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A New Hybrid Approach using Time-Domain Reflectometry Combined with Wavelet and Neural Network for Fault Identification in Wiring Network

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Abstract ***____****The modern power electric network is subject to insure more and more complicated functions; the main functions are transfer of energy and information. The faults in wiring cables constitute one of worst problems of power electric network. In practice, the combination of Time Domain Reflectometry (TDR) and wavelet transform is generally used to detect and localize the faults in electric network. Classically, the identification process based on the decomposition of fault signal on details and approximations using Discrete Wavelet Transform (DWT) build some errors both at fault position and in fault nature. For solving this problem a new and improved method which combines the time domain reflectometry, wavelet transform and neural network is proposed in this paper. First, the response of the transmission line is obtained using the Finite Difference Time Domain method (FDTD) applied to transmission line equations, then, the obtained results are analyzed with DWT. Finally, Neural Network method (NN) is applied to solve the inverse problem for reducing the error of fault location affecting the branches of electric network.*

Keywords: *fault, reflectometry, wavelet, neural network, transmission line.*

I. Introduction

Electric wire networks constitute the main artery in most modern systems, such as transportation systems, industrial machinery, buildings, power distribution systems, etc., where the transfer of energy and information is necessary to guarantee the performance of a system. Several cables types are used in practice; however their implantation is different according to the nature of the transmitted signal, to the voltage level or the environment conditions in which the system evolves. Energy networks use cables whose constitution is different from those used for data because these cables are designed to distribute energy on very long distances throughout a country or a continent.

The development of power electric network make that some conductors are responsible for security functions, the necessity of monitoring the wire diagnosis is important to detect and locate electric faults. These anomalies can be the origin of simple dysfunctions and/or imply serious consequences for the system or the environment.

Time domain reflectometry is generally used to detect and localize the defect in transmission line. While hard faults like open and short circuit conditions cause long reflection. Soft ones are caused by simple deformation in the wire or local modification of the electrical parameters [1]. Wavelet transform is applied to the time domain results in order to identify the position and the type of the damage [2].The approximations and details may be extracted using a discrete sampling or successive filtering technique. A DWT at level 1 yields wavelet coefficients at a scale of 2^1or a time windows of 2, a DWT at level 2 yields wavelet coefficients at a scale of 2^2 or a time window of 4, and so on; if we continue to filter and down sample each successive approximation coefficient, we increase the scale by a factor of 2 at each level of analysis. Thus, the DWT coefficients are function of the scale and position of the fundamental analyzing wavelet. Wider time windows yield better large scale and low frequency information; narrower time windows yield better small scale and high frequency information [3].

Because DWT coefficients are functions of the scale and position of the fundamental wavelet, they generate some errors in the localization and the type of fault.

In this paper, we use the single-ended voltage to extract efficient features for fault locating in transmission lines. In this regard, a combination of the Time Domain Reflectometry (TDR) and DWT are used to extract features out of one cycle of voltage signal after fault inception. Then, the NN method is used to reconstruct the network geometry.

The main advantage of our proposed approach is the fact that is based on the reflectometry signal measured at only one location of the wiring network; the fault can be located with very high precision.

II. Wave Propagation Model

The propagation in a Multiconductor Transmission Line (MTL) can be modeled by a RLCG circuit model [4], Writing Kirchhoff's law, and taking the limit as $\Delta z \rightarrow 0$ leads to the following differential equations maintaining the integrity of the specifications

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$$\frac{\partial}{\partial z}v(z,t) = -R.i(z,t) - L.\frac{\partial}{\partial t}i(z,t) \quad (1)$$

$$\frac{\partial}{\partial z}i(z,t) = -G.v(z,t) - C.\frac{\partial}{\partial t}v(z,t) \quad (2)$$

Where 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 [4].

The time-domain analysis of the MTL equations is determined by the Finite Difference Time-Domain (FDTD) method [4]. In this method the space variable (line axis) is discretized in Δz increments, the time variable t is discretized in Δt increments and the derivatives in MTL equations are approximated by finite differences. The length of the spatial cell size Δz and sampling interval Δt is chosen by insurance of the stability on the time stepping algorithm $\Delta t = \Delta z/v$, with v is the velocity of the propagation in the wire.

