sciendo Journal of Electrical Engineering, Vol. 76, No. 2, 2025, pp. 116-123

Artificial neural networks applied to faulted section location in distribution network

Kristijan Čvek[1], Krešimir Fekete[2], Zvonimir Klaić[3], Ružica Kljajić[4]

Recently, there has been an increase in the usage of novel devices in distribution networks for fault locating and detection, such as fault indicators (FI). They provide additional data sets that can help with faulted section location (FSL). This paper proposes an artificial neural network (ANN) method that uses the FI statuses to determine the FSL in a radial distribution network. The advantage of this approach is its high accuracy, and the method does not require the analysis and calculation of any electrical variable. This method simplifies FSL since it requires no previous comprehension of electrical variables such as voltage, current, etc. It is unaffected by fault types, making it easy to implement in a distribution network. The proposed method for FSL is tested on the IEEE 33 bus system: different fault scenarios are simulated, including single fault, multiple faults, and loss of information, all with distributed generation (DG) in the distribution system. A method based on ANN shows high accuracy and can detect faulted sections even in the case of information losses. The used method attained an accuracy of 92.1% in the DN with a single fault, 90% in the DN with multiple faults, and 94.1% in the DN with multiple faults and DGs.

Keywords: artificial neural network, fault section detection, fault indicator, power distribution network

1 Introduction

In contemporary distribution network fault detection (FD) is crucial to maintaining the reliability of the power supply. The distribution network (DN) is far more prone to faults than the transmission network due to its topology and large size [1]. The methods for fault detection can be divided into three groups: fault classification (FC), fault location (FL), and their combination. FC is a detection class that detects the type of fault, e.g., single-phase, three-phase, etc. FL is a detection class that searches for the location of the fault. By reviewing the literature, a lot of researchers deal with both problems of FD. Various FL methods for distribution systems have been proposed [2], such as computer intelligence methods like ANN, Support Vector Machine (SVM), and Random Forest (RF) used in FD [3]. ANN FL methods significantly decrease time and prevent human error. Therefore, ANN-based FL methods were employed by numerous researchers to locate distribution system faults [4]. The local current and voltage signals are used by the ANN for FL determination to estimate the faulted section [5]. The suggested hybrid method was built as embedded software and verified using simulations of the Electromagnetic Transients Program [6] and Alternate Transient Program [7]. An effective method for locating a single-phase to-ground fault under direct fault and through grounding resistance fault in DN is provided in the literature [8]. This method is based on the power line by setting zero-sequence current and voltage. A resonant grounding system examines the parallel resonance process that takes place during a single-phase high-impedance fault. In literature [9], characteristic frequencies linked to each potential FL are calculated using fault distance information. To determine the traveling wave caused by the fault's most important frequency components, a transient analysis is suggested to assess the traveling wave's spectral content. To determine the FSL, the authors in [10] used the Bayesian Compressed Sensing approach to obtain the sparse solution of the fault current. According to the simulation results, for a variety of fault circumstances, the location success rate is greater than 95%. The quantities that the authors in [11] utilize are voltage magnitude, angle, and sequence components that are obtained using distributed non-synchronized monitoring devices that are connected to secondary substations. The three-phase line current measurements acquired at a single substation relaying point were analysed using the discrete wavelet transform to extract characteristic features [12]. A multi-layer ANN model that served as FL predictors and FL classifiers, respectively, was then given these characterristics. The literature [13] makes use of synchronized voltage and current measurements at the DG unit interconnection, which may adapt to modi-fications in the system architecture for all types of faults with different fault resistances on all system segments, with extremely positive outcomes. The use of electrical variables in FL and FC approaches, which necessitates online monitoring and measurements and may incur additional costs, is a significant drawback. The equipment required to read these variables is complex and costly. Authors conducted research in the literature [14] to develop and put into practice a real-time fault location

Faculty of Electrical Engineering, J. J. Strossmayer University of Osijek, Kneza Trpimira 2b, 31000 Osijek, Croatia
[1]kristijan.cvek@skole.hr, [2]kresimir.fekete@ferit.hr, [3]zvonimir.klaic@ferit.hr, [4]ruzica.kljajic@ferit.hr

https://doi.org/10.2478/jee-2025-0012, Print (till 2015) ISSN 1335-3632, On-line ISSN 1339-309X

laboratory-scale model using accessible hardware components. The system is equipped with an inbuilt fault location mechanism that uses impedance to calculate the distance to the fault.

