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RESEARCH ARTICLE

Artificial Neural Networks: Modeling and Comparison to Detect High Impedance Faults

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ABSTRACT High impedance faults constitute one of the biggest challenges in electrical power systems. In overhead distribution systems, faults are caused by tree branches that touch the electrical grid or by the rupture of energized conductors on low conductivity soils. They are also known as low-current faults, which are not detected by conventional protection systems, compromising the quality of the power supply and causing hazardous risks to the electrical system. This paper aims to address the problem of high impedance faults detection using Artificial Neural Networks: two Multi Layer Perceptron networks, being one Neural Pattern Recognition and another Neural Fitting, and a Convolutional Neural Network. The neural networks are trained and analyzed in scenarios based on a medium-voltage distribution grid model, located in the Basque Country, Spain. The network topologies are implemented, repeatedly trained considering multiple architectures, and validated in other scenarios with different location, time, and duration of the fault using the Matlab software. After, the criteria of accuracy, reliability, security, safety and sensitivity are evaluated. At last, a comparative analysis between them is carried out, and from the results obtained, a superior performance of the Convolutional Neural Network in compared to the Multi Layer Perceptron networks is observed.

INDEX TERMS High impedance faults, detection, electrical system, artificial neural network, modeling, performance comparison.

I. INTRODUCTION

Electrical power distribution systems are susceptible to failures, which can be understood as abnormal operating conditions of some equipment at one of the system primary voltages [1]. Overhead electrical power distribution systems are exposed to adverse conditions and weather phenomena, making them more vulnerable to failures, such as those caused by tree branches touching the electrical grid, or even by the rupture of conductor cables on insulating surfaces of low conductivity, such as asphalt. These types of failure are considered High Impedance Faults (HIFs), also known as low-current faults, whose current values are below the starting values of traditional overcurrent relays, in the distribution feeders [2], [3]. Thus, HIFs are not detected by conventional protection systems [4], compromising the quality of electricity supply and causing high risks such as hazardous shock, fires, and even deaths [2]. HIFs are also considered a threat to facility assets and can cause irreparable damage [5], [6], [7], [8].

The concern with this type of fault is not recent. In 1949, the Power Systems Relaying Committee Working Group concluded that it was impossible at that time to develop techniques for detecting HIF [9]. However, especially in the last four decades, many researchers have been working to develop techniques that can detect, classify, and/or locate this type of fault [3], [6], [10], [11]. Despite the several studies presented in the literature, this research problem still lacks a definitive solution that presents high reliability and security in terms of detection and differentiation between the occurrence

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of HIF and other events common to distribution systems, such as switching loads or capacitors bank [6], [12], [13].

HIFs detection techniques can be divided into passive techniques, which are based on the fault signature identified by an instrumentation system and detection algorithms, and active techniques, which aim to identify fault conditions through high frequency signals injected into the electrical system [3]. In this research, passive techniques are addressed, since they have the advantage of not being invasive to traditional electrical systems. The main passive techniques used for HIFs detection are the analysis of Low Order Harmonics, Artificial Neural Networks (ANNs), Wavelet Transform, Fuzzy Logic, among others. Although all these techniques work relatively well, they have drawbacks when applied to complex or different systems from what they were trained, such as need for expensive equipment, yield insatisfactory results in real world situations, computational complexity, technique time consuming and difficult to implement, and high incidence of false positives in HIF detection tests and in the presence of capacitor banks [3].

A recurring concern over the years has been that most of the proposed techniques and methodologies are capable to detect HIFs, but they often confuse fault with normal system events, generating false positives, usually in situations such as switching capacitor banks and energizing transformers [6], [13], [14]. Therefore, it is possible to state that an adequate and permanent solution for HIF detection is still lacking, although many attempts have been made by the scientific community. In recent years, techniques based on ANNs can be highlighted as promising. On the other hand, there is still a gap in research related to this topic, as they do not justify the ANN topology choice nor by which way their architectures are defined, being used different types of networks, in different contexts, without carrying out validation tests in scenarios with different location, time and duration of the fault. In other words, the procedures involved often based rely on trial and error, reducing the objectivity of ANN-based techniques [3], [6], [15].

