Detection and Location of Defects in Wiring Networks using Time Domain Reflectometry and Neural Networks

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This paper presents a new technique to reconstruct faulty wiring networks and/or to localize the defects affecting the branches of the wiring network from the time domain reflectometry response. The method is also for characterization of defects in branches on the network. The direct model for wave propagation along the transmission lines is modelled by RLCG circuit parameters computed by finite elements method (FEM) or analytical solution and the Finite Difference Time Domain (FDTD) method. Neural Networks (NNs) are used to solve the inverse problem. A set of experimental results is carried out in order to validate the calculations.

***Index Terms*—Time domain reflectometry, Finite Difference Time Domain (FDTD) method, neural networks, network fault diagnosis, multiconductor transmission lines (MTL).**

I. Introduction

In thirty years, the length of cables on board of cars has increased more than tenfold, from about 200 to 4000 meters.

As wires in all transportation mean are aging, they are exposed to different types of problems. In this area, reliability becomes a safety issue [1].

Wiring networks can be affected with two types of faults: “soft ones” are created by the discontinuities of the impedance in the wire due to different kinds of defects (insulation, radial crack, and degradation of connector [2]…). “Hard faults” are open and short circuits. For the first type of faults, the time-domain response of the faulty wiring presents reflections depending on the fault impedance in the place of the defects. In the case of hard faults the structure of the network as well as the response changes. According to the application domain, the defects of cables may have catastrophic consequence [1] and there is now a crucial challenge to design smart embedded diagnosis systems able to detect defects in real time.

A number of methods have been developed to locate and characterize the faults on the wires [1]. The most widely used technique for testing wires is reflectometry [1]. It is based on the same principle as the radar. A high frequency electrical signal is sent down the wire, where it reflects from any impedance discontinuity. The difference (time delay or phase shift) between the incident and reflected signal is used to locate the fault on the wire.

Interpreting the results obtained with reflectometry instrument for a wiring network requires great expertise, as the reflectometry response can be very complex. However the reflectometry response itself is not self-sufficient to identify and locate the defects in the wire. There is the need to solve efficiently the inverse problem which consists to deduce some knowledge about the defects from the response at the input of the line.

Several methods have been proposed to locate and characterize faults on wiring networks. In a baseline approach, the response of the faulty network is compared with either the pre-measured or simulated response of its (known) healthy configuration. With this method it is extremely difficult to detect and locate defects in faulty wiring networks affected by two or more faults. Only the first fault near to the test point can be detected. Also the location of the fault on the branches cannot be identified. In Bayesian approaches, the essential idea is to assign a quantifiable measure of certainty of belief to all possible variables (permittivity, impedance, location of the faults) [3]. In [4] Time domain signal restoration and parameter reconstruction of a simple nonuniform RLCG transmission line is performed using the wave-splitting technique and the compact Green functions technique. These two last methods allow to find faults in simple electrical wirings only.

An alternative approach is to use a direct model in an iterative procedure and to minimize the difference between the simulated response and the measured one [5]. However such numerical solutions are computationally expensive and are not compatible to real time diagnosis. For embedded systems an adequate solution is then to build a behavioral model adjusted “off-line” with a database according to the information’s about the wiring network topology and to use it “on-line”, if required, for solving the inverse problem. The neural networks (NNs) are good candidates since they are universal and parsimonious approximators and they can approximate a wide range of functions provided that they are previously trained [6]. The novelty of the approach presented here is to rely on numerical modeling of the wiring network (direct problem) and the use of neural network in order to determine the fault parameters from the measurements of the reflectometry response.

II. Wave Propagation Model

The propagation in a multiconductor transmission line MTL (including *n* conductors) can be modelled by a RLCG circuit model [7], as shown in figure 1;

Writing Kirchhoff’s law, and taking the limit as $\Delta z \rightarrow 0$ leads to the following differential equations:

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$$\frac{\partial}{\partial z}[V(z,t)] = -[R].[I(z,t)] - [L].\frac{\partial}{\partial t}[I(z,t)] \tag{1}$$

$$\frac{\partial}{\partial z}[I(z,t)] = -[G].[V(z,t)] - [C].\frac{\partial}{\partial t}[V(z,t)] \tag{2}$$

where [*V*] and [*I*] are *n x 1* vectors of the line voltages and line currents, respectively. The position along the line is denoted as *z* and time is denoted as *t*. The *n x n* matrices [*R*], [*L*], [*C*] and [*G*] contain the per-unit-length parameters which are computed either by a finite element approach or analytically for simple configurations.

