A Distributed Diagnosis Strategy using Bayesian Network for Complex Wiring Networks

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Abstract: In this paper, we propose a distributed diagnosis strategy by using reflectometry in highly complex wiring networks. Although the problem of sensors number optimization is greatly studied in the literature, it is not well investigated in complex wiring networks diagnosis. Our proposed approach is based on two principles which are diagnosis sensors number and location optimisation using Bayesian Networks and measure uncertainty estimation. It consists in four steps: (1) sensors implementation in a deterministic case, (2) influential parameters on diagnosis measure identification, (3) diagnosis measure modelling using Bayesian Networks, (4) sensor number and location optimization. Here, our objective is to minimize both sensors number and a wire diagnosis measure uncertainty.

Keywords: complex wiring network, distributed strategy, reflectometry, Bayesian Networks, uncertainty estimation.

1. INTRODUCTION

In recent years, we have witnessed a paradigm shift in the automotive and aeronautic industries. The appearance of "X-by-wire" technology, replacing the traditional mechanical and hydraulic control systems with electronic ones, increases embedded systems complexity. Moreover, cumulated wire length rise up to 4 km in a modern car and 400 km in an aircraft AUZANNEAU [2012]. A part of these wiring networks have been identified as likely responsible of several tragic mishaps such as the crash of TWA Flight 800 in July 1996 and Swissair Flight 111 in September 1998. Monitoring, diagnosis and maintenance are considered as a nightmare when wire harness is out-of-sight or unreachable without dismantling the external structure. It is also highly expensive in terms of money, time, resources, risk and persons. Each year, US Navy spends 1.8 million person-hours for its aircraft wiring systems maintenance FURSE and HAUPT [2001].

Reflectometry is a powerful technique for detection and localisation of electric faults in wiring networks. The idea is to inject a wideband test signal down the wire. During its propagation, a part of its energy reflects back to the injection port when it crosses impedance discontinuities. Then, a received signal analysis, called "reflectogram", gives location information about the detected wire fault.

In the literature, many types of reflectometry techniques are proposed. The main difference between these varieties lies on the injected test signal type and reflected signal processing techniques. Time Domain Reflectometry (TDR) uses a pulse (Gaussian, rectangular,etc.) as a test signal and measures the time delay between the injected and received signal to determine the fault location. Frequency Domain Reflectometry (FDR) uses a set of sinusoidal waves as a test signal and analyses the phase and/or magnitude of the reflected wave FURSE et al. [2003]. Although FDR and TDR have proved their efficiency in fault detection and localisation for single wires, they are not so efficient in complex wiring networks. Indeed, both need to use a high voltage signal to detect intermittent faults. However, the test signal levels may interfere with the native ones, if applied while the target system (aircraft, automobile, etc) is running.

For those reasons, researchers have focused on innovative methods for "on-line" diagnosis in wiring networks aiming at reducing the consequences of intermittent and arc faults. To do so, other types of reflectometry have been proposed such as Sequence Time Domain Reflectometry (STDR) SHARMA et al. [2007] and Spread Spectrum Time Domain Reflectometry (SSTDR) that inject a pseudo-noise code TAYLOR and FAULKNER [1996], WEI and LI [2011] to diagnose wires in real time. These methods are able to detect and locate faults on live wires even when the test signal level is well below the noise margin of the signal already on the wire.

In order to limit the bandwidth allocated to system signal and reduce inter-signal and Electromagnetic Compatibility (EMC) interference, Multiple Carrier Reflectometry

(MCR) NAIK et al. [2006], AMINI et al. [2009] and Multi-Carrier Time Domain Reflectometry (MCTDR) LELONG and OLIVAS [2009] are proposed for fault detection and location in a complex and very complex wiring network. Indeed, both operate in a parallel testing mode thanks to multiple carriers use. The most interesting characteristic of the latest methods is their flexibility to diagnose and monitor live wires in a much shorter time.
In practice, a distributed diagnosis strategy is necessary when multiple reflectometers (referred also as diagnosis sensors) are implemented in order to guarantee a reliable and continuous diagnosis in complex wiring system. A multi-sensor architecture offers better robustness, reliability and network coverage. However, there are major problems associated with such an architecture (Fig.1): sensor reliability, optimal sensor number and location, signal processing, data exchange, sensor communication, resource allocation (bandwidth and memory), etc.

