

FAULT LOCATION OPTIMISATION USING GOLD RUSH OPTIMISER IN GEOTHERMAL HYBRID POWER PLANT

Sushma Verma^{1,*}, Provas Kumar Roy², Barun Mandal² and Indranil Mukherjee³

Received: December 27, 2024; Revised: March 03, 2025; Accepted: April 08, 2025

Abstract

With fossil fuel still happening to be the major source of input to power generation globally, the environmental complications caused by it are becoming more conspicuous. This is particularly reflected in the huge amount of CO₂ emissions taking place globally due to the high percentage use of fossil fuel. In this context, renewable energy combined with conventional energy in the form of hybrid energy offers a sustainable and environment friendly solution. But, in cases where the renewable input is from the core of the earth in the form of Geothermal energy, proper optimisation of it combined with conventional source becomes an important aspect. The presented paper focusses on optimisation technique using a novel algorithm “Gold Rush Optimiser” (GRO). The simulation of the hybrid power system has been done in MATLAB simulink. The study considers a maximum transmission line length of 300 km and a minimum absolute percentage error of 0.0001 for the stated fault location. The results obtained with the proposed algorithm are highly accurate compared to other optimisation techniques. It efficiently determines locations with remarkable precision and speed, owing to its faster convergence rate. GRO’s potential in fault location optimisation keeps expanding as power grids get smarter and more decentralized.

Keywords: Fault Location Optimization; Geothermal Power Plant; Gold Rush Optimiser; Hybrid Power System; Simulink; Transmission Line

Introduction

Major production of electrical power in the world is done by coal. The reserves of coal are estimated not to last long. The entire world is looking for alternatives in future. In the future, coal usage would not be suitable for inhabitable climate. The existing challenge for mankind is to develop environmental friendly competitive alternatives as quickly as

possible. Production of power from geothermal source is one of the highly sought out options in this context regarding production of green energy. These plants generate electricity by using geothermal energy. The boiler in a coal plant is replaced by the heat energy entrapped within the earth’s mantle. Sharmin *et al.*, in his study, has explained that the

¹ Department of Electrical Engineering, Techno International Newtown, Kolkata 700157, India. Email: sushsehdev@yahoo.com*

² Department of Electrical Engineering, Kalyani Government Engineering College, Nadia 741235, West Bengal, India. Email: roy_provas@yahoo.com; barunelectrical@gmail.com

³ Department of Civil Engineering, Aliah University, Kolkata, India. Email: drindranilmukherjee.ce@aliah.ac.in

* Corresponding author

DOI: <https://doi.org/10.55766/sujst8026>

Suranaree J. Sci. Technol. 32(5):010365(1-12)

increased energy demand can be sustainably met by using geothermal sources (Sharmin *et al.*, 2023). Energy extracted from geothermal sources has many important applications in various fields (Gudmundsson, 1988; Sharmin *et al.*, 2023). Energy authorities have also considered the usage of geothermal energy to generate power. This type of use is known as indirect utilisation of geothermal energy, as it allows the heat source to be converted indirectly into electrical power.

As per Claudiu Costea (Claudiu, 2009), Geothermal energy has shown itself to be dependable, affordable, sustainable, and ecologically benign. According to research, combining geothermal energy with photovoltaic (PV) or solar thermal technology improves total efficiency (Li *et al.*, 2020; Wainaina Kariuki *et al.*, 2025). When geothermal output varies, wind energy can be used to supplement it by supplying extra electricity and boosting system efficiency (Jalilinasrabad *et al.*, 2013; Bamisile *et al.*, 2022).

Based on the energy supply and power demand, individual geothermal power plants can range in size from 100 kW to 100 MW. In addition to national grid uses, the technology can be used for mini-grid and rural electrification. When compared to traditional fossil fuel and hydroelectric plants, geothermal power plants have a number of unique advantages.

According to Gupta *et al.* (Gupta and Roy, 2007), in addition to lowering infrastructure expenses, geothermal plants minimize environmental pollution because they don't require fuel burning. As geothermal wells and power plants need to be built simultaneously, the initial cost of geothermal power plants is higher. Author Hari Om *et al.* (Om *et al.*, 2025) states geothermal energy, as a promising renewable resource due to bare minimum emission of carbon dioxide, non dependence on weather which harnesses the thermal energy of the earth (Svalova, 2018).

Renewable energy sources, such as solar, wind, hydropower, bioenergy, ocean, and geothermal energy are regarded as clean and green energy sources since they are naturally regenerated more quickly than they are used (Owusu and Asumadu, 2016). Fossil fuels' carbon footprint and market volatility make them unsustainable for forthcoming energy needs, the world is aiming for carbon neutrality by 2050-2070 (Chen *et al.*, 2022; Wang *et al.*, 2022). Around 830 million tons of carbon dioxide is emitted every year by conventional sources (Mosca *et al.*, 2020; Diaz *et al.*, 2022).