In this context, this paper addresses the modeling of HIF detection from three ANNs topologies that stand out in the literature: two Multi Layer Perceptron (MLP) networks, being one Neural Pattern Recognition (NPR) and another Neural Fitting (NF), and even a Convulational Neural Network (CNN). All ANNs are trained in the same set of scenarios, but are validated in different scenarios than those used in training, considering variations of fault location, time and duration. These scenarios are based on a real medium-voltage distribution grid with five feeders, located in Basque Country, Spain [16]. The ANNs are implemented, trained and validated using MATLAB software. After the validation of the ANNs, the criteria for accuracy, reliability, security, safety and sensitivity are evaluated. At last, a comparative analysis is realized of the three ANNs topologies in an equitable path. Then, the more accurate ANN topology for the HIF detection and distinction from other normal system events is obtained from the results, considering the established criteria.

The remaining paper is organized as follows. Section II summarizes the main related works in the field. Section III presents research materials and methods, i.e., HIF model, validation and training scenarios for HIF detection and the investigated ANNs. Section IV shows the simulation results and also makes a comparative analysis of the three ANNs topologies in an equitable path. Finally, Section V presents the paper's main findings and conclusions, as well as the possibility of future works.

II. RELATED WORKS

In literature, different methods are proposed for detecting HIF. Sedighizadeh et al. [15] provide a chronological bibliographic review of researches on this topic, presenting the historical evolution of fault modeling. The authors present 225 related papers, of which 169 address the proposition or use of algorithms for HIF detection and/or localization. Ghaderi et al. [3] carry out a comprehensive literature review survey on HIF, with emphasis on detecting, modeling and localizing techniques, resulting in 133 papers. Gomes and Ozansoy [6] cites the works of Sedighizadeh et al. [15] and Ghaderi et al. [3], indicating that, although there are surveys on this topic, it is not easy to find a comprehensive contextualization of how and when research in this field unfolds. These authors present the progress and development historical narrative based on the most cited papers since the beginning of this research subject, resulting a total of 131 papers, among which 94 on HIF detection methods, 7 on location, and 5 on HIF modeling.

Based on a literature review, the main works related to HIF detection methods with emphasis on the use of ANNs are presented below. According to Ebron et al. [17], it was in the 1990s that RNA-based techniques emerged, and they are widely used to this day. Baqui et al. [18] propose a hybrid method that combines the ANN and wavelet transform for HIF detection. Sulaiman et al. [19] propose an intelligent approach Probabilistic Neural Network (PNN) combined with advanced signal-processing techniques such as Discrete Wavelet Transform (DWT). Tonelli et al. [20] present a comparison of two intelligent systems that aim to identify and classify different critical situations such as HIF. Silva et al. [21] apply a neuro-fuzzy learning method based on the use of the wavelet transform to detect HIF in medium voltage electrical networks. Lucas et al. [22] perform HIF detection in smart grid using wavelet transform and ANNs, four types of mother wavelet are tested and combined with four ANNs architectures, a better performance is observed with type Symlet 2 wavelet and Adaptive Artificial Neural Network (AANN) architecture. Wang and Dehghanian [23] state that monitoring devices and protection relays are unable to detect HIFs, so they propose an online monitoring system embedded with analytics machine learning that ensures the detection of HIF in power systems.

Zhang et al. [24], [25] consider features of a smart grid and different types of wavelets, and employ a transfer learning method for HIF detection. Niazazari et al. [26] use a CNN and DWT to detect HIF. Fan and Yin [27] present an analysis of CNN's differentials, using transfer learning to solve the problem of missing data; in which different scenarios of HIF variation and other system operations, such as switching loads and capacitors bank are used, the performance of CNN is compared to a MLP and the cross-entropy loss calculation for performance analysis is done. Ledesma et al. [28] describe a new method for locating and identifying HIF in medium voltage networks of unbalanced distribution systems, considering: load variation, reconfiguration, distributed generation, fault resistance variation, inaccuracy in feeders data, and protection devices operations, this method is based on ANN and it considers data from synchronized measurement units. Veerasamy et al. [29] propose a DWT based graphical language classifier algorithm for HIF detection in medium voltage distribution networks, the method of classifier is developed using virtual instrumentation LabVIEW facility.

Moradzadeh et al. [30] utilize the frequency response analysis method to identify and locate HIF, the interpretation of results associated with the frequency response analysis procedure is considered a weak point of the method, other techniques such as Support Vector Machine (SVM), Decision Tree (DT), k-Nearest Neighbors (k-NN), CNN, Long Short Term Memory (LSTM), and a hybrid model of convolutional LSTM (C-LSTM) are used together to overcome the problem. Aziz et al. [31] present a novel approach that utilize deep two-dimensional CNNs to extract features from 2-D scalograms and detect faults in photovoltaic systems. Rai et al. [32] propose a deep learning method for HIF detection, considering convolutional autoencoders that learn unsupervised from HIF signals, eliminating the need for multiple non-fault or normal system condition scenarios during training. Rai et al. [33] propose a new approach for HIF detection and classification based on a state-of-the-art deep learning model, the transformer network, stacked with the CNN, while the transformer network learns the complex HIF pattern in the data, the CNN enhances the generalization to provide robustness against noise. Mohammadi et al. [34] use the Conditional Generative Adversarial Network (CGAN) technique with the CNN classifier for the first time to detect HIF. Teimourzadeh et al. [13] state that majority of existing methods still suffer from false detection of HIF, so they propose a CNN and the hybrid model of Deep Reinforcement Learning (DRL) to identify and locate single-phase to ground short circuit faults in transmission lines.

