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Wiring networks diagnosis using time-domain reflectometry and support vector machines

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Mostafa Kamel Smail¹ ✉, Abderrahmane Boubezoul², Housseem R.E.H. Bouchekara³, Yamine Sellami¹

¹Institut Polytechnique des Sciences Avancées, 63 boulevard de brandebourg, 94200 Ivry-sur-Seine, France

²UPE-IFSTTAR/TS2/SIMU&MOTO, F-77447 Marne la Vallée Cedex, France

³Department of Electrical Engineering, University of Hafr Al Batin, Hafr Al Batin 31991, KSA

✉ E-mail: mostafa-kamel.smail@ipsa.fr

Abstract: An efficient diagnosis method dedicated to embedded wiring network based on reflectometry technique is developed in this study. The proposed methodology is based on the two complementary steps. In the first step, the time-domain reflectometry (TDR) method is simulated, by RLCG (R : resistance, L : inductance, C : capacitance and G : conductance) circuit model and the numerical finite-difference time-domain method, and at the same time the datasets are created. In the second step, the support vector machine (SVM) algorithm is combined with a principal component analysis to identify the faults on wiring network from the TDR response. Two types of SVM models have been used in the diagnosis procedure: SVM classifiers and SVM regression models. In order to illustrate the performances and the feasibility of the proposed approach, numerical and experimental results are presented.

1 Introduction

The apparition of X-by-wire (or drive by wire) technology that consists of replacing mechanical or hydraulic systems by electronic ones, and also the complexity of modern systems, implies increasing the length of the cable [1]. As an example, cable lengths of up to 4 km in modern cars and up to 400 km in civil planes can be found.

Regardless of their application area, the cables can be subjected to several degradation mechanisms, e.g., chemical, electrical or mechanical, or just aging, causing faults and failures in different systems. These defects can be regrouped into two categories. When the degradation is simple and local, it creates a small impedance variation, which leads to a so-called soft fault. When a soft fault gets worse, the hard fault (open or short circuit) appears. Both faults can lead to tragic consequences, especially when the wires are an important element of the security of critical systems. For example, after investigation, the origins of the crashes of TWA flight 800 in 1996 and Swiss Air flight 111 in 1998 have been traced to defective wiring networks of the aircraft [1].

Several efforts have been undertaken to develop means that can easily and efficiently test the wiring network degradation status. They can be categorised into two groups: the first solution is based on reflectometry techniques. The idea behind these methods is based on propagating a signal in a cable and monitoring its reflections due to the impedance discontinuity [1]. In frequency-domain reflectometry (FDR), a sine wave signal is used while in time-domain reflectometry (TDR), a timed pulse is used. For each of these domains, various derived methods have been proposed. The most famous techniques for TDR are the sequence TDR (STDR) that transmits a pseudorandom digital code, and SSTDR (spread STDR) where the pseudo-noise (PN) code is used [1–3]. In the second wiring diagnosis category, few notable methods are X-ray and thermal imaging along with some electrical techniques such as capacitance and inductance sensors [4], and the standing wave ratio method. In this paper, a TDR-based method is used.

In order to evaluate the reflectometry measurement data, several simulation models have been proposed that may also be grouped into two classes: analytical and numerical. The analytical solutions consist of determining the reflection coefficient at the input of the wiring network with respect to the shape topology. Their main advantage is that they can give a response in both time and

frequency domains. However, they do not have access to small impedance variations along the wires. Besides, the numerical solution is built on the RLGC (R : resistance, L : inductance, C : Capacitance and G : conductance) circuit model that generates the telegraph's equations solved using a numerical approach like the finite difference time domain (FDTD) method. The model can determine the impedance discontinuity in a complex wiring network. This paper uses the numerical FDTD method.

