Fault Diagnosis and Location Method for Active Distribution Network Based on Artificial Neural Network

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Abstract—A fault diagnosis and location method of artificial neural network (ANN) based on regularized radial basis function (RRBF) is proposed. The phase angle feature of fault voltage and current signal is analyzed. The proposed method adopts synchronized amplitude and phase angle feature for fault diagnosis based on RRBF neural network. The fault diagnosis and location for the distribution branch is researched in the IEEE 13-bus active distribution network (ADN) system. The diagnosis accuracy and location precision is analyzed considering the effect of different input signals, fault position, and fault resistance. The simulation result demonstrates that the location method based on phase angle feature shows higher accuracy. The RRBF fault diagnosis and location method aims to solve fault in ADN and lays the foundation to maintain ADN system stability.

1. INTRODUCTION

Active distribution networ (ADN) which consists of distributed generation (DG), transmission, and distribution is an important part of power system. The ADN is regarded as a new distribution system of power grid, for its improved energy efficiency and maximized utility [1]. Different from high voltage transmission system, ADN has more complicated topological structures, more inconstant power flow, and more various grounding fault conditions [2]. Due to wide geographical area and the susceptibility to external factors, ADN is facing the challenge of more prominent and mostly inevitable electric power faults [3]. Faults in ADN are considered as the main contributor to supply interruptions. Therefore, the development of efficient and
precise fault diagnosis method has received a lot of research interest in recent years [4], [5].

The modified impedance-based fault location algorithm [6] and the transient traveling wave method [7] are proposed for fault location. In [8], a novel impedance-based fault location method is used to determine the possible fault points. In [9], a frequency domain technique is proposed to locate the internal winding fault in power transformers. The performance of the magnitude and the phase angle signals are analyzed. In [10], the local mean decomposition is used for fault location and detects the arrival time of the initial traveling wave at each measurement.

In addition to traditional fault diagnosis methods, various soft computing techniques such as support vector machines (SVM), fuzzy logic, genetic, and artificial neural network (ANN) algorithm have emerged as powerful tools in protective applications [11]. The regression model of the SVM function was applied for the fault location estimation [12], [13], faulted phase selection [14], and transient stability detection [15].

Due to the efficiency, robustness, and reliability of the fuzzy logic [16], [17], the fault diagnosis and location methods were proposed based on the fuzzy inference system (FIS) method [18], [19], wavelet singular entropy, and fuzzy logic [20]–[22]. Genetic method was used in high-voltage direct current (HVDC) system for fault location in [23]. A fault diagnosis method using genetic algorithm was proposed in [24], which is only suitable for single fault or single power source. Moreover, the phase current and voltage signals are input to different ANN location models [25], fuzzy-ARTMAP classification neural network model [26], and adaptive neuro-fuzzy models [27] to locate and classify fault. Active phase feature vector is identified for fault diagnosis and location based on different fault quantity characteristic. Fault location methods research the fault phase amplitude characteristic, but the phase angle signal of the voltage and current is neglected.

Due to the DG attached to ADN, the distributed resource can provide power for the fault zone constantly to maintain the system stability. Since there is a significant change in the current direction when ground fault occurs, this research proposes an improved method that utilizes the phase angle feature of the voltage and current for fault diagnosis and location.

2. IMPROVED RBF NEURAL NETWORK MODEL

2.1. Radial Basis Function

The radial basis function (RBF) network is a three-layer feed forward network combining linear statistical distribution model and non-linear perceptron model. The RBF structure has a topology consisting of three layers: input layer, radial basis hidden layer, and output layer. Each output node in the output layer is defined as [28]–[30]

\[ f_i(x) = u(x_i) + \varepsilon_i \]

\[ 1 \leq i \leq n \]  

where \( f(x) \) is the output vector; \( u(\cdot) \) is a known smooth function; \( \varepsilon \) is the error; normally distributed with mean zero and variance. The problem to be considered is to estimate the function \( u(\cdot) \) from the observed data, for which we use the RBF network.

