



A SINGLE-TERMINAL FAULT LOCATION METHOD USING HYBRID PSO-GA OPTIMIZATION AND DISTRIBUTED PARAMETER LINE MODELING

Ali Adnan Ajel*¹, Kassim Al-Anbarri²

^{1,2}Electrical Engineering Department, Mustansiriyah University, Baghdad, Iraq.

¹<https://orcid.org/0009-0006-0975-3801>, ²<https://orcid.org/0000-0001-8002-7913>

E-mail: * eng.aliadnan88@uomustansiriyah.edu.iq; alanbarri@uomustansiriyah.edu.iq

ARTICLE INFO

Article History

Received: February 28, 2026

Reviewed: March 30, 2026

Accepted: April 05, 2026

Published: May 29, 2026

Keywords:

Fault Location Techniques,
Transmission Line Fault,
Single Ended Fault Location,
Practical Swarm Optimization,
Genetic Algorithm,
Iteration and Noninteraction
Method.

ABSTRACT

Correct and fast fault localization of high voltage overhead transmission lines is a primary need toward ensuring the stability and sustainability of present day power systems. The traditional methods of fault location such as impedance-based and travelling-wave methods are known to be limited by the following factors: sensitivity to fault impedance variations, reliance on synchronized multi-terminal measurements and expensive communication infrastructure. This paper proposes a new single-terminal fault location architecture that resolves these limitations by taking advantage of a special and deterministic post fault system state with neither long-range data nor inter-substation communication. The algorithm proposed is based on a model of distributed parameter transmission lines, which is able to faithfully model the electromagnetic behavior of long transmission lines. Clark transformation is used to transform the coupled three-phase system to decoupled modal networks, which allow each of the sequence components to be analyzed separately. The native genius here is that the momentary operation window is strategically used wherein, the remote-end circuit breaker has cleared the fault, yet the local-end breaker is not activated. One effect of this short time interval is that the current at the receiving-end is zero, and so the fault location equation is completely deterministic and does not require the remote source impedance parameters. The nonlinear objective function obtained is then solved with the help of a hybrid metaheuristic algorithm that combines Particle Swarm Optimization with a Genetic Algorithm. The combination takes advantage of the fact that PSO is very good at local exploitation and GA is very good at search exploration, which has the effective effect of avoiding premature convergence and guiding to the global optimum with high accuracy. The validity of the proposed approach is supported by thorough MATLAB/Simulink simulations that have been made on a real 400 kV, 239 km transmission corridor between Iraq and Iran. Evaluation of faults of various types, such as single line-to-ground, line-to-line, double line-to-ground, and three-phase faults, indicates that the hybrid PSO-GA technique can always provide significantly higher localization accuracy than the standalone PSO and non-iterative benchmark techniques without increasing the computation time (less than 0.5 seconds).



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I. INTRODUCTION

High-voltage overhead transmission lines are the vital element of electricity networks of modern electric power systems, which carries bulk electrical power over regional and national borders. They are by nature vulnerable to a broad range of fault causing occurrences such as lightning hits, heavy wind loading on conductors that causes galloping, ice formation, wild fires and encroachment of vegetation [1],[2]. Not only do the incidences of such faults destroy the delivery of power to the consumers, but they also cause cascading instabilities that may jeopardize the integrity of the rest of the interconnected grid [3]. As a result, the quick and accurate determination of fault positions is still one of the most operationally critical issues the engineers of power system protection have to deal with in modern times. The cost of transmission line faults is enormous.

Unscheduled disconnections lead to immediate losses in the utilities, penalties by the regulations, and indirect expenses incurred by industrial and commercial consumers whose operations rely on the continuous availability of power [4]. The process of fault localization by making use of manual inspection is not only time-consuming but also hazardous to carry out in long-distance transmission corridors especially those that cover tough terrain, thus increasing the economic cost of any given fault event [5]. Automated algorithmic fault location systems are thus essential tools in the operations of modern grids, as they allow maintenance crews to be guided to the fault location as precisely as possible and restore service in the short time possible. Among the algorithmic fault localization techniques, impedance based single terminus method has received a lasting interest, as it is operationally simple and does not depend on inter-substation communication links [6]. These techniques estimate the fault location by calculating the apparent reactance that is observed at the local terminal using measurements at fundamental frequency of voltage and current taken at the local terminal. Nonetheless, they are highly inaccurate due to the existence of fault resistance, remote-end load infeed and uncertainty in source impedance parameters all these cause systematic estimation errors, which deteriorate the localization performance [7], [8].

Different correction methods have been suggested to overcome these limitations such as additions of pre-fault load current compensation and iterative process of refinement, but still, residual errors exist in highly resistive fault conditions [9]. Two-terminal measurements, that take advantage of simultaneous voltage and current measurements at each end of the fault line, are significantly more accurate, removing the remote infeed ambiguity of single-terminal models [10]. Such methods require a credible phasor measurement unit infrastructure and communication channels with high availability between substations that are reliable to deploy practically [11]. However, fault conditions do not always guarantee the integrity of the communication links and the synchronization requirements add extra costs on infrastructure which might not be justifiable on all transmission corridors [12]. These are factors that drive the further investigation of high-accuracy single-terminal methods, which are independent of any communication infrastructure. The travelling-wave fault location paradigm is another measurement philosophy that approximates fault distance by the propagation time of transient electromagnetic waves that are produced at the fault point [13]. The most recent developments in high-speed signal processing hardware and time-domain reflectometry have rendered these techniques more practicable [14]. However, in a networked environment, it is still difficult to identify the wavefront accurately due to interference by reflections at impedance discontinuities, parallel line coupling and transient waveforms produced by switching [15].

