Journal University of Kerbala, Vol. 14 No.4 Scientific . 2016

The Faults Detection and Categorization for a Part of Iraqi Electricity Power Transmission Grid Based on Neural Network Techniques

كشف وتصنيف الاخطاء لجزء من شبكة النقل الطاقة الكهربائية العراقية مستنداً على تقنيات الشبكة العصبية

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Abstract

Modern power systems are characterized by the instant isolation of faults especially in the high voltage transmission lines. Therefore, the faults detection and categorization are very important to get a stable power system, and keep on integrity of the electrical equipment.

This paper focuses on using the Artificial Neural Networks (ANNs) as a technique of Artificial Intelligence to detect and categorize faults of the Basra-Karbala transmission line. The measurements of three phase voltages and current of the power system are used as input signals to the proposed design of neural networks. All types of faults that may occur in the studied transmission line are taken into account, while the high accuracy of the detection and categorization of faults are considered in the design. The adopted radial power system which is used as the case study, consists: main power station is connected with a substation across the transmission lines, transformers, bas bars, circuit breakers, and loads. The proposed design includes three ANNs instead of one to reduce the complexity and minimize response time. The performance of the studied power system and the operation results of ANNs are assessed by simulation.

Keywords: Faults Categorization, Radial System, Artificial Neural Network (ANN), Neurons, Backpropagation.

الخلاصة:-

تتميز الانظمة الكهربائية الحديثة بالعزل الفوري للخطأ خصوصاً في خطوط النقل ذات الفولتية العالية. لذا يعتبر كشف وتصنيف الاخطاء من العوامل المهمة جداً للحصول على نظام كهربائي مستقر بالأضافة الى الحفاظ على سلامة الاجهزة الكهربائية. يركز هذا البحث على استخدام الشبكات العصبية الصناعية كتقنية للذكاء الصناعي في كشف وتصنيف الاخطاء لخط نقل الطاقة بين مدينتي البصرة و كربلاء. قراءات الفولتية والتيار لنظام القدرة ثلاثي الاطوار استخدامت كأشارت دخل للتصميم المقترح للشبكة العصبية. كل انواع الاخطاء التي ممكن ان تحدث في خط النقل المدروس تم اخذها في بالحسبان، بينما دقة كشف وتصنيف تلك الاخطاء في تصميم الشبكة العصبية تم اخذها بنظر الاعتبار. النظام الكهربائي الشعاعي المعتمد كدراسة حالة يتكون من محطة قدرة رئيسية موصلة مع محطة فرعية عبر خطوط النقل والمحولات وقضبان التوصيل وقواطع الدورة الكهربائية والاحمال. التصميم المقترح يتكون من ثلاث شبكات عصبية صناعية بدلاً من واحده لتقليل التعقيد وخفض زمن الاستجابة. ان اداء نظام القدرة المدروس ونتائج عمل الشبكة العصبية الصناعية تم تقييمه بأستخدام المحاكاه.

1. Introduction

In recent years, the electrical power systems activities are expanded widely. Modern power systems operating requires stability and high reliability through the use of many protection and detection devices. As a result, the protection of these systems is an urgent need. According to previous statistics, about 87% of the faults in power systems are occurred in the transmission lines [**1**]. The transmission lines faults are the most common faults because of weather (such as lightning strokes, rain, heavy snow, etc.), accidents (such as falling trees, collapse of the insulating material, etc.), and many other reasons. The disturbances in transmission lines due to the faults, can generally generate a variety of electromagnetic transients in the power system. The faults current and the normal flowing current are interfering, and this will be causing excessive currents that leads to system failure. Hence, the faults detection and the protection of those lines is an important issue in electrical power system to prevent any undesirable events [**2**].

In a three-phase system, the fault is a contact between two or more of conductors with each other, or between one and more of conductors with the ground. Therefore, faults are mainly classified into two types: line to ground faults and short circuit faults. Moreover, the line to ground faults are classified to a Single Line-to-ground (LG) faults, Double Line-to-Ground (LLG) faults, and three line to-ground faults (LLLG). The LG faults are the most common type of unbalanced faults, which represents approximately 70% of faults. While the LLG faults represents about 15 % of faults. While, the line to line to line to ground fault (LLLG fault) which is an infrequent balanced faults, represents 3% of faults. On the other hand, the short circuit faults are classified to Line to Line (LL) faults, and three line (LLL) fault. The LL fault represents about 10% of faults, while the LLL faults is rarely occurred and represents at most 2% [**3**] .All types of transmission line faults are illustrated in Fig. 1.