The RBF network, a class of single hidden layer feed forward networks, is expressed as a linear combination of radially symmetric non-linear basis functions [31] as follows:

\[ u(x_i) = \sum_{j=1}^{m} \phi_j(x_i) \cdot \omega_j \]

where \( \phi_j(x_i) \) is the basis function. Each basis function forms a localized receptive field in the input space, and the most commonly used function is the Gaussian basis:

\[ \phi_j(x; C_j, \sigma_j) = \exp \left(-\frac{\|x - C_j\|^2}{2\sigma_j^2}\right) \]

\[ 1 \leq j \leq m \]

where \( \sigma_j \) is the width parameter; \( C_j \) is the center of the RBF; \( \| \cdot \| \) is the Euclidean norm.

2.2. The Regularized OLS Algorithm

The RBF network parameters in the multi-layer perceptron are calculated based on non-linear optimization techniques [28]. Owing to the requirement that the centers should suitably sample the input domain, some previous research [32] cannot guarantee adequate performance [28].

If the centers and widths are optimized in supervised learning as parameters, the number of parameters will exceed the sample size. This serious problem is called overfitting [28]. The training data contains the noise or the stall threshold is not appropriate, which may generate the overfitting. To prevent overfitting [33], theROLS learning procedure is applied in this paper to selected centers so that adequate RBF networks can be derived.

TheROLS method is utilized to decrease as much as the regularized squared error and forms an efficient procedure for the RBF neural network. From Eqs. (1), (2), and (3), the multiple input multiple output (MIMO) system [34] can be expressed as

\[ W = [w_1 \ w_2 \ \cdots \ w_n] \]
Define the regularized error reduction ratio \([rerr_k]\) due to \(v_k\) as [33]

\[
[rerr]_k = \sum_{j=1}^{n} (v_j^T v_k + \lambda) s_j^2 / F^T F \tag{10}
\]

Based on the above regularized error reduction ratio, significant regressor \(\Phi_j\) can be selected in a forward-regression procedure. The selection is terminated at the \(h\) stage when

\[
1 - \sum_{k=1}^{h} [rerr]_k < \xi \tag{11}
\]

is satisfied [33], where \(\xi\) is a chosen tolerance. The training process ends. The regularized radial basis function (RRBF) weight parameter vector and the corresponding function center \(C_j\) is calculated.

This paper utilizes the ROLS algorithm to improve the RBF neural network. Due to the significant feature of the fault current and voltage, the input vector of the RRBF neural network contains the phase angle signal measured by phase measurement unit (PMU).

3. POWER SYSTEM MODEL AND FAULT FEATURE ANALYSIS

3.1. Power System Model

The ADN power system model is a standard IEEE 13-bus. The active electric transmission and distribution power system are shown in Figure 1. The power system comprises 13 buses, 6 loads, and 13 \(\pi\)-mode branches. The renewable resource model was connected to the 13th bus. Fault signals are taken from PMU units on each bus in the distribution network. The system model is simulated in MATLAB. The transient voltage and current signals of the fault zone in ADN system are researched.

3.2. Fault Feature Analysis

It is assumed that a typical A-B-C phase to ground fault with a fault resistance 100 \(\Omega\) occurs at 20\% length of the 11–13 distribution branch. The fault occurs at 1 sec and is cleared at 3 sec. The proposed method utilizes the phase signals of current and voltage for fault diagnosis and location. The amplitude and phase angle signals of voltage and current in fault zone are measured by PMU. The three phase current and voltage change of amplitude and phase angle signals are shown in Figure 2.
When fault occurs, the current amplitude signal changes rapidly in the traditional distribution network. Due to the addition of the renewable resource, the renewable resource can supply the load to operate steadily. The voltage amplitude of the fault branch changes little about 1.893%. The renewable resource is a PQ resource that the active power is constant. The basic harmonic amplitude vibration of the current is not significant. The branch resistance changes rapidly on account of the ground resistance when fault occurs. Based on this concept, there is a phase angle change for fault branch in contribution with the renewable resource in Figure 2(d). The phase angle reduces with a large slope. Therefore, this paper utilizes the phase angle signal for fault diagnosis and location.