Further deployment costs are imposed by the high sampling rates and accuracy time devices needed to implement fault location, which restricts the widespread use. Over the last few years, the use of artificial intelligence and machine learning in fault location increased tremendously [16, 17]. Convolutional neural networks and long short-term memory networks are deep learning models that have shown encouraging outcomes in learning intricate fault signature design designs on huge past datasets [18], [19]. Nevertheless, the reliance of data-driven approaches on large datasets with labeled data, data sensitivity to changes in operating conditions not modeled in the training data, and physical interpretation remain issues that restrict their use in unconditionally in safety-important protection systems [20]. The use of metaheuristic optimization methods offers a physically based alternative to the data dependency of machine learning methods in order to solve the inherently nonlinear fault location problem [21]. Hybrid algorithms which are a synthesis of particle swarm optimization and genetic algorithm operators have been especially effective in trade-offs between exploration of the global solution space and local optimization, both resulting in better convergence properties relative to both algorithms used alone [22], [23]. Combined with precise distributed parameter line models and modal decomposition using the Clarke transformation, these hybrid optimizers provide a strict and computationally inexpensive framework of fault localization at single terminals [24]. This paper constructs and confirms a framework of this kind on one of the real 400 kV, 239 km transmission system, and shows uniform benefits of accuracy over the current benchmark procedures over all types of major faults

II. THE HYBRID PSO-GA

The rationale of the integration of Particle Swarm Optimization and a Genetic Algorithm is due to the complementary nature of the behavioral traits of each method separately. PSO exhibits a great potential of enhancing the search in the already-identified promising regions of the solution space by refining the candidate solutions with higher fitness values. In contrast, GA works with a more liberal philosophy of exploration, as it repeatedly works on unexplored spaces by selection, crossover and mutating operators. Putting these two opposite types of behavior into one unified framework results in an optimization process that is more balanced and more resistant to premature convergence to suboptimal solutions simultaneously [22]. In the suggested model, optimization will start fully under the control of PSO. A random distribution of an initial population of candidate solutions, each of an encoding of a possible fault distance, fault resistance pair is distributed across the search space. Successive iterations enable each particle to update its position, by concurrently taking into account both its best historically identified position and the best position ever identified by any of the swarm member, which enables the population to self-organize towards successively better solutions.

The switch to the hybrid operation is controlled by a probabilistic switching. A uniform sampling of the interval [0, 1] is done to get a random number at every iteration. Once this value has reached this threshold of 0.8, at an approximate rate in the statistics of twenty percent, the existing PSO population gets transferred directly to the GA module as its initial population, which then undergoes genetic operators to further optimize it [21]. This selective and uncommon activation performs two fundamental functions, viz.: To recover population diversity lost in PSO convergence, and to avoid stagnation, as well as to escape local optima that PSO would otherwise falsely recognize as the global optimum. The polished population is then fed back to PSO and the cycle repeated in much the same way until convergence is reached. Each particle is associated with a potential solution vector in an N-dimensional domain in accordance with the conventional PSO update rules. Formally, the i th particle's location is defined as:

$$X_i = (x_{i1}, x_{i2}, \dots, x_{in}) \quad (1)$$

Additionally, every particle keeps a record of its historically ideal location, which is stored in a specific memory vector.

$$P_i = (p_{i1}, p_{i2}, \dots, p_{in}) \quad (2)$$

According to the following formulation, every particle in the swarm moves around the search space with a distinct velocity vector:

$$V_i = (v_{i1}, v_{i2}, \dots, v_{in}) \quad (3)$$

The Particle Swarm Optimization (PSO) model consists of particles, each of which is a potential solution, but maintains a record of the present coordinates as well as an optimal historical location (the p_{best}). Also, the global best position (g_{best}), the optimal value of p_{best} reached by any population member, is shared by the swarm population. This strategy follows a social learning process, whereby a particle reacts by modifying the behavior based on its personal experience as well as the behavior of other particles. A major characteristic of PSO is that not every particle in the swarm is going to search alone - the advancements of other particles within the swarm have an active influence on the behavior of movement and convergence of all other particles within the swarm. To be more exact, the new location of each particle is computed by its velocity which in turn relies on two randomly selected elements that jointly determine the trade-off between the exploration of new areas and exploitation of known good solutions:

1. Cognitive Component:

This is the term that means the impact of the own history of a particle on its movement. It is the deviation of the current position of the particle with respect to the best position which has been personally visited by the particle (p_{best}). This is literally a part of an individual memory, in other words, it draws the particle back to the best answer it has ever found, and it is also indicative of its aptitude to teach itself.

2. Social Component:

This term is used to measure how the swarm behavior affects an individual particle. It is the distance between the current position of a particle and the optimal solution of any particle in the whole population (g_{best}). With the addition of this term, every particle is attracted to the area of the highest potential known to date found by the group effectively simulating the way people in a swarm can use the knowledge available to them and collaborative actions.

The combination of these two elements forms a dynamic equilibrium between the cognitive and the social parts which pushes each particle to believe in its own experience on one hand and to believe in the wisdom of the swarm on the other.

This updating formalism is implemented mathematically by use of a velocity equation. More specifically, the velocity of every particle will be altered in line with the subsequent formulation of Inertia Weight Approach (IWA):

$$v_i = w \cdot v_i + c_1 \cdot r_1 (P_i - X_i) + c_2 \cdot r_2 (P_g - X_i) \quad (4)$$

Where:

v_i denotes the velocity vector of the i th particle.