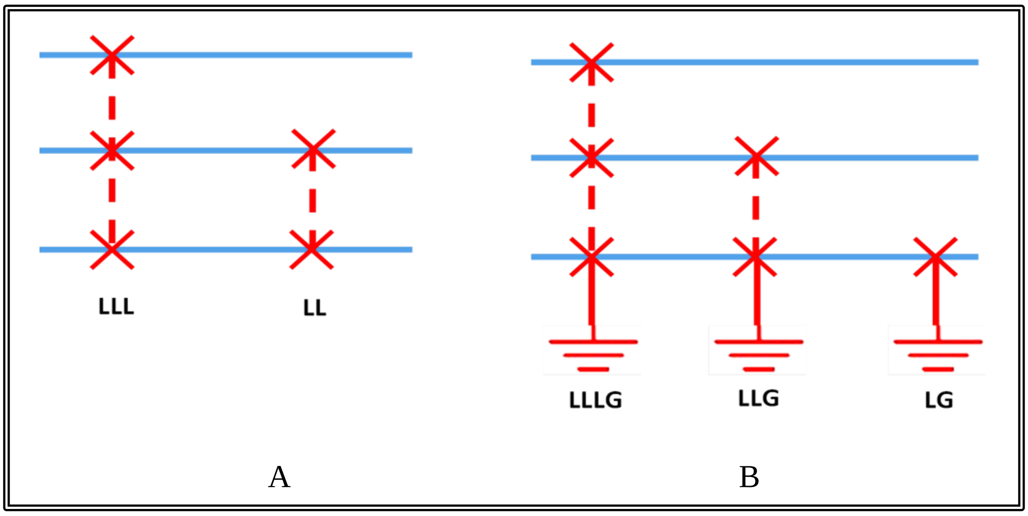


Fig.1: Types of faults: A. Short circuit faults, B. Line to ground faults [**3**]**.**

The effects of faults in the transmission lines do not only confine on the equipment, but also exceeds to affect the power quality. Therefore, it is very necessary to determine the type of fault, and work on removing it as soon as possible. Artificial intelligence is important approach that has been used to classify the type of faults [**4**,**5**,**6**,**7**]. There are many artificial intelligence techniques such as Artificial Neural Networks (ANNs), Fuzzy Logic, Fuzzy Neuron, and Fuzzy Logic-Wavelet based system.

At recent years, there are many researches has been achieved in this area. **Gafari, et al.** [**8**] simulated a three-phase symmetrical fault in Nigerian 28-Bus, 330kV transmission grid, by using two different MATLAB based programs. The first program loads flow studies which determines pre-fault conditions in the power system based on Newton-Raphson method. The second one determines fault current magnitudes for three-phase short-circuit on the power system. **Rajveer** [**9**] focused on detecting ground faults on electric power transmission lines by using artificial neural networks. **Majid, et al.** [**10**] proposed a method to classify the faults of three-phase transmission line network by using a wavelet transform and genetic algorithm. **Shaaban, et al.** [**11**] focused on identification of simple power system faults by using information conveyed in the wavelet analysis. **Roy, et al.** [**12**] proposed a technique to classify the power quality disturbance based on the distorted signals energy. The Discrete Wavelet Transform (DWT) and ANNs were used to extract the energy distribution features at a different levels of resolution. While, **Eisa, et al.** [**13**] exploited the Back-Propagation (BP) neural network architecture as an approach for fault detection, classification and isolation in a transmission line system.

In this work, categorization of the balanced and unbalanced faults except of a three-phase short circuit fault for Basra-Karbala electrical transmission line is completed based on artificial neural network. The studied power system consists of the power station, step-up and step-down transformers, circuit breakers, loads, transmission line and sub-station. The samples of three-phase current and voltage are measured for a normal operation case and for all types of faults at the sending side of power system which is in Basra city. These samples are applied as inputs to proposed ANNs system to categorize type of faults. Hence, The ANNs system will be able to detect the fault, recognize its type, and determine in which phase it occurred. This information will help the staff of power station to rapidly do essential actions to protect the electrical equipment and devices from any disturbances, and solve the problem to return the system to its normal state.

The rest of this paper is organized as follows. In section 2, the studied power system is explained in details. While in section 3, the problem of determining the fault type in transmission line is modeled to be solve by Artificial Neural Networks. The back propagation algorithm is used to train neural networks. In section 4, the studied power system and proposed ANNs system are simulated by using the SimPower System and Neural Network Toolbox in MATLAB environment. The performance of ANNs is evaluated via calculating the classification rate of each designed ANN. Finally, in section 5, the conclusion and main points of this work are stated.