Looking into the advantages of geothermal sources, this paper also explores the probable advantages of this source in conjunction with

conventional source. Although there are some disadvantages, which prevent their broad usage, such as initial cost of setting the plant, geothermal resources are generally found in areas that are tectonically active, but they are not found everywhere. Skilled human resources is required for operation and maintenance of a geothermal plant, which again imposes certain restrictions. The novelty of the work is emphasized by the fact that the paper has made an attempt to categorically report on the possible optimisation of geothermal with other conventional sources and while comparing the optimisation results with other optimisation techniques for varied combinations.

The connection between the geothermal source and conventional source is done by a long transmission line. Transmission lines are most vulnerable to diverse kinds of faults as they ply openly in the atmosphere. However, the output of the system reduces due to these faults.

For efficient and smooth functioning of a power system network, quick location of fault is very important for mending and repairing of lines so that the system operation can be restored quickly. Researchers and industry persons have carried out varied studies for the design of an efficient and reliable power system. Their studies are mainly based on quick and accurate identification of transmission line defects. The researchers have studied finding accurate location of fault points (Gaur *et al.*, 2022; Liang *et al.*, 2022; Moradzadeh *et al.*, 2022; Rezaei *et al.*, 2022; Xie *et al.*, 2022).

Different methods exist for detection of fault location points. These methods can be described as follows:

I. Impedance measurement based method. In this method, the apparent impedance measured by a relay or fault locator is used to estimate the distance to a fault on a transmission line (Dalcastagne and Zimath, 2008; Hashim *et al.*, 2017; Dzienis *et al.*, 2015).

II. Traveling waves rooted approach. It is an advanced technique used to determine the exact location of a fault on a transmission line by the analysis of electromagnetic wave which is generated on occurrence of fault (Lei *et al.*, 2015; Abeid *et al.*, 2017; Naidu and Pradhan, 2018; Anane *et al.*, 2021; Mousaviyan *et al.*, 2022).

III. Higher frequency constituents of potentials and amperes based approaches caused by symmetrical and unsymmetrical faults on transmission line, called as faults based methods (Mardiana *et al.*, 2010; Huynh *et al.*, 2019).

IV. Approaches rooted on Intelligent retrieval techniques like Artificial Neural Networks (ANN), machine learning (Voutsinas *et al.*, 2023) support vector regression (Amroune, 2022), genetic

algorithm (GA) (Geneid *et al.*, 2022), deep learning etc (Chaitanya *et al.*, 2016; Jain and Moses, 2016; Saravanan and Rathinam, 2012; França *et al.*, 2022; Fahim *et al.*, 2021).

V. Approaches based on fuzzy logic systems (Jiao and Wu, 2018; Tabari and Sadeh, 2022).

VI. Wavelet analysis techniques based approaches (Jimenez *et al.*, 2021; Ahmadipour *et al.*, 2022)

VII. The study conducted by Liu *et al.* (Liu *et al.*, 2023) thoroughly examines transmission line modeling frameworks for fault location, including lumped/distributed parameter models in the time domain mode, reports a maximum error for 4.1339% for A-G (with RL method) and 0.017% for A-G fault (symmetry method).

VIII. The Adaptive Network-Based Fuzzy Inference System (ANFIS), a fuzzy expert system and Artificial neural network (ANN), is suggested in the study by Mustari *et al.* (Mustari *et al.*, 2019) and reports a maximum error of 1.5%.

IX. The study conducted by Lavend *et al.* (Maner and Lavand, 2018) offers a fault location technique when both terminals have access to disturbance fault recorded data. This study reports greatest fault location error of 1%.

X. The study by Ahmed *et al.* (Ahmed *et al.*, 2017) uses the Teaching Learning Based Optimisation (TLBO) strategy to estimate the location of faults in two terminal transmission lines. The study reports an error of 0.04% for A-G fault with a fault resistance of 1 ohm for a fault occurring at 150 km and 0.044% for AB-G fault at 50 km using GA approach.

XI. In the study conducted by Rao *et al.* (Ankamma and Bizuayehu *et al.*, 2015). A novel method for locating faults on electricity transmission lines is presented in this research. Utilizing the phasor readings at one end of the line, this method makes use of the current advantages of digital technology and numerical relaying, which may be used for offline analysis. With this method, precise fault distance position is obtained after one cycle from the fault's onset and only the end of the data is used. The study reports an error of 0.8234% for a line to ground fault with a fault resistance of 84 ohm at a location of 18 km.