X_i represents the current position vector of the particle.

w is the inertia weight, a parameter governing the momentum of the particle by scaling the influence of its previous velocity.

c_1 and c_2 are positive acceleration coefficients that scale the cognitive and social guidance components, respectively.

P_i and P_g signify the particle's personal best position (p_{best}) and the swarm's global best position (g_{best}), respectively.

r_1 and r_2 are stochastic elements, uniformly distributed random numbers within the interval $[0, 1]$, introduced to preserve population diversity and facilitate stochastic exploration.

As a result, each particle's future position is decided by a weighted stochastic mixture of its unique past experience (p_{best}) and the swarm's collective knowledge (g_{best}). Particles can traverse a continuous solution space in the basic PSO formulation since the search domain is usually unbounded.

The inertia weight in Eq. (4) was kept constant at 1.0 during the optimization process for the purposes of this investigation. The algorithm's behavior was made simpler and the computational burden of adjusting adaptive inertia weight strategies such as defining minimum and maximum bounds as mentioned in Eq. (5) was eliminated by choosing this configuration, which guarantees a constant and uniform convergence rate. It is mentioned that there are other approaches; for example, the method proposed in Ref.[25] dynamically adjusts the inertia weight during each iteration.

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} \times iter \quad (5)$$

In this formulation, w_{max} and w_{min} denote the initial and final inertia weights, respectively, while $iter_{max}$ and $iter$ represent the maximum permitted iterations and the current iteration count. This equation implements a linear decrement of the inertia weight, thereby systematically reducing the exploration (diversification) tendency of the swarm over time. As a result, the resulting computed velocity moves search agents increasingly towards the areas of p_{best} and g_{best} resulting in more exploitation (strengthening). Nevertheless, there is one significant shortcoming of the adaptive inertia weight strategy, which has been mentioned above.

The positional update for each particle is subsequently determined by the following relation:

$$X_i^+ = X_i^- + v_i \quad (6)$$

where X_i^+ is the updated position, X_i^- is the position at the previous timestep, and v_i is the velocity vector computed from Eq. (4). Through this iterative process, the collective population navigates the solution space, orienting itself toward regions of improved fitness. The emergent intelligence of the swarm, fueled by this combined effort, facilitates convergence upon a globally optimal or near-optimal solution.

The GA is implemented as a function whose inputs are the PSO population (particle), the previously obtained best solution, the population size, the upper and lower bounds of the variables, and the number of decision variables. As shown, 50% of the population is considered as the crossover population, and the remaining 50% is assigned as the mutation population.

Based on the crossover and mutation percentages, as well as the total population size, the numbers of crossover and mutation individuals are calculated. For the genetic algorithm, a maximum of 10 iterations is considered. The optimal solution is initialized with its previous value. A loop is then defined for the genetic algorithm iterations. Inside this loop, an empty population is first created as the initial crossover population. Then, by calling the crossover function, the crossover population is generated. Within the crossover function, two solutions are randomly selected at each step, and two new offspring solutions are produced by combining them.

Similarly, the mutation population is generated by calling the mutation function. In the mutation function, one solution is randomly selected at each step, and one of its variables is randomly modified to produce a new solution. In the next stage, the initial population is combined with the crossover and mutation populations, resulting in the overall population. For this combined population, the individuals are sorted based on their cost function values, such that better solutions are ranked higher and poorer solutions receive lower ranks. Through this process, the first individual of the population becomes the best solution. If the newly obtained solution is better than the previous global best solution (i.e., it has a lower cost), it replaces the previous global best. Finally, the final population of the genetic algorithm is returned as the PSO population. As shown below, for each particle, if the solution obtained from the GA algorithm is better than its previous best solution, it replaces that previous best.

