travelling towards the optimal solution. The velocity clamping-limit sensitivity analysis demonstrated that as particles explore more search space, the ability of the particle to fly past optimum solution increases, as depicted in Figure 5-10. The figure illustrates that as the velocity clamping-limit increases, the likelihood of obtaining a more feasible solution rises, resulting in quick convergence and more efficient algorithm performance.

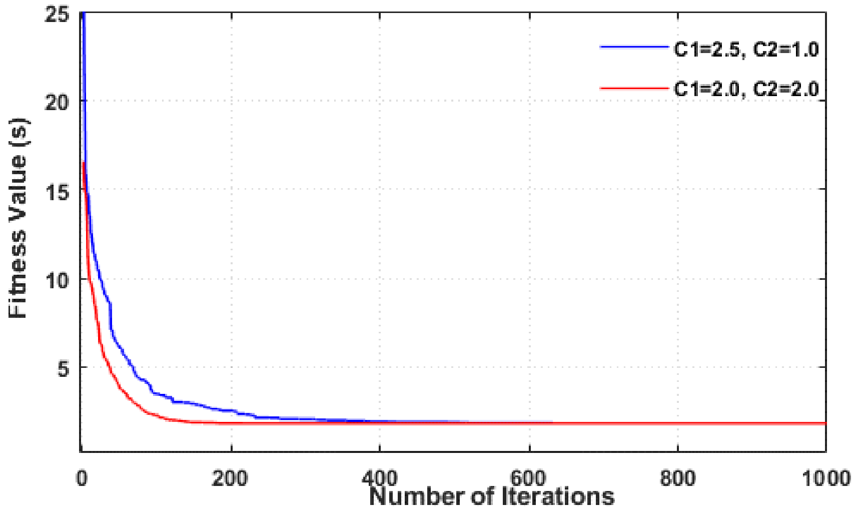

Figure 5-9: The effect of acceleration coefficients with respect to convergence

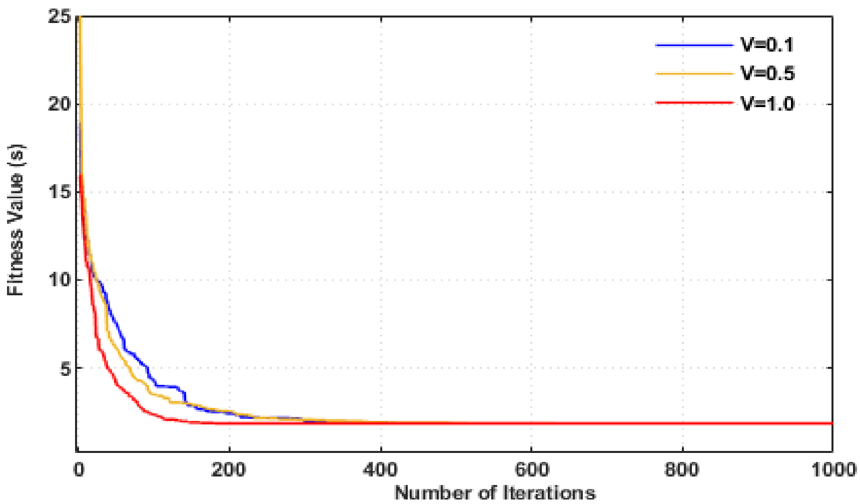

Figure 5-10: Velocity-clamping limit convergence curve

5.4.5 Comparison between MAPSO and other variants

In an attempt to overcome premature convergence in the PSO algorithm, Ref. [157] introduced a novel hybrid algorithm (PSO-DE) which integrates PSO with differential evolution (DE) to solve constraints by adopting a set of feasibility rules [157]. The PSO-DE algorithm provides better performance compared to modified differential evolution (MDE) [72] and differential evolution (DE) [57] hence, PSO-DE algorithm is utilised in this work for comparison purposes. The PSO algorithm with linearly decreasing inertia weight (PSO-LDIW) was proposed in [73], [76] to linearly decrease the weight over time. It was observed that PSO-LDIW algorithm convergence rate is slow toward global solution due to reduced inertia weight which results in difficulty leaving the local optimum [73]. Another variant that integrates PSO with random inertia weight (PSO-RIW) was implemented in [158] and chaotic inertia weight (PSO-CIW) was proposed in [159]. Different PSO variants range are presented in Appendix C-Table C.1. Figure 5-11 depicts convergence curves for MAPSO and other variants.