4. FAULT LOCATION PROCEDURE

In this paper, a fault location method is proposed to prevent overfitting based on RRBF neural network. Figure 3 shows the flowchart of the fault location method, which analyzes the detailed procedure. Both fault diagnosis and location can be carried out. The fault location scheme includes four major steps summarized as below:

**Step 1: Preparatory work**

Before the proposed fault location method is applied, simulation of the ADN system generates the faulted signals of currents and voltages. The fault feature data and the healthy data are extracted from the 13 buses in ADN with PMU, which contain amplitude and phase angle signals of voltage and current. These sample datasets compose the training data.
Step 2: Training progress

Based on the training data, the RRBF method is used to train the fault diagnosis model of the whole ADN system. The learning process of the RRBF model involves the allocation of new hidden units and tuning of network parameters. The learning process is terminated when the regularized error reduction ratio goes under the defined threshold in formula Eqs. (9) and (10). Then the fault diagnosis model is built.

It is assumed that a fault occurs in the potential fault branch of the "ith" branch, in the potential fault branch, the two-terminal voltage and current signals of the potential fault branch are extracted. Based on the training data, the separate RRBF neural networks are designed to accurately locate the fault occurring in all potential branches.

Step 3: Fault diagnosis progress

After the proposed RRBF models are built, the proposed method is applied in the synchronous fault diagnosis and location. The feature signals of voltage and current are measured by PMU synchronously, which are input to the fault diagnosis model. The fault diagnosis result $R$ ($R = [r_1, r_2, \ldots, r_9, r_{10}]$), the detailed explanation of which is given in Section 5.1) is calculated result of the proposed method. If the $r_i > r_0$, the fault occurs in the "ith" branch; if the $r_i < r_0$, the ADN system is in healthy status, there is no fault; where the $r_0$ is the fault diagnosis threshold to determine the ADN system status.

About $r_0$: It is evident from the results that although the RRBF gives a high accuracy, there are small fluctuations in the actual RRBF outputs around '1' and '0'; since in practice this cannot be avoided, small threshold levels are built into the RRBF method in order to minimize the degree of uncertainty. In this application, the level is set as: if the output $r_i < 0.3$, the ADN system is diagnosed as in healthy status; and if the output $r_i > 0.8$, the fault occurs in the "ith" branch [36].

Step 4: Accurate fault location

After the fault zone is determined, the current and voltage signals of the two-terminal fault branch are extracted by PMU, which are imported to the fault location model. The accurate fault position is calculated and the whole fault location process operates online. The ADN fault location is carried out synchronously with PMU measurement based on the proposed method.

5. FAULT DIAGNOSIS RESULTS

5.1. RRBF Structure of the Fault Diagnosis Method

The RRBF neural network structure of fault diagnosis method is shown in Figure 4. Three-layer RRBF network comprises multi-dimension inputs: amplitude and phase angle of three phase in each node, and 13 dimension outputs $R = [r_1, r_2, \ldots, r_{12}, r_{13}]$. The output vector contains variable values, which is given 0 or 1 relating to potential fault nodes. The output result approaching 1 indicates that a fault occurs in the corresponding branch. For example, output 0000000010000 indicates that a fault occurs in the 9th bus in ADN.

The training data contains the amplitude and phase angle signal of the fault voltage and current in each bus.
The multiple input $P$ and output vector $R$ is shown as follows:

$$
P = \begin{bmatrix}
U_{a1} & U_{b1} & U_{c1} & I_{a1} & I_{b1} & I_{c1} \\
U_{a2} & U_{b2} & U_{c2} & I_{a2} & I_{b2} & I_{c2} \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
U_{an} & U_{bn} & U_{cn} & I_{an} & I_{bn} & I_{cn}
\end{bmatrix}
$$

$$
R = [r_1 r_2 \cdots r_12 r_{13}]
$$

The proposed fault diagnosis method is trained with fault data in different fault branches. The training sets are generated considering fault in both the transmission and distribution branches of the ADN model. The mean squared error goal for the ANN networks is fixed at 0.01.