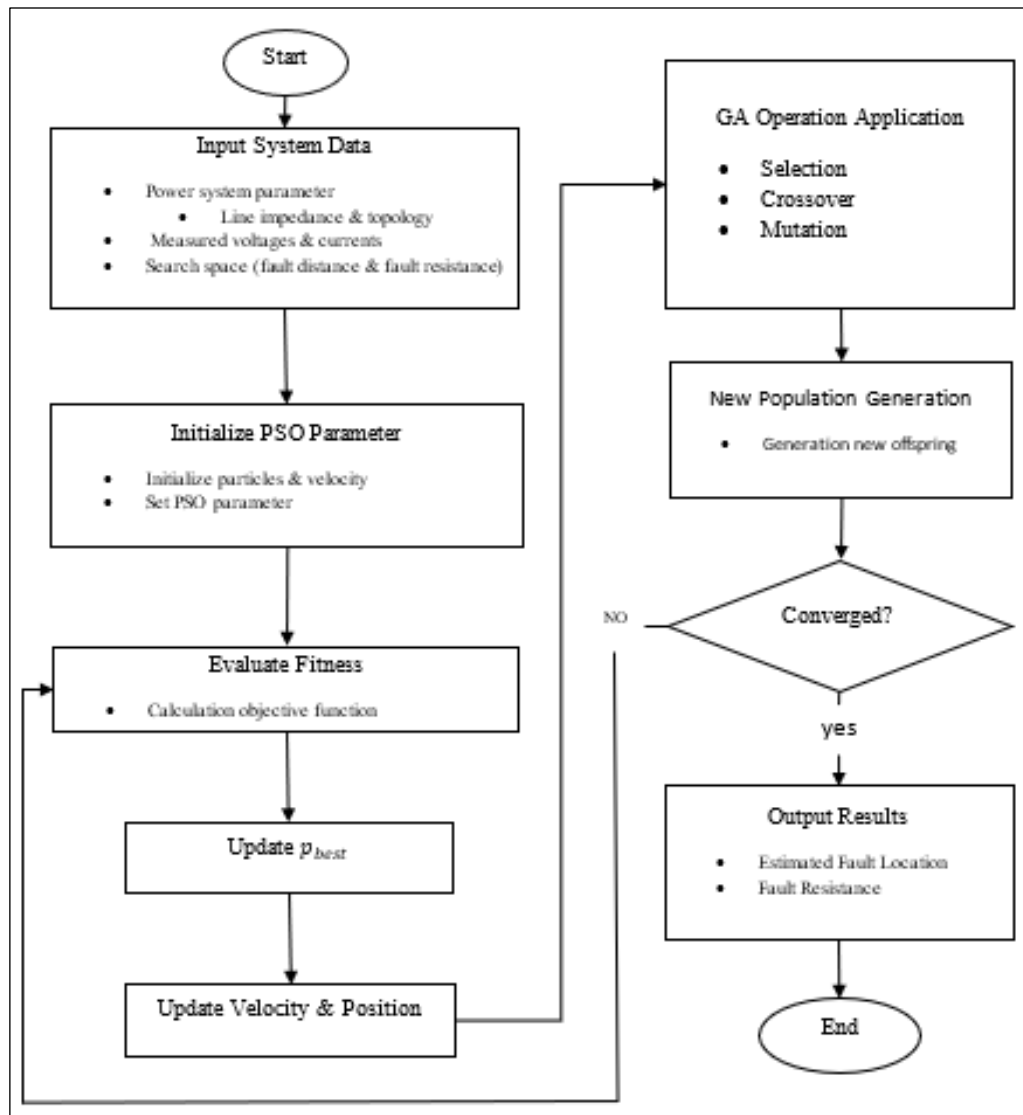


Figure 1: PSO-GA Fault Location Flow chart
Source: Authors, (2026).

III. 3 PROPOSD METHOD

The main benefit of single-ended fault location techniques is their lack of reliance on communication lines, synchronization systems, or remote-end measurements. This intrinsic simplicity is leveraged by the methods suggested in this paper. It creates an objective function based on circuit breakers' consecutive tripping patterns, which is then optimized using the Hybrid PSO-GA method. The way the proposed approach is practically implemented is explained in Figure 1. Using the three phase current waveform measured at the local terminal when a permanent fault occurs, four distinctively different operating modes can be determined. The definition of these states needs to be preceded by the fact that circuit breakers do not interrupt the current immediately, they can interrupt it only when the current has crossed the zero naturally, and it only happens when the trip command has already been sent. There are four states that describe the behavior of the system during the fault event and include:

- **State A – Normal Operation:**

This is the healthy state where the power system is operating normally with all the components working under steady, stable conditions and there are no fault anywhere in the network.

- **State B – Fault Inception:**

At this point, a defect has occurred on the transmission line. Although the fault is present, no protection measure has been undertaken, however, all the protection relays and circuit breakers on either side of the line are closed and in service.

- **State C – Remote-End Isolation:**

The fault has been detected by the protection equipment at the far end of the transmission line and the respective circuit breakers have opened and disconnected and de-energized the remote side of the line. The local-end circuit breakers are however not yet open at this point and thus the fault is still partially energized.

- **State D – Full Isolation:**

The local circuit breakers are also opened and this completes the isolation process. Both ends of the faulted section of the transmission line have been de-energized and disconnected to avoid more fault current flowing.

In State C, the most important analytical condition will occur. At this point, the fault localization problem is no longer dependent on the parameters of the remote system source impedance, as the remote-end current is effectively zero. This detachment eases the fault location formulation and improves the computational strength. As a result, the suggested method's practicality is increased since it just needs local measurement data obtained during this particular operational condition.

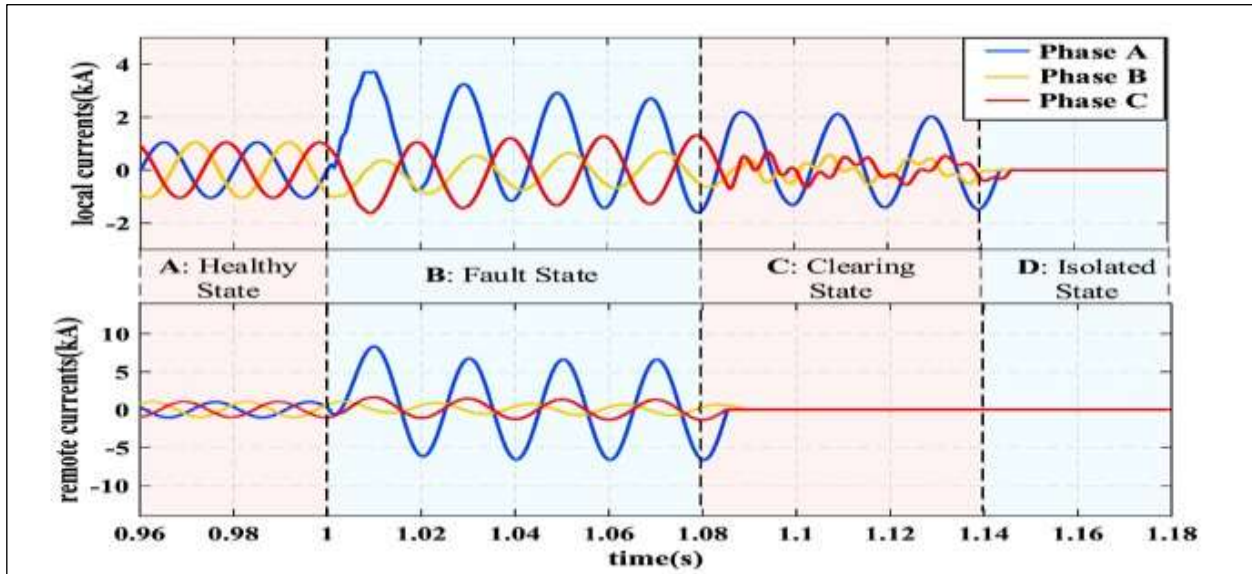


Figure 2: Terminal current under a permanent fault.

