Sensor Selection for Distributed Reflectometry-based Soft Fault Detection using Principal Component Analysis

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***Abstract*—In this paper, a new approach is introduced for the selection of the most relevant sensors to monitor and diagnose soft faults in complex wired networks. Although reflectometry offers good results in point to point topology networks, it introduces ambiguity related to fault location in more complex wired networks. As a solution, distributed reflectometry method is used. However, several challenges are imposed, from the computing complexities and sensor fusion problems, to the energy consumption. In this context, the proposed method combines Time Domain Reflectometry (TDR) method with Principal Component Analysis (PCA) approach. To do so, a distributed reflectometry approach is considered for a CAN BUS network where sensors perform their reflectometry measurements consecutively. The simulated TDR responses are then arranged into a database. With this database, a PCA model is developed and used to detect the existing soft faults. Coupled with statistical analysis based on Hotellings T^2 and squared prediction error, the most relevant sensors to monitor and diagnose the soft faults present in the network are highlighted with a high accuracy.**

***Index Terms*—Time domain reflectometry, Distributed reflectometry, Principal Component Analysis, complex wiring networks, wire diagnosis, soft fault, sensor selection, statistical chart**

I. Introduction

Nowadays, cables exist nearly in almost all domains and are subjected to aggressive operating conditions (i.e. environmental, thermal and mechanical) which may create defects. This situation can have severe consequences such as the crash of TWA Flight 800 in July 1996 and Swissair Flight 111 in September 1998.Therefore, it is a matter of high importance to detect and accurately locate failures in wired networks. In terms of wire diagnosis, different methods are used for this purpose [1]. In the literature, reflectometry methods are among the most widely used for the diagnosis in wired networks [2]. The principle is to inject a wide-band test signal down to the network under test (NUT). During its propagation, a part of its energy reflects back to the injection port when it crosses impedance discontinuities (splices, connectors, faults). The correlation of the injected signal and reflected one returns the reflectometry response of the tested network.

Although reflectometry offers good results in point to point topology networks, however, in more complex wired networks, it introduces ambiguity related to fault location [1]. In such networks, using a single sensor is no longer possible to cover the whole network. This may be explained by the signal attenuation due to the distance and connection complexity. As a solution, distributed reflectometry method is used to overcome ambiguity problems and maximize the diagnosis coverage [3]. It consists in performing reflectometry measurements at different extremities of the NUT. Indeed, the injection of multiple signals down to the NUT leads to computing complexities and sensor fusion problems. On the other hand, energy consumption is a major drawback of this method with respect to environmental constraints. The study on the reduction of the sensors number in complex networks and its impact on the diagnosis quality is provided in [4], [5]. However, it shows further challenges related to bandwidth allocation, communication protocol and noise interference mitigation. Thus, in [6], the cable life profile is included, permitting to reduce the diagnosis cost by avoiding the use of too many sensors in the network. Nevertheless, the reliability of the sensors in emission and reception is considered in the obtained statistics. This reliability differs from a sensor to another and impacts on the fault location.

In this context, this paper introduces a new approach for the selection of the relevant sensors to monitor and diagnose soft faults in complex wired networks. It integrates distributed reflectometry based-data with the Principal Component Analysis (PCA) method. Indeed, for a given network under test (NUT), a distributed reflectometry approach is considered where the sensors perform their reflectometry measurements. These data are used to establish a PCA model which is coupled with statistical analysis tests to check into new measurements. Whenever a fault is detected, the relevant sensors to monitor and diagnose it are highlighted with a high accuracy.

The remaining of this paper is organized as follows. Section II addresses the distributed reflectometry challenges in complex networks. Section III illustrates the proposed distributed diagnosis approach using the PCA method and a statistical analysis tool based on Hotellings T^2 or squared prediction error. Finally, simulation results are provided for a Controller Area Network (CAN) BUS topology.

II. Distributed Reflectometry

In a way or another, signs of weakness or aging will appear in a cable network. This means the manifestation of defects, which can be responsible for the system malfunction leading to severe results if the wires are part of critical systems.

