A Single-End Line-to-Ground Fault Location Method for HVAC Transmission Lines Using Sequential Feed-Forward Neural Networks

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ABSTRACT

The paper presents an Artificial Neural Network (ANN)-based single-ended fault location technique as a practical and robust solution for improving the protection and maintenance of High Voltage Alternating Current (HVAC) transmission systems. The proposed fault location method depends on utilizing multistage predictions implemented by sequential feed-forward neural networks. The proposed method is a single-end-based method that does not necessitate the acquisition of measured signals from the other end. The inputs to the first stage are the voltage and current sequence components derived from the measured signals at the sending end of the transmission system. The training data are optimized using fault analysis theorems to improve the accuracy of fault location prediction. The fault point voltage, obtained from the first stage, is identified as a key parameter. The rationale and justification for its effectiveness and significance are presented in the paper. This parameter is subsequently combined with selected primary data to serve as the input for fault location prediction in the final stage. Extensive testing is performed with the assistance of MATLAB software, considering the effect of various fault scenarios, including different fault resistances, fault inception angles, and load angles. The findings indicate that the maximum error of the proposed method does not exceed 1%, confirming its efficacy in locating line-to-ground faults in HVAC transmission lines.

Keywords-fault location; HVAC; transmission

I. INTRODUCTION

The protection of High Voltage Alternating Current (HVAC) transmission systems is imperative to ensure the stability and reliability of power supply networks. These systems form the backbone of energy transmission, and any failure can lead to significant disruptions affecting both consumers and industries. Accurate and prompt fault identification plays a vital role in minimizing downtime and restoring operations efficiently [1-3]. Fault location is essential for guiding maintenance teams to the exact point of failure, thereby reducing the time required for repairs and preventing the unnecessary inspection of unaffected sections. Effective fault detection not only shortens outage durations but also reduces the economic and operational losses associated with prolonged interruptions. Robust fault location strategies enhance the resilience and sustainability of transmission systems, ensuring reliable electricity delivery in the face of growing energy demands [4-8].

Fault location methods can be categorized as single-ended or double-ended. Single-ended fault location techniques are crucial for simplifying fault detection in transmission systems [9, 10]. These methods rely solely on measurements from one end of the line, eliminating the need for communication links between terminals and reducing system complexity and vulnerability to communication failures. Another key advantage is avoiding synchronization challenges, as the measurements and analyses are confined to a single point, bypassing the need for precise timing coordination between multiple ends [11, 12]. This not only enhances reliability but also reduces the implementation and maintenance costs associated with complex communication systems. Single-ended approaches are particularly beneficial in scenarios where access to remote terminals is limited or where cost constraints prevent the deployment of advanced communication infrastructure. These methods enable efficient and accurate fault location with minimal operational requirements.

Traveling wave techniques are utilized in fault location across different transmission systems. For hybrid systems, a method using modal traveling wave arrival time differences and propagation path ratios was developed by authors in [13]. Another study optimized the operation of traveling wave fault locators in the presence of disturbances [14]. This study employed digital signal processing and statistical tools to improve the accuracy of time-of-arrival detection for fault waves and mitigate the effects of pre-fault disturbances. However, traveling wave-based fault location faces challenges such as signal attenuation, noise interference, and the need for high-speed sampling. These challenges can impact the accuracy of fault location, especially in cases of high-impedance faults or multiple simultaneous faults. Additionally, system complexities such as synchronization requirements, varying line parameters, and the strategic placement of measurement devices complicate implementation and reliability further [15-17]. Furthermore, various traveling wave methods have been introduced to locate earth faults in distribution systems [18, 19].

Various artificial intelligence methods are used for fault diagnosis and location across transmission systems [20-24]. Intelligent recovery methods using deep learning [20, 21] and fuzzy logic [22], are presented. In [23], a method for locating series faults using the group method of data handling is proposed. This method is based on single-end data and is independent of line parameters. In [24], an artificial hummingbird algorithm, inspired by hummingbird foraging, is used to locate faults in overhead transmission lines.