Source: Authors, (2026).

The governing equations are derived using a thorough distributed parameter line model to guarantee a high level of accuracy in fault localization. The Clark transformation, also called the alpha-beta-zero transformation, is then used to simplify this complex three-phase network representation. The interdependent phase values are successfully separated into three separate and independent modal networks mode-0, mode-1, and mode-2 by this mathematical technique. The following is the definition of the transformation matrix that makes this decoupling possible:

$$S_{clark} = \frac{1}{3} \begin{bmatrix} 2 & -1 & -1 \\ 0 & \sqrt{3} & -\sqrt{3} \\ 1 & 1 & 1 \end{bmatrix}$$

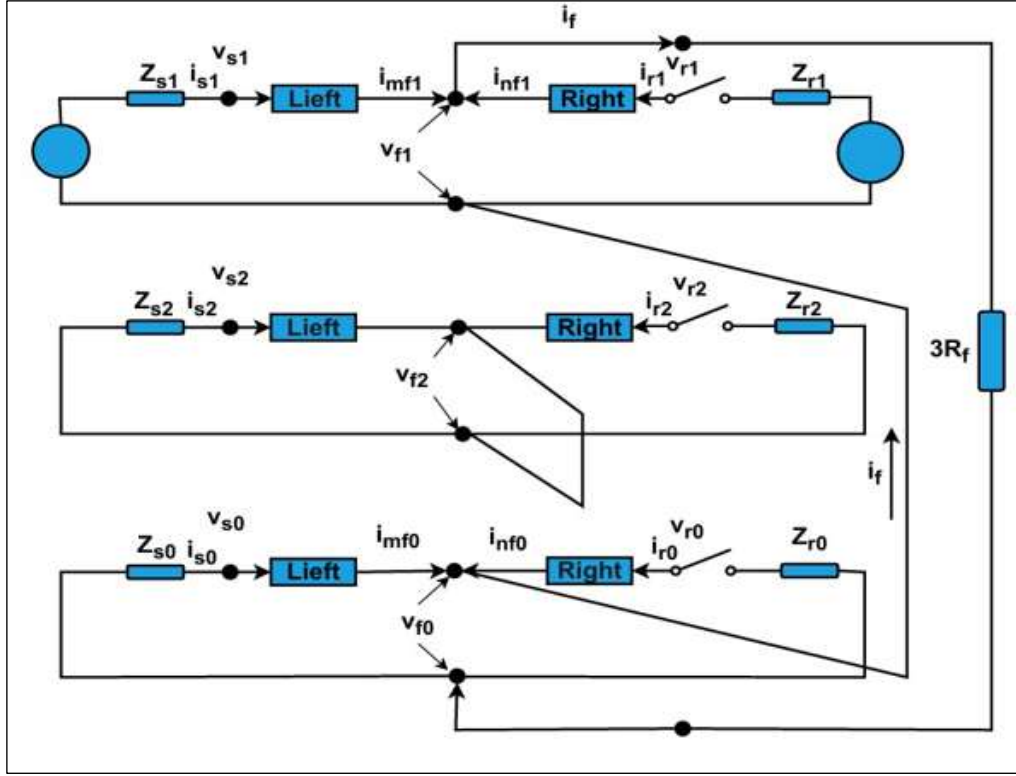


Figure 3: equivalent circuit in the 012 domain for A-G fault
Source: Authors, (2026).

The long transmission line hyperbolic form equation:

$$v_s = v_r \cosh(PX) + i_r Z_c \sinh(PX) \quad (7)$$

$$i_s = i_r \cosh(PX) + \frac{v_r}{Z_c} \sinh(PX) \quad (8)$$

Where $Z_c = \sqrt{\frac{z}{y}}$, Z_c : characteristic impedance
And $P = \sqrt{zy}$, P : propagation constant
 X : distance

As illustrated in Fig. 3, which depicts the single-line-to-ground (A-G) fault model adapted from [24], the total length of the transmission line is denoted as l , with the fault location at a distance d from the local terminal S. The network is characterized by Thevenin equivalent impedances: Z_{s0} and Z_{s1} represent the zero- and one-sequence impedances behind terminal S, while Z_{r0} and Z_{r1} correspond to those behind the remote terminal R. Measurable quantities at terminal S include the zero- and one-sequence voltages and currents, denoted as v_{s0}, v_{s1}, i_{s0} , and i_{s1} . The fault point is associated with sequence voltages v_{f0}, v_{f1}, i_{f0} and i_{f1} , and fault currents $i_{mf0}, i_{mf1}, i_{nf0}$ and i_{nf1} , which are injected into the fault from either side of the line. Quantities at the remote terminal R are designated as v_{r0}, v_{r1}, i_{r0} and i_{r1} . The fault resistance is symbolized by R_f . The sequence voltages at the fault point, which is indicated as v_{f0} and v_{f1} can be computed using the voltage and current that are measured at terminal S. These amounts are calculated in the following analytical expressions:

$$v_{f0} = v_{s0} \cosh(P_0 d) - i_{s0} Z_c \sinh(P_0 d) \quad (9)$$

$$v_{f1} = v_{s1} \cosh(P_1 d) - i_{s1} Z_c \sinh(P_1 d) \quad (10)$$

The entire zero-sequence fault current i_{f0} within the modal domain can be obtained by applying the Clark transformation and using the basic voltage-current relationships controlling the fault location. According to the following formulation, this current is stated as a function of the fault point voltages found in both the one-mode and zero-mode networks:

$$i_{f0} = \frac{v_{f1} + v_{f0}}{3R_f} \quad (11)$$

The substitution of equations (9) and (10) into (11) reveals that the zero-sequence fault current, i_{f0} , is functionally dependent on the variables of fault distance d and fault resistance R_f .