In fact, to enhance the reliability of wired networks or to assist for maintenance purposes, reflectometry methods are among the most widely used. During the signal propagation, a part of its energy is reflected back to the injection point whenever an impedance discontinuity is met. Afterward, the analysis of the reflected signal, usually referred to as the "Reflectogram", is used to characterize the discontinuity.

Reflectometry includes two main families: Time Domain Reflectometry (TDR) and Frequency Domain Reflectometry (FDR) [1]. The main difference is in the injection method and the data processing [7]. In FDR, the analysis is quite easy for a simple point-to-point wire but it turns out to be very complicated for complex networks. The remainder of this paper will focus on the TDR based diagnosis methods.

Despite that reflectometry has proven its efficiency in the simple wire fault detection, it encounters ambiguity problems in the case of complex wired networks. Indeed, in these networks, the signal attenuation due to the distance traveled and multiple junctions makes it no longer possible to use a single diagnosis system to cover the whole network. Even if the distance between the injection point and the fault could be specified, the identification of the defective branch remains ambiguous [1], [8]. To solve that, distributed reflectometry is used. Mainly it implements several reflectometry measurement systems at several ends of the network; nevertheless, several challenges are imposed related to computing complexities, sensor fusion problems and energy consumption.

In this context, we propose to combine TDR distributed reflectometry measurements with the PCA approach to select the most relevant sensors to monitor and diagnose soft faults in complex wired networks. Therefore, sensors number could be reduced and the non-selected ones could be inactivated leading to the reduction of energy consumption, computing complexities and sensor fusion problems.

III. Proposed Method

In this section, we propose to develop an algorithm to automate the detection of a fault in a complex wired network and the selection of the most relevant sensors to monitor the detected soft fault and inactivate the non-selected sensors.

A. Physical Model

One well-known model for a transmission line is the so-called "RLCG model" [9], where the quantities R(resistance), L(inductance), C(capacitance) and G(conductance) are the electrical per-unit-length parameters. The analytic model has been developed in [10]. In the frequency domain, the simulation model can be written using the ABCD matrix formalism [1].

For a cable of length l, propagation constant γ and characteristic impedance Z_c, the ABCD matrix is written as:

$$\begin{bmatrix} A & B \\ C & D \end{bmatrix} = \begin{bmatrix} \cosh\gamma l & Z_c \sinh\gamma l \\ \frac{\sinh\gamma l}{Z_c} & \cosh\gamma l \end{bmatrix} \quad (1)$$

A theoretical model that enables to accurately simulate reflectometry signals, for complex wired network topologies, using the ABCD matrix formalism has been represented in [11]. Indeed, in order to compute the reflection coefficient τ_k for each sensor S_k, in a distributed reflectometry aspect, one just needs to divide the network topology into sub-networks having a simple shape. Then, cascading the equivalent reflection coefficients of those sub-networks.

B. Realization Model

Figure 1 describes the principle of the new approach combining TDR distributed reflectometry measurements with the PCA. It is composed up of three steps:

a) Training Phase: First, the data are collected during fault-free normal operating conditions. To do so, each sensor in the distributed network must do its TDR measurements, consecutively, and send the information to constitute the database. Then, matrix X is constructed in a way that each column variable of it corresponds to a sensor TDR response. Based on this data, a PCA model is developed as in [12]. This model is used in the second step to examine new measurement data.

PCA [13] is a multivariate data-driven modeling technique that transforms a set of m-correlated variables into a smaller