Precisely estimating fault locations remains a significant challenge for protection engineers. However, accurate estimation is crucial for quickly restoring service, reducing outages and revenue loss, and improving network reliability. The proposed fault location method utilizes multistage predictions implemented by sequential feed-forward neural networks. It is a single-end-based method that does not require measured signals from the other end. Extensive testing was performed considering the effects of various fault resistances and fault inception angles. The results indicate the proposed method's robust performance in locating faults in HVAC transmission lines.

II. PROPOSED SINGLE-END FAULT LOCATION METHOD

The training data are optimized through the application of fault analysis theorems, which enhances the accuracy of fault location prediction. A critical outcome of the theoretical analysis is the demonstration that the fault point voltage, obtained during the initial stage, serves as a key indicator of the fault's location. This voltage can be accurately predicted using measured data and facilitates the subsequent stage's estimation of the fault distance. This section provides a detailed rationale and justification for selecting this parameter, emphasizing its strong correlation with the actual fault location. To improve the prediction model further, the fault point voltage is combined with carefully selected primary system data, such as current and voltage measurements from relay points. This combined dataset serves as the input for the final prediction stage, enabling the model to produce more precise and reliable fault location estimates.

When a line-to-ground fault occurs, the three-phase transmission circuit decomposes into three sequence circuits, along with the prefault circuit. Figure 1 illustrates the single-line diagram of a transmission system under fault condition, with the proposed relay installed at one end of the line. Figure 2 depicts the prefault circuit with the fault point voltage $UF_{pre-fault}$ as well as the voltage and current at the sending end, $US1$ and $I_{pre-fault}$. Figure 3 presents the sequence circuits during the fault condition. The parameters r_1, l_1, C_1, r_2, l_2, C_2, r_0, l_0, C_0 represent the resistances, inductances, and capacitances of the positive-sequence, negative-sequence, and zero-sequence networks, respectively. R_F denotes the fault resistance. The change in positive-sequence voltage and current is represented by $\Delta US1$ and $\Delta IFS1$, respectively. $US2$, $IS2$, $US0$, and $IS2$ correspond to the negative-sequence and zero-sequence voltages and currents at the relay location. Z_{x1} and Z_{x0} represent the positive-sequence and zero-sequence impedances up to the fault point, respectively.

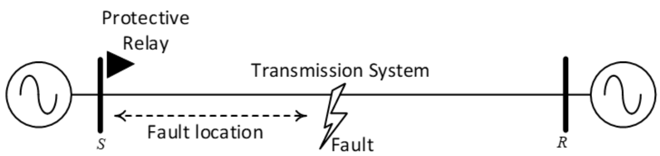


Fig. 1. Single line diagram of a faulted transmission system.

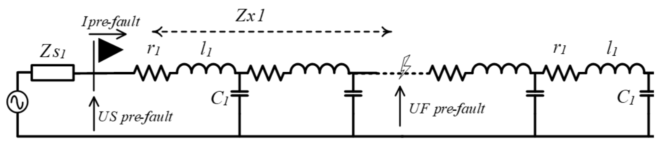


Fig. 2. Pre-fault equivalent circuit.

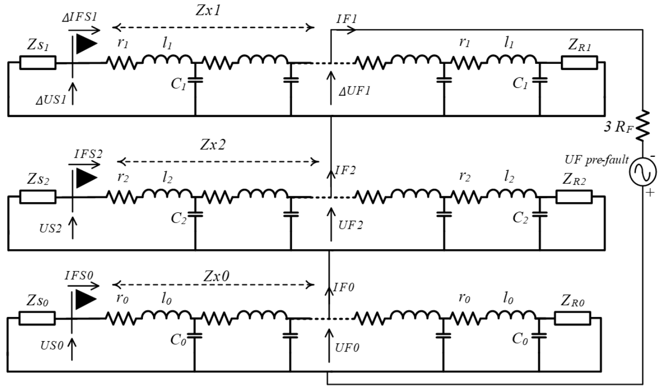


Fig. 3. Sequence circuits of the transmission system under line-to-ground fault.