Shakiba et al. [35] discuss relevant methods proposed since 2015, analyzing the advantages and disadvantages of machine learning techniques for HIF detection. They also identify notable issues in the field of HIF detection, such as voltage amplitude variations and phase changes in power systems, the scarcity of real-world faults for training, noise, and false detection of HIF. Gupta et al. [36] used DWT and machine learning techniques to efficiently detect HIF. They classified features using the t-test's class separability criterion

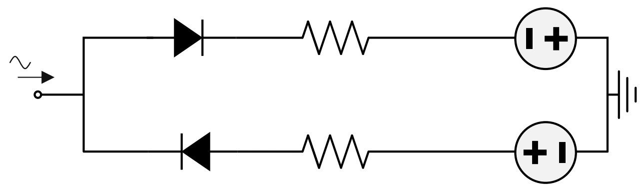

FIGURE 1. HIF model.

and employed the Extreme Learning Machine (ELM) with the four most significant features for classification. Additionally, MLP and SVM networks were used for comparison. Simulation results showed that the ELM method achieved good accuracy compared to other, considering accuracy, reliability, security, and sensitivityGupta et al. [36] Klein et al. [37] detail the architecture of a CNN used for the classification of non-contact partial discharges, considering a combination of CNN stacking and autoencoders for time series classification for the first time. However, the detection of HIF is not the focus of this study.

Despite the large number of published works and the variability of methods and combinations, the research field still lacks comprehensive studies and solutions. One persistent problem that has been recognized over time is the difficulty in distinguishing HIF from normal system events, leading to false positives [13], especially in scenarios involving capacitor bank switching and transformer energization. Gomes and Ozansoy [6] highlight the increasing number of published papers and the prevalence of ANNs and wavelet transform as the predominant techniques employed individually or in combination in HIF detection research. While methods utilizing the wavelet transform offer certain advantages, designing a systematic HIF detection technique based on this transform is challenging due to its limited support in high frequencies and the subjective nature of selecting the mother wavelet, which can result in resolution loss and reduced interpretability [3]. Approximately 23% of HIF detection techniques employ ANNs, which offer their own advantages, but also add complexity to the overall detection algorithm design. Furthermore, while many authors claim the robustness of their techniques, they often lack detailed information regarding the specific architecture of the neural network used, parameters, employed dataset, and evaluation metrics.

III. MATERIALS AND METHODS

A. HIF MODEL

The non-linear model with antiparallel diodes, widely employed in the literature, is used to analyze the HIF, considering that the single-phase short-circuit to earth is predominant, occurring in 63% of faults [7], [38]. Figure 1 shows the generic HIF model.

B. VALIDATION AND TRAINING SCENARIOS FOR HIF DETECTION

Obtaining data is an important step in researching this topic. Real-world voltage and current measurements under