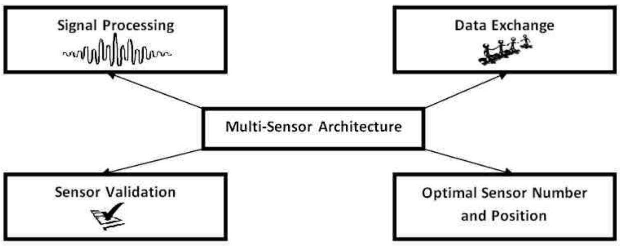

Fig. 1. Multi-Reflectomer Architecture Principles

In this paper, we focus on the number and location of diagnosis sensors that impact the diagnosis measure quality and then, we estimate the level of confidence for each proposed architecture. Firstly, we consider a deterministic case implementation where each wire of the network is related at least to one reflectometer. Secondly, we propose to remove one or more reflectometers from the network and estimate the measure uncertainty. Our main objective is to find the best trade-off between optimal sensors number and wiring network diagnosis reliability with a reasonable maintenance cost.
The remainder of the paper is organized as follows: In section 2, we present an overview of existing diagnosis sensors number optimisation works. In section 3, we introduce our proposed diagnosis approach in a complex wiring network using Bayesian Networks. Finally, we conclude with a brief recall of our proposed strategy and future works perspective.

2. RELATED WORKS

Our work is related to the integration of uncertainties caused by the lack of knowledge in terms of integrated components behaviour and random evolution of the studied environment such as sensors number and location. Indeed, uncertainty requires the use of probabilities that, by propagation, allows access to levels of confidence in the obtained measure GODICHAUD et al. [2009], VILLENEUVE et al. [2011]. In this paper, we focus on the sensors number used to diagnose wiring networks and corresponding confidence levels by using Bayesian Networks.
Although the problem of sensors number optimisation is well studied in the literature STASZEWSKI and WORDEN [2001], NAOREM and MAKARAND [2009], it is not well investigated in complex wiring networks diagnosis using reflectometry. Wiring networks, which can carry information or energy, are composed of different cable types which are connected to each other. Each cable in a network is defined by its own characteristic impedance, propagation velocity, conductivity, permittivity, length, type, etc. In this study, we consider the following hypothesis:

H_1. Each cable has a short length (less than 100 meter) in order to inject high frequency waves to reduce signal attenuation and dispersion.
H_2. Each cable in the network has homogeneous physical properties (permittivity, conductivity, propagation velocity, etc).
H_3. The wiring network is arborescent (no loop). Each cable is either connected to at least 2 other wires or to one load, as depicted on Fig.2 (The J_i are wire junctions)

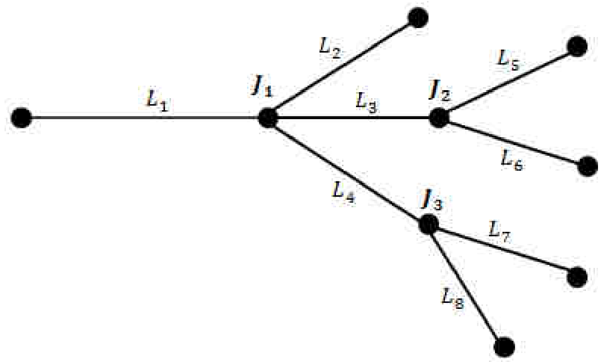

Fig. 2. An example of Complex Wiring Network

Commonly, the number of sensors implemented in a n-branch network is equal to n to ensure a maximum network coverage. In such an implementation, it is clear that all the wires are diagnosed at least by one reflectometer. However, as waves transmit test and system signal through a wire simultaneously and in different directions, these signals may interfere with each other and potentially cause false alarms or useful signals distortion, leading to errors. Moreover, on financial side, the implementation of a great number of sensors in high complex networks, such as those found in automotive and aeronautic industries, is extremely expensive in economic terms but also with respect to the space and volume.
Aiming at reducing the total number of sensors, author in LELONG [2010] has recently proposed to implement N_{sensor} sensors in a complex network where:

$$N_{sensor} = \sum_{j=0}^{J-1} (n_j - 1) \tag{1}$$

where J represents the total junctions number in a network and n_j is branches number (excluding the trunks) of the j^th junction. Equation (1) is established under some assumptions which are: (1) All network trunks are on one or more path(s) from one reflectometer to another. (2)

For each junction with more than one branch, there is at most only one branch that is not related to a reflectometer. Although the number of reflectometers implemented in the network is reduced, the obvious question here is: "How much confidence shall we have in obtained diagnosis measure?".
To answer that question, we aim in this work at finding a good trade-off between the number of sensors and the diagnosis measure confidence by using probabilistic based model.

