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Using Artificial Neural Network Methods to Increase the Sensitivity of Distance Protection

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Abstract: To protect power lines, distance relays are used which can rely on a modified distance resistance. But usually the operating range of these relays changes as the network conditions change (network topology, load value, output value, etc.) and leads to false trips, By using methods that can process information and recognize patterns, for example, the use of micro and intelligent processor algorithms can use the new relays with high precision and thus provide adequate protection. In this study, a distance relay was modeled using a neural network, and it was observed that the neural relay had higher accuracy than the conventional relay. In addition to detecting the fault and its location, type and phase of the fault, three-stage simultaneous protection can be performed. As a result, the number of linear relays can be reduced by using relays based on neural technologies. An MLP (multilayer perceptron) neural network is used to model a sequence of distances.

Keywords: energy; distributed generation (DG); artificial neural networks; Network; Transmission network; Protection algorithms; Distance protection

1. Introduction

The use of fuel sources including coal, oil and natural gas to generate electricity has given rise to many environmental problems, one of which appears to be global warming [1,2]. Consequently, global reliance has increased on finding clean, renewable (environmentally friendly) energy sources such as wind energy, solar energy, tidal energy, biofuels, fuel cells, hydrogen engines, and other technologies with a lower pollution rate, and these units are called distributed generation units. It is relevant to bring power sources as close as possible to electricity consumers using the principles of distributed generation [3,4]. However, the introduction of distributed generation units poses a number of technical problems associated with maintaining the required level of network voltage, power quality, and ensuring the correct functioning of automation systems and relay protection. The nature of the distribution system has changed in the era of distributed generation. Modern distribution systems are designed on the basis of receiving electrical power from network transformers and distributing it to consumers at the average distribution voltage and through the switching centers to consumers at the low voltage level. Thus, the flow of effective power P and reactive capacity Q is always from the highest level of tension to the lowest level. Distributed generation transforms the distribution system from a passive system, as is the case in traditional electric power systems, to an active distribution system. Since the power injected into the distribution network can affect its flow pattern, it must be ensured that it will not reduce the power supply specifications for other network users. With distributed generation in the distribution system, the flow and tension of the network are determined not only by the loads but also by the generators and the loads together. It is possible that the direction of the two-way power flow will be reversed in some branches of the network depending on the size and location of the distributed generation and the size of the loads. Thus, there is a need to expand research on the development of algorithms for protection systems in general and distance protection in particular [5]. there are numerous proposed styles and bias to estimate the position of the faults on the lines. They can be grouped into styles grounded on

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the input impedance [6] styles grounded on surge travelling goods [7–10]. Previous research has focused on improving the efficiency of distance protection by developing a set of mathematical laws to adjust the performance of these protection automation systems [11–17]. Based on Thevenin's laws, a set of algorithms was developed to obtain a more accurate value of damage resistance [18–20]. Or depending on changes in the phase angle of power lines [21,22]. However, these studies did not focus on or examine the integration of distance protection mechanisms in a distribution network containing high-penetration distributed generation devices. Therefore, this study proposed a series of practical steps and applications to improve the sensitivity of distance protection in the presence of distributed generation, using neural network methods, multi-level deep learning and artificial intelligence to more accurately determine the location of the fault and thus accurately calculate the resistance of distance protection, and this in turn led to an improvement in the performance of the protection system.

2. Voltage Levels for the Distribution System

Most of the RDG units are related to the distribution system, which can be classified (Figure 1) according to global systems in terms of the level of voltage into:

- High voltage distribution network HV: Typical voltage levels are 50-110 kV (in the Syrian network 66 kV)
- Medium voltage MV distribution network: Typical voltage levels are 10- 50 kV (in the Syrian network 20 kV)
- Low voltage LV distribution network: levels less than 1000V (in the Syrian network 220/380V).