### 5.2. Fault Diagnosis Result Analysis

The PMU measures phase signals of the voltage and current. In the fault diagnosis progress, the amplitude and phase angle signals are imported to the input vector of the proposed fault diagnosis method synchronously. The fault diagnosis result is defined as the output vector of the RRBF neural network. The output result of the proposed method defines the diagnosis probability of the corresponding fault zone.

The fault diagnosis result in the 13th branch of ADN is shown in Figure 5. It is simulated that a B single phase to ground fault occurs at 1 sec, and the fault is cleared at 3 sec. The transient process of the phase angle change is from 1 sec to 1.35 sec. The fault diagnosis transient result is shown in Figure 5(a). The transient diagnosis result of the 13th bus rises to 0.815 at 1.1 sec, which estimates that the fault occurs in the 13th branch at 1.1 sec. The proposed method can identify the fault zone in ADN accurately in four cycles. The proposed fault diagnosis method can diagnose the fault zone in the transient process when fault occurs.

Comparative study of different input vector containing phase angle and amplitude is shown in Figure 5(b). In Figure 5(b), when a single phase to ground fault occurs, the diagnosis error of the proposed method trained by phase angle and amplitude is 0.053, the diagnosis error of the proposed method trained by amplitude is 0.151. The average error of the proposed method trained by amplitude is 0.184; the average error of the proposed method trained by phase angle and amplitude is 0.0589. Comparing with the method trained by single amplitude, the fault diagnosis method trained by phase angle and amplitude diagnoses fault at a higher precision.

In the 140 verification samples, the fault diagnosis method can monitor the ADN status and identify all fault branch. The accuracy of proposed diagnosis method trained by phase angle and amplitude can reach more than 96.429%.

### 5.3. Fault Diagnosis for Changed Topological Configuration

It is assumed that a B phase to ground fault occurs in the 11–13 branch. To reduce the risk of over-current, the fault branch is isolated and the non-fault zone restores power using switch. The switching operations change the ADN topological structure correspondingly. The changed ADN topological configuration is shown in Figure 6 where the 11–13 branch is isolated with disconnect switch.

Figure 7 shows the fault diagnosis result of the proposed method after the ADN topology connection changes. Comparing the diagnosis result before and after the topology connection changes, the proposed method can diagnose the ADN system both in healthy and fault status accurately. After the topology connection changes, it is
simulated that a C single phase to ground fault occurs at 1 sec in the 6th bus. The diagnosis result shows that the proposed method can diagnose the fault zone at 6th bus accurately. The average error of the proposed fault diagnosis method is 0.165.

After the topology connection changed, the main network remains at a voltage and current stable status. The switch strategy is adopted to protect the normal operation and stability of the main network, which causes the topology connection change. In the above switch strategy case, the proposed method can diagnose most common fault, and does not need a new training process.

6. FAULT LOCATION RESULTS

6.1. RRBF Structure of the Fault Location Method

The network structure of the proposed fault location method based on RRBF is shown in Figure 8. After the fault zone has been diagnosed, the RRBF fault locator calculates the fault position accurately. As shown in Figure 8, the input vector contains the phase angle signals of the both-side established fault distribution branch. The output result is the accurate distance from the fault location to the fault bus. The training sets contain the fault samples at the 5%, 15% ... 85%, and 95% length of the line.

Aiming at the distribution network fault, the fault location of the active distribution branch is mainly researched. In this study, the percentage error is used to measure the accuracy of RRBF fault location method as follows:

\[
\text{%Error} = \left(\frac{\text{Actual location} - \text{Estimated location}}{\text{Total line length}}\right) \times 100
\]

6.2. Fault Location Result Analysis

It is assumed that a fault occurs in the 11–13 branch, which connects to the renewable resource directly in ADN. The fault occurs from 1 sec to 3 sec. Several factors affect the fault location accuracy. The first case is the different fault position which covers the 5–95% of the branch. The second case is that the fault resistance changes from 0.5 to 80 ohm. A set of simulation tests analyzes the proposed fault location accuracy.