2. The Studied Power System

The specifications of studied system are: 400kV, 50Hz. It consists of main power station located in Basra city and sub-station located in Karbala city. These stations are representing the connection areas by a (T) line model of 610 km long. It is divided into two sections; each section is 305km. The single-line diagram of studied system as illustrate in **Fig 2**. The main power station (Al-Hartha thermal power plant) which its capacity (200MW with 11kV) is connected with step-up transformer to feed the transmission line by 400kV across buses B1 and circuit breaker ($C.B_1$). The sub-station is connected across circuit breaker ($C.B_2$) to feed different loads through a step-down tertiary winding transformer (Tr.2) with output voltage of (11kV and 33kV).

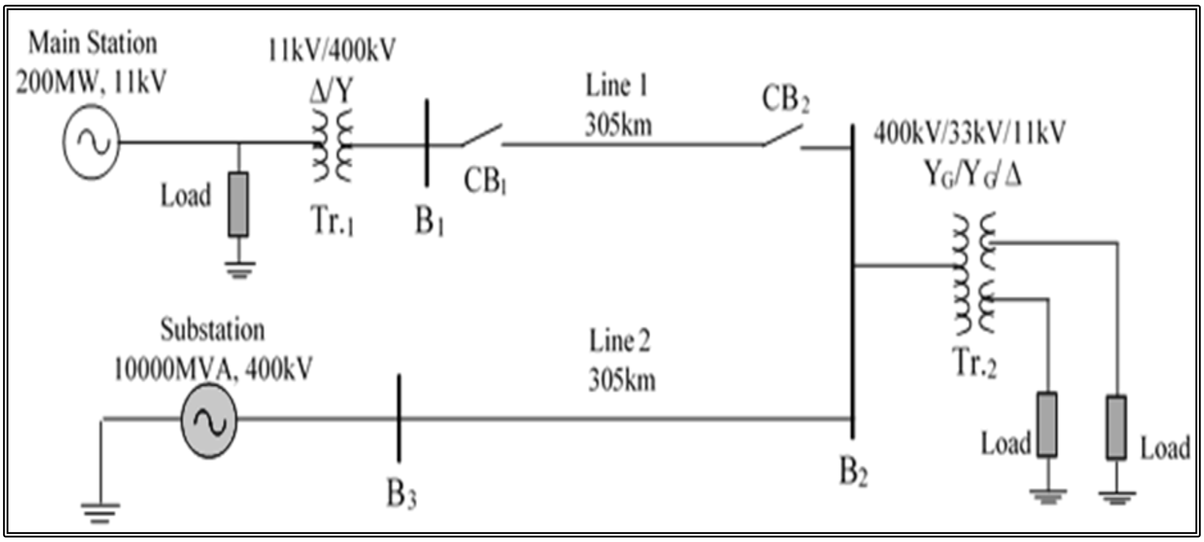


Fig 2: The single-line diagram of the studied power system.

The system components are taken into consideration to be closer to reality as possible. The function of circuit breakers to protect the system from the faults when they occur. There are many loads with different rated power are connected to the system. At main station, 10MW three phase active power load is used. At the tertiary winding transformer, 50Mvar reactive power load and 120MW active power load are used. The system deals with a three levels of voltage (11kV, 400kV and 33kV). The current and voltage samples are measured at the sending side Bus-Bar (B_1) by using three-phase measurement block. These current and voltage samples are used as inputs to ANNs to classify the type of faults.

3. Design of Artificial Neural Networks

Artificial neural network is well-known artificial intelligent technique for solving problems that are difficult to solve by the human beings or the conventional computational algorithms [**14**,**15**]. ANNs can learn and adjust themselves to solve different nonlinear problems via modifying certain weights during training process with offline data. In this work, feedforward ANNs are exploited to recognize the fault types on transmission line of power system between Basra and Karbala.

3.1 ANNs Structure

The structure and operation of ANNs mimic the biological nervous system of human beings. ANN has input layer, output layer, and one or more finite number of hidden layers. Each layer consists of individual elements called neurons or nodes. The number of neurons in each layer is chosen to be sufficient to solve a particular problem. Except the neurons of output layer, each neuron of a certain layer in feedforward network is connected to all neurons of a next layer by synaptic weights [**16**,**17**]. The synaptic weights are initialized with random values. During training process, synaptic weights are modified via learning algorithm to make inputs produce the desire output. The structure of feedforward neural network is shown in **Fig. 3**.