In fact, the names and limits of voltage levels change from one country to another. In Syria, labels such as secondary distribution voltage (220/380 V), main distribution voltage (20 kV), medium voltage (66 kV) and high voltage (230-400 kV) prevail.

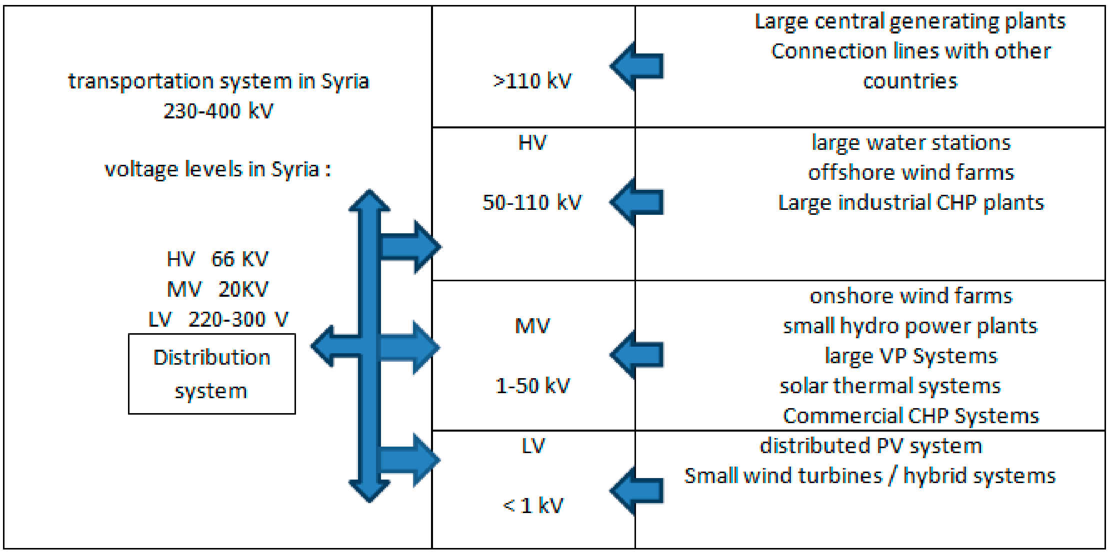

Figure 1. Voltage levels of a typical electrical distribution system and connection points for distributed regenerative generators.

3. An Overview of the Technical Impacts of Distributed Generation on the host Distribution Network

The inclusion of distributed generation in the distribution system generates technical effects in the network, which may be positive, negative or neutral depending on several factors. The main areas that are affected are tension and loss of power, fault levels, reliability, electrical quality, protection and stability, worker safety and network code. Figure 2 shows a graphic representation of the relative sizes of these effects.

