Fault Detection and Location in Power Transmission Line Using Concurrent Neuro Fuzzy Technique

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***Abstract*—In power systems, power transmission lines are an important part of an electrical grid. Thus, it is important to anticipate upcoming faults and their location by predicting them using a powerful artificial intelligence technique to improve power transmission line reliability and sustainability. This paper compares the results of concurrent neuro-fuzzy (CNF) technique applied in different power transmission lines (PTL), to predict the detection faults and their location over two long and short PTL (735 kV, 600 km and 400 kV, 120 km). CNF was used for detecting, locating and classifying faults in PTL. The results show that the utilization of this technique for such task could be time saving for the technical team and could improve the transmission line yield.**

***Index Terms*—Power Systems, Power Transmission Lines, Fuzzy-Logic, Artificial Neural Network, Concurrent Neuro Fuzzy, Faults detection, Faults Classification, Faults Location**

1. Introduction

Fault detection and fault location remain very important for service continuity. Today, the detection and location of faults on high voltage PTL continue to be done by the traditional methods such dispatching of the technical team on the sites, and, the visual search of the defect circuit which subsequently is isolated from the power line for repair and will only be put back into service when the defect is completely isolated [1], [2].

There are 11 fault types that can occur on a PTL including: Single Line 1 to Ground (SLG1), Single Line 2 to Ground (SLG2), Single Line 3 to Ground (SLG3), Double Line 1 and Line 2 (DL12), Double Line 2 and Line 3 (DL23), Double Line 3 and Line 1 (DL31), Triple Line 1, 2, 3 (TL123) and Triple Line 1, 2, 3 to Ground (TL123G) [3], [4], [5].

In most of the cases, the researchers limit themselves to the study of 10 fault types [9]. These researchers do not differentiate TL123 and TL123G faults. Differentiating between these faults will increase the reliability percentage of the system implemented because, in practice, each of these faults has distinct consequences on the protection equipment and on the PTL. The effects of electrical faults are critical. Some of the effects of electrical faults include impact on continuity of service, the energy supplied quality and people safety. Thus, good protection must be sensitive, selective and fast to reduce damage caused by a short circuit.

Due to the non-linear characteristics of an electrical line and unforeseeable disturbances, the search for a defect and its isolation are expensive for companies and often require a lot of working time. Therefore, more researchers are working on the use of new artificial intelligence techniques to predict fault detection and fault location using techniques such as Radial Basis Function (RBF), Support Vector Machine (SVM), Multilayers Perceptron (MLP) and CNF technique. These techniques have been used to detect and locate faults on electrical lines [6], [7], [10], [15]. However, the use of the CNF method remains new. CNF, has been utilized to model the surface roughness in drilling in [11] and [12].

The main objective of this work is to demonstrate the robustness of the CNF technique. This will be done by comparing the results obtained from two PTL of different parameters. The first PTL is characterized by its length of 600 km and its voltage of 735 kV and the second PTL is characterized by its length of 120 km and its voltage of 400 kV. The use of such a method in fault prediction could reduce the time required by the technical team for restarting a PTL and specially to increase the percentage of line reliability [13], [14]. This is beneficial for consumers because service continuity is necessary for a prosperous life in a competitive economic market [15].

There are three contributions that this paper offers. The first is the prediction of 11 faults on the PTL of small and long distance to high or very high voltage, the second is the implementation of a new technique in this power system field and the comparison of the results obtained for the high voltage and very high voltage PTL and, finally, to determine whether CNF can be successfully applied to one or the other PTL studied.

The structure of this paper is as follows: Section 2 will explain how PTL were setup to record the data used, Section 3 will present the technique called CNF applied in PTL. In

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Section 4 the experimental results will be presented and section 5 will present the conclusions.

2. Power transmission lines setup

The PTL that was simulated, for the two studies, is presented in Fig. 1 shown below.

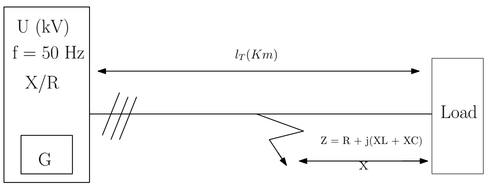

Figure 1. Three Phases transmission line model.

For each experiment, the parameters of the lines were setup as shown in Table 1. The total length of the line of each experiment was divided into 5 equal zones, each of 20 per cent of the lines total length. The voltage and current amplitudes of each fault type were used to detect and classify the fault type and location. Matlab software was used to create faults via Simulink fault breaker block. Figure 2 shows a fault breaker block used.