The simulated or measured reflectometry response of a wiring network inherently contains reflections of the junctions and terminals, and the faults in the affected network. This makes the response very complicated, and it is hard to extract state information of the network under test. Hence, reflectometry by itself is not adequate for wiring network diagnosis. Thus, it must be associated with another method to deduce fault information from the reflectometry response. In this field, numerous solutions have been proposed and can be broadly categorised into two types: the ones that use the forward model in the iterative optimisation method in order to minimise the difference between the measured response and the simulated one with the use of optimisation algorithms like genetic algorithm (GA) or particle swarm optimisation (PSO) [5–7], and the ones that build an adjusted model 'off-line', containing data about the wiring network topology combined in a database, and to be used 'on-line'. The second solution is more common for embedded systems. Our proposed methodology is based on the second inversion approach. In [8] the authors proposed the use of artificial neural networks (ANNs) for the inversion procedure, but as the responses of the wiring network can be considered as high-dimensional data, this technique requires constructing a complex ANN and including a lot of internal parameters to be adjusted. Also, we can mention the shortcomings of overfitting and sinking into the local optimum in the use of ANN. The support vector machines (SVM)-based procedure has proven to be more robust in solving difficult approximation problems compared to the traditional ANN [9]. Also, SVM solution has the major advantages of global optimisation, higher generalisation capacity and capability to deal with high-dimensional data, in contrast to the traditional ANN.

The SVM for fault diagnosis is already employed for the power transmission line [10–12], where the wiring configuration is very simple, no ramifications. In [13] the authors have treated the branched wiring problem; the method is based on the state-

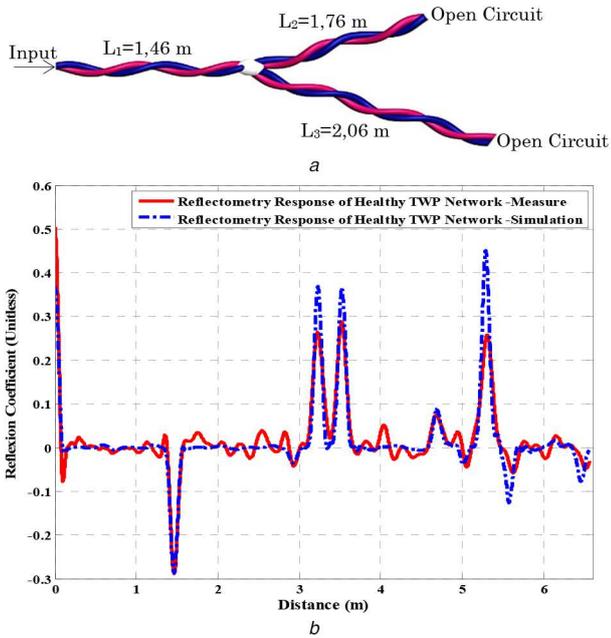


Fig. 1 Validation Example
(a) TWP network and, (b) Comparison between simulation results and measures for the TDR response

transition matrix as direct model and for training the SVM. The limitations of the proposed approach are focused on the forward model that is able to give the response of the topology network only at the input without having access to the impedance variations along the branches. And this could limit the generalisation of the approach to another type of fault. Another limitation that it does not treat fault characterisation.

This paper develops a new wiring network diagnosis methodology. The approach is based on two steps; in the first step, a direct model is established to simulate the TDR of the affected wiring network and create an ‘off-line’ dataset required to train an SVM. In the second step, the SVM combined with a principal component analysis (PCA) is used ‘on-line’ to identify faults from the measured reflectometry response. Two SVM models, classifier and regression, will be used in order to characterise and localise the faults.

2 Forward model

The forward model is needed to predict the TDR of the wiring network and the fault. The model is based on the RLCG circuit model [14].

2.1 RLCG circuit and FDTD method for a multi-transmission line (MTL)

Applying circuit laws on the RLCG circuit allow us writing the following differential (telegraph's equations):

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

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

where line voltages and line currents represented by $n \times 1$ vectors are $[V]$ and $[I]$, respectively, z denotes the position along the line and t denotes the time. The $n \times n$ matrices represent the per-unit-length parameters $[R]$, $[L]$, $[C]$ and $[G]$.

The p - u - l are computed using a numerical approach, like the finite element method or an analytical solution for the known configurations. The FDTD method is used to solve the telegraph's equations in order to reach the time-domain solution. The method consists of discretising the z -axis line in Δz increments and Δt

increments for the time variable t and approximating the derivatives of MTL equations using finite differences.

For the space stepping algorithm to be stable, the size of Δz must be smaller compared to the source signal wavelength λ_{\min} , usually of the order of $\Delta z = \lambda_{\min}/60$. In order to ensure the algorithm stability, the sampling interval Δt is chosen compared with the propagation velocity on the wire v as $\Delta t = \Delta z/(2 \cdot v)$, where v can be considered as $0.5c < v < 0.8c$, and c represents the speed of the light.