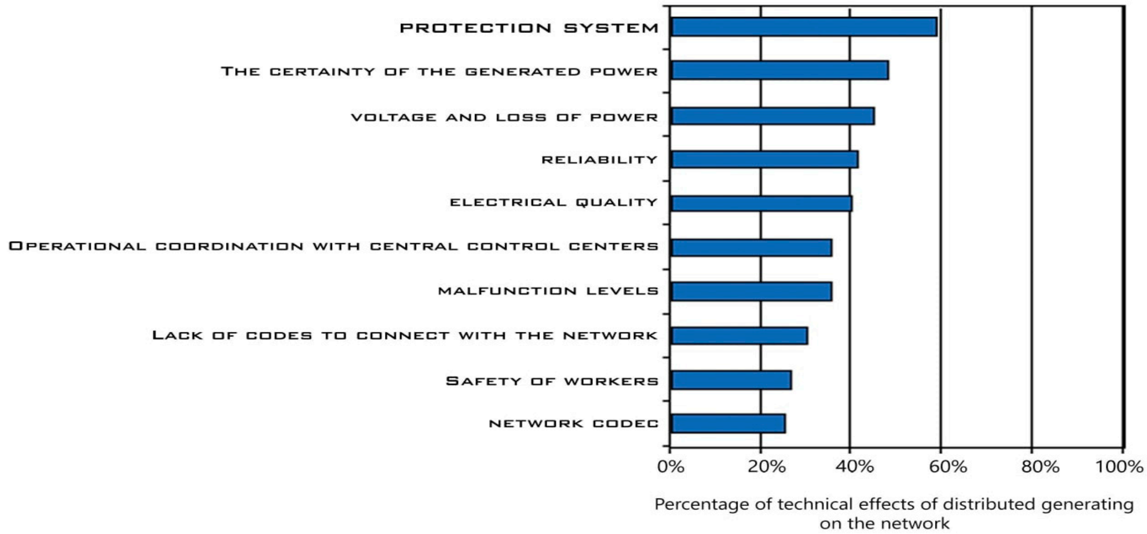

Figure 2. Percentage of the technical effects of distributed generation in the distribution networks.

by analysis the percentages, notice that the greatest impact of distributed generation units lies in electrical protection systems in general. Therefore, this study will focus on developing the mechanism of operation of distance protections in distributed generation networks to increase sensitivity and improve performance. There are a few elements that could have an effect on the overall performance of any relay safety system. Economy is one of the maximum essential elements. Errors aren't common. Therefore, one may also marvel why there's a want to layout a protection system. However, unlucky occasions do happen, and if there's no safety in place, sizeable economic losses can occur. In the occasion of a unmarried fault, if the designed circuit operates quick and accurately, it could lessen downtime and guard device from damage. In addition, it's miles essential to lessen redundancy, i.e., Use most effective the minimal quantity of relays required for the specified safety zone. In a electricity system, it's miles not possible to are expecting the location, kind and timing of any failure. Given the unsure possibilities, the safety engineer ought to broaden a safety scheme primarily based totally at the maximum in all likelihood occasions, beyond occasions, device producer hints and make the proper realistic decision.

4. Algorithm Using Neural Network Methods to Increase the Sensitivity of the Distance Protection System

4.1. The First Test: Correction of the Location of the Astronomical Error Using Neural Networks to the Distance Relay

proposed in this test a method for improve relay fault location estimation by creating a correction point that is added to the set point setting to form a final result based on these steps and devices [23].

Fault parameters➔EMTP (transmission line model)➔input (6 voltages and currents)➔CMC-356 Omicron (test universe device)➔ Distance relay (7SA522)➔Fault location l_{relay}

Estimation edited value based on the voltage and current signals, and then added to the result from the relay [23]. The block diagram of the proposed solution is presented in Figure 3.