The sequence voltages at the fault point are expressed [25, 26] as follows:

$$\begin{bmatrix} \Delta UF1 \\ UF2 \\ UF0 \end{bmatrix} = \begin{bmatrix} \Delta US1 \\ US2 \\ US0 \end{bmatrix} - \begin{bmatrix} Z_{x1} & 0 & 0 \\ 0 & Z_{x2} & 0 \\ 0 & 0 & Z_{x0} \end{bmatrix} \begin{bmatrix} \Delta IFS1 \\ IFS2 \\ IFS0 \end{bmatrix} \quad (1)$$

From the circuit in Figure 3, the voltage at the fault point is:

$$\Delta UF1 + UF2 + UF0 + UF_{pre-fault} = IF * RF \quad (2)$$

From the prefault equivalent circuit [25, 26]:

$$UF_{pre-fault} = US_{pre-fault} - I_{pre-fault} * Z_{x1} \quad (3)$$

Substituting (1) and (3) into (2), we have:

$$\Delta US1 - Z_{x1}\,\Delta IFS1 + US2 - Z_{x2}\,IFS2 + US0 - Z_{x0}\,IFS0 + US_{pre-fault} - I_{pre-fault} * Z_{x1} = IF * RF \quad (4)$$

The positive-sequence and negative-sequence impedances are equal in transmission circuits. Thus, (4) is rewritten:

$$\Delta US1 + US2 + US0 + US_{pre-fault} - Z_{x1}\big(\Delta IFS1 + IFS2 + I_{pre-fault}\big) - Z_{x0}\,IFS0 = IF * RF \quad (5)$$

The positive-sequence voltage, positive-sequence current, the phase voltage, and the phase current measured at the relay point are:

$$US1 = \Delta US1 + US_{pre-fault} \quad (6)$$

$$IFS1 = \Delta IFS1 + I_{pre-fault} \quad (7)$$

$$US = US1 + US2 + US0 \quad (8)$$

$$IS = IFS1 + IFS2 + IFS0 \quad (9)$$

Equation (5) is reconsidered:

$$US - Z_{x1}\,(IS) - (Z_{x0} - Z_{x1})\,IFS0 = IF * RF \quad (10)$$

$$US = Z_{x1}\left(IS + \left(\frac{Z_{x0} - Z_{x1}}{Z_{x1}}\right) IFS0\right) + IF * RF \quad (11)$$

The impedance measured by the relay [25] is:

$$Z_{Relay} = \frac{US}{IS + K * IFS0} \quad (12)$$

$$Z_{Relay} = Z_{x1} + \frac{IF * RF}{IS + K * IFS0} \quad (13)$$

where K does not depend on the fault location and is defined as:

$$K = \frac{Z_{x0} - Z_{x1}}{Z_{x1}} \quad (14)$$

If the fault is solid (i.e. $RF = 0$), the impedance measured by the relay will equal the positive-sequence impedance measured up to the fault point. However, for higher fault resistances, the measured impedance will no longer accurately represent Z_{x1}. It can be concluded that the error arises from the second term of (13), which is a function of the fault point voltage, the measured faulted phase current, and the estimated zero-sequence current derived from the measured data. Among these variables, the only unknown is the fault point voltage. This value can be more easily predicted using the measured data from the first stage than by directly predicting the fault distance. As a result, the fault location distance can be more accurately and straightforwardly determined in the final stage.

Therefore, the proposed fault location method relies on utilizing multistage predictions implemented by sequential feed-forward neural networks. Figure 4 shows the neural networks employed in the proposed method. The inputs to the first network depend on the measured signals at one end of the transmission system, which is the sending end of the tested system. The voltage and current signals, US and IS, are measured, and the sequence components of both signals, including $US1$, $US2$, $US0$, $IS1$, $IS2$, and $IS0$, are also fed to the network. The first network aims to determine the fault point voltage (UF), which is the key parameter. This parameter is then combined with selected primary data to serve as input for fault location prediction in the second stage.