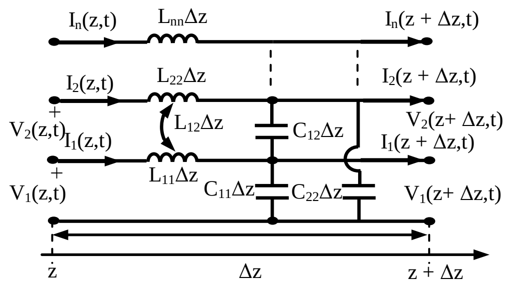

Fig. 1. The per unit length equivalent circuit of a MTL

The time-domain analysis of the MTL is determined by the Finite Difference Time Domain method (FDTD). In this method, the line axis *z* 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.

In this work the length of the spatial cell size Δz and sampling interval Δt are chosen respectively $\Delta z = \lambda_{min}/60$ and $\Delta t = \Delta z/(2.v)$, with λ_{min} is the wavelength of the source signal, and *v* is the velocity of the propagation of the wire. This choice insures the stability on the time stepping algorithm.

A. Validation example

In order to validate the propagation model, two configurations are studied. The first is the MTL shown in figure 2. It consists of three wires with a characteristic impedance of 120 ohms. The height above the ground plane is h= 5cm. The length of the MTL is 1 m.

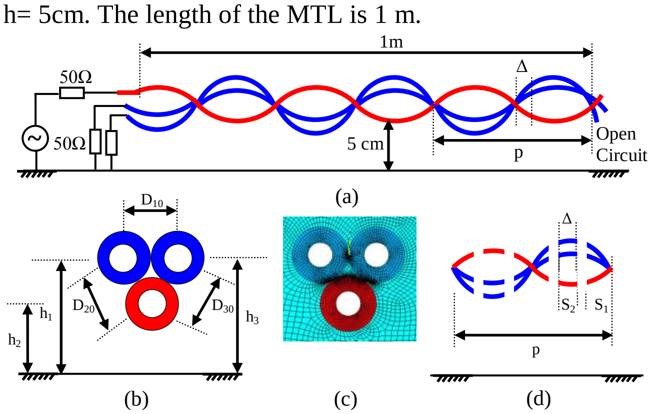

Fig. 2. (a) Twisted Wire Configuration, (b) cross sections of MTL section, (c) mesh of three conductor Transmission Lines with FEM and (d) discretization into uniform MTL sections of length $\Delta = p/N$

To analyze a nonuniform MTL by the transmission line theory, the basic idea is to discretize the nonuniform line into small sections of uniform MTL [8]. The length equal to the twist pitch p is discretized into N sections of length $\Delta = p/N$. Each section is assumed to be a uniform MTL which can be modeled by equivalent lumped parameter circuit, Fig.1. The discretization procedure is schematically represented in Fig.2.d the external parameters, i.e., inductances and capacitances, are calculated analytically, Fig.2.b (or numerically with FEM, Fig.2.c) for each uniform TL section of length Δ.

B. Comparison between measurement and simulations

The impulse response is deduced from measurement of S11 parameters with a Vector Network Analyzer (VNA) in frequency domain from 660 KHz to 2 GHz. The time domain reflectometry is obtained using inverse Fourier transform.