In this regard, optimisation of fault point is studied by many researchers through out the world. Numerous optimisation strategies have been created to increase the accuracy of fault location, particularly in intricate and expansive power systems. The most popular optimisation methods for fault location are as follows: GA uses selection, crossover, and mutation to evolve a population of solutions in order to optimise fault location, drawing inspiration from natural selection (Javad, 2012).

PSO models fault location as a swarm intelligence problem in which particles (solutions) move according to the group's best-known position and their best experience (Ghazizadeh and Ghanbari, 2017), Artificial Bee Colony (ABC) Optimisation mimics the foraging behavior of bees, as bees examine numerous potential solutions to select the optimal fault position (Anh and Matthew, 2020).

Over the previous few decades, several approaches for optimisation have been created to solve the difficulties in optimisation (Zhang *et al.*, 2022; Swelem *et al.*, 2022). The results for lowering the weight of the cantilever beam with GRO are noticeably better than those from earlier studies when taking into consideration the earlier research and the various techniques utilized to lower the cost function (cantilever beam) (Sarjamei *et al.*, 2021). Designing a three-bar truss, a tension/compression spring, a welded beam, a pressure vessel, and a rolling element bearing is also performed using GRO (Lyu *et al.*, 2024).

Looking into the present scenario, the optimisation issue has become quite significant with the increase of populace and factory expansions.

Mainly optimisation techniques are classified into stochastic and metaheuristic. The word "meta" refers to a higher level that performs better than simple heuristics. The exchange of local and global search results is used by the metaheuristic algorithm. Diversification (exploration) and intensification (exploitation) are the two main components of any metaheuristic algorithm (Gandomi *et al.*, 2013).

Advanced artificial bee colony (ABC) techniques, such as the Chaos ABC algorithm and the Chaos particle swarm optimisation (PSO)-ABC algorithm, are used to obtain precise parameter and current estimation at both transmission line terminals. These are improved versions intended to increase exploitation capability, which will result in higher convergence values and fewer iterations. The proposal is used to locate faults on the transmission line at several places, including three-line (L-L-L), three-line to-ground (L-L-L-G), two-line (L-L), two-line to-ground (L-L-G), and line-to-ground (L-G) (Huynh and Ho, 2024).

The humming bird based algorithm called Artificial Humming Bird algorithm (AHA) is implemented to optimise the fault location point in transmission line having a length of 300 km with system voltage of 400kv at different spans for various faults such as line to ground, double line to ground (Verma *et al.*, 2024).

Soft computing techniques are also evolving across various engineering domains such as performance assessment of the two metaheuristic

techniques and their Hybrid for power system stability enhancement with Photovoltaic Static Compensator (PV-STATCOM) by Rajeev Kumar *et al.* (Kumar *et al.*, 2022): provides a thorough analysis of two metaheuristic swarm-based optimisation algorithms: Bacterial Foraging Optimisation Algorithm (BFOA) and Particle Swarm Optimization (PSO), along with their hybrid (PSO-BFOA) approach.

The goal of the study is to reduce power fluctuations in a four-generator, two-area system that is connected to a sizable photovoltaic (PV) farm. To improve system stability in situations where solar power generation is not possible, the PV plant functions as a Static Synchronous Compensator (PV-STATCOM). The results of the study show that the hybrid PSO-BFOA optimiser successfully dampens power system oscillations and enhances overall stability by outperforming the separate PSO and BFOA algorithms in terms of convergence speed and solution quality. This proves the enhanced capability of metaheuristic algorithms.

The capacity of a search algorithm to find the distribution of different solutions inside distinct search space regions is referred to as exploration. Exploitation, however, emphasizes the notion of strengthening the search procedure throughout the potential areas of the solution space in order to find the best answers or improve the ones that are already there. Consequently, the empirical testing has shown a strong correlation between the convergence rate and the exploitation-exploration ability of the particular search strategy. In addition to increasing the likelihood of becoming trapped in local optima, exploitation mechanisms are well known for accelerating convergence toward a global optimum.

Previous studies have reported significant percentage errors in fault location within power systems. These inaccuracies highlight the limitations of existing fault detection methods. To overcome this challenge, the present study employs the novel Gold Rush Optimiser (GRO) algorithm, which effectively minimizes fault location errors in the hybrid power system, offering a more precise and reliable solution. Gold Rush Optimiser employs migration, mining, and collaboration strategies to update the positions of search agents. The Gold Rush Optimisation (GRO) algorithm imitates the actions of gold prospectors in their quest for riches in order to identify flaws in a transmission line. Its adaptive techniques increase precision and cuts down on fault detection time and expense.

Proposed Methodology

The primary objective of this research is to simulate a hybrid power system integrating conventional and geothermal energy sources and subsequently, to accurately identify fault locations within the system. To address the challenge of precise fault detection, a simulink model of the hybrid power system is developed using MATLAB, as illustrated in Figure 1.