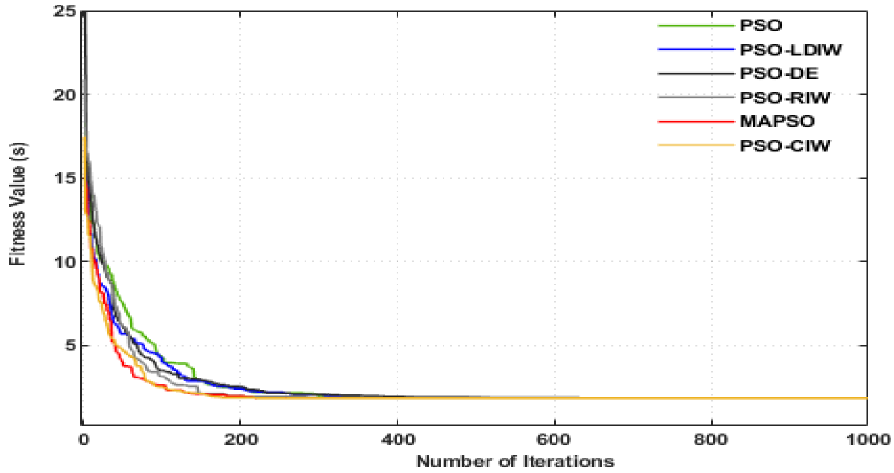

Figure 5-11: Convergence curves of MAPSO and other variants

MAPSO managed to outperform the original PSO, PSO-LDIW, PSO-RIW, and PSO-DE, as seen in Figure 5-11. Furthermore, MAPSO algorithm managed to attain the global optimum solution in the fewest iterations in comparison with other variants; this signifies the algorithms' ability to converge fast while avoiding premature convergence. Although MAPSO and PSO-CIW algorithm allowed particles to explore broader space with greater momentum, MAPSO performs better due to navigating the search space by means of evolutionary state whereas PSO-CIW navigates with respect to chaotic mapping which leads to stagnation. Variants such as PSO-LDIW, PSO-RIW, and PSO-DE failed to converge into the best global solution and were getting trapped in local optima. Other studies [157] found PSO-DE algorithm effective in solving protection coordination problem which disagrees with this work, as can be seen in Table 5-5, the algorithm yielded longer operational speed, and some relays were not selective which violates protection scheme principles.

Similarly, in [160] PSO-LDIW was compared with PSO-CIW which indicates a great difference between the algorithms, the study claimed that PSO-LDIW performs efficiently and robustly, is more stable with better global search capability than PSO-CIW which is contrasting with the results presented in this work. From Table 5-5 it can be seen that MAPSO generates better values of TMS and relay operating time which further proves the algorithms' superiority as compared to the previously proposed optimization techniques. The operating time is further reduced from 6.169 seconds to 4.331 seconds which signifies the effectiveness of the newly proposed algorithm. All overcurrent relays preserve selectivity and protection coordination is achieved in the distribution system. This means abnormalities are removed as soon as possible without affecting the healthy section.

Table 5-5: The sum of relay operating time and TMS values for each variant

Algorithms	Sum of TMS	Sum of operating time (s)
PSO-LDIW	4.52	8.603
PSO-DE	4.49	8.554
PSO-RIW	3.03	7.135
PSO-CIW	2.87	6.830
PSO	3.18	6.174
MAPSO	2.35	4.331

5.4 Testing of protection coordination

This section presents experimental performance results between downstream and upstream overcurrent relays. Analysis includes assessing grading margin, primary and backup operating time for each algorithm.

5.4.1 Protection coordination analysis for relay 1 and relay 3

Interestingly, the sequential operation of relays is adequate. The results computed by means of Matlab are substantiated with simulation model where the overcurrent relay time multiplier settings determined in the earlier section are inserted on the experimental model and simulation are executed. In this instance, GA parameters were evaluated on the draft interface and executed on the runtime interface to yield graphs presented below.