TABLE 1. POWER TRANSMISSION LINE PARAMETERS.

Models	Parameters	
PTL1	U = 750 kV l_T = 600 km X/R = 10 f (Hz) = 50	R (Ω/Km) = 0.01273 L (mH/Km) = 0.9337 C (μF/Km) = 12.74 θ (degrees) = 45 Rf (Ω) = 0.001, 0.01,0.1, 1, 10, 20, 30, 40, 50, 60
PTL2	U= 400 kV l_T= 120 km X/R = 23 f (Hz) = 50	

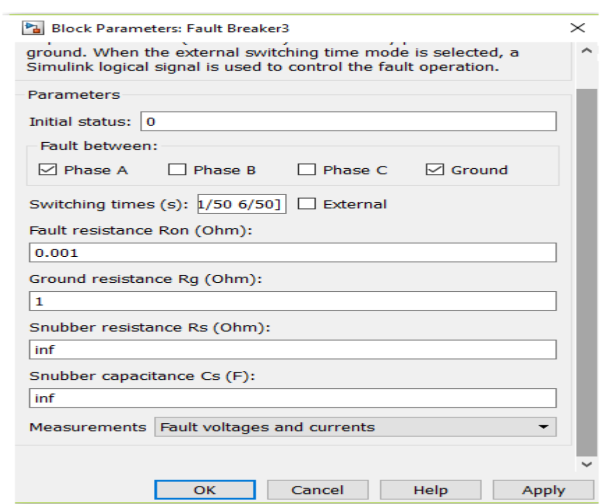

Figure 2. Fault breaker block.

After these parameters were set, 3 phase line voltages V_a, V_b, V_c and phase line currents I_a, I_b, I_c were generated for each fault type. Fault resistance (Rf) was increased from 0.001 Ω to 60 Ω as shown on Table 1. Fig. 3 to Fig. 8 present the waves generated for the different double line fault types for PTL1 and PTL2 at 120 km. As we can see in the different figures, the values of voltages and currents are different depending in the line model simulated.

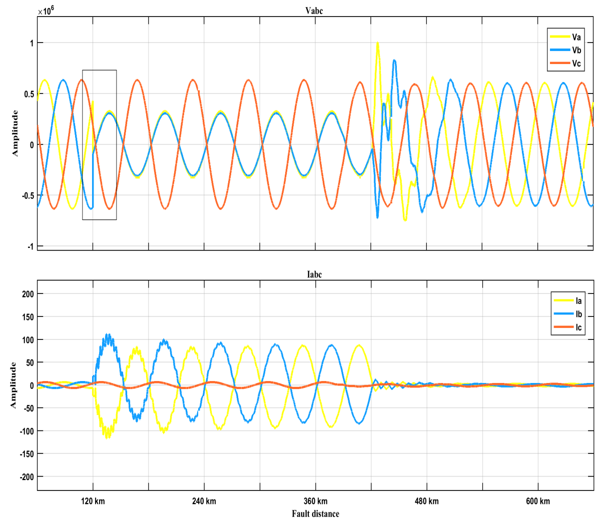

Figure 3. PTL1: DL12 fault with R_f = 1Ω, fault angle = 45°

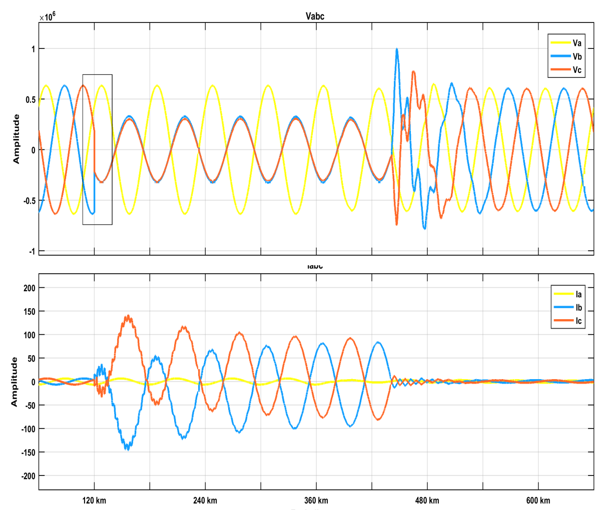

Figure 4. PTL1: DL23 fault with R_f = 1Ω, fault angle = 45°

When a short circuit appears on a PTL, as presented in different figures, we can see that the voltage increases rapidly and the current decreases on the line. In Fig. 3, Fig. 4 and Fig. 5 representing double line fault on PTL model 1, the voltage and current values are higher than on the second PTL model in Fig. 6, Fig. 7 and Fig. 8. Thus, the short circuit current or voltage on PTL depend on the power plant generation. However, the short circuit current and voltage values could depend also on the load being fed, the length of the line, the fault types and its origin.