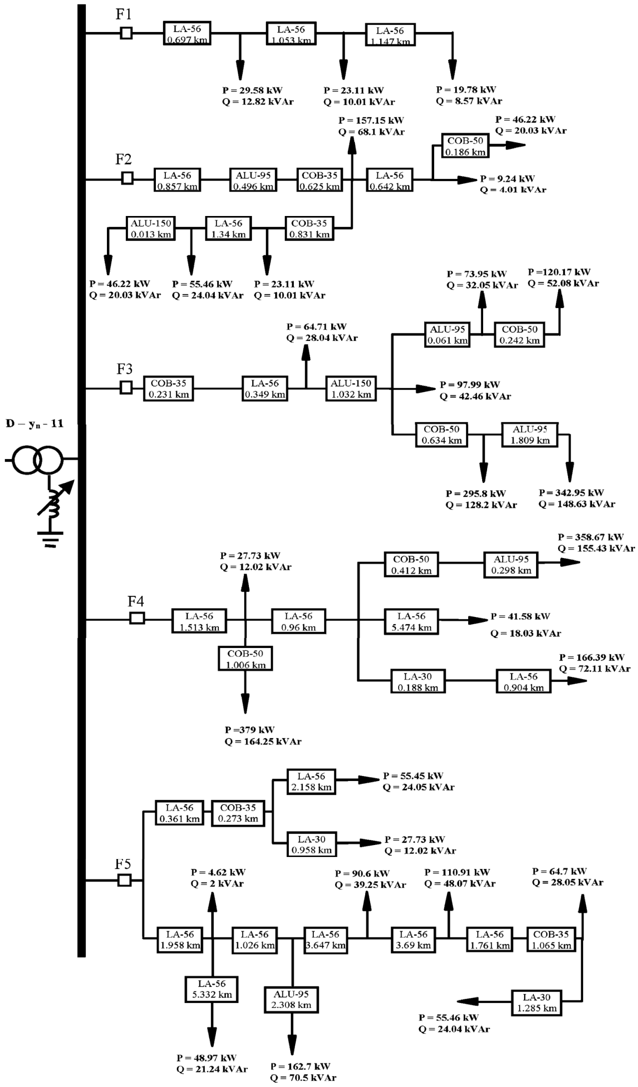

FIGURE 2. Distribution system model presented by Zamora et al. [16].

HIF conditions are expensive and dangerous to obtain, and may be impractical due to space limitations. Moreover, experimental replication of a real HIF in laboratory requires complex high-voltage equipment and strict security measures to mitigate any potential hazards of the HIF arc. Therefore, computer simulation models are often used for analysis [2].

In this research, multiple fault scenarios are created based on a real power grid located in Basque Country, Spain, modeled and validated using real parameters and operating conditions [16]. Figure 2 presents the complete representation of this grid, in which voltage and current measurements are taken in the transformer, at the substation output. It is composed of a medium-voltage branched network, with a substation and five distribution feeders of radial topology and varied extension. These characteristics are considered important in the ANNs sensitivity tests and in the phase-to-ground fault detection. This system has a delta-wye transformer with neutral, transformer ratio of 30 $kV/13.8$ kV and 12 MVA; and 35.7 km of overhead cables and 8.9 km of underground cables. It supplies a set of 98 loads.

Two sets of simulated data are obtained from this electrical system, with variations in geographic location, time and duration of both fault and capacitor bank; one set is used for training and another for validating the ANNs topologies. For the ANNs training 16 simulated scenarios are developed, this number is defined considering the acquisition of at least 100 samples necessary to carry out the CNN tests. The scenarios include different operating conditions of the electrical system, as follows: 5 scenarios with three HIFs (Scenarios 1 to 5); 2 scenarios with two HIFs (Scenarios 6 and 7); 1 scenario with one HIF (Scenario 8); 1 scenario with three HIFs and one capacitors bank is switched (Scenario 9); 7 scenarios with two HIFs and one capacitor bank being switched (Scenarios 10 to 16).

In each scenario, the simulation and grid parameters are equal to the real electrical system determined by Zamora et al. [16], a simulated time of 2 s and a time step of 10^{-6} s are considered. The location, phase, time, and duration of the HIFs vary for each scenario, as well as the location and time of the capacitor bank activation. HIFs resistors are set to 10 $k\Omega$ in all cases [7], [16]. For the NPR and NF networks, the RMS current data of each simulated circuit is used generating matrices of size 198339 × 3. For the CNN, the images of "Time (s) x RMS Current (A)" graphs are used for each scenario. All training scenarios are illustrated in Figure 3, where Scenario 9 is shown in Figure 3(a) as an example where three HIFs and one capacitor bank can be seen; all other scenarios are shown in Figure 3(b), where the x- and y-axis are the same than Figure 3(a) but have been suppressed for better visibility.

For validation and comparative analysis of the results, another set with 5 scenarios is developed. In each, the HIFs are allocated at different points in the electrical system and their duration and occurrence are also varied; the capacitor bank switching is treated similarly. The scenarios are as follows: Scenario A with one HIF; Scenario B with two HIFs; Scenario C with three HIFs; Scenario D with two HIFs and one capacitor bank switching; Scenario E with three HIFs and one capacitor bank switching. Figure 4(a) shows in detail the three-phase RMS currents of Scenario D, while Figure 4(b) depicts the other validation scenarios. The x- and y-axis of Figure 4(b) are the same than Figure 4(a) but are suppressed for better visibility.