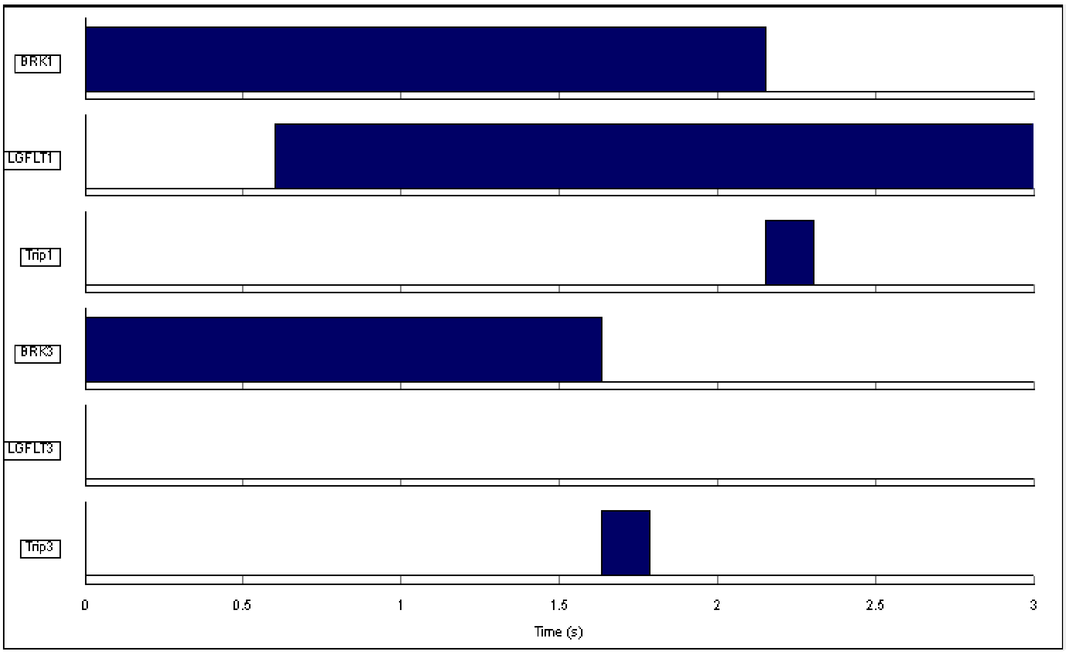

Figure 5-12: Performance analysis of GA on 11kV busbar

Figure 5-12 shows results for relay-1 and relay-3 validation with GA applied. As anticipated, it can be seen from the graph that when a fault denoted by LGFLT 1 occurs at 11kV busbar, a trip command is issued, which subsequently opens the breaker instantly on the signal detection. Relay-1 and relay-3 measured time of operation is 1.510 seconds and 1.015 seconds, respectively. Whereas the calculated operating time for relay-1 and relay-3 is 1.455 seconds and 0.959 seconds separately. The respective grading margins for calculated and measured operating time is 0.495 seconds and 0.496 seconds, which are slightly above the coordination time interval of 0.4. For PSO, relay-1 operated 1.337 seconds after a fault was detected and relay-3 operated 0.886 seconds later. Appropriate relay coordination is achieved with a grading margin of 0.451 seconds which is above the coordination time interval of 0.4 seconds. The calculated operating time for relay-1 and relay-3 is 1.334 seconds and 0.841 seconds. When dual simplex method parameters were inserted, the measured operating time of relay 3 is 1.160 seconds. On the other hand, relay 1 operates 1.560 seconds later. The relays operated as required with a grading margin of 0.4 seconds. However, relays' response time is longer than that of PSO and GA. Overall, the overcurrent relay performance demonstrated that PSO algorithm is most sensitive.

5.4.2 Performance analysis for relay 6, 7 and 11

Relay 6, 7, and 11 are incapacitated to verify protection coordination amongst them. A fault is transpiring at protection zone 11, followed by observations as to whether the upstream circuit breaker clears the fault. Shown in Figure 5-13 is the performance analysis graph for PSO when relay 7 and 11 fail to operate. It can be seen that breaker BRK 6 isolates the faulty section at 0.424 seconds, of which is 0.209 seconds later than the time breaker 7 should have operated and approximately 0.4 seconds later than the time breaker 11 should have opened. For GA, breaker 7 and breaker 11 were required to operate at 0.335 seconds and 0.122 seconds. However, malfunction transpired which resulted in circuit breakers failing to operate, as a result breaker 6 opens at 0.470 seconds to eradicate fault from the system. Dual simplex parameters were utilised of which resulted in breaker 6 opening at 0.472, which is approximately 0.25 seconds later than the time circuit breaker 7 should have opened and about 0.39 seconds later than the time breaker 5 should have operated. From the simulations indicated in Figure 5-13, relays 6, 7, and 11 operating times are calculated, and they preserve constraints set in the PSO algorithm. This substantiates that selectivity is achieved in the distribution systems. Additionally, relay 6 was sensitive enough to discern the presence of abnormalities in the system. Dual simplex and GA operating time is longer than PSO meaning the techniques do not react as quickly as possible when abnormalities exist.

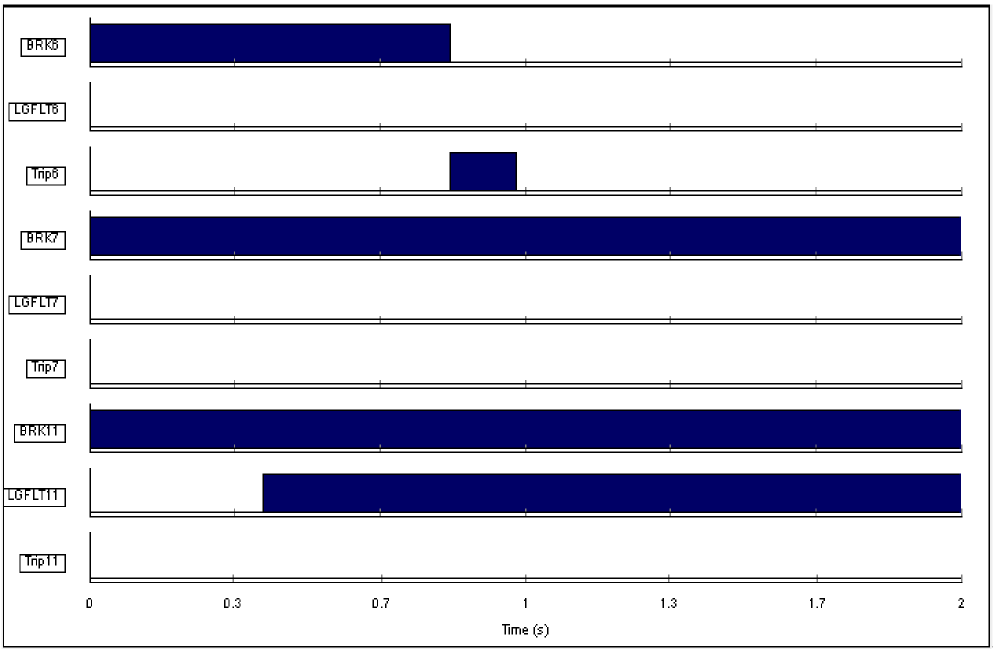

Figure 5-13: Coordination analysis for PSO algorithm

5.4.3 Testing protection coordination for relay 4 and relay 5

In the similar manner, the graph in Figure 5-14 depicts effective functioning of relay 4 with the time multiplier setting of 0.51 attained by means of dual simplex algorithm. Relay 4, and 5 are coordinated such that if maloperation occurs on the circuit breaker adjacent to the fault, the relays closer to the power source must operate. With downstream relay 5 defective, the upstream relay 4 opened, as shown below. For fault at F-5, i.e., when relay 5 malfunctions, relay 4 operates and opens the breaker in 1.039 seconds, which is 0.43 seconds later than relay-5, and they maintain constraints set in the dual simplex method while solving the linear programming problem. This shows that the optimal solution of the TMS of relays was obtained using dual simplex for the relays considered. Dual simplex algorithm managed to accomplish proper protection coordination between relays in the distribution scheme. However, the relay response time is much longer compared to other considered algorithms which violates one of protection principles to eliminate abnormalities from the system as quickly as possible. MAPSO algorithms yields the fastest relay operating time but the stipulated coordination time interval is not preserved.