$$i_{f0} = \frac{v_{s0} \cosh(P_0 d) - i_{s0} Z_{c0} \sinh(P_0 d) + v_{s1} \cosh(P_1 d) - i_{s1} Z_{c1} \sinh(P_1 d)}{3R_f} \quad (12)$$

Within the mode-0 network, the injection current i_{mf0} originating from the local terminal can be formulated from the measured voltage and current at terminal S, as illustrated in Figure 3:

$$i_{mf0} = -\frac{v_{s0} \sinh(P_0 d)}{Z_{c0}} + i_{s0} \cosh(P_0 d) \quad (13)$$

Application of Kirchhoff's Current Law (KCL) at the fault location permits the expression of the remote terminal injection current, i_{nf0} , as follows:

$$i_{nf0} = i_{mf0} - i_{f0} \quad (14)$$

The zero-sequence current at the receiving terminal, i_{r0} , is governed by the fault point voltage v_{f0} and the injected current i_{nf0} from the remote terminal, as defined by the following relationship. It is critical to note that during State C, characterized by the operation of remote-end circuit breakers, the receiving terminal current i_{r0} remains zero due to the de-energization of the line at that terminal. This condition, where i_{r0} , is leveraged as the foundational objective function for the fault location methodology.

$$i_{r0} = -\frac{v_{f0} \sinh(P_0(l-d))}{Z_{c0}} + i_{nf0} \cosh(P_0(l-d)) = 0 \quad (15)$$

IV.4 NUMERICAL VALIDATION

The efficacy of the suggested fault localization plan was confirmed by the means of the feasible simulation studies. The analysis was done based on the real transmission line of the interconnection between Iraq and Iran (DYALA-MERSAD). A 400 kV transmission line has been modeled as a 50 Hz power system and the model has been implemented in MATLAB (Version 2022b) as shown in Figure 4. Positive and zero-sequence parameters were used to characterize the equivalent source impedances: $R_{s1} = 0.065 \Omega$, $L_{s1} = 1.0033 \text{ mH}$, $R_{s0} = 0.3 \Omega$, and $L_{s0} = 3.1067 \text{ mH}$ for the sending end; $R_{r1} = 26 \Omega$, $L_{r1} = 0.14298 \text{ H}$, $R_{r0} = 20 \Omega$, and $L_{r0} = 0.11927 \text{ H}$ for the receiving end. The transmission line was 239 kilometers long overall.

The fault location method that has been developed is supposed to be used with three phase circuit breaker protection system in the AC transmission systems. The major innovation of this method is focused exploitation of the measurement data collected at a particular post-fault operational condition, that is, the interval between clearing remote-end breakers and the activation of local protection devices. It is specifically the set of operational data that this temporal frame presents that is allowable to create a deterministic fault location equation. A MATLAB 2022b framework running an Intel(R) Core (TM) i5-10310U CPU was used for computational performance assessments. The computing burden of the method was measured, and the overall processing time for each fault occurrence was never more than 0.5 seconds. Such low latency attests to the method's practicality for use in Contemporary power systems