C. ARTIFICIAL NEURAL NETWORKS

ANNs are known for their high accuracy in pattern classification and generalization, fast response, noise removal and prediction capabilities. Currently, around 23% of HIF detection techniques utilize ANNs topologies [3]. Despite their advantages, these networks make the overall detection algorithm design more complex. Furthermore, choosing the number of layers and the number of neurons in each layer are

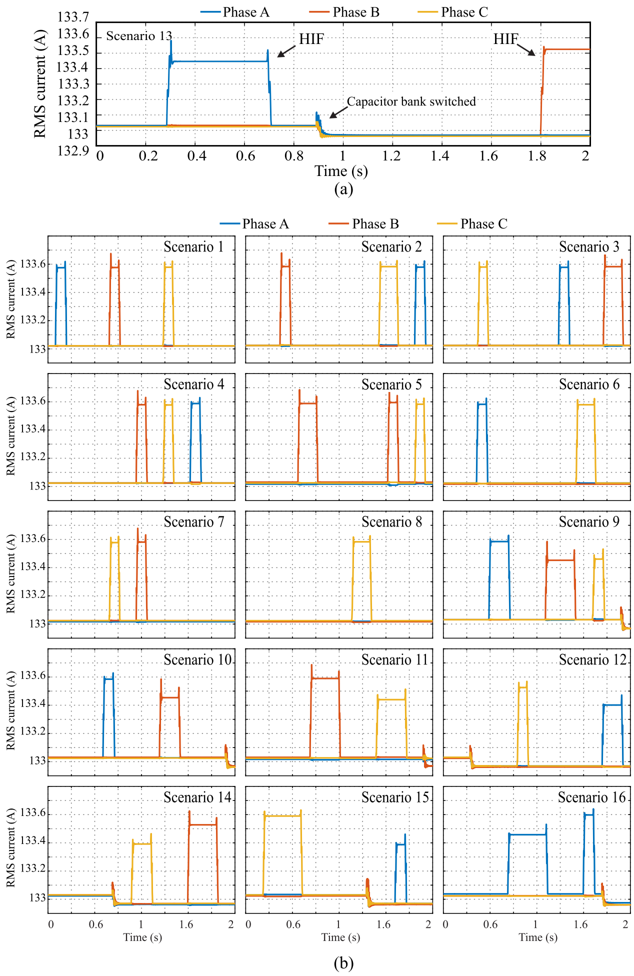

FIGURE 3. **(a) RMS current waveforms of training scenario 9; (b) training scenarios used, all on the same *x*- and *y*-axis scale as in (a).**

trial and error procedures that can reduce the objectivity of ANNs based techniques [39], [40].

Pattern recognition and signal classification and processing are among the many ANN applications, which are of interest in this paper [40]. In this sense, there are feedforward type networks where the output of one layer is used as input for the next layer. They can be classified into three main architectures classes: (i) single-layer networks; (ii) multilayer networks, such as perceptrons (i.e., MLP); and (iii) recurring networks [39]. For electrical power systems problems, the use of MLP networks with retroactive error propagation (i.e., backpropagation algorithm) stands out in the literature, being usual networks with 2 to 4-layers [3].

In this regard, two main types of MLP networks are used in the literature to solve different problems, the NPR and NF [39], [40]. The recent growth in CNN uses for HIF detection is also highlighted [27]. These are the three ANNs topologies of interest in this research, which are trained and validated using software MATLAB®, as well as are compared using an equitable path.

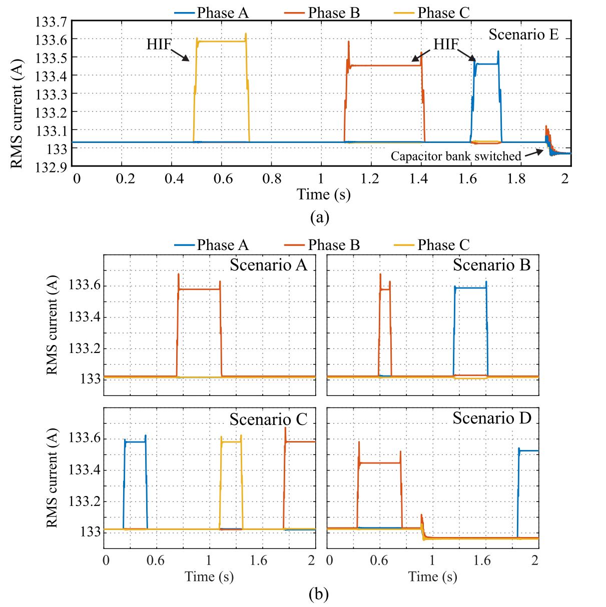

FIGURE 4. **(a) RMS current waveforms of validation Scenario D; (b) validation scenarios used, all on the same *x*- and *y*-axis scale as in (a).**

1) NEURAL PATTERN RECOGNITION NETWORK

In this section, II to IV-layers feedforward NPR networks are initially tested and evaluated. After testing, the 3 and 4-layers are discarded and the 2-layers network is chosen because it is simpler and there were no significant changes in the results, it has hidden sigmoid output neurons and uses the softmax function, which can classify vectors arbitrarily well as long as there are enough neurons in the hidden layer. This network is then trained with scaled conjugate gradient backpropagation and performance evaluation is accomplished using the cross-entropy error calculation. In the results, in addition to the overall error, it is possible to obtain the confusion matrices and characteristic curves.