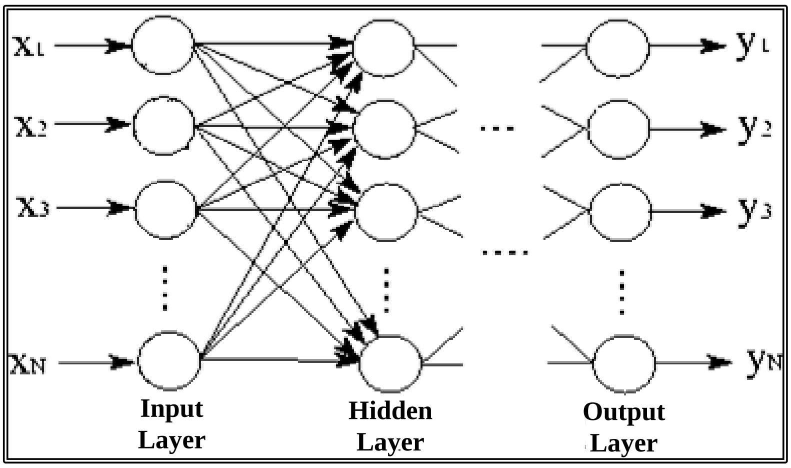


Fig. 3: Structure of feedforward neural network [**16**].

In this work, backpropagation is used as learning algorithm to train ANN. At first, synaptic weights are initialized with random values. Then at each iteration of backpropagation algorithm, one input sample is applied to ANN to produce the actual output. After that, the error is computed between the actual output and desired output. Depending on this error, the synaptic weights are updated to minimize error as the following equation:

$$W_{i+1} = W_i + \Delta W$$

Where W_i is updated value of the synaptic weights, W_i is current value of the synaptic weights, and ΔW which is the updated change of weights, is determined as below:

$$\Delta W = \eta \frac{\partial E}{\partial W}$$

Where η is the learning rate parameter, and $\frac{\partial E}{\partial W}$ is the derivative of error with respect to value of the synaptic weights.

These processes are continued until the error reaches to very small value (approximately zero). At this time, the algorithm converges and the training process is stopped [**18**]. The flowchart of backpropagation algorithm is shown in Fig 4.

3.2 Input Samples

The voltages and currents of three-phase power system are measured at sending side with sampling frequency 5.7 KHz in steady state and all type of faults. Thus, each sample is a vector of six entries: the voltage measurements of three-phase (V_R, V_S, V_T) and the current measurements of three-phase (I_R, I_S, I_T). These samples are used as input to ANNs to categorize the type of faults. Most of samples (85%) are used to train ANN, and rest of samples (15%) are used to test the performance of trained ANN.

3.3 ANNs Design

In a three-phase power system, transmission line faults can be classified to 11 types as shown in **Fig 5**. Because three phase short circuit fault of (RST) phases is rarely occurred, it is not considered in this work. Hence, the designed ANN should be able to recognize the rest 10 types in addition to steady state case dependent on input samples.