In [15] literature, the authors use ANN to classify transformer failures. To avoid the necessary electrical variables and transients, the authors [1] use a new hybrid method combining Discrete Wavelet Transform (DWT) and ANN for FL in DN. Using fault status signals gathered by feeder terminal equipment to provide precise and quick FL has grown in importance as more and more feeder terminal equipment, such as fault indicators (FI), are implemented in DN [16]. When a large fault current flows, the FI switches off the signal and sends it to SCADA [17]. This strategy will not work in the case of DG providing a fault current in the opposite direction. A matrix-based approach for the identification and separation of malfunctioning feeder sections on DN is proposed by authors in the literature [18], wherein FI devices are used. The algorithm operates in two stages: the first stage recognizes the system's radial feeders automatically and displays the topology of the feeders in a matrix form; the second stage recognizes the feeder's defective section automatically and opens the appropriate switches to isolate it. Because the approach uses switch device status detection and measurement device information, it can be used for both single and multiple faults. The authors of [12] employ two ANNs; one ANN is for FC, and the other ANN is for FL. The input for both ANNs is entropy per unit, whose indices are calculated using DWT decomposition of fault transient signals from three-phase line current measurements at a single substation relaying point.

Both approaches have their benefits and drawbacks. Analysing electrical variables and transients is challenging due to factors such as fault types and system parameters. Using status information from FIs simplifies the application of FL in DN. The use of electrical variables and transients has been shown to effectively solve the problem of FSL in DN across various conditions and network configurations. This approach also minimizes technical and financial barriers, making it suitable for modern DNs with diverse configurations and monitoring infrastructure. The reviewed literature shows that existing limits exist in networks with many nodes, where it takes a long time for the methodology to reach the FL conclusion. Comparing this method with existing methods for FSL, it has high accuracy and simplified methodology.

The proposed FSL method is implemented on a standard radial IEEE 33 bus system [19]. Compared to [13], and [20], this paper utilizes only one ANN, which decreases the complexity and increases the time of implementation of the FSL method. In literature [16], a topology search algorithm that uses the status of FI indicators is developed for faulted section location. Unlike [16], method developed in this paper uses the ANN method that uses the statuses of FI indicators as input data, and this method has high accuracy and fast implementation. The contributions of this study are:

- The developed method uses ANN to determine the FSL in DN. ANN model can handle multiple faults on distinct branches in addition to single faults. According to the results, the suggested ANN works well for DN with DGs.
- Developed method based on ANN can detect the faulted section of the distribution network as well as rectify the incorrect status of FI or the information loss.
- The proposed method is tested with different scenarios on the IEEE 33 bus system.

2 DN model description

DN is becoming more advanced with the growing usage of intelligent measuring devices like FIs. The radial feeders have installed FIs at each node, and the node represents a substation from medium to low voltage in the DN. Fault current flows from the substation to the fault location when a fault arises, and the FI data can then be gathered by the FIs. When the fault current passes through the FI, it activates the FI, which sends a binary signal and is reported to the control centre or SCADA.

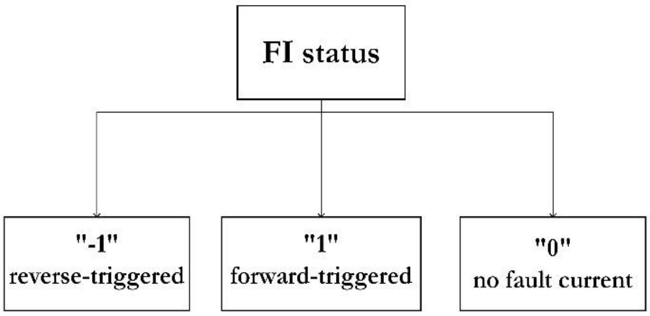

Fig. 1. Operation status of FI

When it detects a fault current flowing in the other direction, reverse triggering takes place, and the status is set to "–1". DGs deliver fault current to the FL. The substation to the end of the line is considered the positive direction, used to identify the fault current's direction. When the forward-triggered FI equipment notices a fault current flowing from the substation to the affected location, it sets its status to "1". The status is set to "0" when no fault current is detected. Three distinct FI functioning states are shown in Fig. 1.

Figure 2 shows the DN used in this paper. It consists of four radial feeders. The entire DN consists of 33 FIs whose operating statuses were described earlier. This study uses "upstream" and "downstream" to describe the interaction between FIs.