3. DIAGNOSIS STRATEGY IN A COMPLEX WIRING NETWORK

There are two possible approaches to tackle our optimisation problem. The first one (used later) is to define the multi-sensor architecture (number and location) from a predefined confidence level to respect. The second one (not shown here) is to characterize the level of confidence in an obtained measure for a multi-sensor architecture which is already implemented. In this work, the proposed method consists of four steps which are:

(1) Implement a deterministic case: each cable is connected at least to one diagnosis sensor.
(2) Define influential parameters to estimate efficiency uncertainty.
(3) Model diagnosis measure using Bayesian Networks.
(4) Optimize the number of sensors by removing one or more reflectometers and estimate efficiency uncertainty.

3.1 Deterministic Case Implementation

Let's start with a deterministic case where the number of sensors in a n-branch network is equal to n as it is depicted by Fig.3. R_i denotes the Reflectometer i.

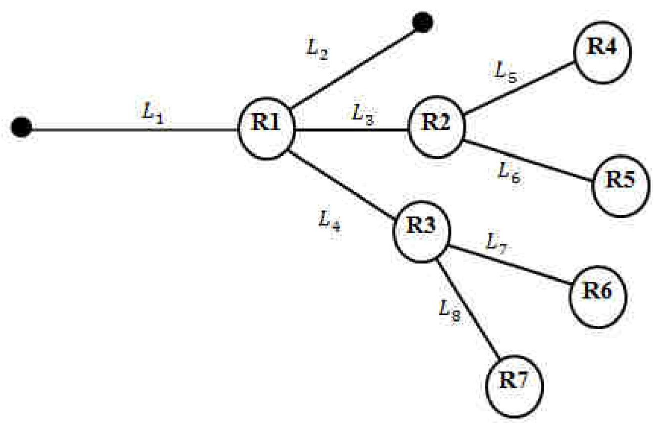

Fig. 3. Reflectometer Employment in a Complex Wiring Network

In this deterministic case, all the network branches are diagnosed at least by one diagnosis sensor which not only enhances the network system coverage, but also increases the diagnosis performance in terms of detection, precise location and reliability. However, when reporting a diagnosis measure result, it is also mandatory to give a quantitative indication of the measure quality in order to estimate its level of confidence. In the absence of such indication, diagnosis measure results can not be compared, either among themselves or relative to reference values (case of healthy network). Therefore, it is necessary to introduce a diagnosis measure estimation in order to evaluate and define a confidence level.
To that end, the identification of the diagnosis main drivers is required. The objective is then to associate a probabilistic value to the states or modalities likely to be taken by the different parameters in order to build a probabilistic based model. This is what we propose at the following sections.

3.2 Influential Parameters Identification

In wiring system diagnosis, the influential factors for the estimation of the measure uncertainty are gathered into groups:

Table 1. Influential Parameters

Group	Parameter(s)
Cable	gauge, conductivity, permittivity, characteristic impedance, propagation velocity.
Signal	type, amplitude, phase.
Sensors	number, location, localization precision.
Network	topology, geometry.
Fault	type,length, width, location.
Analyser	human, machine.
Environment	

In this work, we focus on sensors number and locations as influential parameters. We consider that the other parameters, described in Table 1 related to cable, injected signal, network, fault, analyser and environment are constant among the whole diagnosis tests.

3.3 Measurement Modelling using Bayesian Network

Bayesian Network is a Directed Acyclic Graph (DAG) which encodes probabilistic relationships among variables of interest NAIM et al. [2007]. It is made of nodes representing variables and edges denoting the direct dependencies between these variables.
In order to reduce Bayesian Network implementation difficulties, we propose to divide the procedure into several steps: (1)wiring network decomposition, (2) sub-network definition,(3) Bayesian Networks design, and (4) integration into a global Bayesian Network PRZYTULA and THOMPSON [2000].