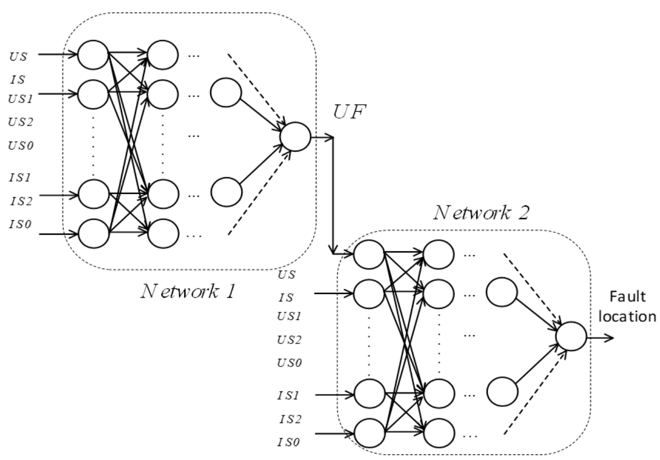


Fig. 4. Proposed sequential feed-forward neural networks to determine the fault location.

III. TEST SYSTEM

The test system is simulated with the help of MATLAB software. The transmission system is 300 km in length and integrates two grids operating at 50 Hz. The parameters of the transmission circuit are summarized in Table I, and the parameters of the grids are outlined in Table II.

TABLE I. SIMULATED TRANSMISSION LINE PARAMETERS

Parameter	Value
r_1 (Ω/km)	0.0305
r_0 (Ω/km)	0.275
l_1 (H/km)	0.9708e-3
l_0 (H/km)	3.268e-3
C_1 (F/km)	13e-9
C_0 (F/km)	5e-9

TABLE II. GRID SOURCE PARAMETERS

Parameter	Value
Phase voltage (kV)	400
Frequency (Hz)	50
Short circuit level (MVA)	50e3
X/R ratio	10

IV. VALIDATION RESULTS

A. *Performance of Trained Neural Networks*

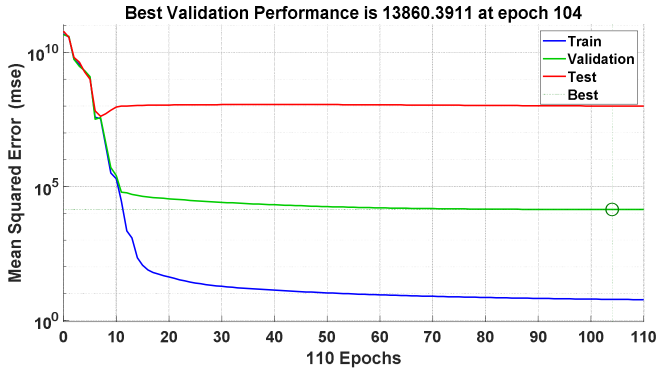
The data required for training the neural network are obtained by simulating different cases of faults with changing fault location from 20 km to 280 km with a step of 20 km, and with changing fault resistance from 0.01 Ω to 200 Ω with a step change by 20 Ω. The obtained data are categorized into 80% for training, 10 % for validation, and 10 % for testing.

Both networks are created using a four-layer feed-forward network with sigmoid hidden neurons and linear output neurons. The network is trained using the Levenberg-Marquardt backpropagation algorithm. Figure 5 depicts the performance of the first network after training, with a regression factor of 0.99985 for all trained samples. Figure 6 shows the performance of the second network after training, with a regression factor of 0.99998 for all data.