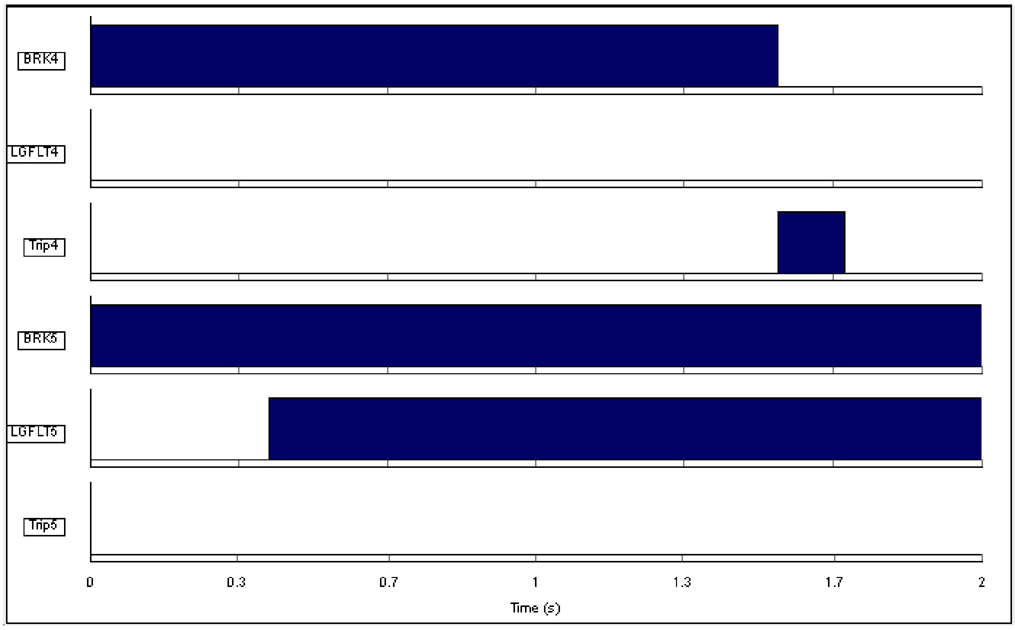

Figure 5-14: Performance analysis of the dual simplex method for relay 4 and 5

5.4.4 Protection coordination analysis for relay 9 and relay 10

To test system coordination for relay 9 and 10, the relays are effectuated to malfunction by disabling the trip command that governs the circuit breaker to open for shortcomings on its protection zone. The simulations are conducted by permitting fault occurrence and observe upstream relays' behaviour. Subsequent is the simulation result of relay 10 maloperation; the relay is configured to utilise GA parameters. Operating time for relay 10 while utilising TMS of 0.05 is calculated to be 0.162 seconds. It is observable that fault at zone 10 occurred at 0.399 seconds. As anticipated, breaker 9 opens at 0.287 seconds and isolates faulty apparatus to eliminate further damage to the distribution system.

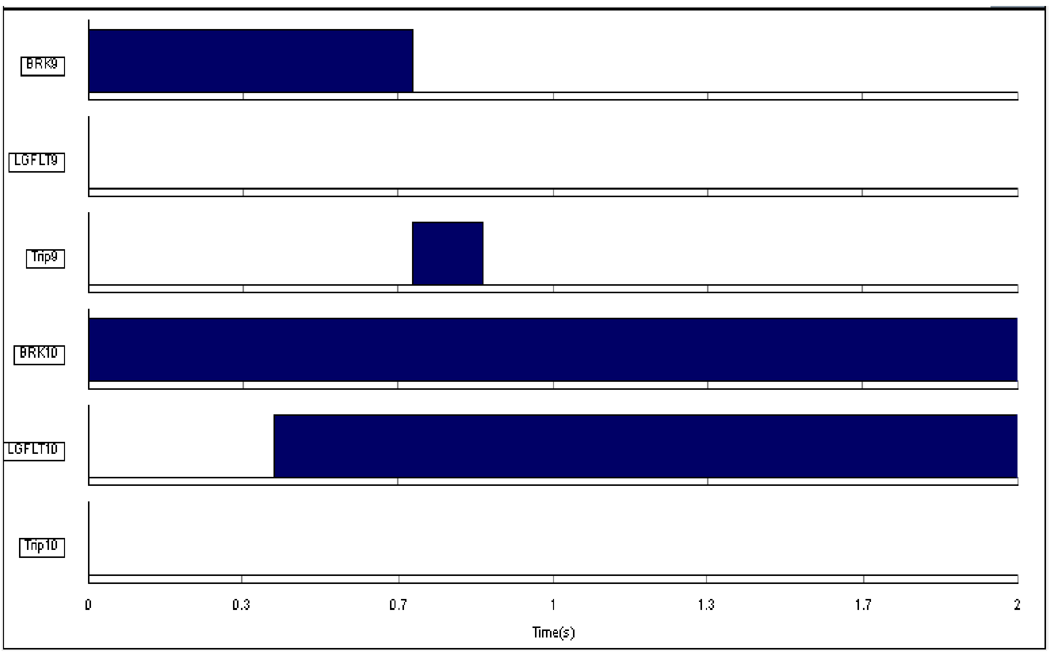

Figure 5-15: Protection coordination for GA on relay-9 and 10

Table 5-6 demonstrates the overall operating times measured during simulations for all primary and backup pairs on the network. It can be seen that PSO provides a slightly smaller operating time for primary relays and backup relays compared to GA. Dual simplex approach constitute the highest overall operating times. Although, PSO algorithm managed to outperform GA and dual simplex algorithms, MAPSO produce a further reduced relay operating time.