6.2.1. Fault Position Effect on Location Accuracy. In Figure 9, it is assumed that a C-phase to ground fault occurs in the 11–13 branch, where the distribution line is 10 km. After the fault zone is determined, the PMU extracts the fault voltage and current signals of the 11th and 13th bus. It is assumed that the fault distance is varied from 1 km to 9 km and the test fault interval is 2 km. The fault occurs at 1 km, 3 km, 5 km, 7 km, and 9 km.
To analyze the fault position effect on the proposed method, the fault location result is shown in Figure 9. Figure 9 compares the fault location error of different position in the 11–13 branch. The five lines show the fault location error at 1 km, 3 km, 5 km, 7 km, 9 km from 13 bus. The average error of the proposed fault location method is 0.518%, 0.213%, 0.095%, 0.164%, and 0.238%. The proposed RRBF fault locator can locate fault distance accurately and the maximum error is below 0.6%. Therefore, the location accuracy of the proposed method can match the actual demand. In Figure 9, considering the various fault position (from 1 km to 9 km), the simulation experiments demonstrate that the accurate fault location range can cover from the 10% to the 90% of the ADN branch.

6.2.2. Fault Resistance Effect on Location Accuracy. It is assumed that the A phase to ground fault occurs at 6.2395 km distance from 13th bus. Figure 10 shows the average error of the proposed fault location method. The fault resistance varies from 0.5 ohm to 80 ohm. In Figure 10, when A phase to ground fault occurs, the fault resistance varies at 0.5 ohm, 5 ohm, 20 ohm, and 80 ohm; the average error is 0.0523%, 0.0367%, 0.0343%, and 0.018%, respectively. The proposed RRBF fault locator can locate fault accurately when low impedance fault and high impedance fault occurs.

When a low resistance fault occurs, the voltage amplitude signal decreases obviously and the current amplitude signal increases rapidly. In Figures 11(a)–(d), when a high resistance fault occurs, the voltage and current amplitude signal changes indistinctively. Since the phase angle of the current signal shows the current direction change, the phase angle signal of the fault current reflects the fault feature accurately in Figures 11(e) and (f). The fault resistance varies from 20 ohm to 1000 ohm, the voltage and current amplitude of the branch changes little about 0.741% and 1.692%; the current amplitude of the branch changes 325.581%. Based on the analysis, the input vector with the phase angle and amplitude signal contains more fault features.

6.2.3. Phase Angle Signal Effect on Fault Location Accuracy. It is assumed that a three phase to ground fault occurs at 5 km. Figure 12 compares the performance of RRBF fault location method trained by phase amplitude and angle, and single phase amplitude. In Figure 12, when the fault resistance is 5 ohm, the error of the proposed method trained by single phase amplitude is 2.624%; the error of the method trained by phase angle and amplitude is 0.0154%. The average error of the location method trained by phase angle and amplitude is 2.624%; the error of the method trained by phase angle and amplitude is 0.0154%. The average error of the location method trained by phase angle and amplitude is 2.624%; the error of the method trained by phase angle and amplitude is 0.0154%. Comparing the fault location result, the method trained by phase angle and amplitude has a better accuracy. When the fault resistance is below 600 ohm, the lowest error is 0.00502%, where the fault resistance is 120 ohm. The proposed fault location method can estimate fault that the fault resistance varies from 5 ohm to 600 ohm accurately.