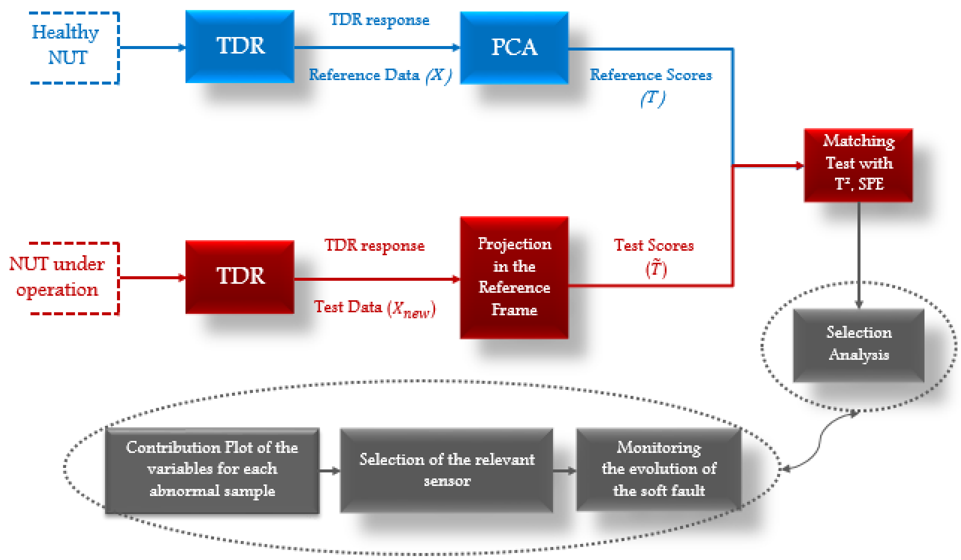

Fig. 1. TDR distributed reflectometry measurements with the PCA approach

set of l-new variables (l principal components, such that $l < m$). Those new variables are uncorrelated and retain most of the original information. After developing a model using good (training) data, the reduced dimension model can be used to detect abnormalities in a robust way [14].

b) Monitoring Phase: Second, when the network is under operation, X_{new}, the new measurement data matrix is built in the same way the reference data matrix X was constructed, after which it will be projected in the reference frame. The new scores T_{new} and the residual $\tilde{T}_{new}$ are then calculated. The detailed analytic calculations can be found in [12].

Monitoring statistics are used for fault detection, i.e. determining whether a fault has occurred or not. To do so, two statistical methods are used. The Q (or Squared Prediction Error: SPE) and the Hotellings T^2 statistics [14]. These tests are used for evaluating the fault presence. They display the variations that are not interpretable by the retained PCs in the residual and the principal sub-spaces. The confidence limits Q_α and T^2_α for those tests are calculated using the data X which is used for the construction of the PCA model in step one. If at a specific sample, the Q or T^2 value falls outside the confidence limit, then a fault exists.

c) Sensor Selection Analysis : Finally, whenever a fault is detected, we proceed by the selection analysis step. For each detected faulty sample, the analysis starts with plotting the contribution of the variables, constituting the new measurement data matrix X_{new} (i.e. sensors TDR responses), in its Q or T^2 value. By doing so, we can inspect the variables that highly influence this sample Q or T^2 value. Therefore, choosing the most relevant sensor to monitor the evolution of this fault and inactivate all other sensors.

IV. Results: A CAN Bus Network

Figure 2 represents a CAN BUS topology. This network is composed up of several sections, namely, B1 to B7. Their respective lengths are 2.5m, 2.5m, 5m, 10m, 2.5m, 5m and 10m. Six 1.5m cables, denoted by B'1 to B'6, are used to connect the electronic functions to the bus for accessing the network. At the end of each of those cables, we place a matched diagnosis sensor to ensure the communication. The characteristic impedance of all the cables is set to 100Ω, i.e. $Z_c = 100\Omega$.

First, in the normal fault-free operating conditions, each sensor injects the test signal consecutively. TDR responses are then obtained and used to constitute the reference data matrix X. X is thus formed up of six variables. Each variable $\bar{R}_{Si}$ is a column vector of the matrix and corresponds to the CAN BUS network reference TDR response for the sensor Si, such that:

$$X = [\bar{R}_{S1}\ \bar{R}_{S2}\ \bar{R}_{S3}\ \bar{R}_{S4}\ \bar{R}_{S5}\ \bar{R}_{S6}] \qquad (2)$$

The data matrix X is then used for the construction of the PCA model. Table I indicates that the cumulative variance of the first two scores is 92.28% that is greater than the limit set in [12]. This implies that the variables in X are highly correlated and that the data is well described by a two principal components model.