To define the neurons number, NPR networks from 10 to 300 neurons are tested for each of the 16 training scenarios. This range proved to be sufficient for all scenarios, so that an evolution in the method performance is observed, as well as the moment when it becomes stagnant or tends to regress. Thus, it is possible to define, for each scenario, the NPR network with the best performance. In this paper, 80% of data are used for training, 10% for validation and 10% for testing [6], [41].

The NPR network with the best performance is chosen for each scenario based on criteria such as the error by cross entropy closer to zero, the best percentage of hits in the confusion matrix, and therefore better graphically representing the respective training scenario. Table 1 shows a summary of the selected networks for each scenario, describing the NPR network with the best performance and its respective characteristics: neurons number, average general performance value, accuracy according to the confusion matrix, and total time required for training.

TABLE 1. Characteristic of the selected NPR network for each training scenario.

Scenario	Neurons number	Performance	Accuracy	Time (s)
1	275	0.0466	95.0%	225.68
2	100	0.0131	98.0%	251.81
3	200	0.0134	98.0%	441.92
4	100	0.0128	98.0%	251.35
5	300	0.0086	98.9%	818.74
6	150	0.0021	99.7%	242.73
7	125	0.0050	99.3%	398.48
8	275	0.0008	99.9%	247.95
9	200	0.0063	99.0%	713.36
10	300	0.0101	98.6%	449.51
11	300	0.0112	98.8%	984.20
12	200	0.0050	99.3%	272.42
13	150	0.0007	99.9%	337.87
14	275	0.0059	99.3%	468.78
15	300	0.0041	99.4%	478.30
16	225	0.0045	99.5%	361.02

TABLE 2. Characteristics of the selected NF network for each training scenario.

Scenario	Neurons number	Performance	R^2	Time (s)
1	150	362.1359	0.8722	19354
2	200	66.7234	0.9772	40119
3	225	80.6319	0.9723	41052
4	300	72.7231	0.9696	87919
5	300	36.3606	0.9878	51631
6	225	10.6404	0.9952	15532
7	275	24.6971	0.9856	29157
8	100	2.8089	0.9983	2573
9	150	31.7023	0.9921	29920
10	275	60.5250	0.9751	113680
11	275	71.2494	0.9831	23195
12	300	32.7256	0.9870	45911
13	275	0.5718	0.9998	74104
14	100	19.7041	0.9945	7235
15	175	24.7620	0.9934	19002
16	250	14.7340	0.9961	53556

2) NEURAL FITTING NETWORK

In curve fitting problems, an NF network is expected to map a dataset of numerical inputs and a set of numerical targets. For this research, 2 to 4-layers feedforward NF networks are also tested. The 2-layer network is chosen because it is simpler and there were no significant variation in the results when compared to multiple layers, it has sigmoid hidden neurons and linear output neurons, it fits arbitrarily well to multidimensional mapping problems, when it has consistent data and enough neurons in the hidden layer. This network is trained with the Levenberg-Marquardt backpropagation algorithm, which stands out among others in the literature [42], [43]. The network performance analysis is accomplished using the Mean Squared Error (MSE) calculation and regression analysis.

The same data percentage from the NPR network is used for the NF network, training (80%), validation (10%) and testing (10%), as well as tests with different neurons numbers, 10 to 300 neurons for each of the 16 training scenarios. Once again, the best performing NF for each scenario is chosen based on the MSE closest to zero, determination coefficient R^2 closer to 1, and therefore better graphically representing the respective training scenario. Table 2 presents a summary of the selected networks for each scenario, showing the NF network with the best performance in each case and its respective characteristics: neurons number, average overall performance value, value of R^2 in regression analysis, and total time required for the network training.

3) CONVOLUTIONAL NEURAL NETWORK

CNN is a deep learning network that learns directly from data, eliminating the need for manual feature extraction. They are particularly useful for classifying data and finding patterns in images. The use of CNNs for deep learning is popular because of three important factors: (i) CNNs eliminate the need for manual feature extraction, which are learned directly over the network; (ii) CNNs produce highly accurate recognition results; and (iii) CNNs can be retrained for new recognition tasks, allowing for the reconstruction of pre-existing networks.