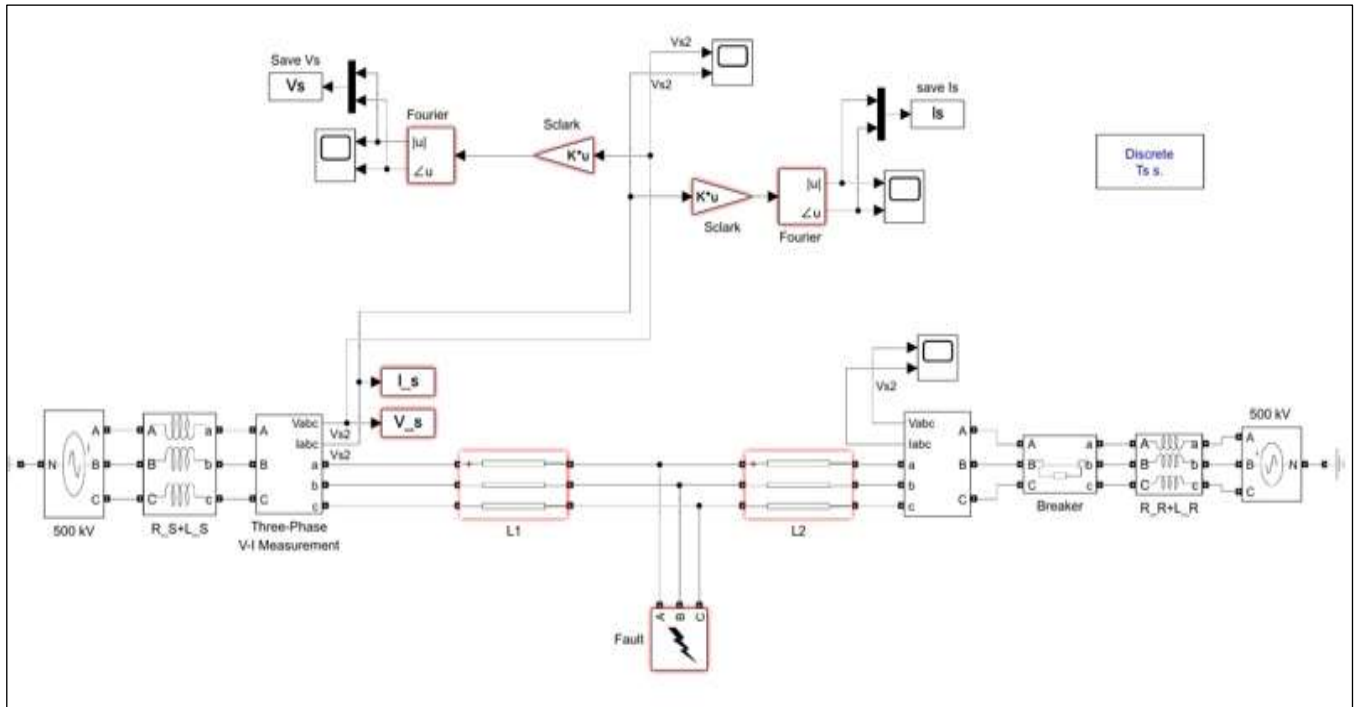


Figure 4: Simulation block diagram
Source: Authors, (2026).

Table 1: A-G fault location result for proposed method.

Scenarios	Actual FL (km)	Estimated FL (km)	Error (km)	Error (%)	Rf Actual Ω	RF Estimated Ω
1	196.59	196.27	0.32374	0.13545	76.281	76.329
2	163.92	163.99	0.076808	0.032137	29.432	29.314
3	44.377	43.647	0.72995	0.30542	26.444	26.562
4	52.204	48.796	3.4085	1.4262	37.155	37.921
5	138.05	137.4	0.64644	0.27048	47.005	47.075
6	59.384	59.003	0.3818	0.15975	65.815	65.895
7	4.8144	4.5311	0.28326	0.11852	90.693	90.755
8	52.949	52.587	0.36205	0.15148	20.309	20.355
9	88.641	88.025	0.61677	0.25806	122.42	122.53
10	219.6	219.06	0.5417	0.22665	29.011	29.081

Source: Authors, (2026).

Table 1 summarizes the results for 10 single-line-to-ground fault scenarios, comparing the actual and estimated fault locations and resistances, along with the calculated error.

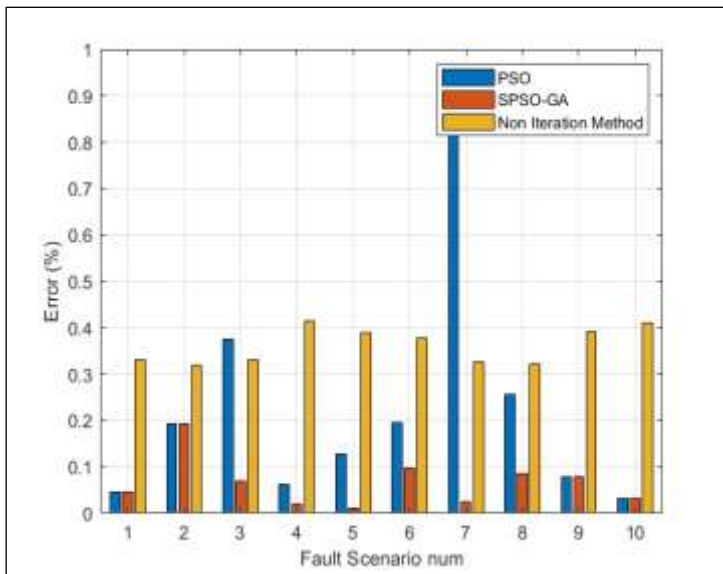


Figure 5: Comparison of fault location error for SLG in 10 fault scenarios for the proposed method, PSO and the noniterative.
Source: Authors, (2026).

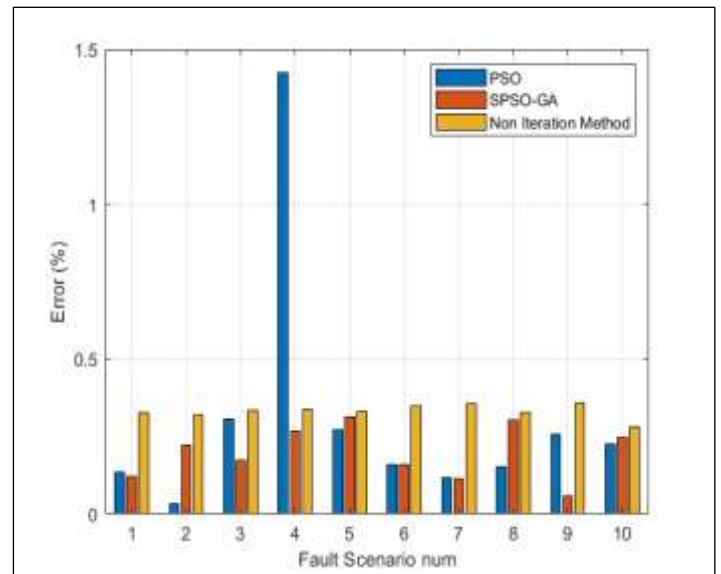


Figure 6: Comparison of fault location error for BC-G in 10 fault scenarios for the proposed method, PSO and the noniterative.
Source: Authors, (2026).