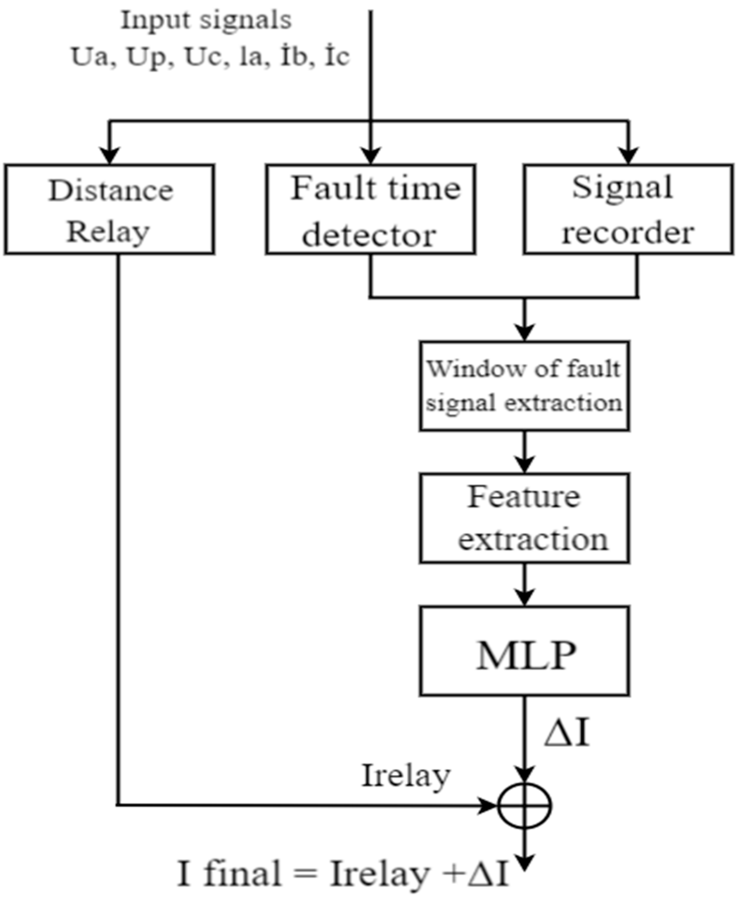

Figure 3. Diagram of the proposed solution [23].

In the traditional case of the operation of distance protections, when electrical faults of various types occur on the electrical power supply lines, the distance protection is activated. Based on the distance between the fault site and the protection site, the resistance value of the distance protection is then estimated, and then the separation is made or not according to that value. In the presented proposal, it is done by: An algorithm that calculates a short time period before and after the protection is activated, to calculate the exact time of signal change. After that, the features are generated from the signal block [23], and using these nonlinear functions, the correction amount is calculated as follows:

$$I_{finaly} = I_{relay} + \Delta_I \tag{1}$$

An MLP neural network was chosen as a nonlinear estimator and trained to ensure that the final result is more accurate than a relay. This approach was chosen to directly estimate the fault location. This model is designed for a 100 km AC transmission line with a voltage of 20 kV (voltage level of the Syrian distribution network) from Teshrin station to the industrial city of Adra (Syria).

4.1.1. Universal Relay Tester SMS-356

OMICRON's CMC -356 universal relay tester and a real distance relay were used to bring the simulation and response closer to reality [24].