A CNN can have tens or hundreds of layers that learn to detect different features of an image. Filters are applied to each training image at different resolutions, and the output of each convoluted image is used as input to the next layer. Like other ANNs, it is composed of an input layer, an output layer and hidden layers between them. These layers perform operations that change the data with the intent of learning specific features from it. Three of the most common layers are: convolution, activation or ReLU, and pooling [44].

In this paper, the images of RMS current plots for each 16 scenarios are used for training the CNNs. Each simulation has a total time of 2 s and a windowing of 0.2 s is performed for each image. This windowing time is chosen because it corresponds to approximately 10 complete cycles of a 60 Hz electrical system, which is enough time to represent different system events. The images are in color, with a size of 168 × 788 pixels, which results in a sufficient number of samples to generate the 60 Hz sinusoidal. In total, 100 images (i.e., samples) are obtained and classified as: (i) 0, for normal system operation condition, including capacitors bank switching; and (ii) 1, for HIF condition (i.e., capturing only the beginning, middle or end of a fault, or a complete HIF). Thus, a total of 50 samples are obtained in each category, 80% are used in training and 20% for testing/validation [24], [26], [27], [41].

Similarly to the other ANNs, the CNN neurons number choice is also subjective and challenging since it requires the definition of parameters such as the filters' size and quantity used in the convolutions, in addition to the number of layers. Approximately 200 different architectures are tested by combining and varying these parameters in order to choose the best CNN for each scenario. This results in a wide range of CNN networks, from low complexity (training time of 0.54 s) to higher complexity (training time of 3h30min). In this paper, the testing values for filter sizes and quantities are equal or

TABLE 3. Best results for NPR network.

Scenario	Performance	Confusion Matrix	Graph
Training	Network 13	Network 13	Network 13
Scenario A	Network 1	Network 13	Network 13
Scenario B	Network 1	Network 13	Network 13
Scenario C	Network 1	Network 11	Network 1
Scenario D	Network 1	Network 3	Network 13
Scenario E	Network 1	Network 3	Network 3

multiple [23], [44], which proves to be a good strategy since the resulting accuracy is over 80% in all tests.

The network choice is done based on complexity (fewer layers and filters), accuracy (greater number of tests with 100% accuracy), and training time. A 3-layers network architecture is then defined since it resulted in the best accuracy indicator (achieving accuracy of 100%, 95%, and 90% in 40%, 25%, and 35% of the performed simulations, respectively); with a training time for this network is $2min11s$.

D. ERROR ANALYSIS AND VALIDATION

The applicability of each ANN is analyzed in the 5 validation scenarios and evaluated according to five criteria, being: accuracy (overall precision), reliability (accuracy in detecting HIF occurrence), security (accuracy in detecting the normal operating state of the system), safety (safety related criteria), and sensitivity (sensitive load related criterion) [3], [6], [45]. These parameters are calculated by:

Accuracy:

$$A = \frac{TP + TN}{TP + FP + FN + TN} \cdot 100\%. \tag{1}$$

Reliability:

$$D = \frac{TP}{TP + FP} \cdot 100\%. \tag{2}$$

Security:

$$S = \frac{TN}{FN + TN} \cdot 100\%. \tag{3}$$

Safety:

$$SF = \frac{TN}{FP + TN} \cdot 100\%. \tag{4}$$

Sensitivity:

$$SN = \frac{TP}{TP + FN} \cdot 100\%, \tag{5}$$

where: True Positive (TP) is the number of correct faults detection, True Negative (TN) is the number of correct decision of healthy conditions, False Positive (FP) is the number of faults that are not detected, and, finally, False Negative (FN) is the number of healthy conditions that are erroneously classified as faults [3].

TABLE 4. Best results for NF network.

Scenario	Performance	Graph
Training	Network 13	Network 13
Scenario A	Network 8	Network 15
Scenario B	Network 1	Network 5
Scenario C	Network 1	Network 5
Scenario D	Network 10	Network 14
Scenario E	Network 11	Network 14

TABLE 5. CNN results in validation scenarios.

Parameter	Value
False positives	0
False negatives	2
Accuracy	96%

IV. RESULTS AND DISCUSSION

A. NEURAL PATTERN RECOGNITION NETWORK

In the training process, 16 NPR networks are obtained, one for each scenario, according to the characteristics presented in Table 1. Each of these is tested for the 5 validation scenarios, totaling 80 different simulations. Table 3 shows the best result obtained for each validation scenario, the evaluation is done by performance, confusion matrix, and graphic representation of the RMS currents (i.e., visual analysis).