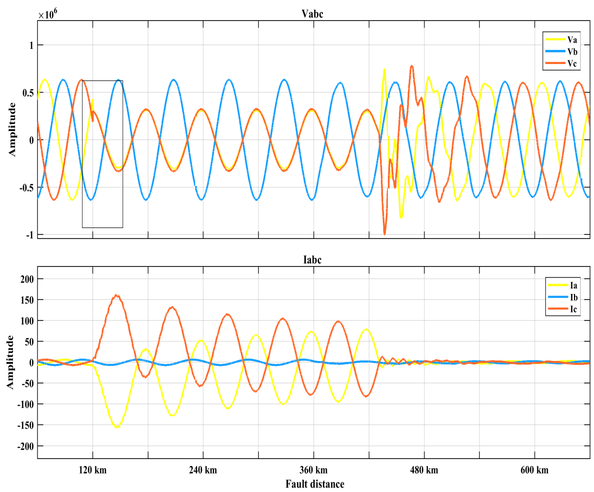

Figure 5. PTL1: DL13 fault with R_f = 1Ω, fault angle = $45°$

In spite of the fact that the fault is caused by a defect between two phases, each time, the third phase will always be affected. It is possible to see on the curves that, after a certain distance travelled by the defect wave, the amplitude of the current and the voltage become zero.

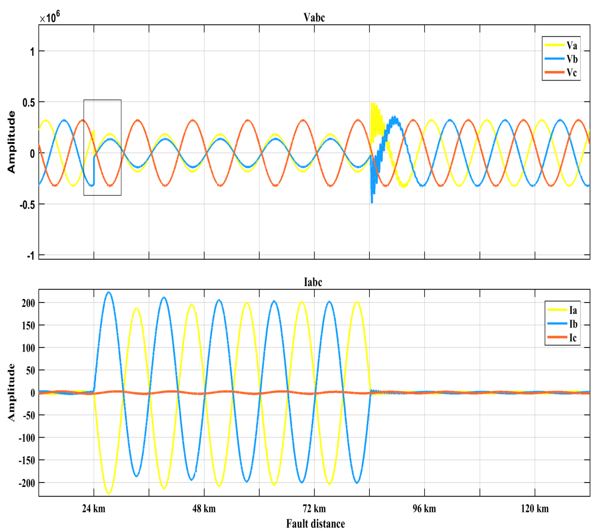

Figure 6. PTL2: DL12 fault with R_f = 1Ω, fault angle = $45°$

3. Concurrent Neuro - Fuzzy Technique

Fuzzy logic (FL) is an integral part of CNF. The application of CNF technique needs one to master FL. CNF is an artificial intelligence technique that combines the data learning by the artificial neural network while the FL method defines the rules [16]. Fig. 9 presents the general configuration of hidden layers. This structure was determined using standardised data of post faults.

Six inputs were set for V_a, V_b, and V_c short-circuit voltages between the phase 1, phase 2, phase 3, and the