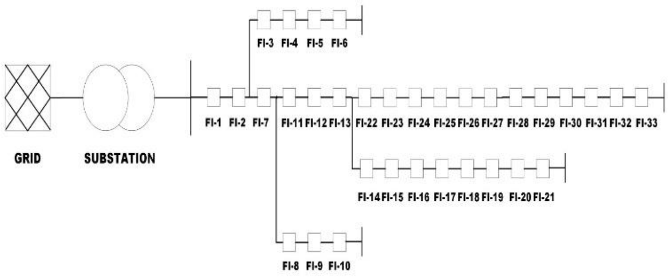

Fig. 2. IEEE 33 bus system with FIs

In Fig. 2, FI-1 is closer to the substation than FI-2, hence it is upstream of FI-2. FI-2 is downstream of FI-1. When a fault occurs, FI-3 and FI-8 are downstream of FI-2, whereas FI-2 is upstream of them both. In a DN topology, each FI acts as a node, dividing the feeder into sections. To locate the FSL, first identify the nearest equipment number. For example, if the FSL result is FI-11, it indicates that a fault exists between FI-11 and FI-12.

3 Method for faulted section location using ANN

3.1 Proposed method for FSL

The objective of the proposed approach is to identify the FSL within a specified DN. Figure 3 shows the workflow for identifying faulted sections in a DN using ANN. The method begins with obtaining information on FI status data. The key steps of this method are:

- Step 1: Collecting FI status data.
- Step 2: Determine relationships between FIs.
- Step 3: If FI status information is lost, apply the feature extraction rule (Step 4). If all FIs have status information, skip this step and go to Step 5.
- Step 4: If information on FIs is missing adjust the fixed FI status data with the feature extraction rule.
- Step 5: Fed the ANN with input data.
- Step 6: Predicted values for FSL.

The status of the FI information and its inter-relationship are initially assessed. If any FI information is absent, the FI status is assigned according to the previously outlined rule. The new information is then fed into the ANN, which processes it and returns a classification output and a response as to where the faulted section in the DN is. The output of the ANN represents a classification prediction based on the supervised training of the ANN, which is the answer to where the FSL is in DN. If the FI status information is such that it shows that the section between two nodes is at fault as explained in Section 2, the ANN output is 1, if it is not a fault it output is 0.

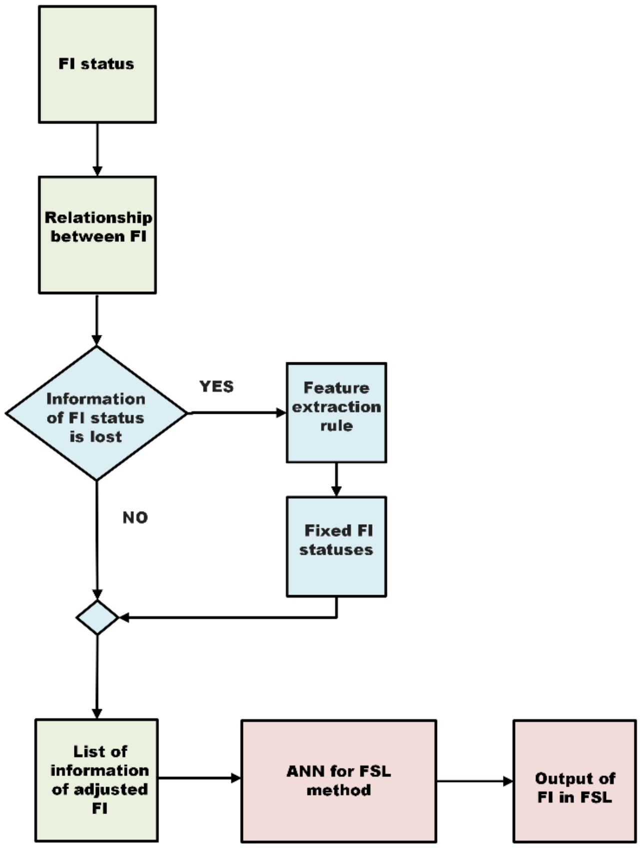

Fig. 3. Flowchart of the proposed ANN FSL method

3.2 Architecture of proposed ANN for FSL

The ANN used in this paper for the FSL problem consists of an input layer, three hidden layers, and one output layer. The ANN structure has a supervised learning algorithm, and it is a feed-forward neural network (FFNN) [21]. Fig. 4. depicts the structure and type of ANN. Blue circles refer to neurons determined by ANN layers.