Table 5-6: Measured operating times for optimization techniques

	MAPSO		**PSO**		**GA**		**Dual Simplex**	
	$t_m(s)$	$t_b(s)$	$t_m(s)$	$t_b(s)$	$t_m(s)$	$t_b(s)$	$t_m(s)$	$t_b(s)$
3-1	0.588	0.882	0.886	1.337	1.015	1.510	1.160	1.560
3-2	0.588	0.824	0.886	1.384	1.015	1.501	1.160	1.562
4-3	0.384	0.588	0.706	0.886	0.917	1.015	1.039	1.160
5-4	0.375	0.384	0.525	0.706	0.563	0.917	0.563	1.039
6-3	0.336	0.588	0.392	0.886	0.594	1.015	0.672	1.160
7-6	0.293	0.336	0.305	0.392	0.310	0.594	0.345	0.672
8-5	0.278	0.375	0.258	0.525	0.298	0.563	0.338	0.563
9-8	0.205	0.278	0.212	0.258	0.223	0.298	0.302	0.338
8-7	0.278	0.293	0.258	0.305	0.298	0.310	0.338	0.345
10-9	0.123	0.205	0.126	0.221	0.162	0.223	0.170	0.302
11-8	0.043	0.278	0.043	0.258	0.122	0.298	0.208	0.338
Total	3.491	5.031	4.127	7.158	4.996	8.239	5.655	8.339

Based on the simulation results presented in the above figures and Table 5-6, the following conclusions are drawn:

a) The time of operation for both main and backup relays obtained by means of dual simplex and GA are slower compared to MAPSO and PSO algorithms.

b) The time multiplier settings are minimised and,

c) The sum of the main relays' operating time has been minimised from 8.339 seconds to 8.239 seconds, and 7.158 seconds, and further minimised to 5.031 seconds.

5.5 The effects of multiple power sources on protective system requirements

The performance of the proposed methods is also verified on the radial network. In this instance, the proposed methodologies are adopted to determine optimal TMS values of the radial network depicted in Figure 5-16. The test network consists of similar parameters as the distribution system in Figure 5-1; however, one power source was removed in order to perform a comparative study with respect to protective relaying qualities. As previously discussed in Chapter 2, both sensitivity and selectivity form part of the stringent protection requirements; hence, these characteristics must be maintained throughout the protection system. Accordingly, the effect of multiple power sources on distribution system sensitivity, selectivity, reliability, and speed was investigated in this study. To maintain sensitivity in distribution systems, the absolute value of coordination constraints, i.e., discrimination time should be minimised by the objective function [75]. According to [107], it is impossible to obtain selectivity for all the possible system configurations with multiple equivalent sources. The author further states that due to the similarity of currents seen by relays, it is impossible to attain selectivity for the system simultaneously. However, this was proven otherwise, the system presented in the previous section consists of two power sources with equivalent parameters and selectivity was accomplished as demonstrated on runtime graphs above. Protective relays were able to eradicate abnormalities speedily with the minimum interruption of system equipment. Studies show that radial schemes are more sensitive in comparison with systems made up of two or more sources [57]. This concept will be investigated in this study along with fitness function values.

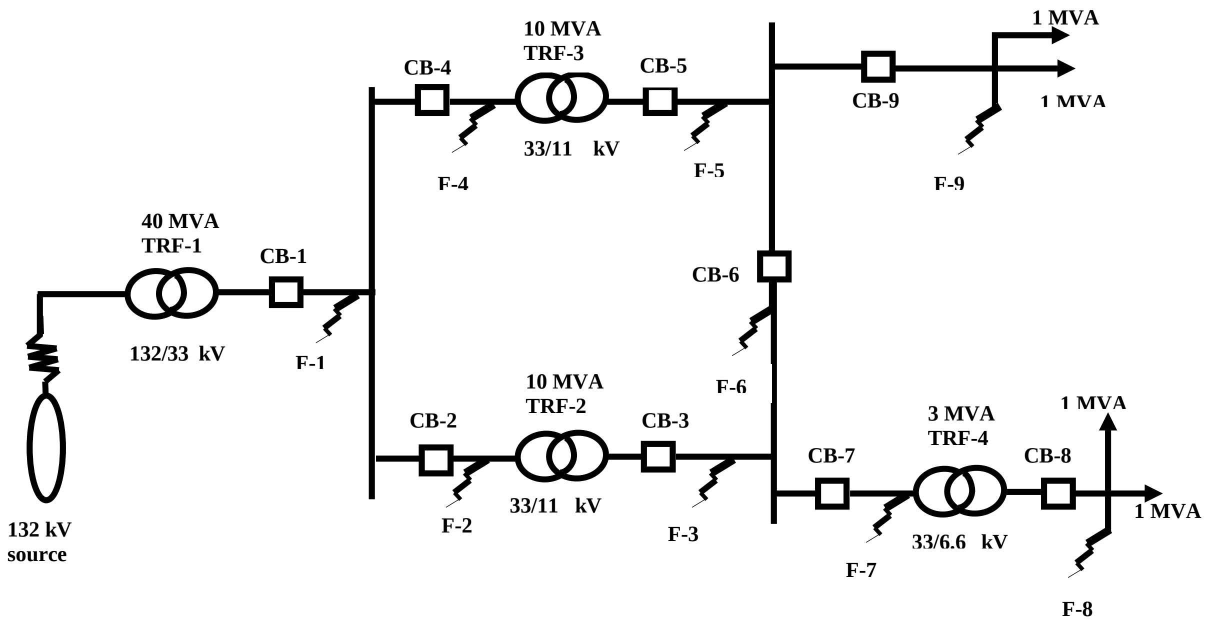

Figure 5-16: System configuration for case 2

In this case study, the simulation is similarly made of 1000 iterations, swarm size of 100 and population size of 100. As seen from the aforementioned section, GA and PSO algorithm converges to fitness values of 3.554 seconds and 3.175 seconds, respectively. Whereas, in a radial distribution network, the function converges faster, i.e., GA and PSO yield fitness values of 2.287 seconds and 2.066 seconds, separately. Figure 5-17 depicts faster convergence characteristics of PSO. That is, in both instances, the red curve is quicker to reach its optimal value than the blue curve. With a smaller number of iterations, the gap between the two algorithms could have been bigger.