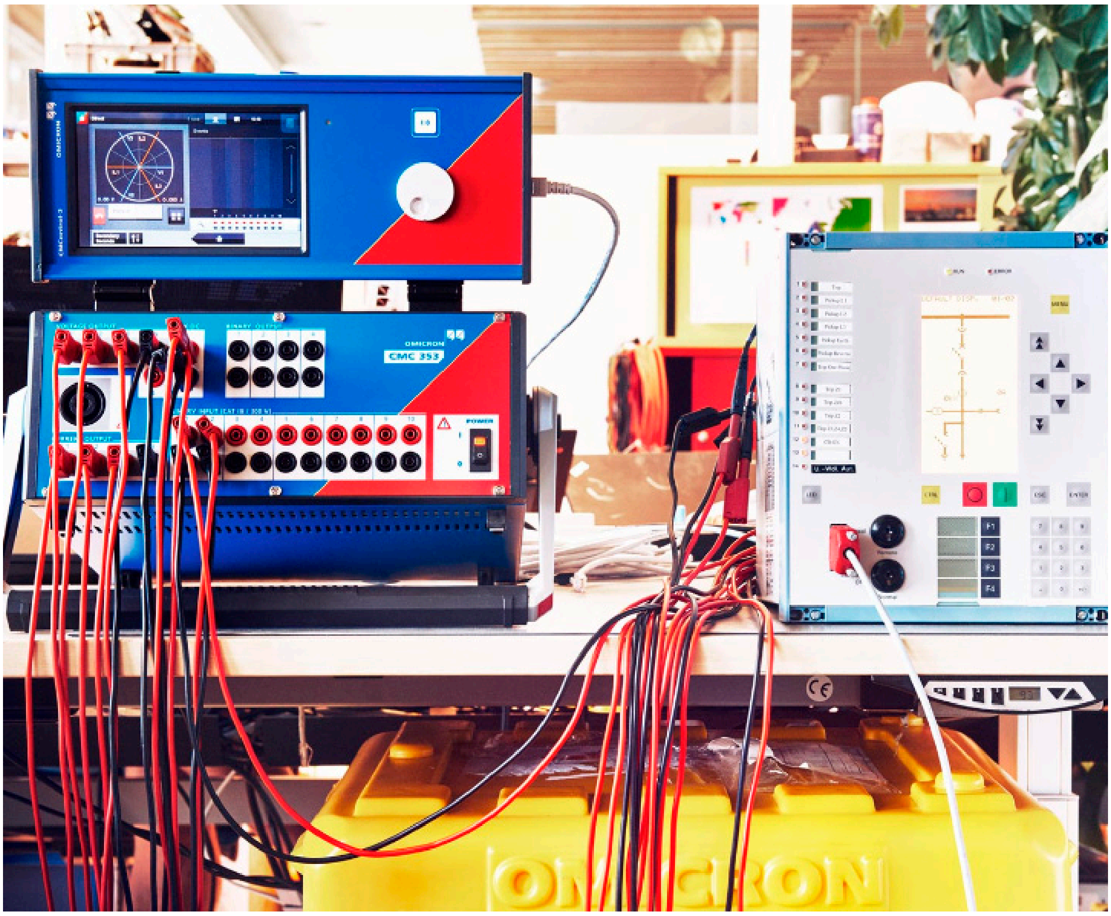

Figure 4. Relay devise CMC -356 from OMICRON [25].

Answers 7SA522 The remote relay will be read back to the computer via DIGSI 4.82 (Digital Information Group) compatible software [25].

4.1.2. MLP (Multilayer Perceptron) network

A multilayer perceptron (MLP) is a modern feedforward artificial neural network, consisting of fully connected neurons with a nonlinear kind of activation function, organized in at least three layers, notable for being able to distinguish data that is not linearly separable. It is a misnomer because the original perceptron used a Heaviside step function, instead of a nonlinear kind of activation function (used by modern networks). is shown in Figure 5.

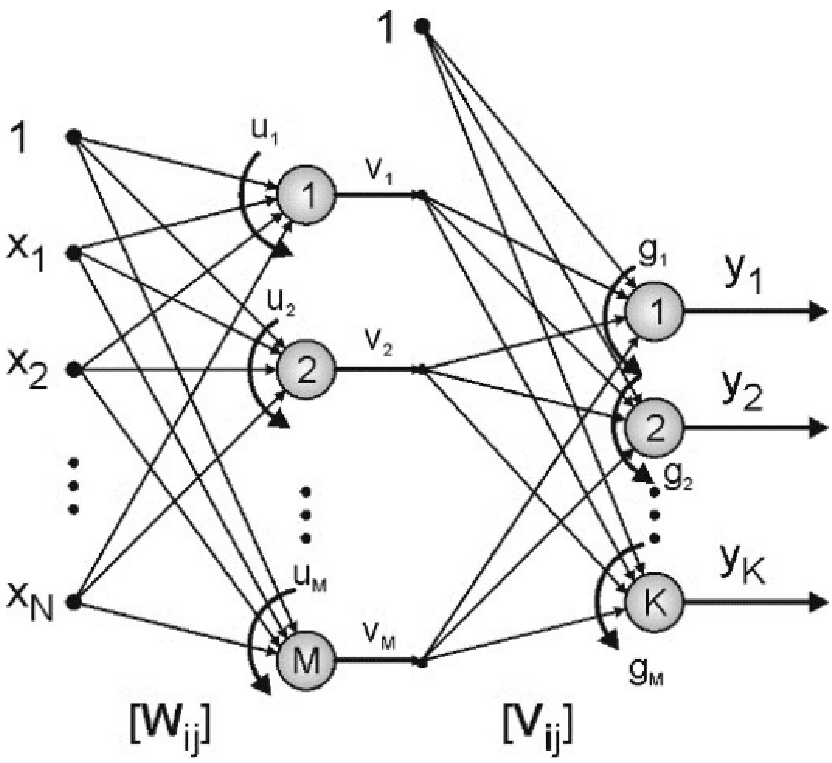

Figure 5. MLP structure layers of neurons network.