Based on traveling wave theory, a fitness function is formulated to minimize the error in fault location, as detailed in the fitness function section. The voltage differential at the fault location should be zero when observed from both the sending and receiving ends.

The fault location is optimised using the Gold Rush Optimiser (GRO).

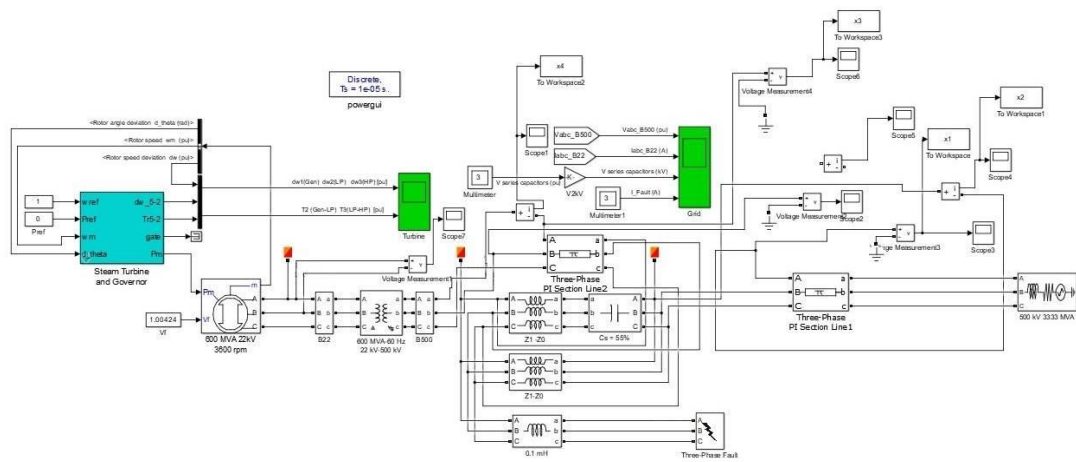


Figure 1. Simulink model of hybrid system

A hybrid power system is modeled in Simulink using MATLAB, integrating a conventional source with a nominal voltage of 500 kV connected to a 22 kV geothermal plant via a step-up transformer rated at 22 kV/500 kV.

The total span of the overhead transmission line is considered to be 300 km. The geothermal plant is simulated based on a steam turbine model, reflecting the process in which heat trapped beneath the Earth's surface is used to heat water, generating steam to drive the turbine and produce an optimal amount of energy. This geothermal source operates alongside the conventional source in the proposed hybrid power system.

This energy happens to be a combination of geothermal and conventional source. The transmission line constants are denoted in Table 1. r , l , and c represent the resistance, inductance, and capacitance per unit length (km) of the transmission line.

Table 1. Constants of Transmission Line

Constant	Magnitude
r (Positive)	0.0275 Ω/km
r (Zero)	0.275 Ω/km
l (Positive)	1.002768 mH/km
l (Zero)	3.4505998 mH/km
c (Positive)	13 nF/km
c (Zero)	8.5 nF/km

Table 2. Parameters of synchronous machine

Parameter	Value
Nominal Power (MVA)	600
Line-Line Voltage (KV)	22
Frequency (HZ)	50
Direct reactance (p.u)	1.65
Direct axis transient open circuit time constant (s)	4.5
Stator resistance R_s (p.u)	0.0045
Inertia constant (p.u)	0.8788

Table 3. Parameters of Steam Turbine and Governor machine

Generator Type	Tandem-Compound
Regulator Gain	1
Speed relay time constant (s)	0.001
Servomotor time constant (s)	0.15
Nominal speed of synchronous machine (r.p.m)	3600
Steam turbine time constant (s)	10
Coefficient of inertia (s)	1.5498
Initial Power (p.u)	2.72×10^{-8}
Rotor angle (deg)	-120.13

The parameters of synchronous machine, steam turbine, and governor is shown in Table 2 and Table 3, respectively.

Various faults simulated are: Phases A to Ground (AG), B to Ground (BG), C to Ground (CG), A to Phase B to Ground (ABG), B to Phase C to Ground (BCG), and C to Phase A to Ground (CAG) at a span of 25 km, 65 km, 185 km and 275 km from the conventional source, which is considered to be the sending station. Different fault resistances considered are 15 ohm, 55 ohm and 105 ohm. The study reports the absolute value of the percentage error in the fault location point, calculated using equation (1) as follows.

$$E_{FL} = \frac{(X_{CAL} - X_{REAL})}{L} \times 100 \quad (1)$$

Where:

E_{FL} = Error in fault location calculation.

X_{CAL} is the calculated location

X_{REAL} is real location

L is total length of line

The findings for the diverse considered instances of disturbances at various distances with varied fault resistances have been reported in the results section.