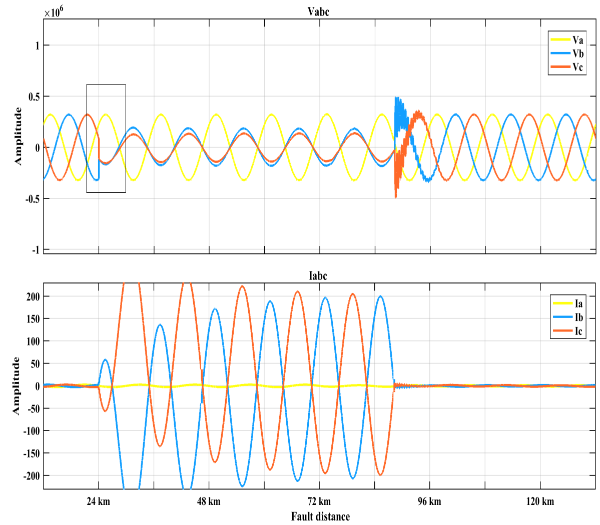

Figure 7. PTL2: DL23 fault with R_f = 1Ω, fault angle = $45°$

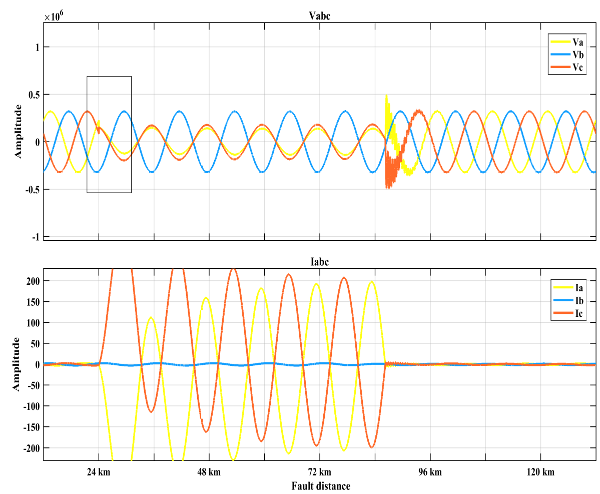

Figure 8. PTL2: DL13 fault with R_f = 1Ω, fault angle = $45°$

ground respectively as well as for I_a, I_b, and I_c short-circuit current in the phase 1, phase 2, and phase 3 respectively. These values obtained were normalized using equation 1, the normalization used is

$$X_n = 2\frac{X - X_{min}}{X_{max} - X_{min}} - 1. \tag{1}$$

Where X_n is the normalized data, X_{min} represents the minimum values and X_{max} the maximum values. In layer 2, three FL conditions were applied:

$$N_a = P_{na} - P_{nb}, \quad N_b = P_{nb} - P_{nc}, \; and \quad N_c = P_{nc} - P_{na}. \tag{2}$$

P_{na}, P_{nb}, P_{nc}, P_a, P_b, and P_c parameters for equations

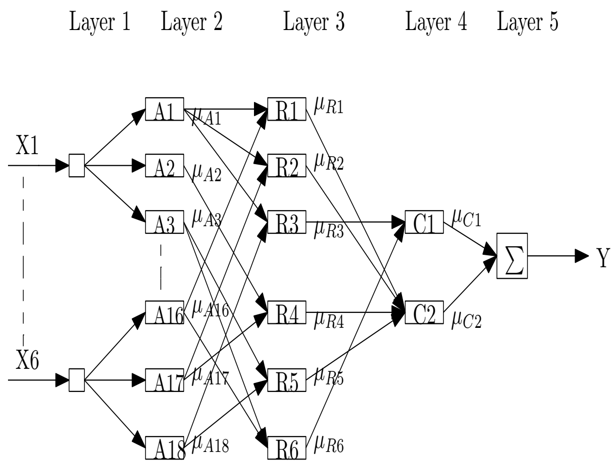

Figure 9. Concurent Neuro - Fuzzy Architecture.

(3) and (4) respectively were found as follows:

$$P_{na} = \frac{P_a}{max(P_a, P_b, P_c)}, \qquad P_{nb} = \frac{P_b}{max(P_a, P_b, P_c)}, \qquad P_{nc} = \frac{P_c}{max(P_a, P_b, P_c)}. \tag{3}$$

where:

$$P_a = \frac{I_a}{I_b}, \qquad P_b = \frac{I_b}{I_c} \qquad and \qquad P_c = \frac{I_c}{I_a} \tag{4}$$

Then, 18 neurons were used: six numbers of inputs $\times$ 3 conditions. For this experiment, six membership functions: Very small (V_S), small (S), medium (M), average (A_V), high (H) and very high (V_h) assisted in the classification of each fault. Fig. 10 represents the graph of membership functions used and Table 2, the value ranges that corresponded to each category of membership function obtained.

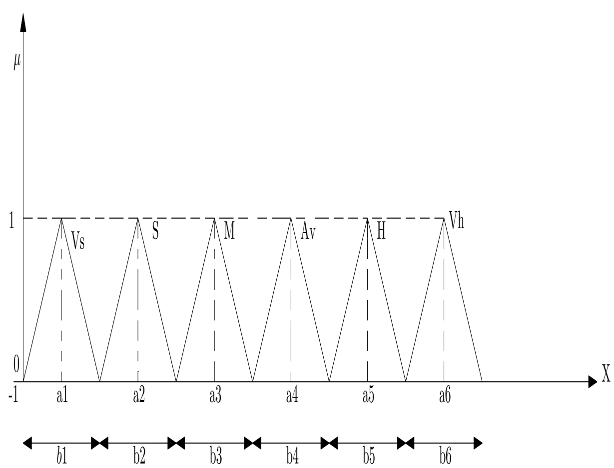

Figure 10. Concurent membership function.