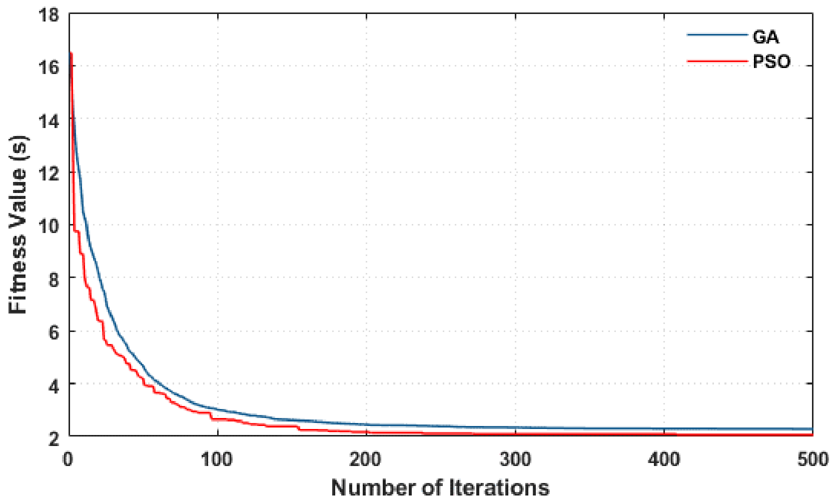

Figure 5-17: Convergence of GA and PSO

In both cases, PSO provides TMS values for overcurrent relay that are slightly smaller than GA and dual simplex parameters, see Table 5-7. The comparative study demonstrates PSO algorithm effectiveness and efficiency in resolving constrained optimization problems and particularly with respect of convergence speed. Furthermore, the study illustrates that PSO manages to attain best optimum solution at least iterations comparing to other techniques in both cases. With regards to result quality, PSO performed robustly and demonstrated the ability to avoid premature convergence. In contrast, GA kept on learning improved solutions until converging into the final iteration and in spite of GA faster convergence at the beginning of the search. As evidenced by its poorer performance in comparison to PSO, the likelihood of converging prematurely at the starting of the algorithm is still an issue to be investigated. Due to the time requirement of optimum overcurrent relays coordination, the optimization technique needs to discover the best fitness value to eliminate faults promptly. Through the comparison between the GA and PSO algorithm on the optimal overcurrent relays coordination the PSO is much faster than the GA, especially when the size of the distribution system decreases. Therefore, the PSO is much better than the GA and dual simplex algorithm.

Interestingly, the tabulated TMS parameters are within the stipulated interval and the optimum solution was attained through the utilisation of evolutionary algorithms and dual simplex method. As previously stated, the aim is to give adequate time for the relays and circuit breakers near to the fault to eradicate the defects from the network before the backup relay connected with the adjacent segment to the source opens its circuit breaker. Therefore, the sum of primary relays' operational time is minimised to mitigate damages affiliated to abnormalities in the system. It was substantiated in Case 1 above that the objective function was minimized from 8.339 seconds to 8.239 seconds and further minimised to 7.158 seconds. Similarly, Case 2 managed to minimise the objective function from 5.023 seconds to 4.834 seconds and further minimised to 3.685 seconds. In terms of protection coordination, the relays for both instances operate accordingly with coordination time interval (CTI) ≥ 0.4. However, relay response when fault transpires is much longer for GA and dual simplex algorithm, which violates one of the protection principles to isolate the fault speedily.

Table 5-7: Comparison of the time multiplier values

	Case 1			**Case 2**		
	GA	**PSO**	**Dual Simplex**	**GA**	**PSO**	**Dual Simplex**
TMS 1	0.72	0.66	0.75	0.54	0.49	0.57
TMS 2	0.69	0.57	0.73	0.48	0.36	0.51
TMS 3	0.57	0.50	0.69	0.45	0.30	0.47
TMS 4	0.45	0.46	0.51	0.22	0.25	0.33
TMS 5	0.30	0.28	0.30	0.19	0.21	0.22
TMS 6	0.22	0.21	0.25	0.14	0.17	0.19
TMS 7	0.18	0.17	0.19	0.13	0.11	0.17
TMS 8	0.15	0.13	0.17	0.11	0.15	0.18
TMS 9	0.13	0.11	0.15	0.02	0.02	0.07
TMS 10	0.09	0.07	0.09	-	-	-
TMS 11	0.05	0.02	0.13	-	-	-
$\sum TMS$	3.55	3.18	3.96	2.28	2.06	2.71

5.5.1 Protection coordination analysis for Case 2

Considering the network shown in Figure 5-16, downstream and upstream relays are arranged to operate in the following tripping sequence R_9-R_8-R_7-R_6-R_5-R_4-R_3-R_2-R_1. For a radial system, the coordination study is performed for the distribution feeder relays with upstream relays and breakers. Failure of the primary and second breaker to function, the breaker near the power source should operate and open. Consequently, the simulation study was conducted to observe systems' behaviour when abnormalities exist. The plots were observed on the runtime interface and the relays operating times were measured and compared with the theoretical results.