4.1.3. Simulation and numerical results

ATP/EMTP software was used to simulate a real 100 km long, 20 kV power transmission line (Syria). Error scenarios when creating samples are given. Location of damage: one of N = 23 positions on the line (at a distance of 5, 10,..., 95 km

- short circuit 0, 1, 2, 3, 4, 5 Ohm;
- types of emergency situations: single-phase, two-phase, three-phase short circuit, two-phase short circuit to ground;
- line load: 30%, 50% and 100% of the rated line load.

This gave a total of

$$N \times K \times P \times Q = 23 \times 6 \times 4 \times 3 = 1656 \; cases$$

Additionally, to test the effect of fault time (relative phase) on the results, cases were created for short circuit resistance R - fault = 1 ohm at positions (10, 40, 80, 110 km) and M = 10 fault time in 2 ms steps (to cover the entire 20 ms period) of 50 Hz signals). This means:

- Short circuit point location one of
  N = 4 addresses (10- 40- 80-110 km),
- Short circuit resistance R - fault : 1 Ohm,
- Fault time: one of the values M = 10 (+00 ms, +02 ms,..., +18 ms).

This resulted in an additional

$$N \times P \times Q \times M = 4 \times 4 \times 3 \times 10 = 480 \; cases$$

Total 1656+ 480 = 2136.

4.1.4. Fault Location Using Remote Relay

Using the simulated data from the ATP / EMTP, the data was first regenerated using a CMC - 356 tester to feed the selected 7 SA 522- V 4.7 distance relay. Test suites allow the recorded data to be

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"replayed" and transferred to a similar data relay, which greatly simplifies the analysis of identified failures. [26]. The statistics of these comparisons are presented in Table 1,

Table 1. Simulation results of distance protection without MLP.

Type malfunctions	Average position error (km)	Average relative position error (%)
1-ph short circuit	0.19	0.151
2-ph short circuit	0.157	1.31
2-ph fault in ground	1.96	1.65
3-ph short circuit	0.55	0.48
Average	1.08	0.91

Table 2. Number of grouped by fault.

Type malfunctions	Samples in the training set	Samples in the test set
1-ph -F	372	164
2-ph- F	352	182
2-ph –F to G	386	178
3-ph-F	340	192
Average	1450	716

Table 3. Maximum errors DR 7SA-522 and after correction using Multilayer perceptron.

Method	Maximum error (km) actual .	maximum error (%)
7SA522	9.2	8.32
7SA522 With Multilayer perceptron	2.78	2.49

5. Determination of Fault Resistance (Distance Protection Resistance) Based on Neural Network Technology for Single-Phase Earth Fault for 20 kV Power Line—Southern Grid, Syria

To simulate the ANN-based method, a 20 kV power transmission line with a length of 100 km.The transmission line is modeled using the pi model. Model of the proposed transmission line using Matlab / Simulink. The ground resistance of the simulated system was 100 ohms, and the system frequency 50 Hz. Other values to the transmission line are given in Table 4 [28].

Table 4. Technical characteristics of the simulated power system.