The simulated hybrid system can yield good solution in diverse geographical conditions considering the demography features like windy areas, desert areas along with conventional or non conventional energy source may be wind, solar or biomass.

Fitness Function

The fitness function is designed to minimize the error between the estimated and actual fault locations using the travelling wave theory. Formulation of fitness function is done on the basis of traveling wave theory as explained below. In order to direct the search process toward the best answers, the fitness function is essential. The program prioritizes exploration and exploitation based on the fitness values.

Figure 2 illustrates the three-phase overhead line prototype in single phase for the considered hybrid system assuming distributed parameters (Ghazizadeh, 2013). A_{cs} and A_{GR} denotes the sources of voltage at Phase A's sending and receiving terminals, respectively in Figure 2 (Ghazizadeh, 2013).

Figure 3, below represents the distributed model of the hybrid system from the sending end (s1) to the fault point station (x1).

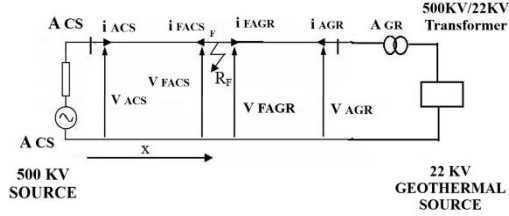


Figure 2. Single line diagram of the system

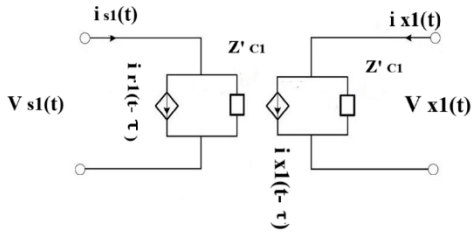


Figure 3. Line distributed model from sending station to fault point

The equations that follow are derived using Figure 3 (Sadeh *et al.*, 2000).

$$i_{s1}(t) = \frac{1}{Z_c} \times V_{s1}(t) + I_{r1}(t - \tau) \quad (2)$$

$$i_{x1}(t) = \frac{1}{Z_{c1}} \times V_{x1}(t) + I_{x1}(t - \tau) \quad (3)$$

The dependent current sources are represented by I_{r1} and I_{x1} in equations (2) and (3), respectively, and are defined in equations (4) and (5):

$$i_{r1}(t - \tau) = \frac{\left(\frac{-R'}{4}\right)}{Z_{c1}^2} [V_{s1}(t - \tau) + Z_{c1}' \times i_{s1}(t - \tau)] - \frac{\left(\frac{R'}{4}\right)}{Z_{c1}^2} [V_{x1}(t - \tau) + Z_{c1}' \times i_{x1}(t - \tau)] \quad (4)$$

$$i_{x1}(t - \tau) = \frac{\left(\frac{-R'}{4}\right)}{Z_{c1}^2} [V_{x1}(t - \tau) + Z_{c1}' \times i_{x1}(t - \tau)] - \frac{Z_c}{Z_{c1}^2} [V_{s1}(t - \tau) + Z_{c1}' \times i_{s1}(t - \tau)] \quad (5)$$

Where:

τ = The amount of time it took for the wave to reach the fault terminal from the transmitting station.

Z_c = The characteristic impedance of the conductor for transmission.

R' = Line resistance between the fault point (x1) and the sending station (s1).

$$Z_{c1}' = Z_{c1} + \frac{R'}{4} \quad (6)$$

$$Z_{c1}'' = Z_{c1} - \frac{R'}{4} \quad (7)$$

Equation (8) can be used to derive the voltage as a function of the transmitting end potential and ampere at the transient location after canceling the current i_{x1} from Equations (2)-(5).

$$V_{xs1}(t) = \left(\frac{A + B - C \times D}{E} \right) \quad (8)$$

Where:

$$A = Z_c'^2 [V_{s1}(t + \tau) - Z_{c1}' \times i_{s1}(t + \tau)] \quad (9)$$

$$B = Z_c''^2 [V_{s1}(t - \tau) + Z_{c1}'' \times i_{s1}(t - \tau)] \quad (10)$$

$$C = \left(\frac{Z_{c1}' \times R'}{4} \right) \quad (11)$$

$$D = \frac{\left(\frac{R'}{2}\right)}{Z_{c1}'} \times V_{s1}(t) + 2 \times Z_{c1}'' \times i_{s1}'(t) \quad (12)$$

$$E = 2 \times Z_c^2 \quad (13)$$

Likewise, as shown in equation (8) it is possible to express the potential at the transient location as a function of the receiving end potential and ampere.