For calculating the currents and voltages distribution, we solve a matrix equation f([X]) = [0]. The matrix equation can be expressed as follow:

$$f([x]) = [A][X] - [B] = [0] \quad (3)$$

In this section, we use a formalism based on the discretization of the transmission lines equations by the FDTD method [4]. This first step allows us to define the [A] matrix composed of two sub-matrices [A1] and [A2] as:

[A]: matrix of topological representation of the circuit; [A1]: sub-matrix deduced from the representation of the propagation tubes (coupled transmission line); [A2]: sub-matrix deduced from the Kirchhoff's laws (KCL and KVL) for the junctions (extremities and interconnections networks); The resolution of the matrix equation (3) at every time step Δt gives the currents and voltages in every node of the network [5].

III. Wavelet Theory

The advantage of the wavelet transform is that the band of analysis can be adjusted to allow high-frequency and low-frequency components to be precisely detected. Wavelet analysis lets us capture these two different aspects of a signal as approximation coefficients and detail coefficients [6]-[7].

The approximations and details may be extracted using a discrete sampling or successive filtering technique; to extract the approximations and details as independent signals, we can pass the original signal through a pair of complementary low-pass and high-pass filters to get two signals [6].

The decomposition tree is shown in figure 1. The DWT maps the one dimensional time domain signal F (t) into two dimensional signals as:

$$F(t) = \sum_k c_j(k)\,\emptyset(t-k) + \sum_k \sum_j d_j(k)\varphi(2-jt-k) \quad (4)$$

Where cj(k) and dj(k) are approximate and detail coefficient respectively; Ø (t) and φ(t) are scaling and wavelet functions respectively and j is the decomposition level.

The choice of mother wavelet is very important in detecting and localizing different types of transients fault. The daubechies (dB) mother wavelet is the commonly used and suitable for protection applications [8, 9]. In this paper db4 wavelet is used which decomposes the signal effectively.

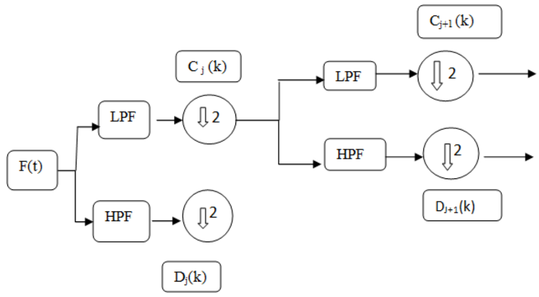

Fig. 1. Illustration of tree decomposition.

IV. Proposed Approach

A. Hybrid TDR-DWT (WTDR)

In practice, the TDR signal can't gives complete information about the fault location and nature, for this reason, we usually needs to use more and more efficient and intelligent mathematical algorithms. Several works [2, 10] use different algorithms based on wavelet, genetic algorithms, etc..., every one of these works has a limited degree of precision. In this paper, we propose a new and accurate algorithm which is based on the combination of TDR, DWT and neural network (NN).

At first, the input voltage signal of the difference between the response of healthy network and the response of faulty network is deduced from the FDTD method applied to MTL equations by solving the matrix equation (3), the resulting signal is decomposed on approximation coefficients $c_i(k)$ and detail coefficients $d_i(k)$ using DWT. The approximations correspond to the low frequency components of the signal; the details characterize the high frequency components.

The energy E of each detail can be calculated based on the coefficients s_i derived from the DWT [11]:

$$E = \sum s_i^2 \quad (5)$$

Then the detail of higher energy is selected and the time appearance of the max coefficient in the case of Open Circuit (OC) or min coefficient in the case of Court Circuit (CC) is calculated which permit to calculate the fault location in the detail higher energy.

B. WTDR-NN

The Neural Network is applied to solve the inverse problem [12]-[13] and reduce error between real fault position and its time appearance in the detail coefficients higher energy.

Multi-Layer Perceptron (MLP) NNs are used. The structure of NNs consists two layers with hyperbolic tangent activation functions in the hidden layer and the output layer constituted of a single neuron having a linear activation function. The datasets desired to train the NN were generated based on WTDR method described above. The datasets are constituted of examples linking the WTDR result (time appearance t of coefficient max or min (s)) to the position of the fault.