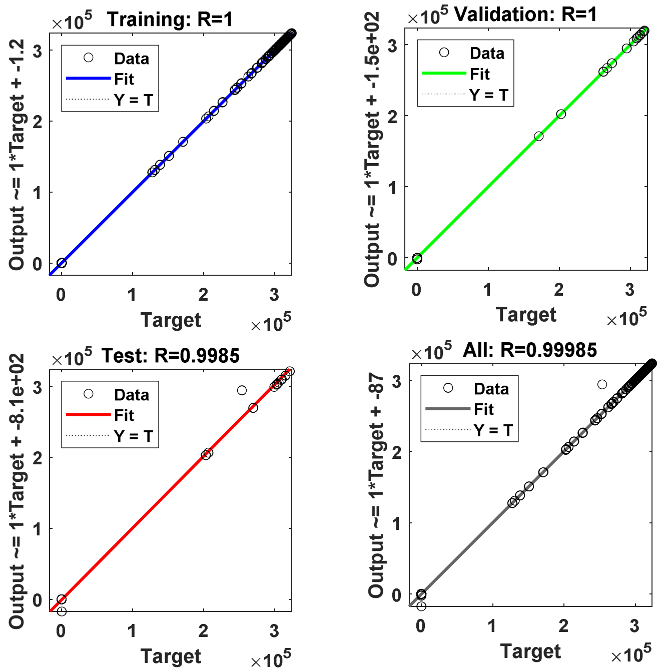
B. *Testing Networks with New Data*

The created networks are tested with new data that were not included in the training. Different test cases are simulated with altered fault resistances and different fault inception angles. Figure 7 presents the results obtained with altered fault resistances and a fault location at 75 km. As shown, the fault location is determined with good accuracy, with the error not exceeding 0.33%. Figure 8 shows the results obtained with altered fault inception angles and a fault location at 165 km. As shown, the fault location is determined with good accuracy, with an error not exceeding 0.08%. Furthermore, the presented method was tested with an earth fault occurring at 200 km, with varying load angles ranging from 10° to 75°, as shown in Figure 9. The results confirmed the efficacy of the method across various load angle changes. The error percentages are calculated as follows:

$$Error\ \% = \frac{|Estimated\ location - Target\ location|}{Total\ length} * 100 \qquad (15)$$

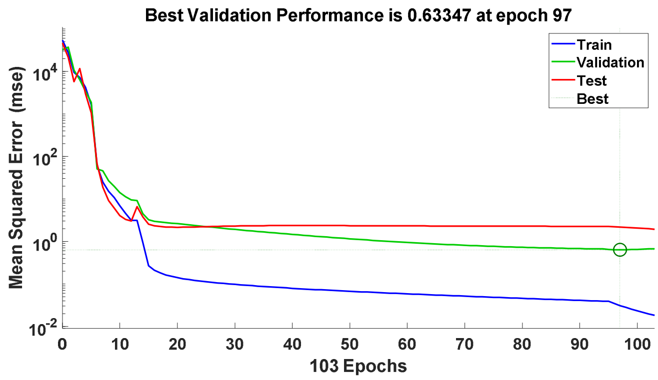


(a)

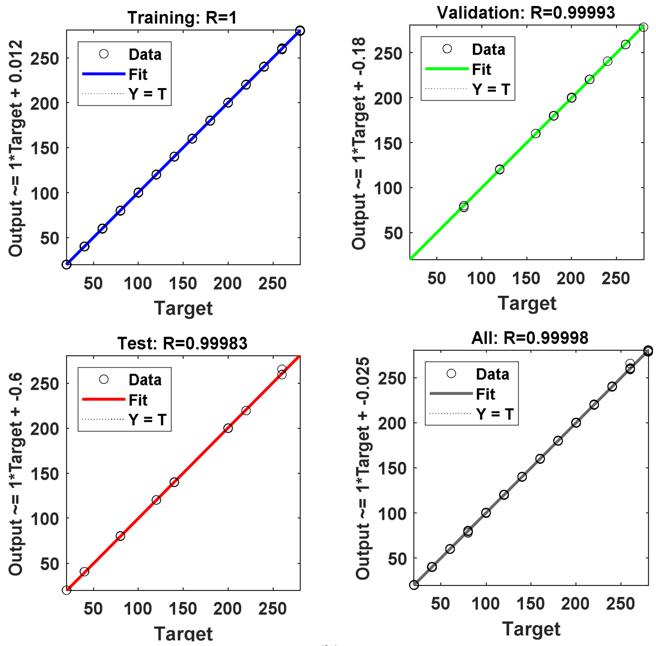


(b)

Fig. 5. Performance of the first trained network: (a) best validation performance, (b) regression factor.



(a)



(b)

Fig. 6. Performance of the second trained network: (a) best validation performance, (b) regression factor.