(1) **Wiring Network Decomposition:** When the monitored network topology is extremely complex, embedded diagnosis may need high computing power and processing time to extract relevant information. To overcome these drawbacks, a solution is to distribute the diagnosis inside the network architecture. Then, the wiring network is divided into sub-networks with simpler topologies (in the deterministic case of Fig.3, each sub-network is composed by a single wire). The sub-networks are monitored by dedicated diagnosis systems AUZANNEAU et al. [2007], AUZANNEAU and RAVOT [2007].
(2) **Sub-Network Definition:** After selecting one of the sub-networks for modelling, we need to gather some technical knowledge on that sub-system. This

knowledge may be collected from different sources such as: user manual, testing procedures, statistical information on diagnosis and monitoring and also experts.
In our case, we assume that that some kind of TDR is used to diagnose our wiring network and two types of faults are considered: open circuit and short circuit. We should recall here that each sensor injects a pulse through its corresponding cable which reflects back to the injection port when it crosses impedance discontinuities. Then, the analysis of the received signal gives information (detection and location) about the detected wire fault. In our model, Γ is the reflection coefficient of the wave at the fault, where $\Gamma = 1$ for an open circuit and $\Gamma = -1$ for a short circuit, as depicted on the example of Fig.4.

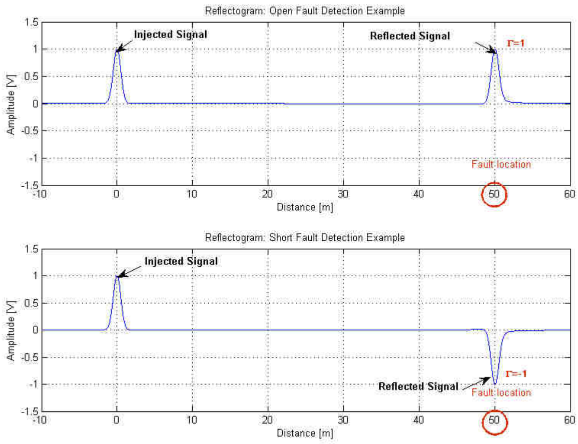

Fig. 4. Obtained Reflectogram Example: Open and Short Circuit Fault

(3) **Bayesian Networks Design:** In this step, the information gathered during sub-network definition and the presence of wiring diagnosis experts are required. As Bayesian Network construction is an iterative process, this phase may be repeated several times. Let's discuss about Bayesian Network design for a wiring sub-network. We assume that the cable to diagnose is perfect (there is no additional noise). We define the variables of interest in Table.2.
The probabilities are provided by diagnosis or maintenance experts. Following, the Bayesian Network may be tested in the presence of diagnosis experts. We notice that our obtained Bayesian model has a simple structure and a low number of probabilities to assess. Thus, it is very attractive in terms of minimal time processing, low complexity implementation and configuration, and minimal resource allocation such as memory.

(4) **Global Model Integration:** In this step, we integrate wiring sub-networks in a global Bayesian Network. To do so, we create an additional top-level integration network. The network selects the subsystem(s) that is (are) defined by diagnosis measure as the source(s) of fault(s).
We should notice, here, that the Bayesian Networks for sub-networks are not isolated from each other.

Table 2. Variables of Interest

Variable	Description	Modality
Sensor_State	diagnosis sensor state	Functioning
		Faulty
RSignal_Nature	reflectogram nature	No pic
		Positive pic
		Negative pic
Fault_Nature	detected fault nature	No Fault
		ShortCircuit
		OpenCircuit
Signal_Injection	pulse signal injection	Yes
		No
Signal_Reception	reflected signal reception	Yes
		No
Sensor_Reliabilty	sensor reliability quality	Low
		Medium
		High
		Very High