$$V_{xr1}(t) = \left(\frac{A1 + B1 - C1}{D1} \right) \quad (14)$$

Where:

$$A1 = Z_{rc}'^2 [V_{R1}(t + T - \tau) - Z_{rc}' \times i_{R1}(t + T - \tau)] \quad (15)$$

$$B1 = Z_{rc}^{*2} [V_{R1}(t - T + \tau) + Z_{rc}'' \times i_{R1}(t - T + \tau)] \quad (16)$$

$$C1 = \frac{Z_{rc}' \times R_r'}{4} \times \left[\left(\frac{R_r'}{2} \right) \times \frac{V_{R1}(t) + 2 \times Z_{rc}'' \times i_{R1}(t)}{Z_{rc}'} \right] \quad (17)$$

$$D1 = 2 \times Z_c^2 \quad (18)$$

Where:

T = The time it takes for the wave to travel between the sending and receiving (S1 and R1, respectively).

R_r = Opposition offered by the overhead conductor between the fault point (x1) and the receiving end (R1)

$$Z_{rc}' = Z_c + \left(\frac{R_r'}{4} \right) \quad (19)$$

$$Z_{rc}' = Z_c - \left(\frac{R_r'}{4} \right) \quad (20)$$

In any case of the data used for the computation, the voltage at the fault's location should be unique (Ahmed *et al.*, 2017). Because of this, the two extracted voltages have to be always equal. Equations (8) and (14) can be used to produce the following equation since the potential across the overhead wire is continuous

$$F(V_s, i_x, V_r, i_c, t, \tau) = V_{xs}(t) - V_{xr}(t) \quad (21)$$

Since there must be no difference between the voltages, equation (21) should be accurate. The objective or fitness function is denoted as

$$F = \left(\frac{L_1 + L_2 - M - (N + O - Q)}{S} \right) \quad (22)$$

Where:

$$L1 = Z_c^{*2} [V_s(t + \tau) - Z_c' \times i_s(t + \tau)] \quad (23)$$

$$L2 = Z_c^{*2} [V_s(t - \tau) + Z_c' \times i_s(t - \tau)] \quad (24)$$

$$M = \frac{Z_c' \times R}{4} \times \left[\left(\frac{R}{2} \right) \times \frac{V_s(t) + 2 \times Z_c' \times i_s(t)}{Z_c'} \right] \quad (25)$$

$$N = Z_{rc}^{*2} [V_r(t + T - \tau) - Z_{rc}' \times i_r(t + T - \tau)] \quad (26)$$

$$O = Z_{rc}^{*2} [V_r(t - T + \tau) + Z_{rc}' \times i_r(t - T + \tau)] \quad (27)$$

$$Q = \frac{Z_{rc}' \times R_r'}{4} \times \left[\left(\frac{R_r'}{2} \right) \times \frac{V_{R1}(t) + 2 \times Z_{rc}'' \times i_{R1}(t)}{Z_{rc}'} \right] \quad (28)$$

$$S = 2 \times Z_c^2 \quad (29)$$

To determine the place of fault, the fitness function, represented by equation (22) must be minimized. This study uses GRO to minimize the fitness function (Kamran, 2023).

The flowchart of GRO is represented in Figure 4. Novelty of GRO, as compared to other optimisation techniques, is that this algorithm differs from more conventional optimisation methods such as Genetic Algorithms (GA), Particle Swarm Optimisation (PSO), and Differential Evolution (DE) by introducing novel strategies modeled after gold prospectors looking for gold. GRO draws inspiration from human decision-making in gold panning, in contrast to PSO, which imitates swarm behavior, and GA, which use evolution-based selection. It (GRO) integrates migration, mining and collaboration.

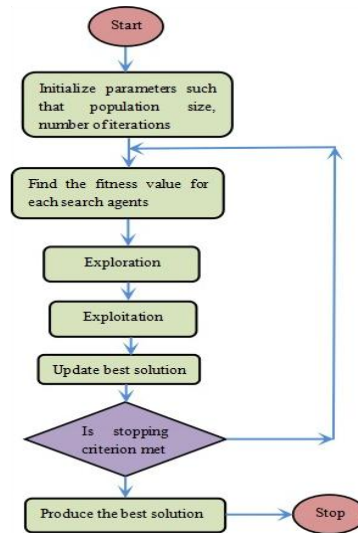


Figure 4. Flowchart of GRO

GRO is adaptable and effective in finding the best answer because of these adaptive tendencies. GA and PSO are two examples of metaheuristics that suffer from premature convergence.

GRO dynamically modifies its step sizes to transition from global exploration to local refining. GRO does not rely on derivatives, in contrast to gradient-based techniques (such as Newton's method).

It is perfect for situations that are noisy, nonlinear, or non-differentiable, such as power system fault location. Conventional approaches, such as impedance based techniques, have trouble with transient circumstances and fault resistance uncertainty. Without the need for exact mathematical modelling, GRO uses adaptive movement algorithms to locate faults in the best possible locations. It can withstand noise and changes in system characteristics.