To model network shape, transmission conditions must be applied at the junctions. Equation (3) gives the reflection coefficient that can be calculated at each impedance discontinuity as

$$\Gamma = \frac{Z - Z_0}{Z + Z_0} \quad (3)$$

where the characteristic impedance of the wires is denoted by Z_0 , and the impedance at the discontinuity (mismatch) is denoted by Z . The value of Z is equal to Z_0/n if the wires have equal impedances. Thus, the previous equation becomes

$$\Gamma = \frac{(Z_0/n) - Z_0}{(Z_0/n) + Z_0} = \frac{1 - n}{1 + n} \quad (4)$$

2.2 Validation

The validation phase is very important in the proposed methodology. On the one hand, it allows us to validate the forward model, and on the other hand, it enables us to build the dataset for training the inverse model. The MTL network shown in Fig. 1a, consists of twisted wire pair (TWP) in a Y-shaped network with a characteristic impedance of 120Ω and loaded open circuit, is considered. The lengths of the cables are indicated in Fig. 1a. The key issue to analyse a non-uniform MTL using the transmission line theory is to discretise the non-uniform wire to a small section of uniform MTL [15].

For the experimental setup, the vector network analyser (VNA) of the frequency range between 600 kHz and 2 GHz is used. The inverse fast Fourier transform (IFFT) of the frequency measured of S_{11} parameters is used in order to obtain the TDR response.

In Fig. 1b, the measured and simulated TDR responses of the wiring network given in Fig. 1a are presented. A comparison illustrates a significant similarity between the responses, especially in the locations and amplitudes of the principal peaks. Due to the impedance mismatch between the TWP impedance ($Z_{TWP} = 120 \Omega$) and the VNA input impedance ($Z_{VNA} = 50 \Omega$), a reflection (at 0 m) is observed. The reflection at 1.46 m indicates the length of L_1 ; the first or main branch. The reflection at 3.22 and at 3.52 m is caused by the load of the secondary branches L_2 and L_3 (open circuit). The round trips between the input, junction, and the ends of the branches induce several reflections after the main reflections of the wiring network configuration at 1.46, 3.22 and 3.52 m. Notice that the differences between the responses are due to the difference between simulated and real characteristic impedance along the TWP.

3 Inverse model

Solving the inverse problem for the wiring network diagnosis using the proposed method is organised in three phases; detection, localisation and characterisation as shown in Fig. 2. The detection phase consists of comparing the TDR response of the wiring network under test with that of the healthy one. This can be done by calculating the mean square error (MSE) estimator, for example. If the values of MSE are less than a certain tolerance, the wiring network is designated as healthy. Otherwise, the algorithm progresses to the next phase. For the localisation and characterisation phases, the design parameters (parameters to be calculated) depend on the fault type. If the wiring network is affected by a soft fault, the position and impedance of the fault are the design parameters of the optimisation process. For a hard fault,