Current and voltage signals measured from real power systems usually contain noise. Therefore, noise is added to the measured signals in order to simulate noise conditions occurring in real ADN power system. It is assumed that a three phase to ground fault with 20 dB noise signal occurs at the 5 km distance from 13th bus. Figure 13 compares the RRBF fault location performance for different fault
resistance under 20 dB noise. In Figure 13, when the fault resistance is 5 ohm, the error of the proposed fault location method trained by single phase amplitude is 2.643%; the error of the method trained by phase angle and amplitude is 1.823%. In Figure 13, to locate the ground fault with 20 dB noise, the RRBF locator trained by phase angle and amplitude shows a better performance. The average error of the proposed method trained by phase amplitude is 4.205%, the average error of the method trained by phase angle and amplitude is 1.209%. When the fault resistance is below 600 ohm, the lowest error is 0.0473%, where the fault resistance is 120 ohm. The proposed fault location method can protect the ADN branch from fault resistance 0.5 ohm to 600 ohm. Therefore, the RRBF location method is simple and robust for both noise conditions and various fault parameters.

It is assumed that a 120 ohm three phase to ground fault occurs at 6.2395 km from 13th bus in the renewable resource branch. The fault occurs at 1 sec and is cleared at 3 sec. The output result of the fault locator based on different phase vector is compared in Figure 14. From Figure 14, the location method trained by amplitude and phase angle can locate the fault precisely at 1.4 sec. The
method trained by phase amplitude locates the fault at 1.45 sec. The average error of the proposed method trained by phase amplitude and angle is 0.0236%, while that trained by single phase amplitude is 1.943%. As the analysis above in Section 3, when the short circuit fault occurs, the phase angle signal of the 13th branch changes in a wide range, meanwhile, the amplitude of the voltage and current decreases insignificantly. As a result, the fault location method trained by phase amplitude and angle shows better accuracy in locating fault.

7. CONCLUSION

This paper applies a novel synchronous fault diagnosis and location method for common fault in ADN. The proposed method extracts fault feature from voltage and current phase angles to diagnose and locate fault. The RRBF method is applicable to diagnose and locate fault at a high precision. The advantageous features of this method are as follows:

1. This paper analyzes the variation progress of the fault transient current/voltage phase angle. The time variant character of voltage and current phase angle is analyzed, which can provide an efficient feature to diagnose and locate fault.
2. The adequate neural network is derived based on RRBF method to prevent overfitting. Then the RRBF network could provide great performance for high speed of fault diagnosis and location in the distribution network.
3. The proposed method consists of two stages: (1) a fault zone diagnosis stage, (2) an exact fault location stage. The fault zone diagnosis stage is important for complex adaptive distribution systems, and can greatly accelerate the speed of fault location.
4. The phase angle signal is extracted to improve the accuracy of the fault diagnosis and location method. The proposed method is appropriate for common fault in ADN. The low impedance and high impedance fault can be located precisely, in which case the fault resistance varies from 0.5 ohm to 500 ohm.

This paper improves the RRBF method to solve the fault diagnosis and location for ADN containing renewable resource. The improved method maintains high precision and rapid response, and can isolate the common fault timely. The fault diagnosis and location method can monitor the power system synchronously and maintain the stability, which lays the foundation for adaptive distribution system restoration.

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REFERENCES

[1] G. Mokryani, Y. F. Hu, and P. Papadopoulos, “Deterministic approach for active distribution networks planning with high penetration of wind and solar power,” Renew. Energ., vol. 1, no. 113, pp. 942–951, 2017. DOI: 10.1016/j.renene.2017.06.074.
[2] A. Bahmanyar and S. Jamali, “Fault location in active distribution networks using non-synchronized measurements,” Int. J. Elec. Power, vol. 1, no. 93, pp. 451–458, 2017. DOI: 10.1016/j.ijepes.2017.06.018.
[3] M. Pignati, L. Zanni, and P. Romano, “Fault detection and faulted line identification in active distribution networks using synchrophasors-based real-time state estimation,” IEEE T. Power Deliver, vol. 32, no. 1, pp. 381–392, 2017. DOI: 10.1109/TPWRD.2016.2545923.
[4] S. R. Madeti and S. N. Singh, “Online fault detection and the economic analysis of grid-connected photovoltaic systems,” Energy, vol. 1, no. 134, pp. 121–135, 2017. DOI: 10.1016/j.energy.2017.06.005.
[5] K. M. Sun, Q. Chen, and P. Zhao, “Automatic faulted feeder section location and isolation method for power distribution systems considering the change of topology,” Energies, vol. 10, no. 8, 2017. DOI: 10.3390/en10081081.
[6] R. Dashti and J. Sadeh, “Applying dynamic load estimation and distributed-parameter line model to enhance the accuracy of impedance-based fault-location methods for power distribution networks,” *Electr. Pow. Compo. Sys.*, vol. 41, no. 14, pp. 1334–1362, 2013. DOI: 10.1080/15325008.2013.819950.