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In our work, the parameters are the lengths of the branches Li, the number of the output neurons corresponds to the number of estimated quantities Li, the training domain is describes as follow: the estimated parameters (Li) is regularly discretized, between 0 to L. First, the examples of the training dataset are presented to the NN. After a first training iteration, the output of the NN is compared to the one contained in the dataset. For reducing the error obtained at the output, Levenberg–Marquard algorithm is used to adjust the variables of the NN. Finally, the generalization capability of the NN is assessed by calculating the Mean Square Error (MSE) obtained on the test set which contains input/output data not included in the previous set.

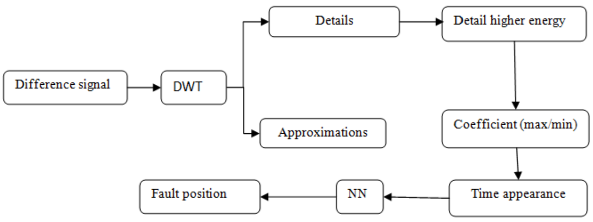


Fig. 2. Diagram of proposed algorithm.

V. Results And Discussion

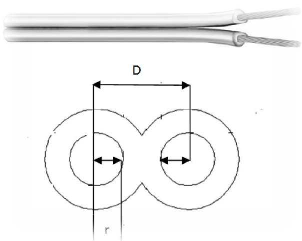
A. *Validation*

In order to validate our model, the geometric configuration of used network and the cable cross section shown in Fig 3.a has been considered been where r = $0.5e^{-3}$ m, and is D = $2.06e^{-3}$ m. The distributed parameters L, C, R and G can be calculated using formulation done in [15].The FDTD method is used to simulate TDR responses for the configuration shown in figure 3.b. At first, comparison between our numerical results and real measurements published by [10] is performed for a complex network (fig. 3.b). The network includes six branches. L1 = 1 m, L2 = 0.60 m, L3 = 2.25 m, L4 = 4.25 m, L5 = 1.75 m, and L6 = 1 m.

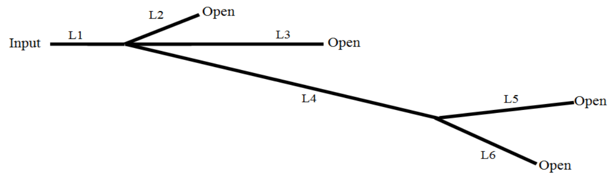
A raised cosine pulse was used as a source signal [15].

$$e(t) = \begin{cases} 0.5(1-\cos(2\pi F t)) & 0 < t < \frac{1}{F} \\ 0 & otherwise \end{cases} \quad (6)$$

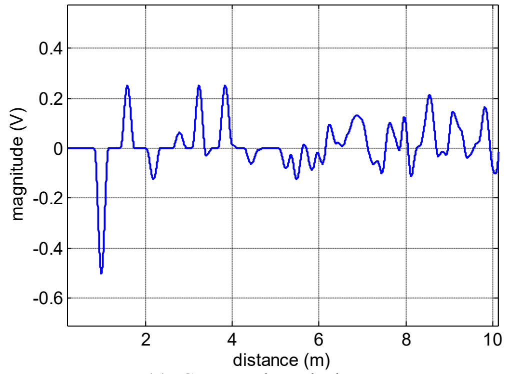
Where F is the pulse frequency.



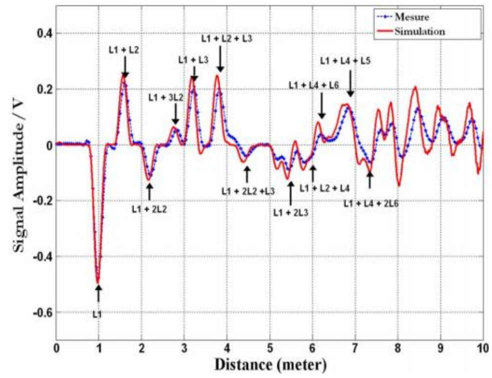
(a).Cross-section of the used cable



(b). Configuration of network under study
Fig.3. Network under study



(a). Computed results by FDTD.



(b). Published results by [11].
Fig.4. Network reflectometry response.

This validation shows that our simulation results based on resolving transmission line equations by FDTD are very close to the measured result in [10] even better then simulation ones in [10]. This fact comforts our proposed approach and allows us to use our proposed model to make a detailed investigation.