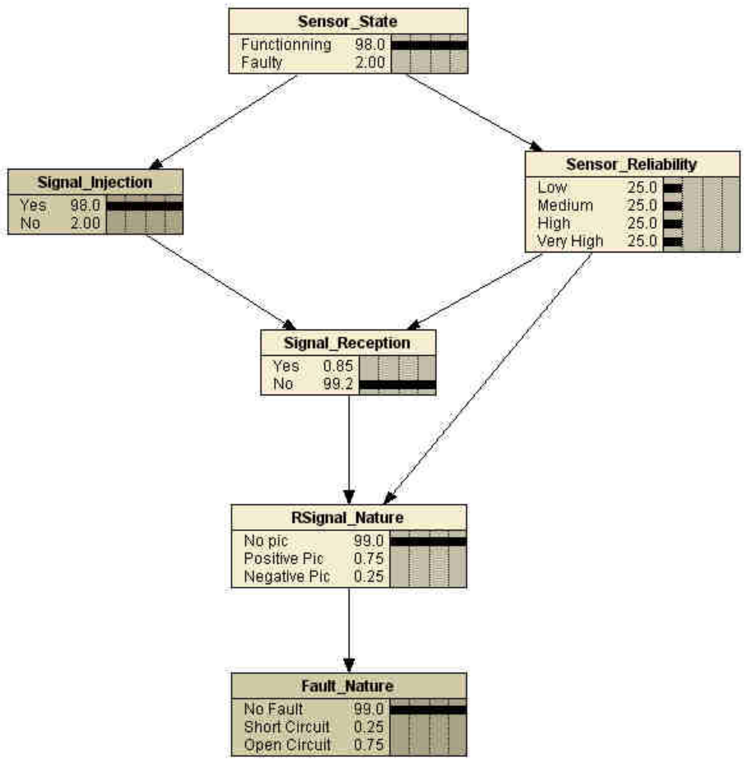

Fig. 5. The Bayesian Network structure.

Each diagnosis sensor may see its own sub-network and a part of other sub-networks causing information redundancies. So, each Bayesian Network should keep track during sub-network modelling of the influences of its sub-networks neighbours. The simplest solution is to apply a communication protocol between diagnosis sensors to share information and decision. This is not the purpose of this paper.

After obtaining a measure of the diagnosis in a complex wiring network using Bayesian Networks, it is mandatory to estimate the level of confidence in this measure for our deterministic case. The steps to be followed for evaluating and expressing the diagnosis measure uncertainty are well described in ISO [1995].

3.4 Sensor Number and Location Optimisation

In this step, we aim at reducing the number of sensors in the network with respect to a predefined confidence level (for example 90%). We can tackle this problem by different manners. In one hand, we may randomly remove sensors one by one from the network and estimate at each time the measure uncertainty until we reach a predefined confidence level. In the other hand, we may decompose our network in several generic networks of "Y" or "star' shape AUZANNEAU et al. [2007] as depicted by Fig.6. We note here that each sub-network has only one junction (or ramification). We propose to implement a single sensor

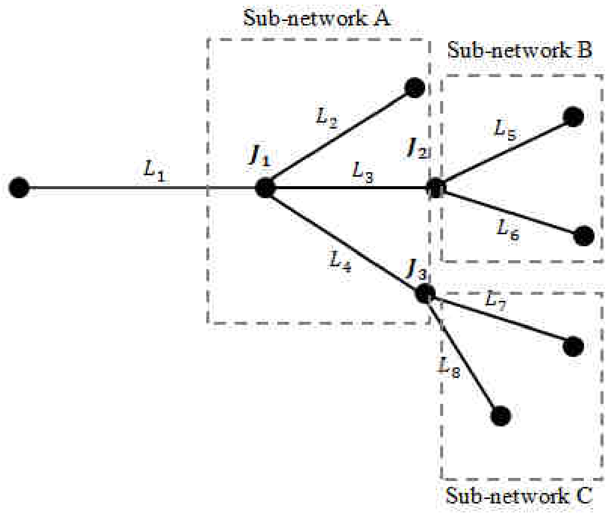

Fig. 6. Complex Wiring Network Decomposition

in each sub-network. Then, we apply the 4 steps process previously described using Bayesian Networks. After obtaining diagnosis measure results, a step of confidence level estimation is introduced to qualify the obtained measure. It is clear that using this approach reduces the number of sensors in the network with respect to some confidence levels and then decreases ambiguities caused by signals interference and information redundancy without neglecting the important cost reduction in terms of purchase, implementation, configuration and maintenance.
In order to validate our approach, we need to compare different sensors implementation procedures, described previously, in terms of diagnosis measure quality, processing time, resource allocation and of course cost which will be the purpose of future works.

4. CONCLUSION

In this work, we proposed a wiring network distributed diagnosis strategy using reflectometry. In the context of complex and very complex wiring networks, we divided the process into several steps: network decomposition, subnetwork definition, Bayesian Networks design for each subnetwork, and finally integration into a global Bayesian Network to extend measure result.
We aimed in this paper at finding a good trade-off between minimal sensors number and wire diagnosis measure uncertainty. Thus, to tackle sensors number optimisation problem, we proceeded in stages. Firstly, we implemented multi-sensor architecture in a deterministic case. Secondly, we defined influential parameters on diagnosis measure. Then, we modelled diagnosis measure using Bayesian Network. Finally, we proposed two different approaches to optimize the sensor number and location in wiring networks. As future works, we will implement and test our proposed strategy to extend the optimal number and location of diagnosis sensors in complex networks.

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