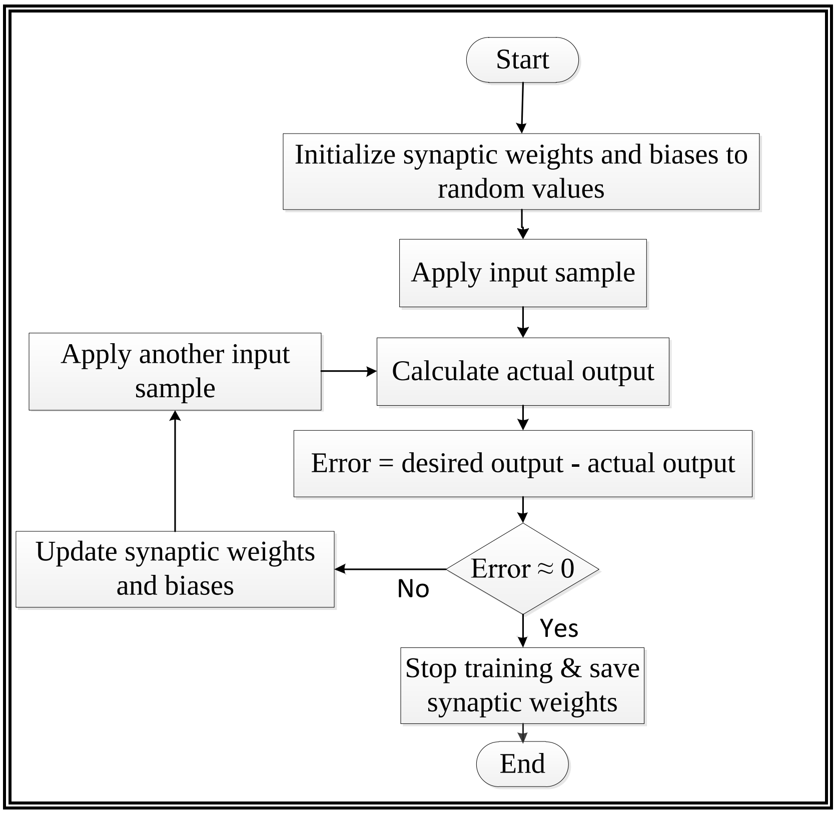


Fig 4: Flowchart of backpropagation algorithm

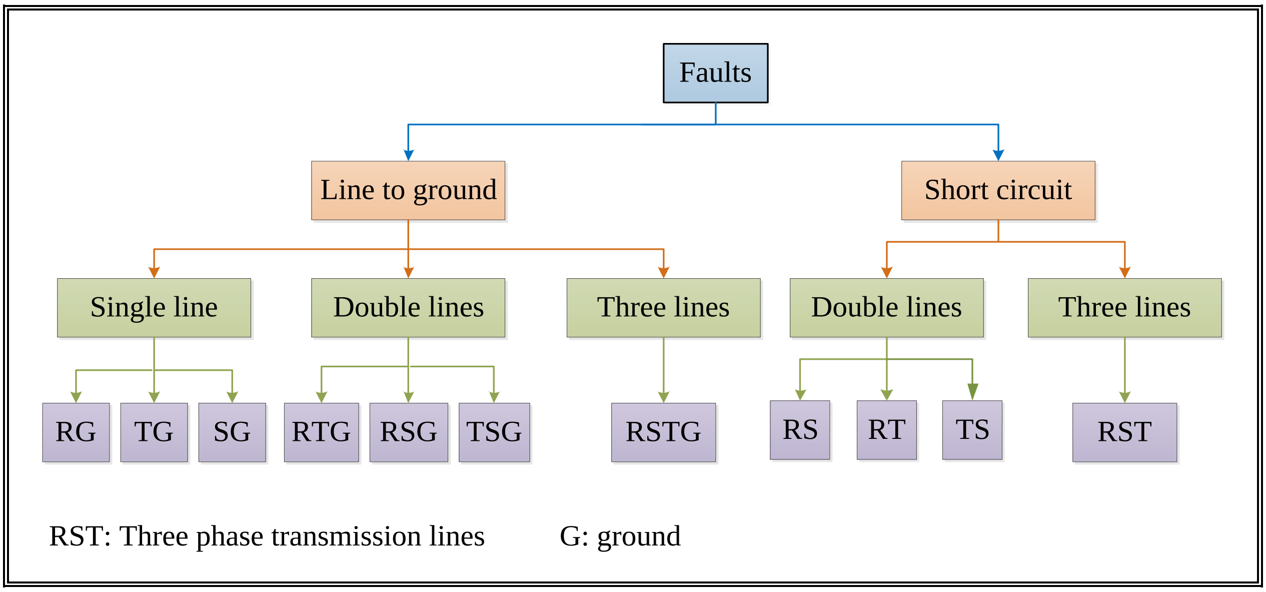


Fig. 5: Types of transmission line faults.

The problem of classification of fault type can be solved by one ANN. However, the ANN will be more complex and need long training time. To reduce the complexity of ANN, and decrease the computation and training time, the problem is solved via designing three ANNs instead of one. The first ANN is used to classify the input samples into three categories: steady state, double line short circuit faults, and line to ground faults. The second one is activated by first ANN when double line short circuit fault is occurred, and it used to classify the double line short circuit faults into three possible types. The third one is also activated by first ANN when line to ground fault is occurred, and it is used to classify the line to ground faults into possible seven types. Hence, the fault type and fault line are clearly known by using this structure of ANNs with less response time. The inputs of all three ANNs are voltage and current samples of three phase. The designed system is illustrated in Fig. 6.