B. *Parametric study*

After validation our MTL model, we interest to hard faults (Open Circuit OC) affecting two networks configurations:

1) *Case of Y-network*

In this case the faulty Y-network fig. 5, made of a single junction J and of three lossless branches L1 = 500 m, and L3 = 200 m, L2 = 300 m. The hard fault is created at unknown length (LX) on L2 branch. The network configuration is indicated in figure 5. A Gaussian pulse with equation $V(t) = e^{-\alpha(t-\beta*dt)^2}$ where $\alpha=(4/(\beta*dt))^2$ and $\beta=5$ was injected. Our purpose is to detect the fault position (LX) using our proposed approach.

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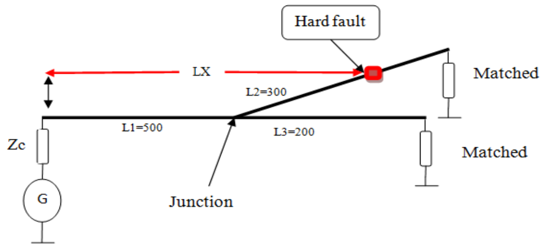
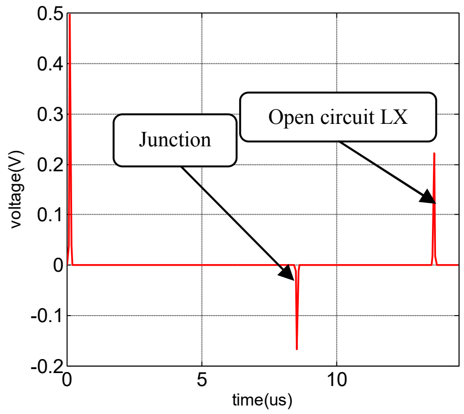
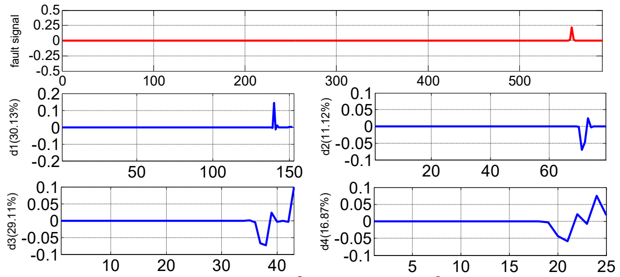


(a). Matched Network

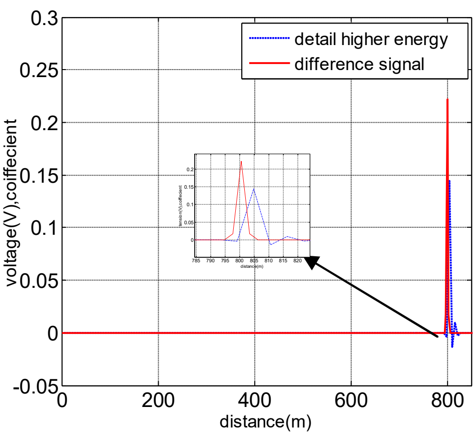


(b). Network reflectometry

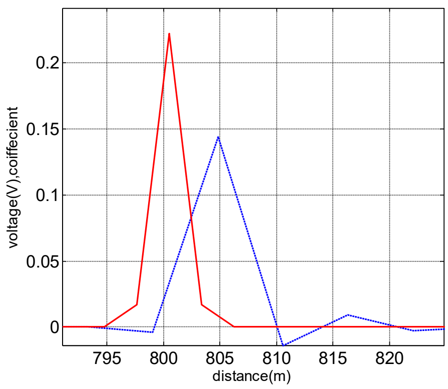


(tmax=1.45*10^{-5} s, dt =4.88*10^{-8} s)

(c). Decomposition of difference signal with DWT (first four details of higher energy (d1=30.13%, d2=11.12%, d3=29.11%, d4=16.87%)



(d) .Error between the detail higher energy and the voltage difference signal.