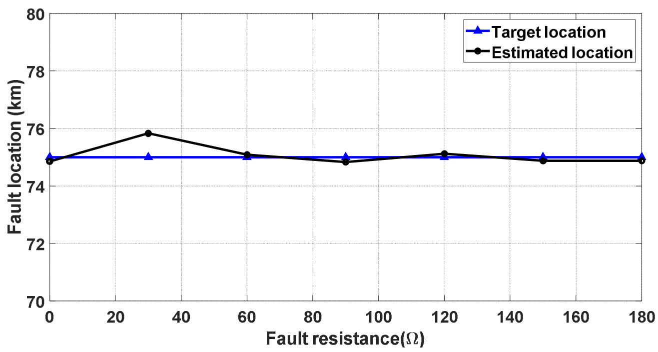


Fig. 7. Testing the neural network with new data including different fault resistances.

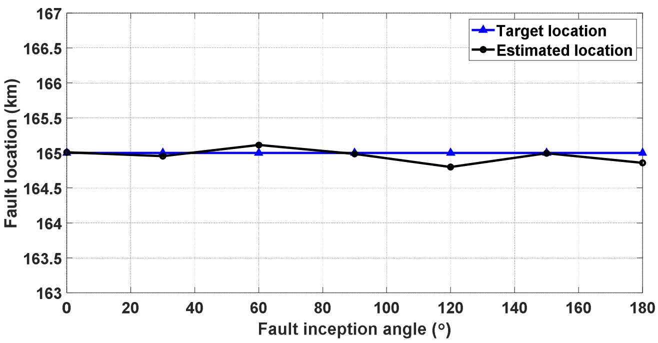


Fig. 8. Testing the neural network with new data including different fault inception angles.

Furthermore, the developed neural networks were evaluated using randomly generated test cases. The simulated test system was tested under fault scenarios with randomly selected fault locations, fault resistances, and fault inception angles. The neural networks demonstrated strong performance in accurately identifying fault locations. The results, as presented in Table III, indicate a maximum error of only 0.95%.

TABLE III. RESULTS WITH RANDOM TEST CASES

Fault location	Fault resistance	Fault inception angle	Error (%)
193	88.7	33	0.27
156	55.9	58	0.54
203	103.9	64	0.95
124	103.0	28	0.15
87	144.0	31	0.48
144	30.6	66	0.79
73	62.3	48	0.22
241	176.8	51	0.09
67	29.2	59	0.85
192	39.5	36	0.65
289	98.2	69	0.79
141	29.9	23	0.07
189	102	31	0.44

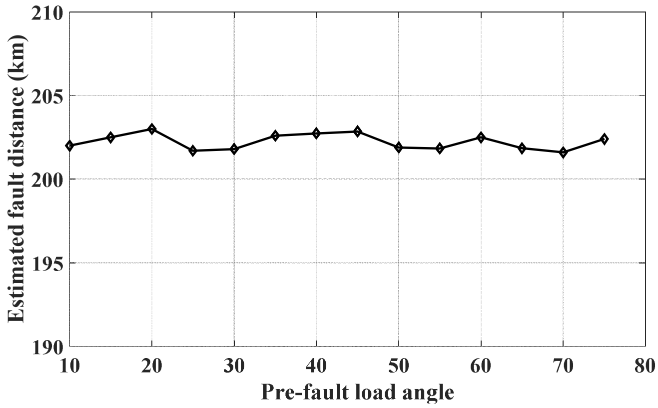


Fig. 9. Testing the presented method using the neural network under an earth fault occurring at 200 km, with varying load angles.

V. CONCLUSION

The proposed single-end fault location technique demonstrates an effective solution for enhancing the protection and maintenance of High Voltage Alternating Current (HVAC) transmission systems. The efficacy of this method is demonstrated by its ability to locate line-to-ground faults with a high degree of accuracy. This objective is realized through the implementation of multistage predictions facilitated by sequential feed-forward neural networks, which utilize measurements from the sending end of the transmission line. The fault location prediction process involves the implementation of fault analysis theorems, with the objective of optimizing the training data. The fault point voltage, as determined in the first stage, serves as a key parameter for accurately identifying the fault location in the second stage. Extensive testing was conducted under various fault scenarios (different fault resistances, fault inception angles, and load angles) to confirm the robustness and reliability of the approach, and the maximum error obtained was less than 1%. This renders the proposed method a valuable tool for improving fault location and reducing downtime during maintenance in transmission networks.

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