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5 authors, including:

Abderrzak Laib
Université de M'sila

M. Melit
University of Jijel

B. Nekhoul
University of Jijel

Khalil El Khamlichi Drissi
Université Clermont Auvergne, Clermont Ferrand, FRANCE

Soft Fault Identification in Electrical Network Using Time Domain Reflectometry and Neural Network

A. Laib[1(✉)], M. Melit[1], B. Nekhoul[1], K. El Khamlichi Drissi[2], and K. Kerroum[2]

[1] LAMEL Laboratory, University of Jijel, BP 98 Ouled Aissa, 18000 Jijel, Algeria
abderrzaklaib@yahoo.fr, melit@univ-jijel.dz
[2] Pascal Institute, Blaise Pascal University, Clermont-Ferrand, France

Abstract. Time Domain Reflectometry (TDR) is commonly used to detect and localize hard faults in electric network. Unfortunately, in the case of soft fault especially in the case of complex network (network with several branches) it remains very difficult to detect the affected branch. In order to resolve this problem, we propose a new approach based on the Time Domain Reflectometry combined with Neural Network method (NN); the response of the electric network is obtained by applying the Finite Difference Time Domain method (FDTD) on the transmission line equations and the inverse problem is solved using Neural Network, very acceptable results are obtained basing on our new strategy which is capable to: define the fault by given the correct value of both of resistance and position, define the state of electrical network online, detect and localize more than one soft fault.

Keywords: Soft fault · Inverse problem · Neural network
Time domain reflectometry

1 Introduction

The most widely used technique for wire fault location and identification is Time Domain Reflectometry (TDR) where a specific signal is injected into the wiring network at the injection point and the reflected signal is analyzed. This last signal contains information about wire impedance, wire length, loads and sources …etc. In practice, different kinds of reflectometry methods are developed such as Time-Frequency Domain Reflectometry (TFDR), Spectrum Time Domain Reflectometry (STDR) [1, 2] and Multicarrier TDR (MCTDR) [3]), However, these techniques can locate hard faults (open and short circuits) that generate big reflection but they are not always capable to locate the small anomalies such as frays or chafes, diverse works have demonstrated success in locating faults such as [4] where TDR is combined with wavelet and Neural Network in order to detect and locate hard faults and in [5, 6], use the baseline method, in this last the output signal of the faulty wiring is compared with the output of the healthy wiring in order to detect and locate soft faults. This baseline approach is a

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natural efficient find of soft fault, but it is not able to define the nature of faults by given the exact resistance values. Another way although known reflectometry is an efficient method to diagnose simple topologies, it remains limited in the case of complex multi branch networks., also it remains limited in the case of electrical network affected by two simultaneous soft faults where they are not able to detect and locate theme in alternative approach Genetic Algorithm (GA) [7], Particle Swarm Optimization (PSO) [8], is to use a direct model in iterative procedure, where each one from previously methods is applied to the inverse process after generated TDR response and compared with measured one, however the inconvenient of these methods is computationally expensive where they need very long time for diagnosis. For solving these two problem (soft fault detection and localization, diagnosis online) a new approach is proposed for solving these two problems at the same time, it based on the combination of the Time Domain Reflectometry (TDR) and Neural Network (NN), where the response of the transmission line is obtained using the Finite Difference Time Domain method (FDTD) applied to transmission line equations, and NN method is applied to solve the inverse problem for identifying the faults.

2 Wave Propagation Model

RLCG circuit model is used for modeling Multiconductor Transmission Line (MTL) where the differential equations are defined by:

$$\frac{\partial}{\partial_z}[v(z,t)] = -[R]\cdot[i(z,t)] - [L]\cdot\frac{\partial}{\partial_t}[i(z,t)] \tag{1}$$

$$\frac{\partial}{\partial_z}[i(z,t)] = -[G]\cdot[v(z,t)] - [C]\cdot\frac{\partial}{\partial_t}[v(z,t)] \tag{2}$$

[R], [L], [C] and [G]: are the per-unit-length parameters, respectively, the series resistance, the series inductance, the shunt capacitance and the shunt conductance [9]. z and t: are space and time variables respectively.