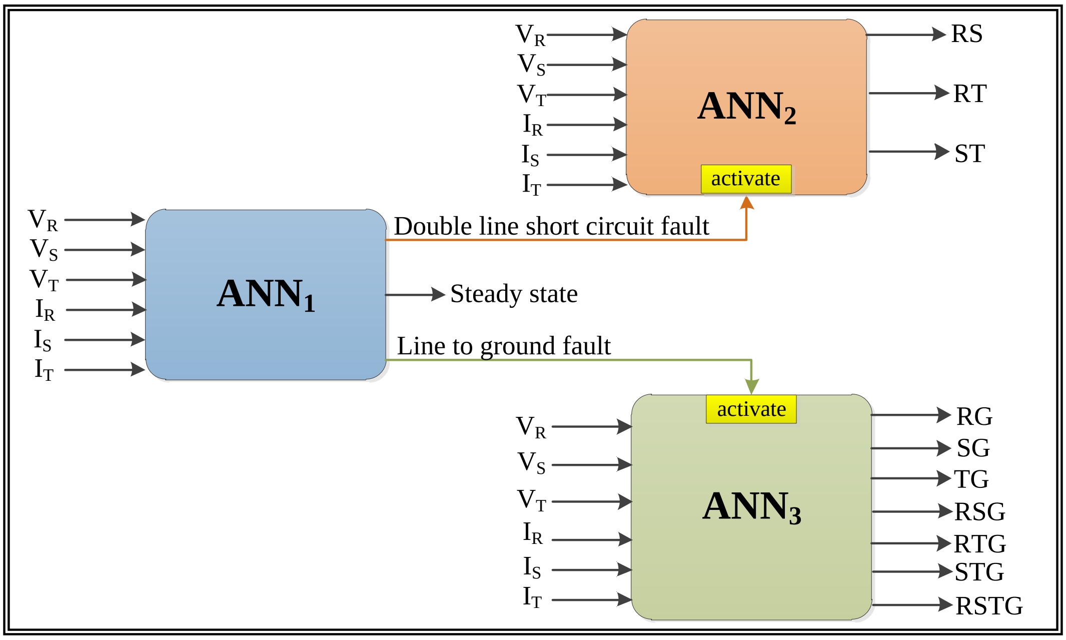


Fig 6: The proposed design of ANN system for fault categorization.

In designed ANN system, only ANN_1 is running all times. In normal case, output neuron of steady state is active (its value equals to one). When fault is occurred on transmission line, ANN_1 classify it into double line short circuit or line to ground. If occurred fault is classified as double line short circuit, output neuron of double line short circuit will be active. This leads to activate ANN_2 which classifies fault into three possible types of double line short circuit faults. On the other hand, if the occurred fault is classified as line to ground, output neuron of line to ground will be active. This leads to activate ANN_3 which classifies fault into seven possible types of line to ground faults. Hence, ANN_2 and ANN_3 are not running all times. Consequently, the response time of the ANN system is significantly decreased.

4. Simulation and Results

To evaluate performance of the proposed ANN system, we simulate it via using MATLAB software. The power system is done by using Simpower toolbox. After that, we run the system and measure voltages and currents of three-phase power system at sending side with sampling frequency 5.7 KHz in steady state and all type of faults. Each sample is a vector of six entries (three-phase voltages and currents) [V_R V_S V_T and I_R I_S I_T]. Therefore, each ANN in this work has six neurons in the input layer. These samples are applied to ANNs as inputs.

The designed ANNs are simulated by using Neural Network Toolbox (NNT) [**19**].Categorization of faults is a kind of pattern recognition problems. Thus, scaled conjugate gradient backpropagation is selected as training algorithm because it is fast and produces suitable result for pattern recognition problems [**20**]. In addition, tangent sigmoid is chosen as activation function for hidden layers, while softmax is used for output layer. Number of hidden layers and number of neurons in each hidden layer are chosen based on trial and error technique. Moreover, number of hidden layers and number of neurons in each hidden layer should be as fewest as possible to reduce the complexity of ANN and computation time. For each designed ANN in this work, we simulate a large number of networks with various combinations of hidden layers and different number of neurons in each hidden layer to search for the most suitable size network with best classification performance.

4.1 ANN_1

The designed ANN_1 should classify input samples into three categories: steady state, line to ground faults, and double line short circuit faults. Therefore in the output layer, ANN_1 should has three neurons which are corresponding to these categories. The number of used samples for steady state is 1149 and for each kind of fault is 383. As a result, the total number of samples is 4979. 85% of total samples (4232 samples) are used in training process, while the rest of samples (747samples) are used to assess the performance of the network. After extensive search for best network, the one with only one hidden layer that has 30 neurons is chosen to perform the classification task. Hence, the architecture of designed ANN_1 will 6-30-3. After training process, the value of one neuron of output layer will be approximately one which represent the category of input sample, while the values of the other two will be roughly zero.