[7] S. Hasheminejad, S. G. Seifossadat, and M. Razaz, “Ultra-high-speed protection of transmission lines using traveling wave theory,” *Electr. Pow. Syst. Res.*, vol. 1, no. 132, pp. 94–103, 2016. DOI: 10.1016/j.epsr.2015.11.014.

[8] R. Dashti and J. Sadeh, “Fault section estimation in power distribution network using impedance-based fault distance calculation and frequency spectrum analysis,” *IET Gener. Transm. Dis.*, vol. 8, no. 1, pp. 1406–1417, 2014. DOI: 10.1049/j.iet-gtd.2013.0633.

[9] M. Al-Shaer and M. Saied, “Recognition and location of transformer winding faults using the input impedance,” *Electr. Pow. Compo. Sys.*, vol. 35, no. 7, pp. 785–802, 2007. DOI: 10.1080/1532500601715157.

[10] X. Q. Fan and Y. L. Zhu, “Fault location using local mean decomposition on traveling waves with three current measurements in an overhead conductor,” *Electr. Pow. Compo. Sys.*, vol. 43, no. 19, pp. 2196–2204, 2015. DOI: 10.1080/15325008.2015.1058870.

[11] S. S. Gururajapathy, H. Mokhlis, and H. A. Illias, “Fault location and detection techniques in power distribution systems with distributed generation: a review,” *Renew Sust. Energ Rev.*, vol. 1, no. 74, pp. 949–958, 2017. DOI: 10.1016/j.rser.2017.03.021.

[12] X. T. Deng, R. X. Yuan, and Z. F. Xiao, “Fault location in loop distribution network using SVM technology,” *Int. J. Elec. Power*, vol. 1, no. 65, pp. 254–261, 2015. DOI: 10.1016/j.ijepes.2014.10.010.

[13] Z. Moravej, M. Pazoiki, and M. Khederzadeh, “New smart fault locator in compensated line with UPFC,” *Int. J. Elec. Power*, vol. 1, no. 92, pp. 125–135, 2017. DOI: 10.1016/j.ijepes.2017.05.002.

[14] S. Ekici, “Support vector machines for classification and locating faults on transmission lines,” *Appl. Soft. Comput.*, vol. 12, no. 6, pp. 1650–1658, 2012. DOI: 10.1016/j.asoc.2012.02.011.

[15] P. Pavan and S. N. Singh, “Support vector machine based transient stability identification in distribution system with distributed generation,” *Electr. Pow. Compo. Sys.*, vol. 44, no. 1, pp. 60–71, 2016. DOI: 10.1080/15325008.2015.1091863.

[16] Mauro S. Tonelli-Neto, José Guilherme M. S. Decanini, and Anna Diva P. Lotufo, “Fuzzy based methodologies comparison for high-impedance fault diagnosis in radial distribution feeders,” *IET Gener Transm Dis.*, vol. 11, no. 6, pp. 1557–1565, 2017. DOI: 10.1049/iet-gtd.2016.1409.

[17] S. Adhikari, N. Sinha, and T. Dorendrajit, “Fuzzy logic based on-line fault diagnosis and classification in transmission line,” *SpringerPlus.*, vol. 5, no. 1002, pp. 1–14, 2016.

[18] P. C. Chen and M. Kezunovic, “Fuzzy logic approach to predictable risk analysis in distribution outage management,” *IEEE T. Smart Grid*, vol. 7, no. 6, pp. 2827–2836, 2016. DOI: 10.1109/TSG.2016.2576282.