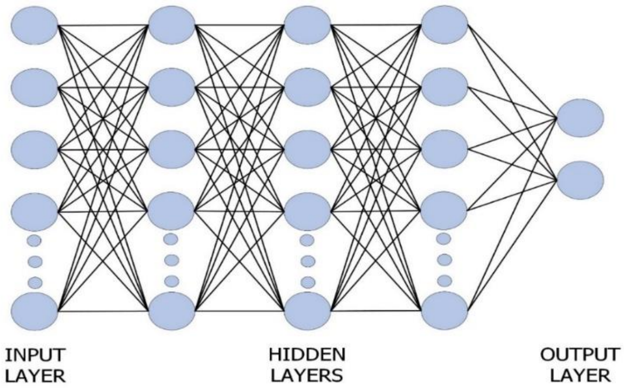

Fig. 4. Proposed ANN for FSL method type and structure

The ReLU activation function was used in the input layer and hidden layers in this ANN model. The sigmoid and SoftMax activation functions were also experimented upon, but we found that ReLU showed better performance. In the output layer, the sigmoid activation function is used because it proved to be the best for classification. The training dataset provides the ANN with knowledge about the problem, which is then stored in synaptic weights between neurons during training. Exploratory experiments were conducted with varying numbers of hidden layers, hidden layer neurons, learning rates, and activation functions. For the FSL challenge, ANN training with the quasi-Newton approach (L-BFGS) outperformed the Scaled conjugate gradient (SCG) training algorithm. The input layer consists of 35 neurons. The first and second hidden layers consist of 128 neurons, while the last third hidden layer consists of 64 neurons. These numbers of neurons in each layer proved to be optimal due to the high accuracy and short implementation time of the model.

When working on one fault in the DN, the ANN model has 33 independent variables and two dependent variables. 33 independent variables are the FI statuses, while one dependent variable is the FI label. FI label is a variable for ANN, which means if the combination of FI status is accurate, then FI label represents the FI number where the fault occurred. For example, if a fault occurred on a section between FI-4 and FI-5, then the statues of FI-1, FI-2, FI-3, and FI-4 must be 1 and all others either 0 or -1, so the FI label will be 4, a number representing on which section of DN the fault occurred. The other dependent variable is FSL, which can be either 1 or 0. FSL is a variable for ANN that means if the FI status combination and FI label are correct, then the FSL is a logical 1, which means that all FIs are well activated and FI label is correct that ANN knows on which section in the DN is fault, and if the FSL is logical 0, it means that the FI status combination is not accurate or FI label is not correct that the fault does not exist or is not in the section that FI combination or FI label suggests. When working on multiple faults in the DN, ANN has 33 independent variables and four dependent ones. 33 independent variables are the FI statuses, while two dependents are the FI labels for each fault that occurs in DN. The other two dependent variables are FSL, which can be either 1 or 0 for each fault that occurs. A logical 1 means that the fault is at that location, while 0 is not.

The proposed method is tested in four different scenarios. Each subsequent scenario is more complex than the previous one and requires a larger training data set for the ANN. In the first scenario, there is one fault in the DN, and there is no DG implemented in the DN. In the second scenario, there are two faults in the DN at the same moment, and there is no DG implemented in the DN. The third scenario is with DG implemented in DN. The last scenario is the most complex, as in this scenario there is a missing information status on the FI. A different number of training cases is used in each scenario. In the first scenario, the ANN was trained with 280 cases of a single fault in the DN and tested with 51 cases to determine the accuracy of the ANN model. In the second scenario, the ANN was trained with 480 cases with two faults at the same time in the DN and tested with 51 distinct training cases to determine the model's accuracy. In the third scenario, the ANN was trained with 500 fault cases in the DN and then tested with 51 cases to determine the ANN model's accuracy. In the last scenario, the ANN was trained as in the third case, but it was tested with 55 cases with an additional feature extraction rule that decides the status of the FI.

An extraction rule from the literature [16] was added, where the authors successfully filled in the missing information of FIs using this rule. The rule states that if the FI before and after the FI with missing information is "1," then the assumed value of unknown FI status is "1". This specific rule was selected due to its simplicity, as it can determine an FI's state by analyzing two nearby ones. The limitation of this rule is not applicable if two adjacent FI statuses are lost.

4 Results and analysis of different scenarios for FSL

To analyse FSL in radial DN, four different scenarios are defined:

- Scenario A: There is only one fault in the radial DN. DGs are not implemented in this scenario.
- Scenario B: Two faults are occurring at the same time in the radial DN. DGs are not implemented in this scenario.
- Scenario C: Two faults are occurring at the same time in the radial DN. DGs are implemented in this scenario.
- Scenario D: Similar to scenario C, but with missing information on FIs.

Table 1 summarizes all the results of this paper.