This model is actualized by writing Kirchhoff's laws and taking the limit as $\Delta z \to 0$. Finite Difference Time Domain (FDTD) method is used to determinate the time-domain solution of the MTL, this method samples the space variable (line axis) in Δz increments also the time variable t is discretized in Δt increments, the finite differences is used to approximate the derivatives in MTL equations. The length of the spatial cell size Δz and the sampling interval Δt are chosen by insurance of the stability condition $\Delta t = \Delta z / v$.

v: is the wave propagation speed or velocity of propagation trough the transmission lines.

The currents and voltages are calculated by solving the matrix Eq. (3) [10].

$$f([x]) = [A][X] - [B] = [0] \tag{3}$$

The vector [X] includes the unknown currents and voltages at all nodes in the network and each line multiconductors. The [A] matrix is composed in two sub-matrices [A1] and [A2] where: [A1]: sub-matrix derived from terminal conditions for all tubes (coupled transmission line); [A2]: sub-matrix derived from the Kirchhoff's laws (KCL and KVL) for the junctions (extremities and interconnections networks). [B] Is the excitation vector. Once matrix [A] and vector [B] are determined the solution of matrix Eq. (3) at every time step Δt yields the currents and voltages in every node of the network.

3 Proposed Approach

3.1 Neural Network

In general, Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) use a direct model in iterative procedure, where the parameters of theoretical model are fitted by adjusting the difference between the simulated response and the measured one using the iterative procedure. However the numerical solution is computationally expensive, furthermore, the diagnosis process will be more complicated. For solving this problem, the neural networks [11, 12] are good candidates, where it can be adjusted offline with a database includes information about the wiring network topology in order to use it online if required, also they can approximate a wide range provided which are previously trained. The topologies of used neural network is Multi-Layer Perceptron MLP, the retained structure containing input layer, one or more hidden layer and output layer. Each layer is composed of nodes and in the totally connected network considered, here each node connects to every node in subsequent layers (Fig. 1). The hidden unit nodes have the hyperbolic tangent activation functions and the outputs have linear activation. The Levenberg–Marquardt algorithm is used to adjust the variables of the NN.

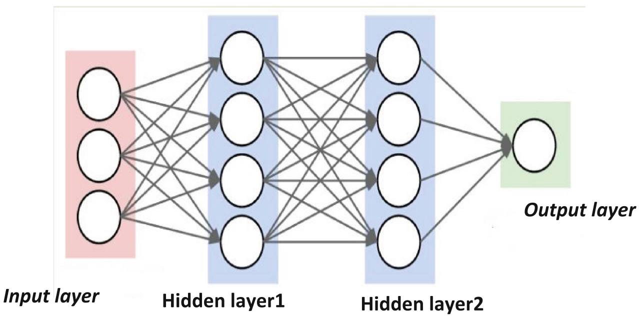

Fig. 1. Multi-layer perceptron neural network

3.2 Hybrid TDR-NN

At first, the signal of voltage difference between the response of healthy and the response of faulty network is used from the input of electrical network. Two groups of candidate features are extracted based on TDR difference signals. The max voltage amplitude in the signal of difference is selected with it corresponding time appearance, here the first group of candidate is the time appearance (t) of the magnitude max which is used to localize the fault and the second group of candidate is the max voltage magnitude which is used to define the nature of faults by given the exact resistance value. The inverse problem is used by applying the NN to detect and localize faults in electrical network. Multi-Layer Perceptron (MLP) NNs are used. The structure of MLP composed of two layers NNs with hyperbolic tangent activation functions in the hidden layer and of a single neuron having a linear activation function in the output layer. The datasets desired to train the NN were formed based on TDR method described above. The datasets are constituted of examples linking the time appearance (t) to the position of the fault, and the max voltage amplitude to it corresponding fault resistance Fig. 2, the training domain is as follow: the examples of the training dataset deduced to the NN, the output of the NN is compared to the one contained in the dataset. The error at the output obtained is reduced by Levenberg–Marquardt algorithm where is used to adjust the variables of the NN. The generalization capability of the NN is examined by calculating the Mean Square Error (MSE) obtained on the test set which contains input/output data not contained in the previous set.