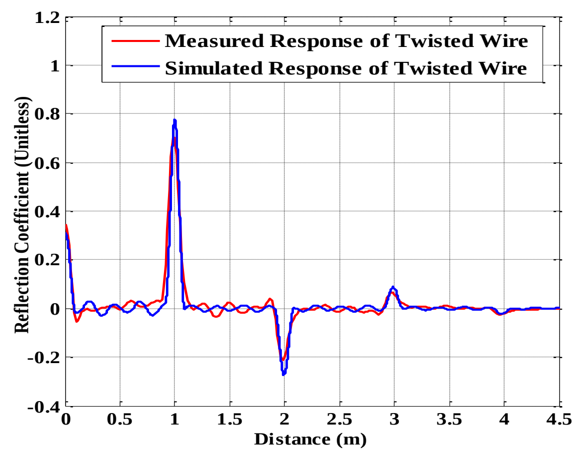

Fig. 3. Comparison between simulation results and measures for the TDR response

Figure 3 presents a comparison between simulated values and measured for the time domain reflectometry (TDR) response of the studied MTL. For the simulated response, a Raised cosine pulse with a rising time of 2 ns, and the voltage at high state of 1volt was used as source. The first reflections occur because of the mismatch between the input impedance (Z_I=50 ohms) and the impedance of the MTL (Z_C=120 ohms). The second reflection at 1 m gives information about the length and the load (Open end) of the MTL. The third, fourth and fifth reflection respectively in 2 m, 3 m and 4 m are due to the round-trips. The small reflections between these main reflections are due to the difference between real and simulated distribution of the MTL and change in impedance along the wire.

C. Reflectometry response for a complex wiring network

In this second configuration the FDTD method is used to simulate the TDR responses for complex network (Figure 4.a). The network includes five branches. The type of termination of the branches is indicated at the end of the branch. The measured impulse response is obtained with a VNA in a frequency band between 660 KHz and 2 GHz.

Figure 4.b illustrates a good agreement between measures and simulation results, both for positions and amplitudes of the main peaks. The difference between the simulated and measured values may be due to variation between the ideal and actual characteristic impedance of the cable, and also to the impedance of the connection as well as the loss that was not accounted for in the model.

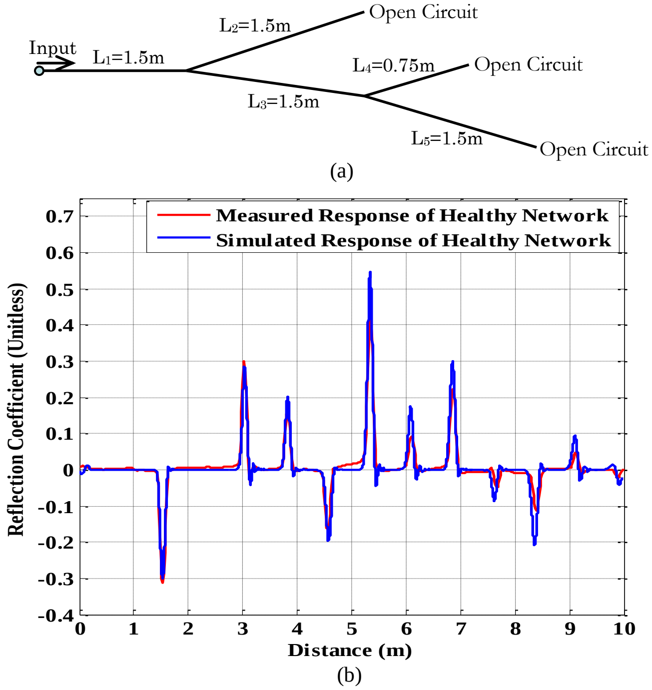

Fig. 4. (a) Studied network topology and (b) Comparison between simulation results and measures for the TDR response

III. INVERSION BY NEURAL NETWORKS

Neural Networks are flexible, fast and potentially able to model complicated functions and represent complex input/output relationships [9] [10].

A. *Design of NN*

Multilayer perceptron (MLP) NNs are used. The retained structure consists of two layer NNs with hyperbolic tangent activation functions in the hidden layer and an output layer constituted of a single neuron having a linear activation function.

The datasets required to train the NN were created thanks to the finite difference time domain method. The datasets are constituted of examples linking the reflectometry response to the position of the fault. In the case of hard faults the parameters are the lengths of the branches L_i. The number of the output neurons corresponds to the number of estimated quantities L_i. This approach is preferred to a single network (with as many outputs as branches) in order to avoid too complex NN including many internal parameters. The training domain is as follows: the space of estimated parameters (L_i) 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. In order to reduce the error obtained at the output, the variables of the NN are adjusted according to Levenberg–Marquard algorithm.