The NPR network obtained in Scenario 13 (i.e., called Network 13) is chosen, since it is one of the networks that appears more often as best result in the simulation results shown in Table 3. It is also highlighted that this network presented good training performance as previously presented in Table 1).

B. NEURAL FITTING NETWORK

Similarly to the previous section, 16 NF networks also are obtained in the training process according to the characteristics presented in Table 2 and each network is tested for the 5 validation scenarios, totaling 80 different simulations. Table 4 presents the best result obtained for each validation scenario considering their performance and graphical representation of the RMS currents (i.e., visual analysis).

Results in Table 4 show heterogeneity since none network demonstrated overall superior performance. However, the NF network obtained from Scenario 13 (i.e., called Network 13) is chosen for the final comparison in reason of being the best performing network during training (Table 2) and for this scenario being the same chosen for the NPR analysis. It is also observed that the NF networks overall presented results with greater noise than NPR networks. Furthermore, another performance issue of the NF network is that, in many cases, the validation scenarios results were inverted or mirrored and with an unexpected decrease of RMS current value at the fault time.

C. CONVOLUTIONAL NEURAL NETWORK

In all 5 validation scenarios, three-phase RMS current plot images are used for the CNN validation. Each image is

TABLE 6. Comparison of results of the three ANNs.

Parameters	NPR	NF	CNN
Accuracy	76.92%	23.08%	96%
Reliability	72.72%	18.18%	91.30%
Security	100%	50%	100%
Safety	40%	10%	93.10%
Sensitivity	100%	66.67%	100%

windowed every 0.2 s, resulting in 50 samples of size 168×788 pixels, this same methodology was used to train the network. Considering all samples, 27 represent normal system operating conditions (of which, two with capacitors bank switching) and 23 represent HIF situations (of which, 9 capture the fault ending, 3 only the middle of the fault, and the remaining samples capture either the beginning of the fault or all of it). Table 5 presents the results for the CNN validation.

The overall percentage of accuracy in the classification of samples for the CNN network is 96%. It failed to classify two images: (i) one that captured only the middle of a fault, that is, it did not capture the current increase during the HIF beginning, nor the current decrease during the grid's restoration; and (ii) another that captured only the fault ending with the current decreasing in time.

D. COMPARISON OF ANNS PERFORMANCE

The validation results indicate that, among the two MLP networks, the NPR gives better results and converges more efficiently. In addition, the NF network does not seem suitable for this research problem, with below expected performance and random/unknown behavior during validation; also, a higher computational cost and training time are needed for NF networks. Furthermore, despite showing good accuracy in verification tests, when the NF network is applied in other scenarios (with variations in fault location, time, and duration) it does not converge correctly.

Regarding the CNN, it is observed that it efficiently captures most cases of HIF, does not confuse the fault with other normal system events, such as capacitors bank switching, which is one of the current challenges in HIF detection methods. Also, parameter variation such as the HIF location and timing do not affect its accuracy since the CNN operates differently from the others.

To carry out a fair comparison among the three ANNs, the accuracy, reliability, security, safety, and sensitivity of all tested networks are calculated. Table 6 presents the results considering the number of hits and errors of each network, with regard to HIF and normal system operation, using the previously described 5 validation scenarios.

The superior performance of CNN for HIF detection is observed in Table 6, when compared to NPR and NF networks. It is also important to mention that the training time of the former is shorter than the latter. The CNN network topology is hence more indicated for HIF detection solutions.

V. CONCLUSION

The detection of HIF in electrical power distribution systems remains a serious and unsolved problem. In this paper, the modeling, analysis, and comparison of a HIF detection method were carried out using three ANN topologies: two MLP networks (i.e., NPR and NF), and a CNN. All ANNs were trained on a set of 16 scenarios and validated on a set of 5 different scenarios, considering variations in fault location, time and duration. These scenarios were modeled based on a real distribution grid. The networks were trained repeatedly, considering different architectures, and the best performing network was chosen for further tests. These selected networks were then applied to the 5 validation scenarios, where the best performing network architecture among the NPR, NF, and CNN were selected for a quantitative analysis. For an equitable comparison the same criteria of accuracy, reliability, security, safety, and sensitivity were used. From the results obtained, a superior performance from the CNN compared to NPR and NF networks is observed, showing that it is the most suitable network to be used in the HIF detection. For future research, it is suggested to expand this research from its comparison with other AI-based and traditional methods in the literature.

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