GRO is novel because:

- Decision making is influenced by humans and it is more practical and logical. (the actions of gold prospectors).
- A flexible ratio of exploitation to exploration.
- Gradient-free optimisation is appropriate for challenging real-world issues.
- A straightforward but effective strategy devoid of needless complexity.
- More accurate fault finding in power systems when compared to conventional techniques and thereby efficiency is also high.

Table 4, presents the key points of comparison of GRO with other existing optimisation techniques.

Table 4. Comparison of GRO with existing optimisation techniques

Algorithm	Inspiration	Exploration vs. Exploitation	Update Mechanism
1. Gold Rush Optimisation (GRO)	Based on the behaviour of Gold prospectors (migration, mining, collaboration).	Adaptive balance by means of dynamic step sizes.	Position upgraded on basis of mining, migration, and collaboration.
2. Particle Swarm Optimisation (PSO)	Based on Bird flocking and swarm intelligence.	Controlled by inertia weight.	Velocity and location upgrade rules.
3. Genetic Algorithm (GA)	Natural development (selection, crossover, mutation).	Exploration through mutation ; exploitation through selection.	Selection, crossover, and variation.
4. Differential Evolution (DE)	Progressive mutation and recombination.	Strong exploration but slower convergence.	Selection, crossover, and variation.
5. Artificial Bee Colony (ABC)	Based on foraging behavior of a Bee colony.	High exploration in the initial phase, slower convergence.	Onlooker bees upgrade based on the best meal sources.
6. Artificial Humming Bird Algorithm (AHA)	Rooted on natural instincts of the Humming Bird.	Balanced exploration and exploitation.	Based on foraging behaviour of real hummingbirds.

Results

The current and voltage waveforms for a single line-to-ground fault in Phase A, occurring at a distance of 10 km from the sending station, are illustrated in Figures 5 and 6 below.

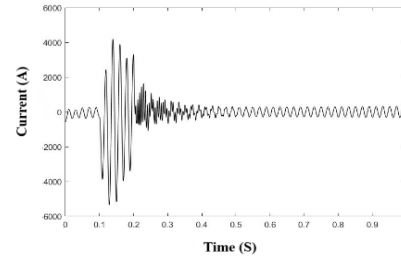


Figure 5. Current waveform for Line to Ground fault in Phase A at a distance of 10 km from conventional source

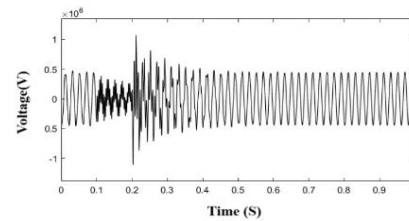


Figure 6. Voltage waveform for Line to Ground fault in Phase A at a distance of 10 km from conventional source

The calculated fault locations for the different spans from the sending station are presented in Table 5 and their respective absolute of the percentage error is presented in Table 6.

Discussion

Compared to other metaheuristic algorithms and even conventional fault locating techniques, the Gold Rush Optimiser (GRO) offers a number of significant advantages. In contrast to techniques like Particle Swarm Optimisation (PSO) or Genetic Algorithms (GA), GRO strikes a better balance by using a novel mining metaphor in which “miners” look for “gold” depending on resource distribution. Because GRO employs dynamic adjustment of search strategies such as miners change their emphasis according to

resource abundance, simulating real-world mining behaviour, as it frequently converges faster.

This means that defect locations can be identified more quickly and without needless iterations. Particularly in intricate fault settings, certain techniques, such as GA or PSO, are susceptible to becoming stuck in local optima.

The variation of fitness function as illustrated in Figure 7 shows that the graph for AG and ABG fault converges quickly in 40th iteration and 44th iteration with percentage error of 0.002 and 0.0018 respectively. This denotes that the proposed algorithm is quick and efficient to solve the challenge of fault location optimisation.

GRO is more dependable for locating the global optimum fault site because of its adaptive techniques, which enable constant mobility and avoid standstill.

Table 5. Calculated fault locations

Fault Type	Fault Resistance (Ω)		Actual fault location (km)			
			25	65	185	275
A-G	15	Calculated fault location	24.9940	64.9996	184.9979	274.9958
	55		24.9970	64.9979	184.9949	274.9997
	105		25.0000	64.9988	184.9994	274.9958
B-G	15	Calculated fault location	24.9955	64.9946	184.9985	274.9991
	55		24.9931	64.9919	184.9949	274.9985
	105		24.9970	64.9961	184.9937	274.9982
C-G	15	Calculated fault location	24.9970	64.9991	184.9970	274.9982
	55		24.9952	64.9991	184.9952	274.9949
	105		24.9991	65.0000	184.9997	274.9970
AB-G	15	Calculated fault location	24.9934	64.9982	185.0000	274.9997
	55		24.9946	64.9925	184.9925	274.9931
	105		24.9946	64.9955	184.9985	274.9931
BC-G	15	Calculated fault location	24.9961	64.9988	184.9952	275.0000
	55		24.9949	64.9961	184.9979	274.9994
	105		24.9982	64.9994	184.9988	274.9976
CA-G	15	Calculated fault location	24.9979	64.9970	184.9982	274.9985
	55		24.9937	64.9985	185.0000	274.9988
	105		24.9988	64.9988	184.9982	274.9973