Nevertheless, the design of the NN has to be achieved carefully. Indeed, in the classical approaches, a NN can be successfully used only if the number of hidden neuron is correctly chosen. As a matter of fact, a NN having too few neurons will not be able to learn correctly the training set data (underfitting). On the other hand, a NN having too many neurons can lead to an overfitting phenomenon: good learning of the training set data but poor generalization ability. That means that data not contained in the training set will be wrongly approximated. Consequently, in order to have a good learning and a good generalization, the "split sample" method is used. It consists in dividing the input/output database obtained from finite difference computations into three different sets: training, validation, and test sets. The validation and test sets are constituted of data not included in training set. After creating the data sets, several NN are trained for different sizes (up to 50 hidden neurons in this work).

To avoid "overfitting", after training, the NN showing the lowest Mean Square Error (MSE) on the validation set is selected. Finally, the generalization capability of the NN is assessed by calculating the MSE obtained on the test set which contains input/output data not included in the previous sets.

B. *Inversion Results*

Two configurations have been studied. The first example is the faulty wiring Y-network shown in figure 5.a. The network is affected only in one branch with a hard fault (open circuit). In this case the number of parameters is limited to three according to the number of branches (Fig. 6). The undertaken inversion procedure considers three NNs, each one contains 50 neurons in the hidden layer. The input of each NN is the measurement reflectometry response of the faulty wiring network (Γ, L), (Fig. 5.b). In this case the number of the inputs is 20. After 650 iterations the training error reached a level of 10^{-6}. The test and validation sets were formed respectively by 10% and 40% examples of the data sets. The same portions are used for both configurations.

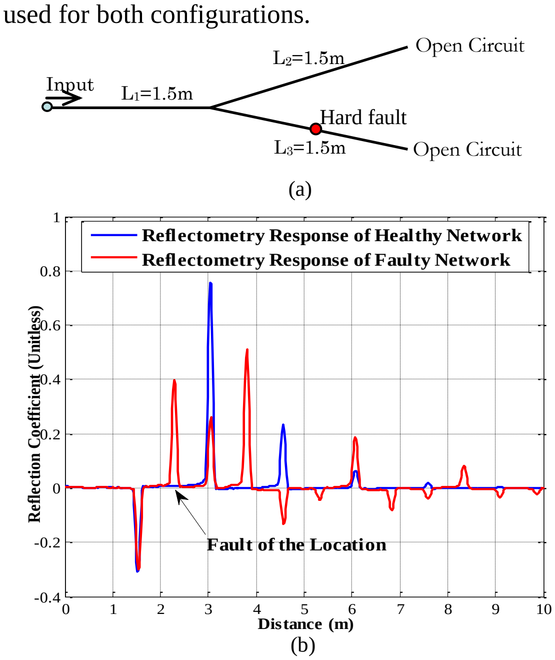

Fig. 5. (a) Network with open ended termination (broken wire) and (b) Comparison between the reflectometry responses of the healthy network and that affected by open ended circuit fault (measures)

Once the training is performed correctly, the capability of the NN is assessed on data issued from simulation that do not exist in the training dataset. These data are randomly chosen in the domain of variation of L_1, L_2 and L_3.

The NN training time, with a data set of about 21000 examples, is about two hours using a PC equipped with Pentium 4 Core Due Processor and 4 Gb of RAM. The creation of needed databases and the training of the NN can be performed "off-line". The inversion carried out with this method is very fast (less than one second with an error of $1.6x10^{-5}$) and can be achieved "on-line". On the contrary, for the same example, an iterative method (Genetic Algorithm; GA), requires 26 min with an error of $2.2x10^{-3}$ to find the state of the wiring network.