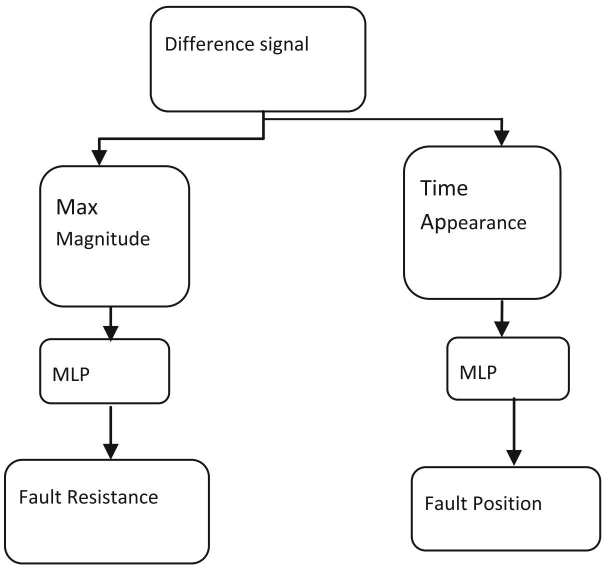

Fig. 2. Diagram of the proposed algorithm

4 Results and Discussion

4.1 Validation

In order to validate our MTL model, the configuration illustrated in Fig. 3b has been considered, this network consists of electric cable with cross section shown in Fig. 3a, this cable is largely used in embarked equipments (train, car, ship, aircraft …etc.), where r = 0.5e–3 m, and D = 2.06e–3 m. The distributed parameters L, and C, R, G can be calculated based on formulation proposed in [13]. The comparison between our numerical results and real measurements published by [7] is carried for a complex network; this last includes six open branches of L1 = 1 m, and L2 = 0.60 m, L3 = 2.25 m, and L4 = 4.25 m, L5 = 1.75 m, and L6 = 1 m.

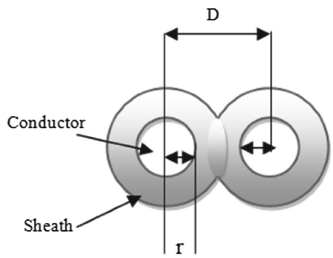

Fig. 3a. Cross-section of the used cable.

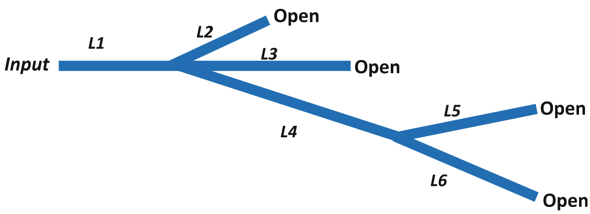

Fig. 3b. Configuration of network under study.

The source signal is a raised cosine pulse [14].

$$e(t) = \begin{cases} 0.5(1 - \cos(2\pi F t)) & 0 < t < \frac{1}{F} \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

Where F is the pulse frequency.

It is shown that our simulation results based on resolving the transmission line equations by FDTD (Fig. 3c) are practically the same to the published one in [7] (Fig. 3d). This fact confirms the validation of our proposed approach and permit to use our model to make a detailed investigation.

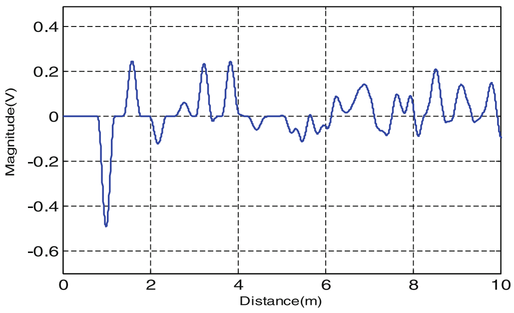

Fig. 3c. Network reflectometry response, our calculated result.

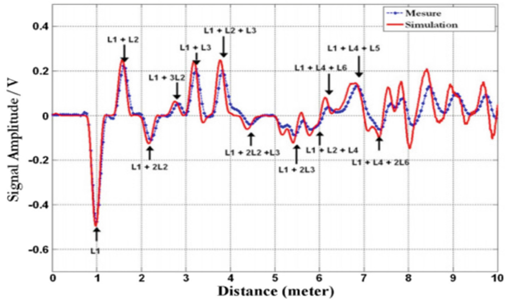

Fig. 3d. Network reflectometry response, published results by [7].

4.2 Parametric Study

In this part, we consider the network configuration represented in Fig. 3b. In the first case, a soft fault (local change on the characteristic impedance) in branch L2 at LF1 = 1.4 m from the input is considered (Fig. 4a). We notice that, the soft fault is represented by a localized change of characteristic impedance ΔL (ΔL = 2 cm) in the two cases. We consider different values of the fault impedance (Zc + ΔZc), each one is corresponding to ΔZc, different as illustrated in Fig. 4b.