Table 1. Results and analysis of scenarios

Scenario	Accuracy
A	92.1%
B	90%
C	94.1%
D	94.1%

4.1 Results and analysis for scenario A

Assume a single fault exists on FI-20's downstream segment in the IEEE-33 node DN (Fig. 5.). When a fault current flows from the substation to the fault location, the forward-triggered FI equipment, shown with black squares on Fig. 5. (FI-1, 2, 7, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20), is activated.

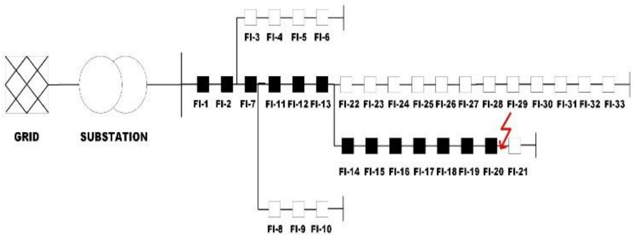

Fig. 5. An example of a single fault in the DN

Extensive simulation experiments were conducted to evaluate and validate the suggested method. Figure 6 depicts the confusion matrix obtained during testing for Scenario A. The blue squares represent the correct response per prediction class for the ANN models, whereas the red squares represent the incorrect replies. The accuracy may be estimated using the confusion matrix. Accuracy can be calculated from the confusion matrix by summing the blue squares and dividing by the total number of blue and red squares. In scenario A, the accuracy is 92.1%.

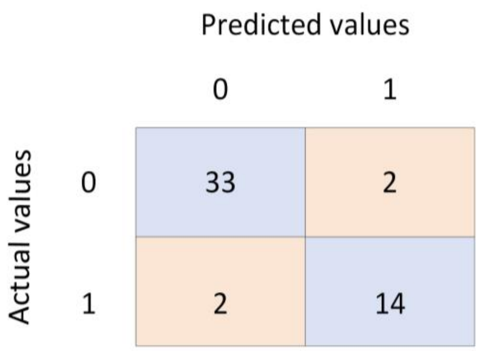

Fig. 6. Confusion matrix for Scenario A

4.2 Results and analysis for scenario B

In this scenario, multiple faults exist at the same time in the IEEE-33 node DN (Fig. 7.). Assume that one fault exists on FI-23's downstream segment, and another fault exists on FI-9's downstream segment. When a fault current flows from the substation to the fault location, the forward-triggered FI equipment, shown with black squares in Fig. 7. (FI-1, 2, 7, 8, 9, 11, 12, 13, 22, 23), is activated.

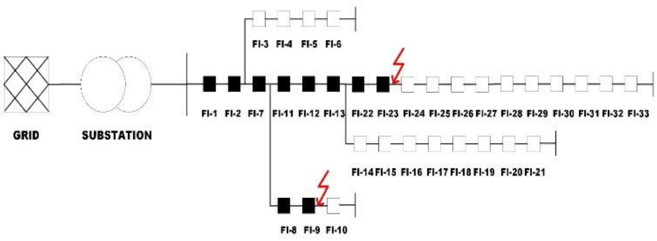

Fig. 7. An example of multiple faults in the DN

Figure 8 depicts the confusion matrix obtained during testing for Scenario B. The blue squares represent the correct response per prediction class for the ANN model, whereas the red squares represent the incorrect replies. The accuracy may be estimated using the confusion matrix, and it is 90% for scenario B.

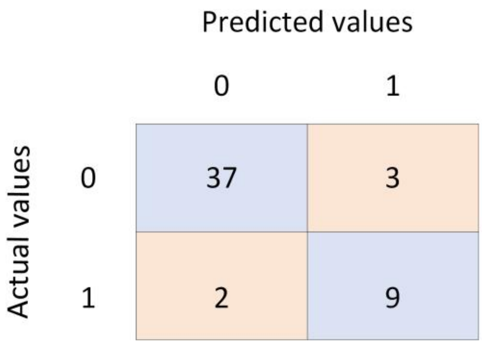

Fig. 8. Confusion matrix for Scenario B

4.3 Results and analysis for scenario C

Figure 9 depicts a DN with two DGs to test the performance of the suggested method in terms of the DG condition. Assuming that one fault location is on the nearest downstream part of FI-3, another is on the nearest downstream section of FI-14. The fault current will flow from the substation to both the first and second fault locations. The forward-triggered FI between the substation and fault locations is shown with black squares in Fig. 9 (FI-1, 2, 3, 7, 11, 12, 13, 14) and defined as "1". In DN, two DGs send fault current to fault sites, resulting in reverse triggered FIs and shown with blue squares in Fig. 9. (FI-6, 5, 4, 10, 9, 8). Reverse-triggered FIs have a state of "–1".