The different FL conditions used to set CNF technique parameters are:

TABLE 2. DIFFERENT RANGES OF THE MEMBERSHIP FUNCTION.

Categories	**Range**
V_S	[-1, -0.8]
S	]-0.8, -0.0034]
M	]-0.0034, -0.025]
A_V	]-0.0025, -0.002]
H	]0.002, 0.14]
V_h	]0.14, 1]

- If N_a is V_h and N_b is H and N_c is V_S then SLAG,
- If N_a is V_S and N_b is V_h and N_c is H then SLBG,
- If N_a is H and N_b is V_S and N_c is V_h then SLCG,
- If N_a is V_S and N_b is V_h and N_c is M then DLAB,
- If N_a is V_S and N_b is H and N_c isV_h then DLBC,
- If N_a is V_h and N_b is V_S and N_c is S then DLAC,
- If N_a is V_S and N_b is V_h and N_c is A_V then DLABG,
- If N_a is V_S and N_b is S and N_c isV_h then DLBCG,
- If N_a is V_h and N_b is S and N_c is S then DLACG,
- If N_a is S and N_b is S and N_c is H then TLABC, and
- If N_a is S and N_b is S and N_c is V_h then TLABCG.

For the purpose of this experiment, to determine the location, the telegraphs equations in [17] were used as shown in equation (5), (6) and (7).

$$f(A_i, B_i) = \frac{1}{\gamma_i} \arctan(\frac{A_i}{B_i}), \tag{5}$$

with

$$A_i = VS\cosh(\gamma_i l_T) - Z_c I_s \sinh(\gamma_i l_T) - VR \tag{6}$$

and

$$B_i = I_R Z_c + VS\sinh(\gamma_i l_T) - Z_c I_s \cosh(\gamma_i l_T). \tag{7}$$

Where, VS is voltage sending, VR is voltage received, l_T is total length of the line, Z_c is line impedance, γ_i is constant of propagation, I_S is current sending and I_R is current received. The error distance in percentage is computed as follow:

$$l(\%) = \frac{f(A_i, B_i)}{l_T} \times 100. \tag{8}$$

70 % of the data set was used to train the algorithm and 30 % to test it. These percentages gave the best prediction accuracy both for the fault classification and the fault location.

4. Experimental results

Fig. 11 and Fig. 12 present the defuzzification area of the predicted output by the CNF technique for the PTL 1 and the PTL 2, respectively. In this case, the defuzzification output has been tested for each fault type at 120 km on the transmission line, with R_f = 10ω, and a fault angle of 45°.

Fig. 13 and Fig. 14 present the evaluation of the double line (DL) faults' error. The error has been calculated by

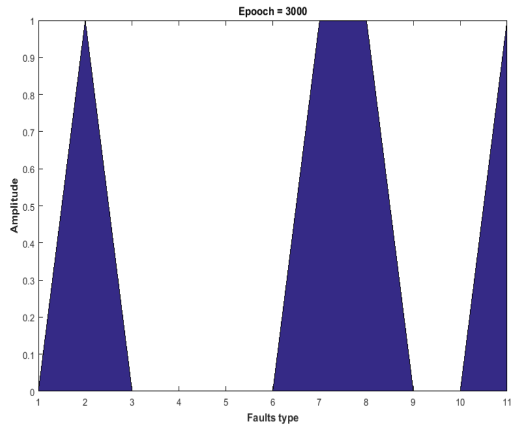

Figure 11. PTL 1: CNF defuzzification output.

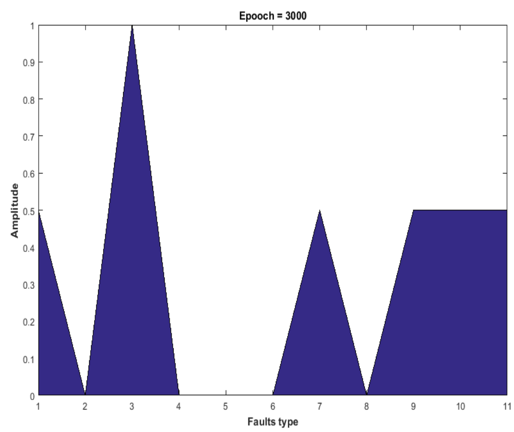

Figure 12. PTL 2 CNF defuzzification output.