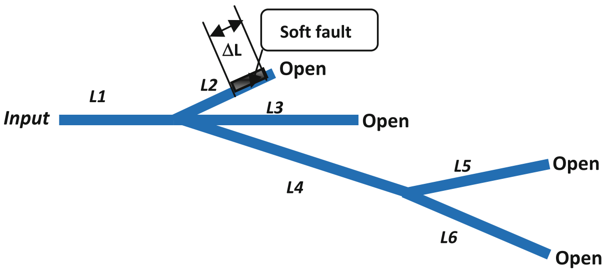

Fig. 4a. Configuration under study with soft fault at L2.

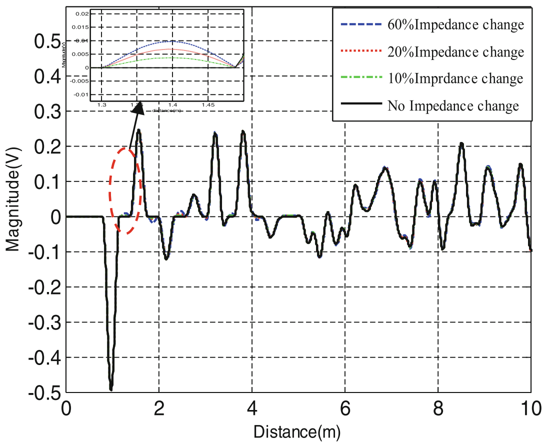

Fig. 4b. Network reflectometry response (input).

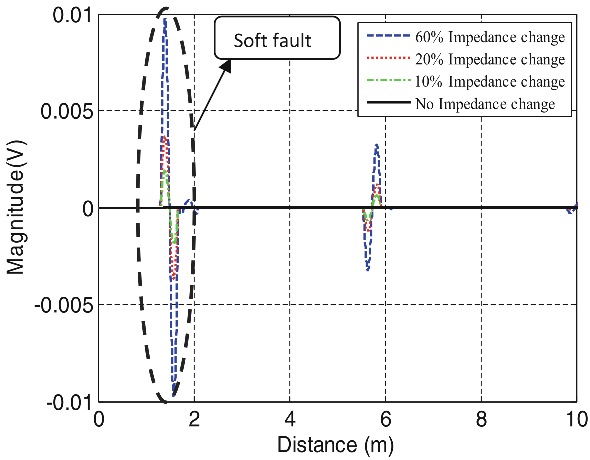

Fig. 4c. Difference signal between healthy and faulty network (input)

The second one involves networks affected by soft fault in branch L5 at LF2 = 6.25 m from the input (Fig. 5a).

Figures 4b and 5b shows the reflectometry response in case of one soft fault situated at two different positions (F_{L2} = 1.4 m at L2 (Fig. 4a) and F_{L5} = 6.25 m at L5 (Fig. 5a)), it is clear that in the two cases, the reflectometry signals of the soft fault (Figs. 4c and 5c) generates some small variation in the reflectometry response, based on these two figures it's not possible to deduce anything about the fault position or anything else. However, if we make a difference between the response of healthy and faulty networks as in Figs. 4c and 5c, we remark some reflections of the signal in the vicinity of the fault position which are proportional to the fault resistance.

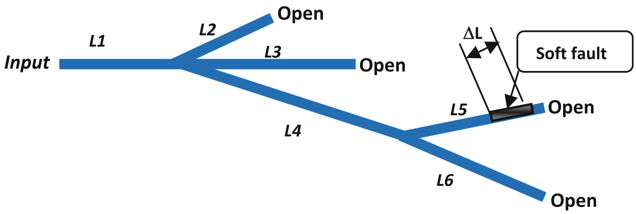

Fig. 5a. Configuration under study with soft fault at L5.