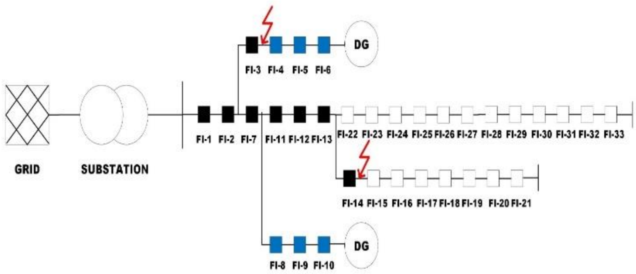

Fig. 9. An example of multiple faults with DGs in the DN

Figure 10 depicts the confusion matrix obtained during testing for Scenario C. The blue squares represent the correct response per prediction class for the ANN model, whereas the red squares represent the incorrect replies. The accuracy may be estimated using the confusion matrix, and it is 94.1% for scenario C.

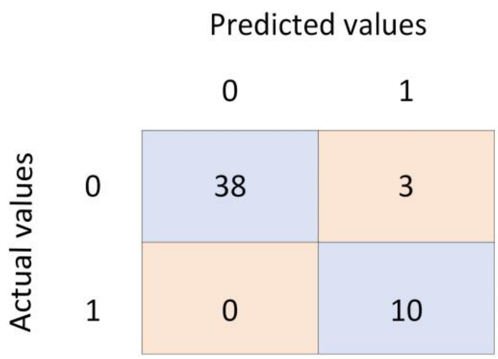

Fig. 10. Confusion matrix for Scenario C

4.4 Results and analysis for scenario D

The proposed method is tested for performance under information loss circumstances. A rule is added to account for the lack of FI status information. The rule states that if the FI before and after the FI with missing information is "1," the unknown status is also "1". If the information for FI-11 and FI-23 is lost, their status will be "1" as shown in Fig. 11.

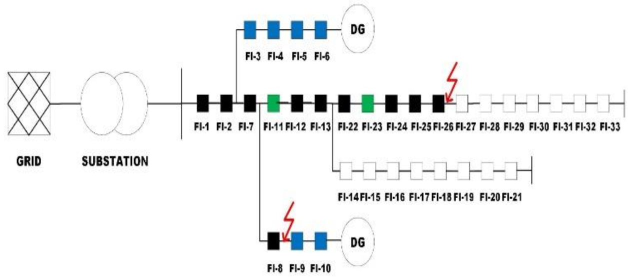

Fig. 11. An example of multiple faults with DGs and information lost in the DN

Figure 12 depicts the confusion matrix obtained during testing for Scenario D. The blue squares represent the correct response per prediction class for the ANN model, whereas the red squares represent the incorrect replies. The accuracy may be estimated using the confusion matrix. For scenario D, it is 94.1%.

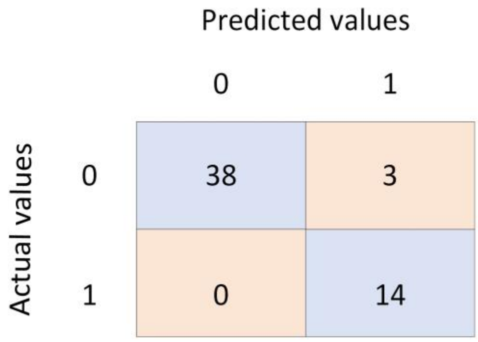

Fig. 12. Confusion matrix for Scenario D

4.5 Error analysis of method

As can be seen in the previous subsections, the results are not perfect. This method has misclassi-fications. The reason that these misclassifications occur is because the huge amount of the training data and testing data of the ANN method, the greater the probability of noise such as overlapping faults. Potential limitations of this method, as well as any other method based on deep learning, are the huge amount of data for training and testing the model.