(e). Error between the detail higher energy and the voltage difference signal (zoom)

Fig.5. Reflectomertry response analysis (Y network)

The undertaken inversion procedure considers three NNs each NNs contains 33 neurons in the hidden layer, and for the second configuration each NNs contains two hidden layers (25, 20) neurons with hyperbolic tangent activation functions and the output layer constituted of a single neuron having a linear activation function, the input of every NNs is the results of WTDR (time appearance (t) of coefficient max(s)) and the output data set is the estimate quantities of line (Li), The number of examples input/output database is 507 examples for first (Y-network) configuration for each NN and about 525 examples for second configuration (five lossless branches) for each NN. Each dataset is randomly divided into two different sets: training set (80% of all samples) and testing set (20% of all samples).

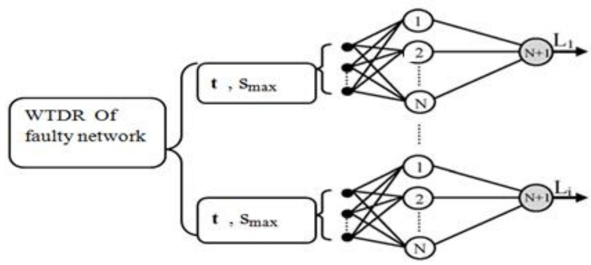


Fig. 6. Flowchart of the inversion procedure

TABLE I. Comparison Of The Fault Localization Obtained With Standard WTDR And Our New Proposed Approach Based On Neural Network (Y-Network).

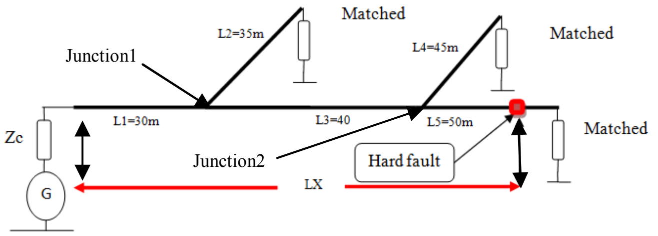
Exact length (m)	WTDR_RN (m)	WTDR (m)	erre WTDR_RN (m)	erre WTDR (m)
LX1 = 791.46	791.46	790.46	$0.14*10^{-4}$	0.99
LX2 = 671.68	671.68	670.889	$0.36*10^{-4}$	0.8
LX3 = 578.47	578.47	577.82	$0.19*10^{-4}$	0.64

Fig. 5, 6 and table I confirm the efficiency of our proposed approach in the identification of hard fault. It is shown that WTDR technique is sufficient to detect the fault, in the other side; it's not capable to locate (length of faulty branch) the fault with exact precision. For this raison, we have used the neural network method to solve this problem; we see that the length of faulty branch (LX) is accurately determinate. In order to confirm our proposed approach we have chosen tree arbitrary positions of the fault (LX1, LX2 and LX3) done in table 1.

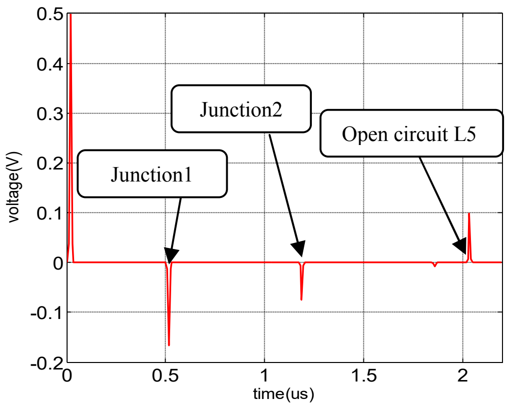
The inversion carried out with this method is very fast (less than 1seconde with an error less than $1.5*10^{-5}$) and can be achieved "online". However, an iterative method (Genetic Algorithm; GA), requires 9.57 min with an error $9.54*10^{-4}$ and 2.41 min with error $9.54*10^{-4}$, in the case of Particle Swarm Optimization (PSO) to find the state of same configuration wiring network (Y-network) [16].

2) Case of complex network

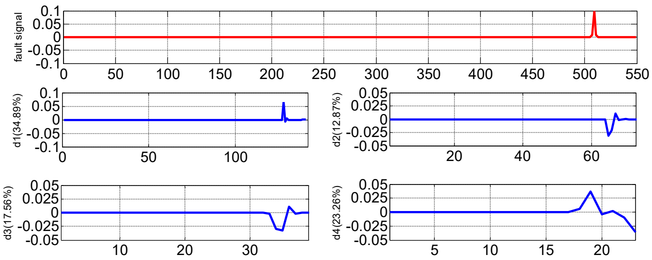
This second configuration includes five lossless branches and two junctions J1, J2 (fig.7.a)The fault position (LX) is unknown.