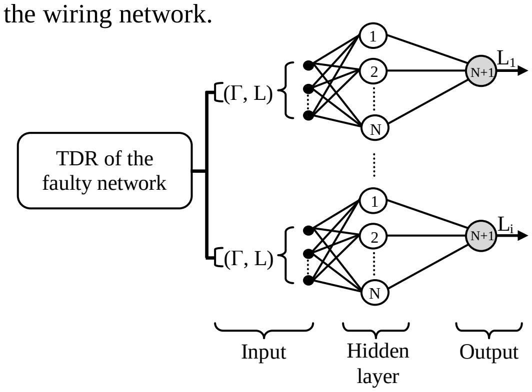

Fig. 6. Flowchart of the inversion procedure

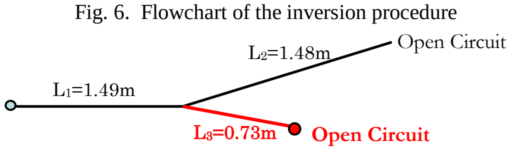

Fig. 7. Network reconstructed from the reflectometry response of the faulty network.

The results obtained show clearly the performance of the NN inversion. The new lengths of the different branches illustrate the location of the fault, (Fig. 7).

In the second configuration, the wiring network shown in figure 4.a is considered. It includes two hard faults (open circuits) in branches L_2 and L_4.

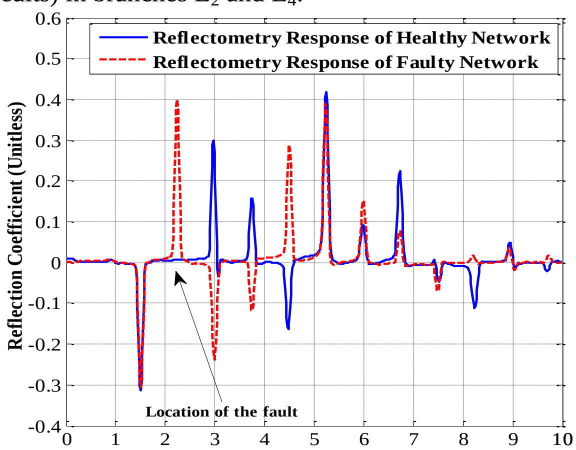

Fig. 8. Comparison between the reflectometry responses of the healthy network and that affected by two open ended circuit fault (measures)

The figure 8 compares the reflectometry responses of the wiring network before and after the fault. From this figure the distance between the location of the fault and the test point is clear. However it is still not clear which branch the fault lies on. The locations of the faults in the wiring network are masked by other prominent reflections resulting from junctions and terminations in the network. In this case the number of NNs is five according to the number of branches of the wiring network. Each NN contains 60 neurons in the hidden layer. The new wiring network reconstructed affected with an open circuit is illustrated in figure 9. The lengths of the branches L_2 and L_4 give the location of the faults in the network.

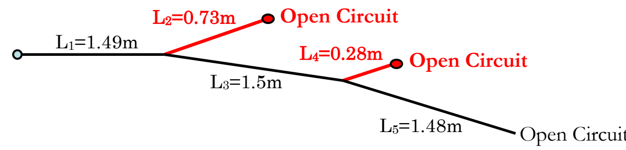

Fig. 9. Network reconstructed from measurement reflectometry response of the faulty network, localized hard faults

In order to illustrate the advantage of the NNs compared to the GA, the same discretizations of the wiring network branches are used. The healthy state of the wiring network is obtained in about 1 hour using GA. With NNs the training time took 4 hours, but the time to get the state of the wiring network remains less than one second.

IV. CONCLUSION

A methodology for the diagnosis of complex wiring networks involving MTL was presented. It is based on the finite difference time domain method and neural networks. The approach allows the reconstruction of the wiring network by finding the lengths of the branches. In the framework of smart embedded system for diagnosis, the training of NNs can be performed off-line. While the healthy state of the wiring network can be obtained in real time. Such a methodology provides a significant advantage compared to an iterative procedure like GA. The approach was tested against experimental data and demonstrated to be effective for the localization and characterization of hard defects. The method can be extended to soft faults. In this case the estimated parameters are inductances and capacitances or impedances.

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