5 Conclusion

In this paper, ANN is used for FSL in the DN based on the operating status information of FI. The training data is carefully selected to accurately impart fault features to the ANN. To validate the proposed ANN method, it is applied to the IEEE 33-bus system. Because the approach may be used for inhomogeneous feeders with both overhead and underground cable portions, and because it does not rely on any physical or electrical features of the feeders, fault type, or ground impedance, it is not impacted by DN reconfigurations. With this, FL has made a major advancement in distribution systems that will improve the security and quality of energy supplies. The proposed method accurately locates and isolates both single and multiple faults, as proven by test scenarios. FIs are commonly used in power DN, making it easy to collect fault information. The method's usage of FI status information simplifies its application in DN. The simulated fault circumstances in Python demon-strate that the proposed strategy is effective for locating complex faults in DN. Furthermore, the results of various scenarios, where each subsequent scenario is more complex than the previous one and requires a larger training data set, show that the ANN approach for FL is approximately 90% accurate, depending on the complexity of the fault problem and the ANN's training. Another advantage of this method is that the ANN can recognize which part of the DN is at fault, and the ANN implementation is quick and accurate. This FSL method along with prominent advantages, also has weaknesses, such as dependence on accurate FI data, scalability to larger networks because of the huge training data for ANN. The use of this method in practice enables integration with the existing monitoring and control infrastructure by deploying this model in SCADA systems or utility control centres. Future research can extend the method for meshed networks or larger DNs, testing the method with real-world data or physical testbeds, and introducing electrical variables into the ANN model.

Acknowledgement

The work is supported by the Croatian Science Foundation under the project "Prosumer-rich distribution power network" (project number: UIP-2020-02-5796) and the European Union's Horizon Europe Framework Programme: HORIZONWIDERA-2023-ACCESS-04, Pathways to Synergies – Coordination and Support Action – under the project name SynGRID – Creating synergies in Widening countries on the topic of low-voltage grid management (grant number 101160145).

References

[1] K. Sun, Q. Chen, and P. Zhao, "Automatic faulted feeder section location and isolation method for power distribution systems considering the change of topology," Energies (Basel), vol. 10, no. 8, Aug. 2017, doi: 10.3390/en10081081.

[2] M. M. Irzaei, M. Mirzaei, A. Kadir, E. Moazami, and H. Hizam, "Review of Fault Location Methods for Distribution Power System," Australian Journal of Basic and Applied Sciences, vol. 3, no. 3, pp. 2670–2676, 2009.

[3] S. S. Gururajapathy, H. Mokhlis, and H. A. Illias, "Fault location and detection techniques in power distribution systems with distributed generation: A review," 2017, Elsevier Ltd. doi: 10.1016/j.rser.2017.03.021.

[4] J. Mora-Florez, V. Barrera-Núñez, and G. Carrillo-Caicedo, "Fault location in power distribution systems using a learning algorithm for multivariable data analysis," IEEE Transactions on Power Delivery, vol. 22, no. 3, pp. 1715–1721, 2007, doi: 10.1109/TPWRD.2006.883021.

[5] R. H. Salim, K. R. C. de Oliveira, A. D. Filomena, M. Resener, and A. S. Bretas, "Hybrid fault diagnosis scheme implementation for power distribution systems automation," IEEE Transactions on Power Delivery, vol. 23, no. 4, pp. 1846–1856, 2008, doi: 10.1109/TPWRD.2008.917919.

[6] W. Long, D. Cotcher, D. Ruiu, P. Adam, S. Lee and R. Adapa, "EMTP - a powerful tool for analyzing power system transients," in IEEE Computer Applications in Power, vol. 3, no. 3, pp. 36-41, July 1990, doi: 10.1109/67.56581.

[7] M. Mester, "Alternative Transient Program - The Powerful Tool for Power Engineering Simulations," Acta Electrotechnica et Informatica, vol. 4, p. 43, May 2004.

[8] J. Li, G. Wang, D. Zeng, and H. Li, "High-impedance ground faulted line-section location method for a resonant grounding system based on the zero-sequence current's declining periodic component," International Journal of Electrical Power and Energy Systems, vol. 119, Jul. 2020, doi: 10.1016/j.ijepes.2020.105910.

[9] S. Klyapovskiy, S. You, H. Cai, and H. W. Bindner, "Integrated planning of a large-scale heat pump in view of heat and power networks," in IEEE Transactions on Industry Applications, Institute of Electrical and Electronics Engineers Inc., Jan. 2019, pp. 5–15. doi: 10.1109/TIA.2018.2864114.

[10] B. Yang, K. Jia, Q. Liu, L. Zheng, and T. Bi, "Faulted Line-Section Location in Distribution System With Inverter-Interfaced DGs Using Sparse Meters," IEEE Trans Smart Grid, vol. 14, no. 1, pp. 413–423, Jan. 2023, doi: 10.1109/TSG.2022.3186541.

[11] P. Bountouris, H. Guo, D. Tzelepis, I. Abdulhadi, F. Coffele, and C. Booth, "MV faulted section location in distribution systems based on unsynchronized LV measurements," International Journal of Electrical Power and Energy Systems, vol. 119, Jul. 2020, doi: 10.1016/j.ijepes.2020.105882.