PI-(Positive impedance) [Ω/ km]	0.034 + j0.41241
ZSI-(zero sequence Impedance)[Ω/ km]	0.3003 + j0.1334
OPI-(Original positive Impedance) [Ω]	3.0136 + j43.085
SZI-(Source zero impedance) [Ω]	0135+j43.085
Power [MBA]	100
Voltage [Kv]	20

The most important step in using artificial neural networks is testing the trained network. Network testing is necessary to ensure that the network produces outputs that match new inputs and has good generalization ability to generate outputs [29]. There are a number of methods used to test a trained ANN. In the first testing method, when training an ANN, a best-fit linear regression graph is plotted between the obtained results and the planned results. The slope of this plotted graph is determined by the coefficient R. The R ratio shows how closely the actual results can match the target results. This coefficient varies from 0 to 1. To achieve the best training results, ANN (Artificial Neural Network) should be equal to 1. The network is tested using a test dataset in which the input and

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target output are not present in the training set and the percentage error between outputs is calculated network data and target output data. If the average error rate is an acceptable value, it means that the ANN test has passed and the network can now be used [30,31]. The estimation error when determining the location of damage is found using equation 2.

$$error(\%) = \frac{(actual\ location - desired\ location)}{(line\ length)} * 100 \tag{2}$$

5.1. Troubleshooting in the ANN

LM (Levenberg-Marquardt) learning function and the four-level ANN structure are defined as the ANN structure with the smallest estimation errors [32–34]. A logarithmic sigmoid activation function was used in the first three layers of the defined network, and a linear activation function was used in the output layer[35]. The number of neurons belonging to these layers was defined as 6, 5, 5 and 1, respectively. The general structure of the implemented network, created using Matlab / nntool, is shown in Figure 6