Now, in order to simulate the soft fault, a 20% local variation of the characteristic impedance on the branch B3 of the network is simulated, i.e. $\Delta Z_c = 20\%$. TDR responses for each sensor is then simulated and are shown in Fig. 3. The soft fault is located, respectively, at 6.5m, 4m, 4m, 14m, 16.5m and 21.5m from sensors S1 to S6, with a length d = 0.05m as shown by the weak peak at those distances. The other peaks represent the ramifications on the network. E.g. for S3, the

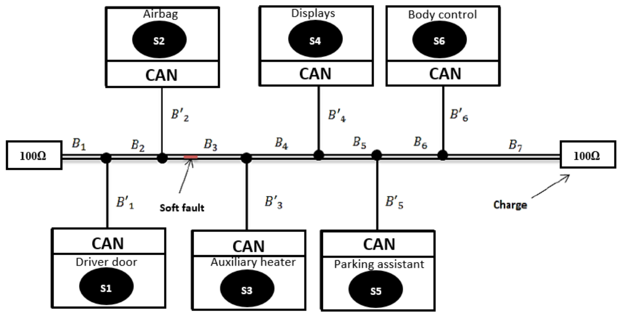

Fig. 2. CAN BUS topology

TABLE I
PCA MODEL VARIANCE RESULTS

PC Number	Variance Percentage	Accumulated Percentage
1	86.67	86.67
2	5.61	92.28
3	4.9	97.28
4	2.06	99.24
5	0.72	99.96
6	0.04	100

first peak at distance 1.5m corresponds to the direct path to the junction (length of LB'3= 1.5m) and so on. Using these faulty model reflectometry data, the new measurement data matrix X_{new} is constructed. X_{new} is defined as follows:

$$\begin{aligned} X &= \left[\bar{R}n_{S1}\ \bar{R}n_{S2}\ \bar{R}n_{S3}\ \bar{R}n_{S4}\ \bar{R}n_{S5}\ \bar{R}n_{S6}\right] \\ &= \left[\mathbf{S_1}\ \mathbf{S_2}\ \mathbf{S_3}\ \mathbf{S_4}\ \mathbf{S_5}\ \mathbf{S_6}\right] \end{aligned} \tag{3}$$

where $\bar{R}n_{Si}$ describes the faulty model TDR response for the sensor S_i such that: $i = 1, 2, \ldots, 6$.
Now, the Q value of each new measurement sample is calculated. Figure 4 represents the Q control chart, with the dashed red line representing the 95% confidence limit (Q_α). It is shown that Q_α has been exceeded by some samples. Thus a fault has occurred. Due to the presence of the several round-trip peaks (represented by several abnormal samples in the Q chart) for the same fault, the criteria used in the case of a single fault, to choose the abnormal sample among those exceeding the confidence limit, is the sample with the highest Q value. Therefore, in our example, the sample number 3283 corresponds to the fault.
Plotting the contribution chart in Fig. 5 of the indicated faulty sample permits to know the variable $(\mathbf{S_1}, \mathbf{S_2}, \mathbf{S_3}, \mathbf{S_4}, \mathbf{S_5}, \mathbf{S_6})$ that highly influences its Q value. Thereby, the selection of the relevant sensor is performed by the Q control test. The contribution of the fourth variable $\mathbf{S_4}$ is almost neglected with respect to the other variables; hence, it does not appear in the contribution plot. Sensor S2 is selected and other sensors could be inactivated. This sensor could be used to monitor the fault evolution for prognosis perspectives based on its reflectometry measurements.

V. CONCLUSION

The proposed method combines TDR method with Principal Component Analysis (PCA) approach. For a given BUS CAN topology, a distributed reflectometry approach is considered where sensors perform their reflectometry measurements consecutively. The TDR responses constitute the data that are collected by a central unit and arranged into a database. With this database, a PCA model is developed and used to detect the existing soft faults. Coupled with statistical analysis based on Hotellings T^2 and squared prediction error, the most relevant sensors to monitor and diagnose the soft faults present in the network are highlighted with a high accuracy. This approach has proven its efficiency in the presence of a soft fault ($\Delta Z_c = 20\%$).