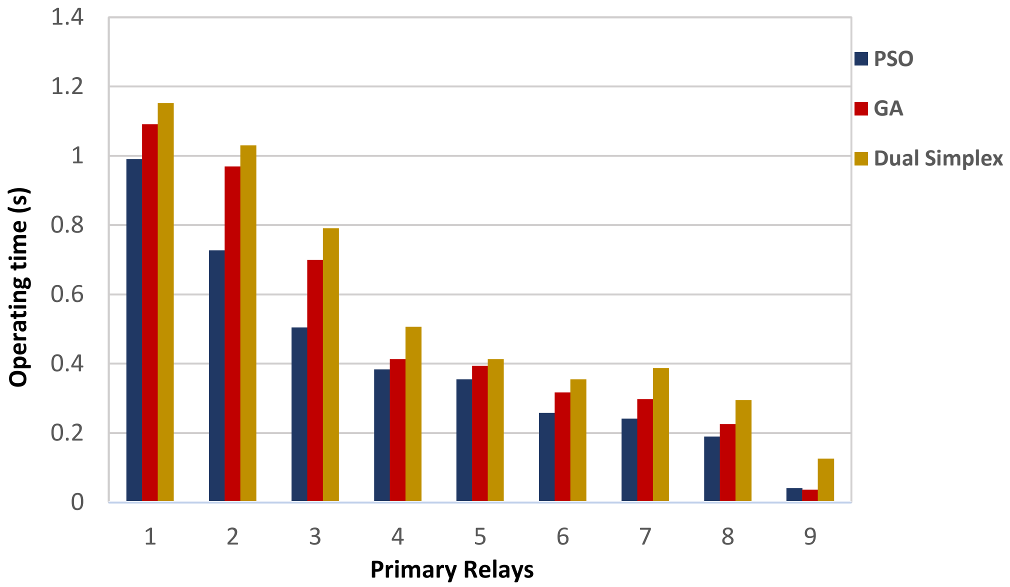

Figure 5-18:Comparison of the primary relay operating time for Case 2

In Figure 5-18, the bar charts of the primary relays' operating time display that particle swarm algorithm managed to minimise operating time further and converges to the global optima with least iterations and therefore performed proficiently than genetic algorithms and dual simplex method. The measured time of operation during simulations is plotted against the respective overcurrent relay. From the results attained, it is clear that the relays time of operation obtained by means of PSO is less than that of GA and dual simplex. Moreover, it was observed during simulations that as the fault type changed, the operational time remained the same, and when the fault was more severe, the relay response time was faster.

5.5.2 Analysis of Protection System Requirements

System reliability was achieved in both case studies, as seen above; the relays operated when abnormalities transpired and refrained from operating at other times. Similarly, sensitivity which is characterised by the detection of faults irrespective of how incipient they may be was preserved. This basic design requirement is mainly affected by changes in pickup currents; lower relay settings result in the protection scheme being too sensitive. In both case studies, the sum of relay operating time (i.e., speed of operation) for PSO was optimized and the relays cleared faults in the shortest time possible, as seen in Table 5-7. Selectivity was also achieved in the second case study, with only faulty equipment isolated from the system. Accordingly, it can be stated that the goal of overcurrent relay coordination problem was attained by ensuring the system is selective with maximise system sensitivity and operational speed. Nonetheless, it is worth noting that these parameters are not independent, as two of them are more likely to decrease when the other one increases [116], [161]. Table 5-8 shows the performance comparison of PSO, GA, and dual simplex algorithms.

Table 5-8: Performance comparison of PSO, GA, and Dual simplex method

	PSO	**GA**	**Dual Simplex**
Speed (relay time of operation)	Faster	Fast	Slower
Selectivity (protection coordination)	Maintains selectivity	Preserves selectivity	Sustains selectivity
Search speed	Fast (Matlab based)	Slow due to handling larger data (Matlab based)	Slower (Matlab based)
Population diversity	Mainly via local and global region	Local region	Based on initial relay settings

5.6 Summary

In this chapter, optimization techniques, namely, Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and dual simplex algorithm were proposed to solve the protection coordination problem. The comparative study conducted demonstrated the robustness of PSO algorithm in solving and handling a constrained optimization problem. The findings depict that PSO algorithm managed to attain global optimal solution in the least iterations in comparison with other considered algorithms; this substantiates algorithms' superiority in terms of convergence speed. Additionally, PSO performed efficiently and robustly and faster than GA, especially when the size of the distribution system decreases. Therefore, the PSO technique is much better than GA and dual simplex method. The PSO algorithm results were further minimised by modified adaptive particle swarm algorithm (MAPSO) algorithm which make the original PSO parameters adaptive. From the computed time multiplier settings values obtained by means of the proposed algorithms, the plots were generated on RTDS to demonstrate systems' response when abnormalities occur on different protection zones. The anticipated operation of relays in explained in theory was verified, it was seen that higher fault current levels results in reduced relay operating times. The system was properly coordinated and protected against asymmetrical faults.

CHAPTER 6

6 Conclusion and Recommendations

This chapter summarizes the conclusions provided in each chapter as well as recommendations and future work. The chapter entails an overview of the main conclusion based on the results presented throughout the dissertation (Chapter 6.1) and it provides directions for future work (Chapter 6.2).