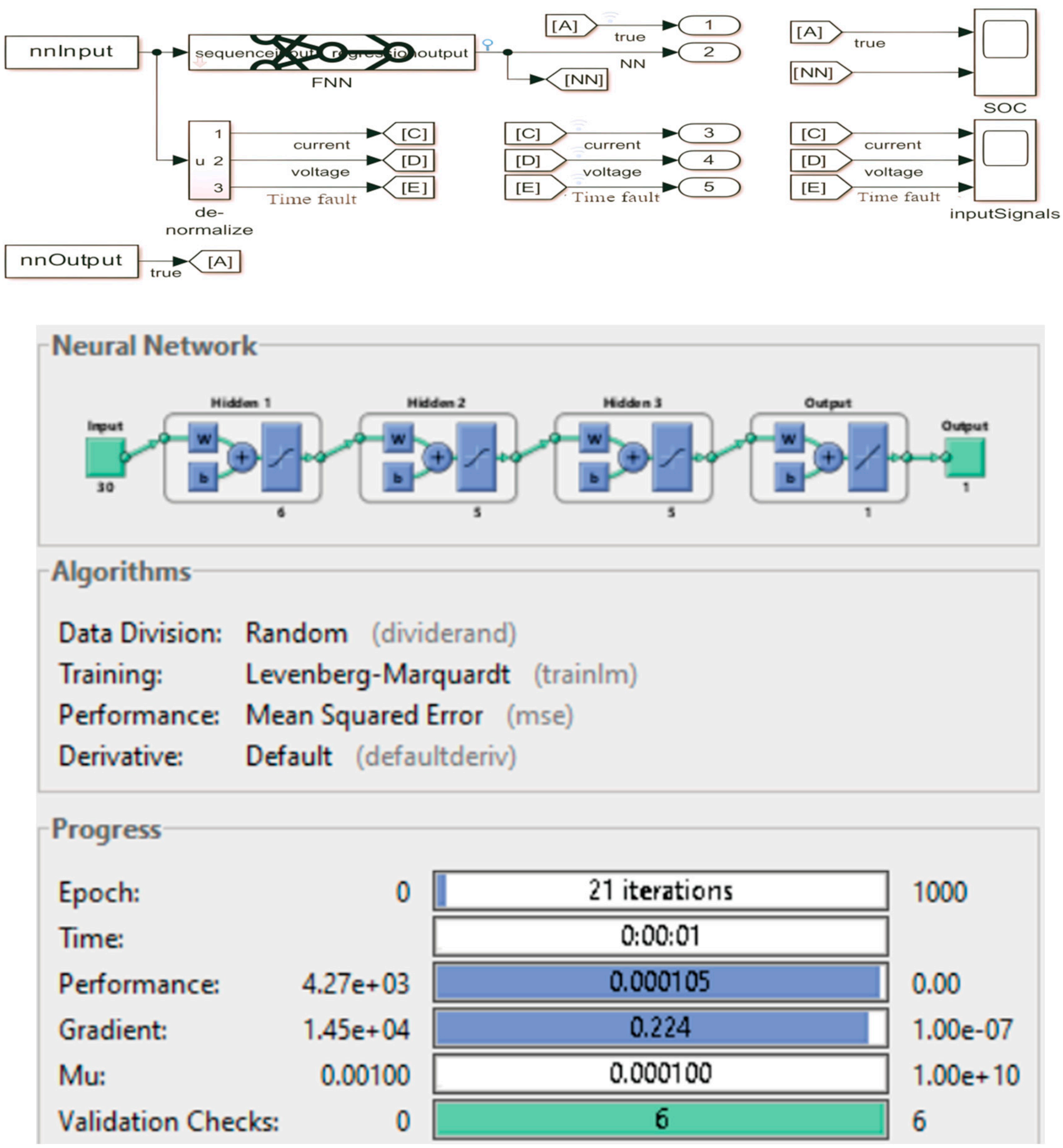

Figure 6. General structure of the Nntool network[18].

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According to the test results shown in Table 14, the largest prediction error is 0.236, the smallest prediction error is 0.0121, and the average absolute prediction error for the test cases is 0.12405. These results show that the accuracy of the algorithm is high. Therefore, this technology can be relied upon in practical applications for protection systems, especially in electrical networks with a high penetration rate[38–42].

Table 5. Incorrect location results.

Actual fault Location (km)	Fault resistance Ω	Suspected location of the fault	Absolute error (%)
10	2	10.2366	0.236
25	50	24.8931	0.106
35	5	35.0595	0.059
55	120	54.7784	0.221
80	3	80.1218	0.121
95	13	94.8768	0.123

6. Conclusions

As a result of changing electrical network parameters, especially electrical distribution networks that have high penetration rates from distributed generation units, such as changing network topology, load values, fault currents, and the level of electrical tension on distribution bars, it is necessary to develop new working algorithms for distance protections to integrate those protections and increase their sensitivity and accuracy.

Transmission lines are part of power systems, but system operators experience a large number of faults. In response, a number of attempts have been made to mitigate the effects of faults on power lines. The purpose of this thesis was to investigate the feasibility of using artificial neural networks as a fault detection mechanism on power lines. There are three methods for protecting power lines, namely fault detection, fault classification and fault location. The focus of this thesis was on the application of artificial neural networks (ANN) for fault detection. The goal of this study was to detect electrical faults and classify them in real time in a simulated environment. For this purpose, the Matlab/Simulink tool was used, which used artificial neural modeling tools.

Network Toolbox and SimPower Systems Toolbox. It has been shown in the literature and document content that ANN is a good method for detecting faults in power lines and can accurately identify faults. The present study also validated its application and that good performance results can be obtained with an ANN suitably trained using validated training data. Many of the goals were confirmed, re-examined and described in detail in the dissertation. One problem that has not been fully explored is fault location using ANN, primarily due to the time constraints of this project. cessation of damage location determination through ANN is reserved as a future study with its diversity. The research methodology used was to conduct a comprehensive literature review followed by an analysis of ANN and its application in fault detection of power lines. The literature review focused on understanding what fault detection is and its many applications. Analysis and Modeling showed that training an ANN requires extensive data preparation. This is by far the most time-consuming component of ANN design and application. It is noted that ANN has many applications and functions, but careful care is required while preparing and formulating the data. The INS fault detector measures faults efficiently and quickly, so the transmission line equipment is more likely to be protected. In addition, the ANN fault detection method has been tested and proven to be accurate for all types of faults.

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