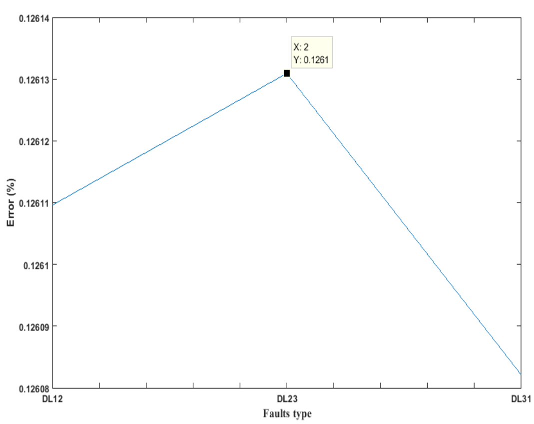

Figure 13. PTL 1: DL faults error at 120 km, R_f = 10Ω, fault angle = 45°.

doing the sum of data which do not satisfy FL conditions and dividing by the number of inputs' data.

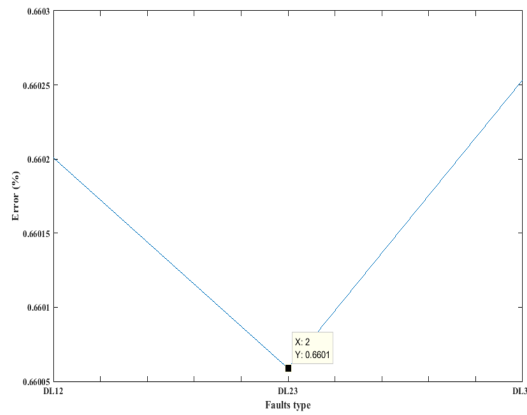

Figure 14. PTL 2: DL faults error at 120 km, R_f = 10Ω, fault angle = 45°.

The prediction accuracy for fault classification and location results are presented in Table 3 and in Table 4, respectively. For these experiments, the prediction accuracy have been considered as the main performance measurement.

It can be seen from Table 3 and Table 4 that CNF technique realised and attained the highest prediction accuracy for PTL model 1 and model 2 when the data increased. Thus, with 2200 data used for the simulation, we are able to have 2.53% prediction accuracy error for fault classification and 0.7693% prediction accuracy error for fault location on PTL model 1. However, in PTL model 2, with 2200 data used for the simulation, we have the prediction accuracy error for fault classification equal to 4.3577% and 2.2358% prediction accuracy error for fault location.

TABLE 3. FAULT CLASSIFICATION PREDICTION RESULTS.

Number of data utilized	**Error (%)**		**Accuracy (%)**	
	PTL model 1	**PTL model 2**	**PTL model 1**	**PTL model 2**
550	4.9002	16.4565	95.0998	83.5435
1100	3.3303	10.5731	96.6697	89.4269
2200	2.5308	4.3577	97.4692	95.6423

TABLE 4. FAULT LOCATION PREDICTION RESULTS.

Number of data utilized	**Error (%)**		**Accuracy (%)**	
	PTL model 1	**PTL model 2**	**PTL model 1**	**PTL model 2**
550	2.9447	8.5584	97.0553	91.4416
1100	1.4993	4.3575	98.5007	95.6425
2200	0.7693	2.2358	99.2307	96.7647

5. Conclusion

This paper presented the use of CNF technique for fault detection, fault classification and fault location. Two power transmission lines were implemented to compare the results obtained and 11 fault types were studied.

In the first PTL model (750 kV), the achievement of CNF accuracy for fault type detecting is 97.47%, 96.66%, 95.09% using 2200, 1100, 550, data set respectively and 99.2309%, 98.5%, 97.05% using 2200, 1100, 550, data set respectively for fault location.

In the second PTL model (400 kV), the achievement of CNF accuracy for fault type detection is 95.7%, 89.42%, 83.54% using 2200, 1100, 550, data set and respectively and 96.8%, 95.64%, 91.44% using 2200, 1100, 550, data set respectively for fault location.

According to these achievement results, it can be see that the CNF technique can be used to predict fault detection and fault location. Thus, for each experiment (fault detection or fault location), the PTL model 1 performed better whether in the prediction of fault classification or fault location. However, in several artificial intelligence techniques the more data you have the more accurate your system is. The increase in data in Table 3 and Table 4 demonstrates this well and give us better results. Then, to increase the accuracy and the sustainability of our technique, it is recommended to use a lot of data and to accurately define your fuzzy rules.

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