The confusion matrix is used as illustrated in **Fig 7** to show the classification rate of the network by using 747 input samples which are not used in training. The green diagonal cells of the matrix demonstrate the number of samples that are classified correctly by ANN_1 and their percent. On the other hand, the red off-diagonal cells show the number of samples that are misclassified by ANN_1. The white cells of last row demonstrate the percentage of correct classified samples and percentage of misclassified samples in each target fault type, while the white cells of last column demonstrate the corresponding percentages in each actual output fault type of the network. The blue cell indicates the total percentage of correct classified samples and total percentage of misclassified samples. It can be shown that classification rate of designed ANN_1 is 98.9%. This implies that ANN_1 can roughly categorize input samples into three types.

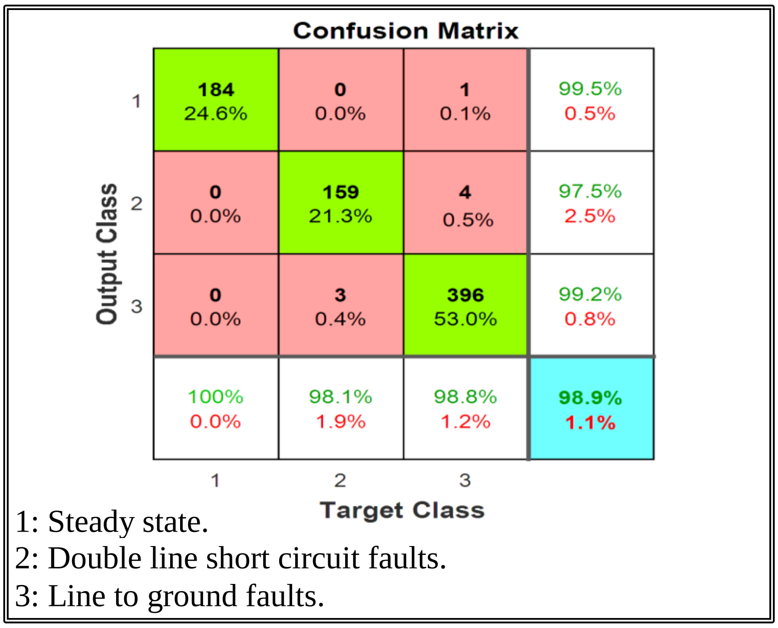


Fig 7: Confusion matrix of ANN_1.

4.2 ANN_2

ANN_2 is activated when output neuron of double line short circuit faults in ANN_1 is effective (its value equals to one). Propose of ANN_2 is to classify input samples of double line short circuit faults into its three types: RS, RT, and ST. Therefore in the output layer, ANN_2 should has three neurons which are corresponding to these types. Only input samples of double line short circuit faults are used in designing ANN_2. 386 samples are used for each case of three types of double line short circuit faults. Therefore, the total number of used samples in ANN_2 is 1158. 85% of total samples (984 samples) are used in training process, while the rest of samples (174 samples) are used to assess the performance of the network. After extensive search for best network, the one with only one hidden layer that has 22 neurons is chosen to perform the classification task. Hence, the architecture of designed ANN_2 will 6-22-3. After training process, the value of one neuron of output layer will be approximately one which represent the type of fault for each input sample, while the values of the other two will be roughly zero.

As ANN_1, the confusion matrix is also shown in **Fig 8** to demonstrate the classification rate of the network by using 174 input samples which are not used in training process. It can be shown that classification rate of designed ANN_2 is 99.4%. This implies that ANN_2 can classify double line short circuit faults into three types. This leads to specify which two lines are faulted.