[12] A. C. Adewole, R. Tzoneva, and S. Behardien, "Distribution network fault section identification and fault location using wavelet entropy and neural networks," Applied Soft Computing Journal, vol. 46, pp. 296–306, Sep. 2016, doi: 10.1016/j.asoc.2016.05.013.

[13] S. M. Brahma, "Fault location in power distribution system with penetration of distributed generation," IEEE Transactions on Power Delivery, vol. 26, no. 3, pp. 1545–1553, Jul. 2011, doi: 10.1109/TPWRD.2011.2106146.

[14] N. M. Khoa and Doan Duc Tung, "Design and Implementation of Real-time Fault Location Experimental System for Teaching and Training University Students", International Journal of Electrical and Computer Engineering Systems (IJECES), vol. 14, no. 1, pp. 109-118, Jan. 2023.

[15] M. A. Elmohallawy, A. Y. Hassan, A. F. Abdel-Gawad, and S. I. Selem, "Transformer Faults Classification Based on Convolution Neural Network", International Journal of Electrical and Computer Engineering Systems (IJECES), vol. 14, no. 9, pp. 1069-1075, Nov. 2023.

[16] G. Li, Q. Chen, and J. Zhang, "Novel faulted section location method for distribution network based on status information of fault indicating equipment," Applied Sciences (Switzerland), vol. 10, no. 17, Sep. 2020, doi: 10.3390/app10175910.

[17] S. Hou and X. Guo, "Research on fault location of distribution lines based on the standing wave principle," Processes, vol. 9, no. 8, Aug. 2021, doi: 10.3390/pr9081436.

[18] K. Sun, Q. Chen, and P. Zhao, "Automatic faulted feeder section location and isolation method for power distribution systems considering the change of topology," Energies (Basel), vol. 10, no. 8, Aug. 2017, doi: 10.3390/en10081081.

[19] S. Meinecke, N. Bornhorst, and M. Braun, "Power System Benchmark Generation Methodology," in NEIS 2018; Conference on Sustainable Energy Supply and Energy Storage Systems, 2018, pp. 1–6.

[20] G. Shen et al., "Fault diagnosis with false and/or missing alarms in distribution systems with distributed generators," Energies (Basel), vol. 11, no. 10, 2018, doi: 10.3390/en11102579.

[21] S. Kaluđer, K. Fekete, K. Čvek, and Z. Klaić, "Application of Artificial Neural Networks to Islanding Detection in Distribution Grids: A Literature Review," Applied Sciences, vol. 13, no. 24, p. 13047, Dec. 2023, doi: 10.3390/app132413047.

Kristijan Čvek received the B. Sc. and M. Sc. degrees in electrical engineering from Josip Juraj Strossmayer University of Osijek, Faculty of Electrical Engineering, Computer Science, and Information Technology Osijek, in 2019 and 2021, respectively, and he is currently pursuing the Ph. D. degree in electrical engineering. His current research interests include applications of machine learning and deep learning in electrical engineering, fault detection and islanding detection in distribution systems.

Krešimir Fekete received the BSc. degree in 2006 and the PhD degree in electrical engineering, from the Faculty of Electrical Engineering, Computer Science and Information Technology Osijek, University of "Josip Juraj Strossmayer" Osijek in 2013. He works as an associate professor in the Power System Engineering Department at the Faculty of Electrical Engineering, Computer Science and Information Technology Osijek, University of Osijek, Croatia. His research interest includes power system analysis, electricity market and power system optimizations. He is a member of IEEE Power and Energy Society and the Croatian National Committee of CIRED.

Zvonimir Klaić was born in Osijek on July 8, 1972. He received his BSc. degree in 2000, MSc. degree in 2006, and PhD degree in electrical engineering, from the Faculty of Electrical Engineering, Computer Science and Information Technology Osijek, University of "Josip Juraj Strossmayer" Osijek. He works in the Power System Engineering Department at the Faculty of Electrical Engineering, Computer Science and Information Technology Osijek, University of Osijek, Croatia. His main interest is in the power quality and smart grids. He has published numerous scientific papers and projects. He is a member of IEEE, the Croatian National Committee of CIGRE, and CIRED

Ružica Kljajić received the B. Sc. and M. Sc. degrees in electrical engineering from Josip Juraj Strossmayer University of Osijek, Faculty of Electrical Engineering, Computer Science, and Information Technology Osijek, in 2009 and 2011, respectively. She is currently pursuing the Ph. D. degree in electrical engineering. Her current research interests include power system stability in transmission and distribution grids.

Received 7 February 2025