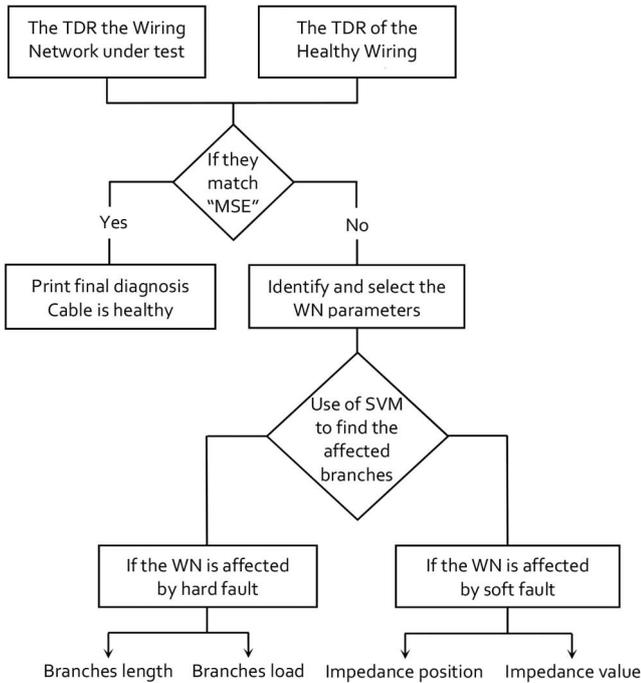


Fig. 2 Flowchart of the proposed diagnosis method

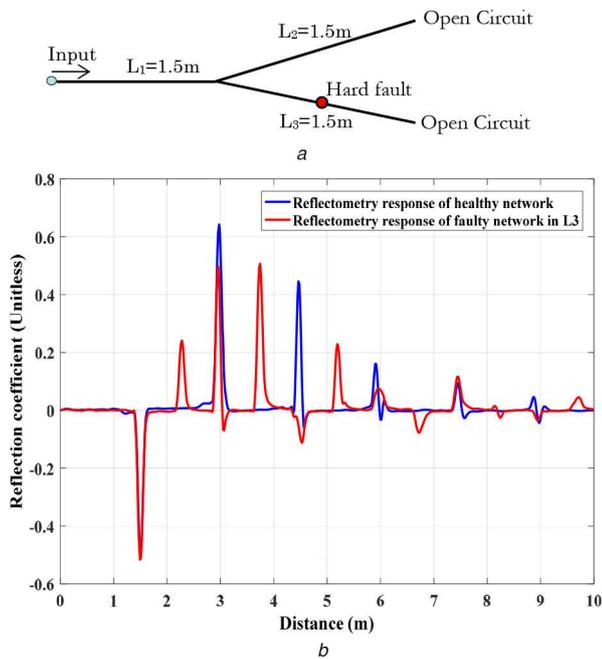


Fig. 3 *Y* wiring network affected by one hard fault and figure (a) Network with one hard fault, open-ended (broken wire) and, (b) Reflectometry responses of the healthy and faulty network (measures)

the design parameters are the branch lengths for the fault location and the secondary branch loads for the fault characterisation, thus, reconstructing the wiring network. In this paper, only hard faults are investigated.

3.1 SVM for wiring diagnosis

In order to achieve the other two diagnosis steps, i.e. localisation and characterisation for a wiring network affected by hard faults, an inverse problem is solved using a supervised learning method, the well-known SVM algorithm [10, 11]. This work proposes to combine SVM with a PCA, which is a powerful tool for dimensionality reduction [16]. In this work, it allows a selection of the significant features of the reflectometry response reducing the number of inputs of the SVM and so the dimension of required training dataset examples.

The forward model is employed to create the datasets required to train the SVM. To construct the datasets, we use examples linking the reflectometry response to the type and position of the fault. For hard faults, the design parameters are the secondary branch loads (open or short circuit) and the branch lengths L_i .

Two SVM model types are developed; one for regression and one for classification [17, 18]. The SVM classifiers are used to identify the fault types (open or short circuit) and to determine which branch is an affected branch. The dataset needed to build the SVM classifiers contain examples linking a reduced reflectometry response to the affected branches and their loads.

The SVM regression model is used to estimate the length of the affected branches. The dataset for training SVM regression contains examples linking reflectometry response to the length of the branches.

The training dataset of N points is given by $D = \{(x_i, y_i)\}, i \in 1, \dots, N$, where $x_i \in \mathbb{R}^d$ is a d -dimensional vector and $y_i = \{0, 1\}$ in the classification case and $y_i \in \mathbb{R}$ in the regression case. The aim of the SVM algorithm in classification and regression is to construct the function h which permits matching each input x_i to output y such that $y = h(x)$, based on the maximum margin.

In our application, the input is the reduced reflectometry response and the output is the fault type for the SVM classifier or the branch length for the SVM regression model. Generally, there is one output for an SVM model, so the number of SVM regression models for wiring network is a function of the number of secondary branches.

To evaluate the robustness of the SVM models, each corresponding database is cut into two sets; a training set and a testing set. In our case, 10% of the samples are devoted to testing. The training set is used to find the best hyperparameters of the SVM model. In order to evaluate the generalisation capability of the obtained model, the testing set is used.

SVM models are built 'off-line'; they are used 'on-line' to localise and characterise the faults from the TDR response of the faulty wiring network. In the next section, numerical results for two fault scenarios on a *Y*-shaped topology are presented.

4 Numerical results

Two test configurations are treated in this section. In the first example, the *Y*-shaped wiring network affected by one hard fault (open circuit), as shown in Fig. 3a, is studied. The second example treats the same network but affected with two hard faults in two different branches, as shown in Fig. 4a.