6.1 Conclusion

As the demand for electricity continues to rise, distribution systems are taking a strain and becoming more complex with increasing loads, voltages, and currents. Additionally, operational challenges such as protection miscoordination which give rise to a higher percentage of power network equipment damage and customer service interruption caused by breakdowns and faults in the distribution feeders as overhead power systems are subjected to either temporary or permanent faults. With proper protection coordination and optimised overcurrent relay settings as well as maximised selectivity, these challenges can be mitigated. This work entailed modelling and simulating overcurrent protection scheme, studying electricity distribution systems, and developing system model based on relevant literature. The protection coordination of overcurrent relays performed by means of conventional time grading method presented satisfactory results, but not global solutions, and the process was laborious. Due to drawbacks presented by conventional optimization techniques, evolutionary algorithms, that is, particle swarm optimization and genetic algorithms, were proposed to solve overcurrent coordination problems in the distribution system. However, setting evolutionary algorithms control parameters to obtain optimal overcurrent relay settings is a long-standing issue. As a result, the tunning of algorithms' control parameters was conducted and the plots depicting the behaviour of algorithms with respect to individual parameter was presented.

The parametric sensitivity study conducted in this research work found that evolutionary algorithms control parameters certainly influence the behaviour of overcurrent relays. The altering of one parameter at a time while keeping others constant was very useful in finding parameters responsible for poor protection selectivity and speed of operation. The experimental results show a reduction in computational efforts and improvement in PSO algorithm convergence. The comparison of PSO, dual simplex method, and GA algorithms depicts that particle swarm optimizer converges faster than genetic algorithms and dual simplex. Although PSO algorithm yield optimum solutions, further modifications were done by introducing PSO variants and making the algorithms' parameters adaptive. The MAPSO algorithm and other variants were proposed to further improve operational speed and system selectivity. The comparative study verified the efficiency and effectiveness of MAPSO in solving overcurrent coordination problems. Protection coordination of overcurrent relay was verified on the distribution network and modelled using RTDS software relays to test proper sequential relay operation during abnormalities. The anticipated operation of relays in explained in theory was verified, it was seen that higher fault current levels results in reduced relay operating times. The findings were discussed and analysed to substantiate existing theories under normal and faulty conditions. System selectivity, reliability, and sensitivity was achieved on all distribution models.

6.2 Recommendations for future work

The work undertaken in this dissertation agrees with theories presented in the literature and the overall results were proved successful; however, it is not limited to the scope covered. Further modifications and studies can be carried out to optimise protection coordination using the same electrical power systems network, as suggested below:

- An extensive sensitivity analysis to gain more insight into the impact of control parameters on PSO and GA algorithms performance can be conducted. This work evaluated each parameter individually which aided in understanding the behaviour of algorithms with regards to discrete parameter; nevertheless, studying a combination of different control parameters simultaneously might help to glean more information on the performance of PSO and GA algorithms.
- Only the impact of population size, crossover rate, and mutation probability on the performance of genetic algorithms were studied which did not yield better results in comparison with particle swarm optimization. Further studies can be conducted to make genetic operators, that is, selection, crossover, and mutation adaptive to circumvent premature convergence in local optima. Moreover, other variants can be used to validate the performance of genetic algorithms by applying them to benchmark problems and perform a comparative study.
- Further recommendations on the application of optimization techniques include the formulation of the optimization problem as a nonlinear problem where both time multiplier settings and pick-up currents are unknown.
- Although the MAPSO algorithm managed to perform effectively and proved its superiority with regards to convergence speed, in some instances, the MAPSO algorithm failed to maintain the stipulated coordination time interval when compared to other variants and algorithms. The performance of MAPSO could improve by incorporating other optimization techniques to further enhance robustness and efficiency.
- A major concern encountered when implementing the proposed algorithms was the computational effort which could have been reduced by using parallel computing. Parallel computing permits the algorithm to execute multiple calculations concurrently, hence, decrease simulation run time.

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APPENDICES

A. Network Specifications

Table A.1: system specifications

Voltage sources parameters			**Load Parameters**		
Voltage	132 kV			Load-1	Load-2
Frequency	60 Hz		P (*MW*)	2.85	0.95
MVA	120 MVA		Q (*MVAR*)	2.85	0.95
Transformer data			S (*MVA*)	1	1
TRF-1	132/11 kV	30 MVA	PF	0.95	0.95
TRF-2	132/11 kV	30 MVA	Frequency	50 Hz	50 Hz
TRF-3	11/6.6 kV	3 MVA			

B. The pseudocode of the MAPSO algorithm

1. Start.
2. Initialise the population.
3. Randomly generate s_i^0 value.
4. Set $v_i^0 = 0$ and $s_i^0 = pbest_i^0$.
5. Determine the value of $gbest^0$.
6. **Let** number of iterations $k = 1$.

   For each particle i

           Determine evolutionary state ES_i^k.

           Update the acceleration coefficients c_1^k and c_2^k.

           Update particles' velocity v_i^{k+1}.

           Determine the fitness function $f(x_i^k)$

       If $f(x_i^k) < f(pbest_i^k)$ **then**

           $pbest_i^k = x_i^k$

         elseif $f(x_i^k) < f(gbest^k)$ **then**

             $gbest^k = x_i^k$

       End If

       If $v_d^{k+1} = 0$

         Reinitialise the particle velocity

     End If

   End For

7. $k = k + 1$
8. Repeat step (6)
9. $k = iter_{max}$

10. Stop.

C. Range of considered variants

Table C.1: Inertia weight ranges used

PSO variants	Inertia weight range
PSO-LDIW [73], [76]	0.4 – 0.9
PSO-RIW [158]	0.5 – 1.0
PSO-CIW [159]	0.0 – 1.0