With this study, the sensor selection is obtained whatever the fault location in the NUT. Therefore, the sensors number could be reduced and the non-selected ones could be inactivated leading to the reduction of energy consumption, computing complexities and sensor fusion problems. The selected sensors could be used to monitor the fault evolution for prognosis perspectives based on its reflectometry measurements.

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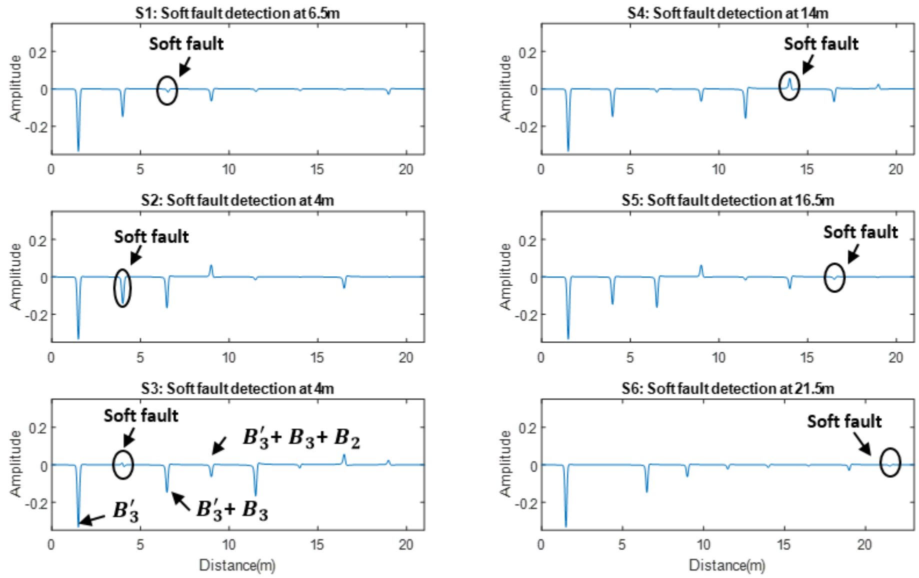

Fig. 3. TDR responses of the modeled CAN BUS topology

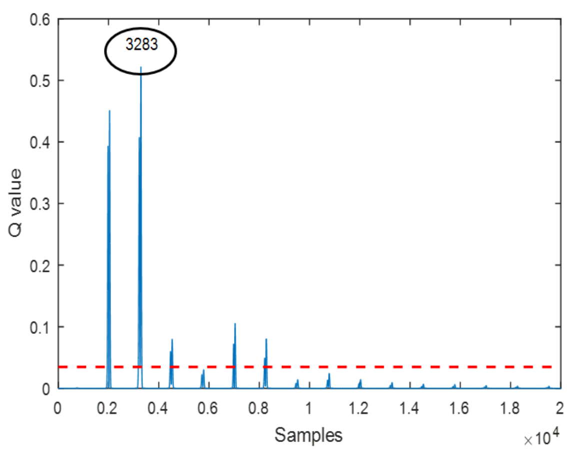

Fig. 4. Q chart of the new measurement samples

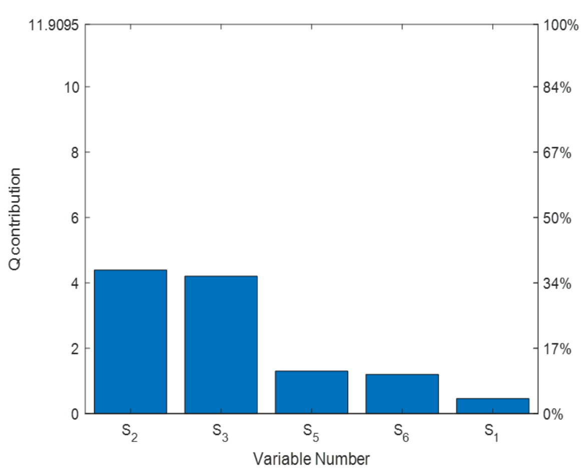

Fig. 5. Contribution plot of the sample 3283