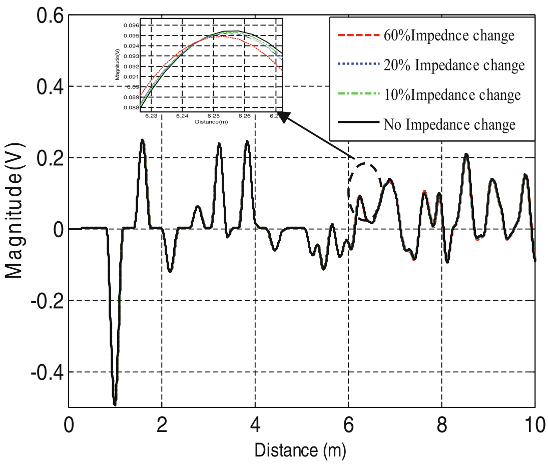

Fig. 5b. Network reflectometry response (input)

b. Network reflectometry response (input)

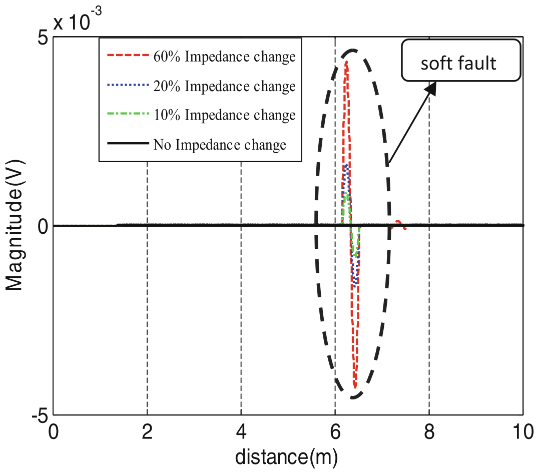

Fig. 5c. Difference signal between healthy and faulty network.

4.3 Case of Network Affected by Two Simultaneous Soft Faults

The case of electrical network affected by two soft faults has been considered; the two faults affect the branches called L2 and L5 respectively with 10% of impedance change at L2 and 60% impedance change at L5. Figure 6 shows the difference signal between healthy and faulty network in case of two simultaneous soft faults. It is shown that the location of the soft faults is clear but it is impossible to define the two soft faults by their resistances.

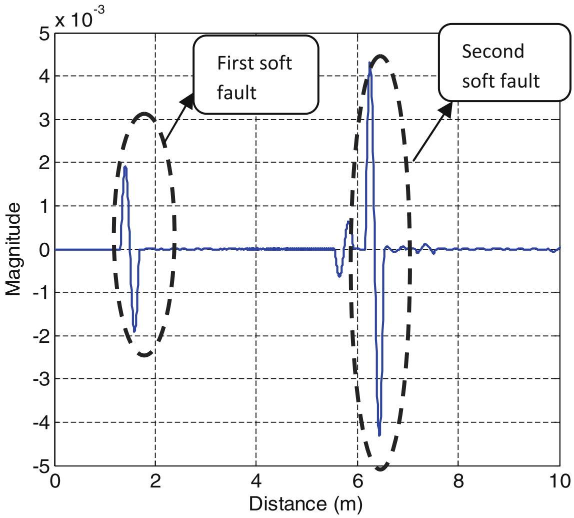

Fig. 6. Difference signal between healthy and faulty network in case of two simultaneous soft faults.

4.4 Inverse Problem

In order to give complete information about the soft faults by defining their resistances, a new proposed strategy has been considered basing of the inverse problem (Fig. 7); where the inverse problem is applied by using four (04) NNs for the two cases. We use the first NNp for the fault localizing in electrical network, the last three NNr are used for the estimation of the faults resistance; where the first NNr1 is used to characterize the faults situated before junctionJ1, the second NNr2 is used to characterize the faults situated between junction J1 and junction J2 and the third NNr3 is used to characterize the faults situated after junction J2 (Fig. 7). This distributed of NNr (NNr1, NNr2, NNr3) has been chosen because of the junction which divided the signal voltage between them; this separation is proposed in order to increase the efficiency of our analysis. The NNp contains two hidden layers (33,25) neurons with hyperbolic tangent activation functions and the output layer constituted of a single neuron having a linear activation function, and NNr contains one hidden layer of (25) neurons with hyperbolic tangent activation functions and the output layer constituted of a single neuron having a linear activation function. The datasets are constituted of examples linking the time appearance (t) to the position of the fault, and the max voltage amplitude to it corresponding fault resistance. The number of examples input/output database is 1580 examples for each NNr and about 1397 examples for NNp each dataset is randomly divided into two different sets: training set (80% of all samples) and testing set (20% of all samples).