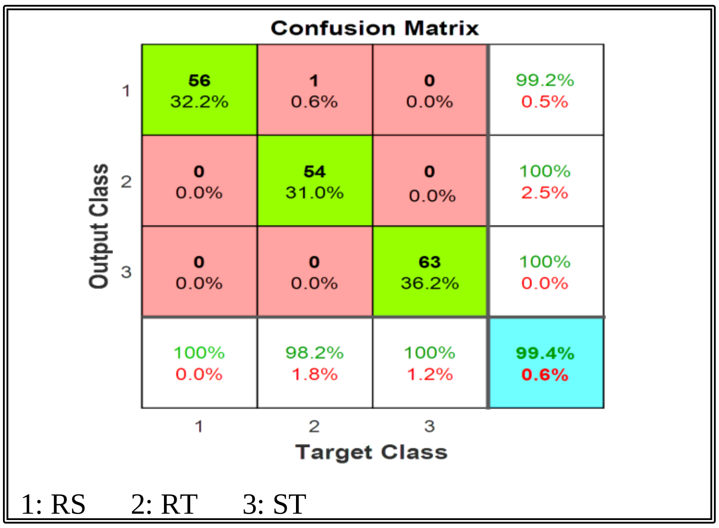
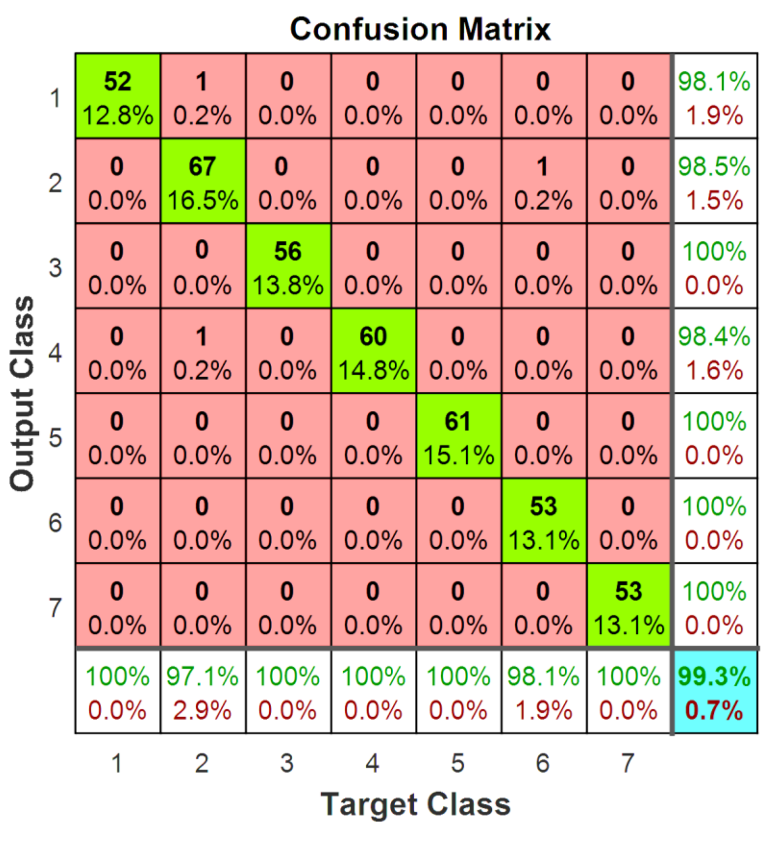


Fig 8: Confusion matrix of ANN_2.

4.3 ANN_3

ANN_3 is activated when output neuron of line to ground faults in ANN_1 is effective (its value equals to one). Propose of ANN_3 is to classify input samples of line to ground faults into seven types: RG, SG, TG, RSG, RTG, STG, and RSTG. Therefore, in the output layer, ANN_3 should has seven neurons which are corresponding to these types. Only input samples of line to ground faults are used in designing ANN_3. 386 samples are used for each case of seven cases of line to ground faults. Therefore, the total number of used samples in ANN_3 is 2702. 85% of total samples (2297 samples) are used in training stage, while the rest of samples (405 samples) are used to assess the performance of the network. After extensive search for best network, the one with only one hidden layer that has 15 neurons is chosen to perform the classification task. Hence, the architecture of designed ANN_3 will 6-15-7. After training process, the value of one neuron of output layer will be approximately one which represent the type of fault for each input sample, while the values of the other six will be roughly zero.

As other networks, the confusion matrix is also shown in **Fig 9** to demonstrate the classification rate of the ANN_3 by using 405 input samples which are not used in training process. It can be shown that classification rate of designed ANN3 is 99.3%. This implies that ANN3 can classify line to ground faults into seven types. This leads to know the faulted line or lines.



1: RSG 2: RTG 3: RG 4: STG 5: SG 6: TG 7: RSTG

Fig 9: Confusion matrix of ANN_3

5. Conclusion

In this work, the problem of categorization of transmission line faults in a certain part of Iraqi international transmission grid is solved by using artificial neural networks. Instead of one ANN, three ANNs are organized in a way to solve the problem with minimum complexity. This leads to decrease the training time and response time. The designed ANNs has classification rate about 99%. Thus, the proposed structure of ANN can effectively categorize the types of faults in three phase transmission line.

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