4.1 *Y* wiring network affected by one hard fault

As stated before, the first investigated configuration is a *Y*-shaped wiring network affected only in one branch. The configuration is composed of three cables with lengths 1.5 m each one, and the secondary branches L_2 and L_3 are loaded with open circuits. The shape is affected in L_2 with an open-circuit fault, as shown in Fig. 3a. Fig. 3b gives a comparison between the reflectometry response of the faulty network and a healthy one. For the reflectometry response of the healthy network, the first reflection gives information about the length of the main branch ($L_1 = 1.5$ m). The second reflection at 3 m is due to the open circuit at the end of the L_2 and L_3 . The other reflections are due to the round trips between the test point, junction, and end of branches.

After comparing and calculating the MSE between the two responses (network under test and the healthy one), the detection phase on the diagnosis procedure is accrued. Note that at this level, the number of faults affected the wiring configuration cannot be determined.

The status of the main (first) branch, affected or not, can be deduced just from the analysis of the difference between the reflectometry response of the network under test and the healthy one. If a peak appears before the significant reflection of the main branch, it is affected; otherwise, it is healthy. In our case, and from

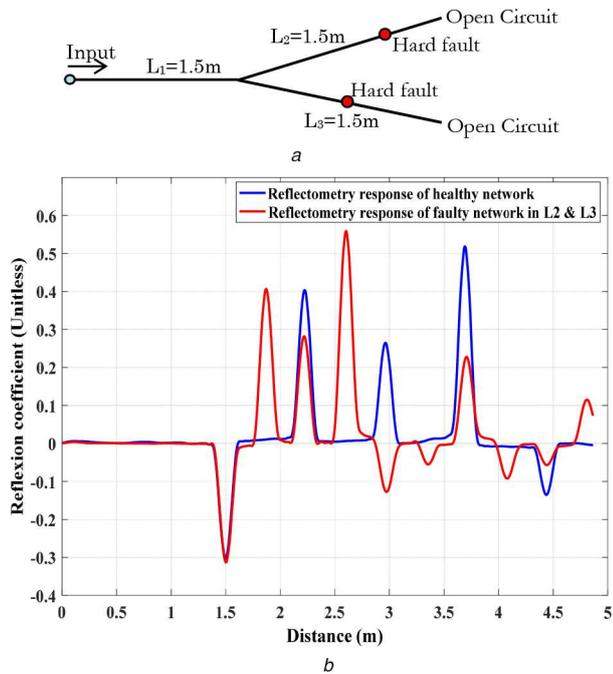


Fig. 4 Y Wiring Network affected by two hard faults
 (a) Network with two hard faults, open-ended (broken wire) and, (b) Reflectometry responses of the healthy and faulty one

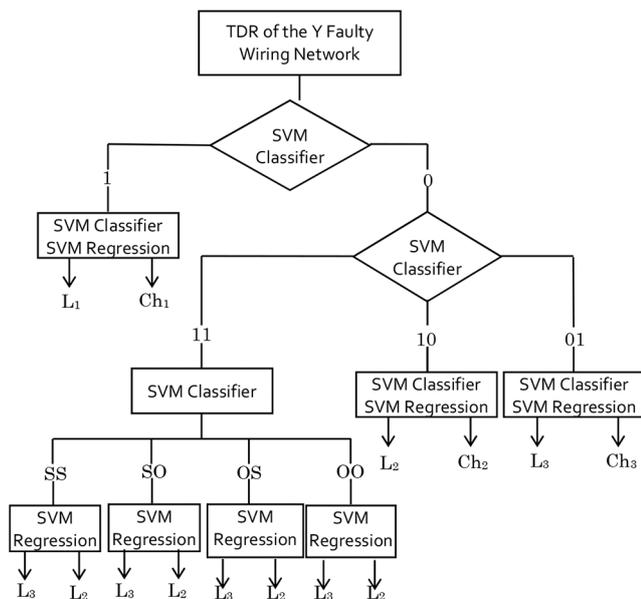


Fig. 5 SVM for Y wiring diagnosis

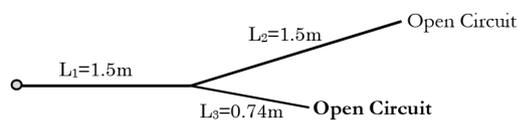


Fig. 6 Wiring network reconstructed from the reflectometry response of the faulty network

Fig. 3b, there is no peak before 1.5 m; thus, L_1 is healthy and it is removed from the design parameters.