[19] A. Yadav and A. Swetapadma, “Enhancing the performance of transmission line directional relaying, fault classification and fault location schemes using fuzzy inference system,” *IET Gener. Transm. Dis.*, vol. 9, no. 6, pp. 580–591, 2015. DOI: 10.1049/iet-gtd.2014.0498.

[20] M. Dehghani, M. H. Khooban, and T. Niknam, “Fast fault detection and classification based on a combination of wavelet-singular entropy theory and fuzzy logic in distribution lines in the presence of distributed generations,” *Int. J. Elec. Power*, vol. 1, no. 78, pp. 455–462, 2016. DOI: 10.1016/j.ijepes.2015.11.048.

[21] A. K. Pradhan, A. Routray, and B. Biswal, “Higher order statistics-fuzzy integrated scheme for fault classification of a series-compensated transmission line,” *IEEE T. Power Deliver.*, vol. 19, no. 2, pp. 891–893, 2004. DOI: 10.1109/TPWRD.2003.820413.

[22] B. Das and J. V. Reddy, “Enhancing the performance of transmission line directional relaying, fault classification and fault location schemes using fuzzy inference system,” *IEEE T. Power Deliver.*, vol. 20, no. 2, pp. 609–616, 2005. DOI: 10.1109/TPWRD.2004.834294.

[23] Y. L. Li, S. Zhang, and H. B. Li, “A fault location method based on genetic algorithm for high-voltage direct current transmission line,” *Eur. T. Electer. Power*, vol. 22, no. 6, pp. 866–878, 2012. DOI: 10.1016/j.etep.1659.

[24] Q. Jin and R. Ju, “Fault location for distribution network based on genetic algorithm and stage treatment,” in *Proc. Spring Cong. Eng. Technol. (S-CET)*, pp. 1–4, 2012.

[25] H. Malik and R. Sharma, “EMD and ANN based intelligent fault diagnosis model for transmission line,” *J. Intell. Fuzzy Syst.*, vol. 32, no. 4, pp. 3043–3050, 2017. DOI: 10.3233/JIFS-169247.

[26] A. A. P. Bscaro, R. A. F. Pereira, and M. Kezunovic, “Integrated fault location and power-quality analysis in electric power distribution systems,” *IEEE T. Power Deliver.*, vol. 31, no. 2, pp. 428–436, 2016. DOI: 10.1109/TPWRD.2015.2464098.

[27] M. J. Reddy and K. B. Mohanta, “Adaptive-neuro-fuzzy inference system approach for transmission line fault classification and location incorporating effects of power swings,” *IET Gener. Transm. Dis.*, vol. 2, no. 2, pp. 235–244, 2008. DOI: 10.1049/iet-gtd:20070079.

[28] T. Ando, S. Konishi, and S. Imoto, “Nonlinear regression modeling via regularized radial basis function networks,” *J. Stat. Plan. Infer.*, vol. 138, no. 11, pp. 3616–3633, 2008. DOI: 10.1016/j.jspi.2005.07.014.

[29] M. Kayano and S. Konishi, “Functional principal component analysis via regularized Gaussian basis expansions and its application to unbalanced data,” *J. Stat. Plan. Infer.*, vol. 139, no. 7, pp. 2388–2398, 2009. DOI: 10.1016/j.jspi.2008.11.002.

[30] S. Tateishi, H. Matsui, and S. Konishi, “Nonlinear regression modeling via the lasso-type regularization,” *J. Stat. Plan. Infer.*, vol. 140, no. 5, pp. 1125–1134, 2010. DOI: 10.1016/j.jspi.2009.10.015.

[31] Y. Araki, S. Konishi, and S. Kawano, “Functional regression modeling via regularized Gaussian basis expansions,” *Ann. I. Stat. Math.*, vol. 61, no. 4, pp. 811–833, 2009. DOI: 10.1007/s10461-007-0161-1.
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