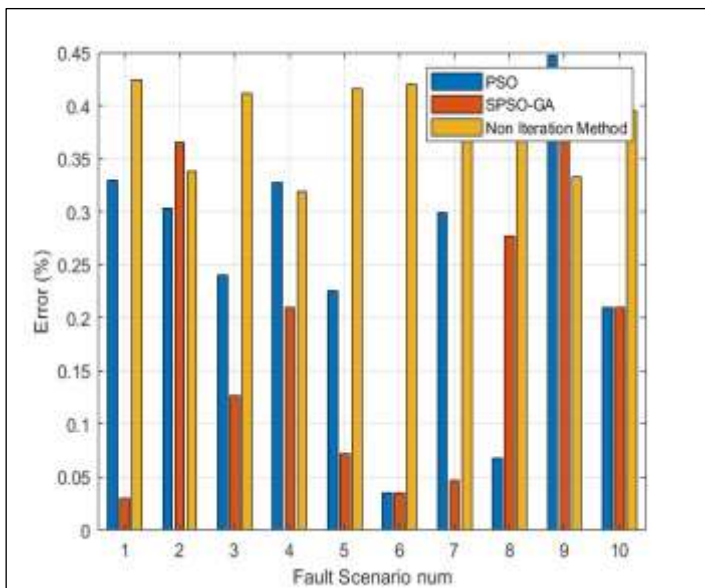


Figure 7: Comparison of fault location error for BC in 10 fault scenarios for the proposed method, PSO and the noniterative.
Source: Authors, (2026).

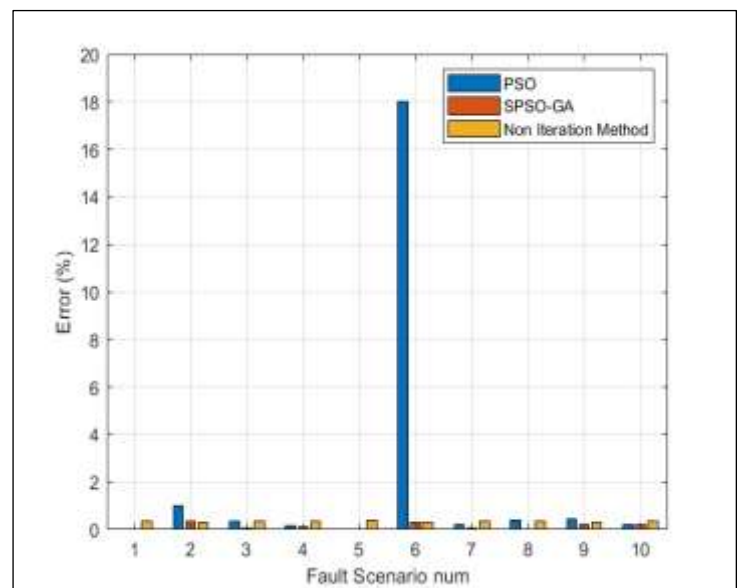


Figure 8: Comparison of fault location error for ABC in 10 fault scenarios for the proposed method, PSO and the noniterative.
Source: Authors, (2026).

V. CONCLUSION

The present paper has introduced a new, one terminal fault location technique that addresses the major shortcomings of the traditional impedance and travelling-wave techniques. The method generates a deterministic problem that is independent of both remote-source parameters and communications infrastructure by means of the strategic use of measurements made at one, temporary post-fault state following remote-end breaker clearance but preceding the operation of local breakers (State C). High modeling accuracy of long transmission lines is guaranteed by the application of a distributed parameter model along with the modal, or Clark, transformation. The main innovation of the given work is the appearance of the PSO-GA hybrid metaheuristic as the main solver of the complex, non-linear objective function which appears in the fault location problem. This hybrid method combines two algorithm pairs effectively over different regions of search, unlike single-method optimizers, which exploit and optimize known solution areas, and GA, which is able to search the search space broadly.

The theoretical effectiveness of the given approach was measured by the means of numerical simulation which was implemented on the model of a realistic high voltage transmission system (400 kV) and with the line length (239 km long). The obtained results of this validation make it clear that the hybrid PSO-GA approach will provide the best results in terms of fault location accuracy than the current techniques hence can be considered to be appropriate in real-life transmission line applications. The hybrid PSO-GA methodology is continually more accurate than isolated PSO and conventional non-iterative solutions on different types of faults (SLG, LL, LLG, LLL). Moreover, the algorithm has high computational efficiency whereby the processing latency is less than 0.5 seconds, which proves its feasibility in real-time implementation in contemporary power system protection systems. Overall, it is possible to conclude that this work also adds a communication-independent, reliable, and accurate fault location solution. It is based on the exclusive approach to measurement and sophisticated hybrid AI optimization in the offer of a convenient tool in enhancing grid reliability and minimizing the duration of outages, which is a considerable breakthrough in the sphere of power system fault analysis.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Ali Adnan Ajel, Kassim Al-Anbarri.

Methodology: Ali Adnan Ajel, Kassim Al-Anbarri.

Investigation: Ali Adnan Ajel, Kassim Al-Anbarri.

Discussion of results: Ali Adnan Ajel, Kassim Al-Anbarri.

Writing – Original Draft: Ali Adnan Ajel.

Writing – Review and Editing: Ali Adnan Ajel and Kassim Al-Anbarri.

Resources: Ali Adnan Ajel.

Supervision: Kassim Al-Anbarri.

Approval of the final text: Ali Adnan Ajel, Kassim Al-Anbarri.

VII. ACKNOWLEDGMENTS

The authors acknowledge the support of the College of Engineering, Mustansiriyah University (<https://webmain.uommustansiriyah.edu.iq>).

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