The next step in the diagnosis procedure, as illustrated in Fig. 5, consists of identifying the parameters to be optimised, or in classifying wires branches (i.e. identifying if the wire branch is affected or not by a fault). The SVM classifier model is used for this purpose. The input of the inversion model is the measured TDR response of the network under test, as shown in Fig. 3b and the output is three classes; 11, 10 or 01, corresponding to if L_2 and L_3 are affected, L_2 is affected and L_3 is healthy, or L_2 is healthy and

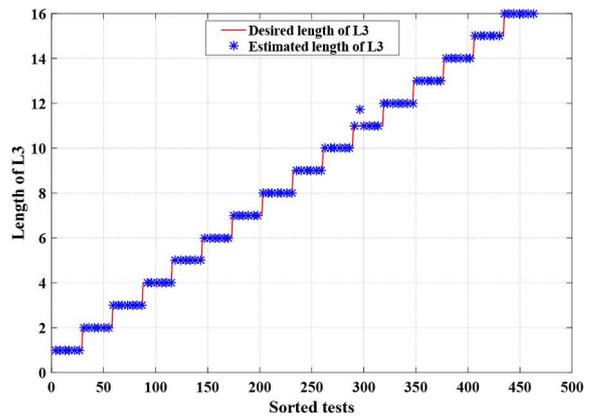


Fig. 7 Set values and predicted values of L_3 (training data)

Table 1 Comparison results SVM, NN with GA, PSO and IBH

	Y with one fault	Y with two faults
actual	0.75	0.75–0.37
SVM	0.74	0.76–0.38
NN	0.73	0.74–0.36
GA	0.77	0.76–0.38
PSO	0.77	0.76–0.38
IBH	0.75	0.69–0.36

L_3 is affected, respectively. In the case study, the identified class is 01. In the last step, the SVM regression model is used to determine an estimation of the new length of L_3 in order to localise the fault. The reconstructed wiring network is given in Fig. 6.

4.2 Y-wiring network affected by two hard faults

In the second case, the same Y-shaped wiring network, but affected by two hard faults, is considered, as shown in Fig. 4a. The input of the proposed inversion procedure is the reflectometry response of the faulty wiring network shown in Fig. 4b.

After the elimination of L_1 from the design parameters and checking if they have a difference between the responses before the peak of the mean branches, the SVM algorithm is applied.

The SVM classifier model, in this case, gives as output 11, signifying that L_2 and L_3 are affected. The output of the SVM regression model is the new lengths of L_2 and L_3 . The new lengths of L_2 and L_3 are 0.76 and 0.38 m, respectively, which represents a good matching between TDR responses of both the actual and reconstructed faulty networks.

The plot of the support vector regression model predicting the branch lengths of L_3 is compared with the training datasets and shown in Fig. 7. Here, both L_2 and L_3 are short-circuited in different positions. The fault localisation of L_3 is well estimated in approximately all the tests, even if L_2 is affected.

In order to illustrate the advantages of the proposed diagnosis technique compared to the iterative techniques (GA [5], PSO [6], improved black hole (IBH) [19], ANN [8]) the same discretisation of the branched wiring network is considered. The comparison results show that the faults are characterised and localised with incomparable computation time, as illustrated Table 1.

The online diagnosis time for GA is 90.6 min and the PSO is 26.3 min and IBH is 20 min, but for the SVM is <1 s. The main advantage of the proposed method compared with the direct inversion techniques like ANN [8] is that is able to use all the TDR response data without being impellent to select the significant parameters using the PCA algorithm. The inputs of the SVM models are set of points constituting a reflectometry response; this can be seen as a high dimension data space, leading to a complex SVM including a lot of internal parameters to be adjusted. A reduction of the dimensionality of the observations is then implemented using PCA.

For the soft fault, SVM classifier models should be used to identify the fault class, i.e. soft or hard fault.

5 Conclusion

In this paper, an efficient technique based on TDR and SVM for the wiring network involving MTL was presented. The proposed methodology allows determining the physical information about the wiring network by finding the branch lengths. The forward problem permits to simulate the time response of the cables, that can be compared to the measured data and used to build the dataset. The inverse problem is solved in two steps; an 'off-line' step to train and build a behavioural model and an 'online' step to reconstruct the wiring network. Furthermore, the algorithm can be exploited in embedded system. Experimental results illustrate the effectiveness of the diagnosis methodology. The proposed approach yields an important advantage compared to the iterative procedures like GA, PSO or IBH, and also the direct inversion methods like ANN. The method can be extended to the diagnosis of complex networks affected by more than one fault. For the soft fault, the optimised parameters are the fault impedance for characterisation and fault position for localisation.

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