Table 6. Absolute value of percentage error for fault location

Fault Type	Fault Resistance (Ω)	Absolute value of %age error for fault locations at (km)			
		25	65	185	275
A-G	15	0.0020	0.0001	0.0007	0.0014
	55	0.0010	0.0007	0.0017	0.0001
	105	0.0000	0.0004	0.0002	0.0014
B-G	15	0.0015	0.0018	0.0005	0.0003
	55	0.0023	0.0027	0.0017	0.0005
	105	0.0010	0.0013	0.0021	0.0006
C-G	15	0.0010	0.0003	0.0010	0.0006
	55	0.0016	0.0003	0.0016	0.0017
	105	0.0003	0.0000	0.0001	0.0010
AB-G	15	0.0022	0.0006	0.0000	0.0001
	55	0.0018	0.0025	0.0025	0.0023
	105	0.0018	0.0015	0.0005	0.0023
BC-G	15	0.0013	0.0004	0.0016	0.0000
	55	0.0017	0.0013	0.0007	0.0002
	105	0.0006	0.0002	0.0004	0.0008
CA-G	15	0.0007	0.0010	0.0006	0.0005
	55	0.0021	0.0005	0.0000	0.0004
	105	0.0004	0.0004	0.0006	0.0009

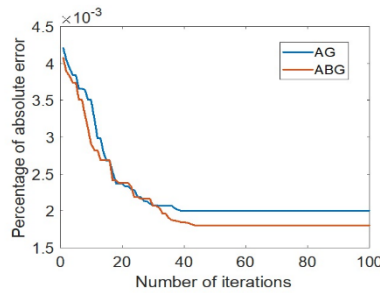


Figure 7. Variation of fitness function for transient AG and ABG at 25 kM with 25 Ω and 105 Ω fault path resistance respectively

The study conducted by Yu *et al.* (Yu *et al.*, 2023) for fault location shows that the maximum value of error for AG fault; considering method (considering asymmetry); is 0.017%. The greatest fault location errors were 1.5% and 1%, respectively, according to the studies by Mustari *et al.* (Mustari *et al.*, 2019) and Lavand *et al.* (Maner and Lavand, 2018). According to Ahmed *et al.* (Ahmed *et al.*, 2017) the largest percentage error utilizing the GA approach is 0.13% when the fault resistance value is 10 ohm and 0.068% when the fault resistance value is 50 ohm.

A. Sanad Ahmed *et al.* (Ahmed *et al.*, 2017) also determined that by applying technique of Teaching learning based optimisation (TLBO) with fault path resistance of 10 ohm, the highest magnitude of percentage error is 0.13% and with fault path resistance of 50 ohm is 0.833%. It is reported in the study conducted by Rao *et al.* in (Ankamma and Bizuayehu *et al.*, 2015) that with phasor measurement method the maximum value of percentage error is 1.568%. In contrast to the previously published studies, the proposed algorithm achieves a significantly greater level of precision. It has been noted that the maximum magnitude of absolute of the percentage error is 0.0027%. It is also noticed that fault resistances and transient types have little effect on location precision.

Conclusions

The Gold Rush Optimiser (GRO) results show a considerable reduction in fault location errors within the transmission line for the following fault cases: A-G, B-G, C-G, AB-G, BC-G, and CA-G. Notably, B-G and CA-G faults indicate inaccuracies as low as 0.0003% and 0.0004%, respectively, while A-G and AB-G faults minimize the absolute percentage error to 0.0001. These results confirm the efficacy of the suggested optimisation method for precise fault identification.

The GRO methodology outperforms traditional approaches including the completely distributed parameter model, TLBO, and phasor measurement techniques, which display higher percentage errors of up to 0.833% and 1.568%. By providing improved scalability across various grid topologies, improved precision in complicated networks, and quicker fault isolation, it successfully tackles the difficulties presented by noisy, non-linear systems.

Because GRO only depends on a clearly stated fitness function, it is more flexible for a range of fault scenarios and grid configurations than impedance-based techniques, which mostly rely on precise system modeling.

In order to improve power network management and reduce transmission line downtime, this study validates the GRO technique as a strong and dependable fault localization option.

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