(a). Matched Network

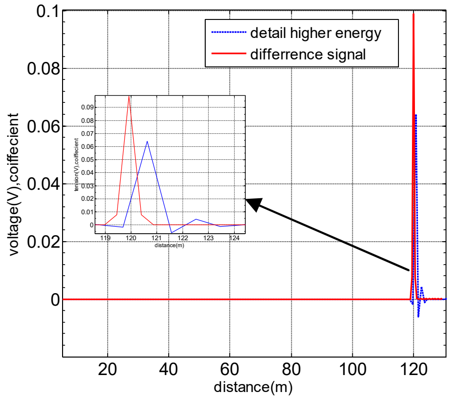


(b).Network reflectometry response (open circuit)

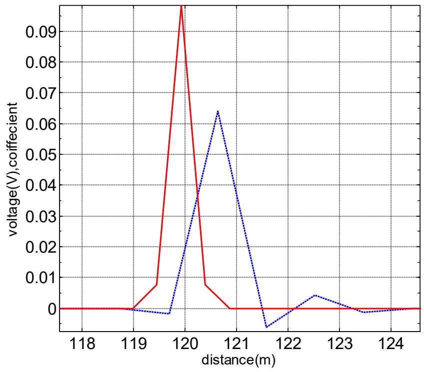


(tmax=$0.22*10^{-5}$ s, dt =$0.8*10^{-8}$ s)

(c). Decomposition of difference signal with DWT (first four details of higher energy (d1=34.89% d2=12.87%, d3=17.56%, d4=23.26%))



(d) .Error between the detail higher energy and the voltage difference signal.



(e). Error between the detail higher energy and the voltage difference signal (zoom)

Fig. 7. Reflectomertry response analysis (YY network)

The inversion procedure considers five NNs according to the number of branches, all details about NNs as same in case of Y network.

TABLE II. COMPARISON OF THE FAULT LOCALIZATION OBTAINED WITH STANDARD WTDR AND THE NEW APPROACH BASED ON NEURAL NETWORK (FIVE BRANCHES WITH OC FAULT).

Exact length (m)	WTDR_RN (m)	WTDR (m)	Erre WTDR_RN (m)	Erre WTDR (m)
LX1 = 93.95 m	93.95	94.05	$0.4*10^{-5}$	0.1
LX2 = 105.16 m	105.16	105.26	$0.8*10^{-5}$	0.1
LX3 = 70.77 m	70.77	70.87	$0.2*10^{-4}$	0.1

Fig 7 and table II confirm the efficiency of our proposed approach in the identification of hard fault in the case of five lossless branches. It is shown that WTDR technique is sufficient to detect the fault, in the other side, it's not capable to locate (length of faulty branch) the fault with exact precision. For this raison, we have used the neural network method to solve this problem; we see that the length of faulty branch LX is accurately determinate for the tree arbitrary lengths (table 2). The inversion carried out with this method is very fast (less than 1second with an error less than $1.5*10^{-5}$) and can be achieved "online". However, an iterative method (Genetic Algorithm; GA), requires 94.60 min with an error $5.75*10^{-4}$

and 26.36 min with error $4.75*10^{-4}$ in the case of Particle Swarm Optimization (PSO) to find the state of the same configuration wiring network [16].

VI. CONCLUSION

In this paper, a new method is proposed for fault localization in transmission line. It is based on the TDR method wavelet and NNs. The electric wiring network is modeled using transmission line approach and the transmission line equations are resolved using FDTD method, the obtained results are validated by comparison with published ones in [10], very acceptable results are obtained.

It is shown that reflectometry and wavelet technique occur some errors in the localization of faults. To resolve this problem, the NNs is proposed in order to reduces the error and ameliorates the localization of the faults, this technique allows the reconstruction of the wiring network by finding the lengths of the faulted branches with very acceptable precision and define the state of network online.

In perspectives works, we wish to extend this approach to treat soft faults.

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