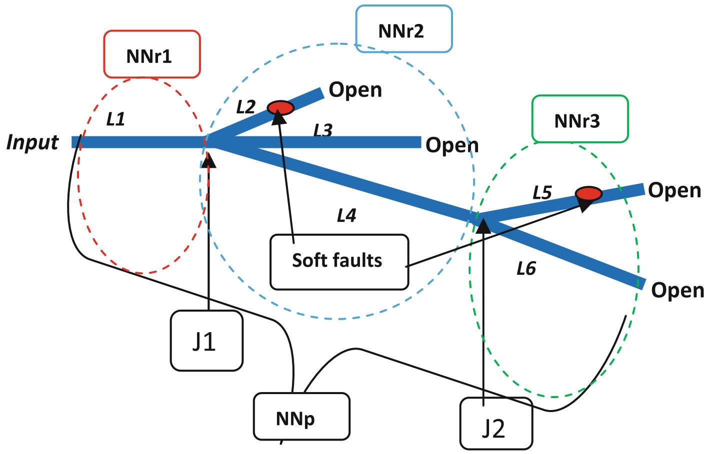

Fig. 7. Illustration of the distributed NN

Table 1. Our calculated results obtained using TDR-NN and published one based on Genetic Algorithm (GA).

	ΔZ = 10% ΔZ+Zc =86.49 Ω	ΔZ = 20 % ΔZ + Zc = 94.34Ω	ΔZ = 60 % ΔZ + Zc = 125.8Ω
soft fault at 1.4 m	86.49	94.34946 Ω	125.7996 Ω
	1.40027m	1.40027m	1.40027m
soft fault at 6.25 m	86.49Ω	94.34Ω	125.8Ω
	6.25034m	6.25034m	6.25034m

(A). CASE OF ELECTRICAL NETWORK AFFECTED BY SOFT FAULT IN BRANCH L2 AND L5

	ΔZ = 10 % ΔZ+Zc = 86.49 Ω	ΔZ = 20 % ΔZ+Zc = 94.34 Ω	ΔZ = 60 % ΔZ + Zc = 125.8 Ω
GA [7]	85.52 Ω	96.13 Ω	124.25 Ω
	5.96 m	6.03 m	5.91 m
NN	86.49Ω	94.34Ω	125.8Ω
	6.25034m	6.25034m	6.25034m

These results presented in Table 1a and b confirms the efficiency of our proposed approach in the identification of soft fault. It is shown that GA occurs some errors both on the localization and the identification (fault impedance) which prove that GA technique is not sufficient to detect and characterize the fault, For this raison, we have used the NN method to solve this problem; we see that the soft fault impedance has been accurately determined, either the soft fault is localized with exact precision (Table 1), we note that the error of soft fault identification $\Delta R = 6.37 * 10^{-5}\ \Omega$.

Table 2 Confirm the efficiency of our proposed approach in computational time diagnosis. The inversion carried out with NN is very fast (less than 1 s with $1.763 * 10^{-4}$ m for fault localization and $\Delta R = 6.37 * 10^{-5}\ \Omega$ for fault identification) and can be achieved "online." On the contrary, an iterative method (Genetic Algorithm; GA), requires 94.60 mn with an error $5.75 * 10^{-4}$ m and 26.36 mn with error $4.75 * 10^{-4}$ m in the case of Particle Swarm Optimization (PSO) to find the state of configuration includes five branches wiring network with hard fault which is generally easy to detect.

Table 2. Comparison of computational time diagnosis obtained with published results and the new approach based on neural network

	Error (m)	Computational time
Genetic Algorithm (GA) Published results by [7]	$5.75 * 10^{-4}$	94.60 mn
Particle Swarm Optimization (PSO) published results by [7]	$4.75 * 10^{-4}$	26.36 mn
Proposed approach based on Neural Network (NN)	$1.763 * 10^{-4}$	Less 1 s

5 Conclusion

In this paper, a new method is proposed for soft fault identification in complex electrical network. It is based on the TDR and NN. The electric wiring network is modeled using transmission line approach and the transmission line equations are resolved using the well-known FDTD method, the obtained results are validated by comparison with published ones [7], very acceptable results are obtained. It is showed in [7] that reflectometry and GA techniques occurs some errors in the faults characterization. To resolve this problem, the NN is proposed in order to reduce the error and ameliorate the identification of the faults and define the state of network online, our proposed approach has been compared with published results in [8]. Our simulation results prove the efficiency of the proposed strategy to detect and locate and define the soft fault in the case of complex electrical network.

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