

## Introduction

PhD work is part of the wired networks diagnosis, which aims at detecting, locating and characterizing accurately electrical faults in complex wired networks. The Multicarrier TDR (MCTDR) [1] or (OMTDR) [2] method, have proved their efficiency in detecting and locating faults in simple wired networks, but they remain limited in the case of complex wired networks. Distributed reflectometry, where several reflectometers (sensors) are placed at different points of the complex network, seems like a good solution to overcome this problem [3], [4]. Although the fault location can be determined with a better accuracy using MCTDR test signal, this is due to its good autocorrelation proprieties and its precise control of the spectrum of the injected signals. We thus exploit simultaneously the reflected part of the signal for diagnosis and the transmitted part for communication between the sensors. Since several reflectometry modules are injecting test signals simultaneously, specific signal processing methods are needed to remove interferences between concurrent modules, called, the interference noise [5]. In section I, we propose a method aims to reduce the dispersion effect of the injected signal. In section II, we present a new method allows cancellation of interference noise. Section III proposes a method ensures the communication between sensors by using the transmitted part of MCTDR signal. Finally, In section IV, we present several methods to merge data between different sensors in order to cancel the fault location ambiguity.

## Methods

### I- New method of dispersion compensation

The proposed method aims to reduce the dispersion effect of the wave throughout its propagation in the cable. The objective is to improve the defects localization accuracy.

$$Y(f) = \text{sinc}(\pi f T_e) \sum_{n=-\infty}^{+\infty} \sum_{k=0}^{N-1} c_k e^{j\theta_k} \delta\left(f - \left(\frac{k}{N} + n\right) f_e\right) \cdot e^{j4\pi f_e \frac{k}{N} \left(\frac{1}{v(f)} - \frac{1}{v_m}\right) \Delta x} \cdot \Gamma_d e^{-2\alpha(f) l_d} e^{-\frac{2\omega l_d}{v_m}}$$

$X(f)$ : MCTDR test signal     $G(f)$ : Compensation dispersion term     $H(f)$ : Cable response

### II-Sensors communications by MCTDR

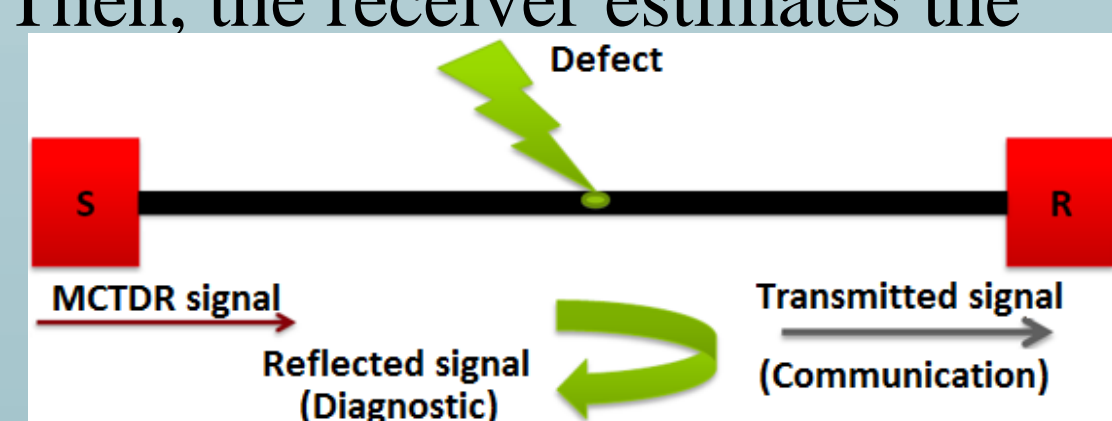
The received signal is given by:

$$Y(f) = \text{sinc}(\pi f T_e) \cdot e^{-\alpha l} \prod_i (1 - \Gamma_i) \sum_{n=0}^{M-1} \sum_{k=0}^{N-1} c_k e^{j(\theta_k - \beta l)} \delta\left(f - \left(\frac{k}{N} + n\right) f_e\right)$$

The phase of this signal is given by:  $\arg(Y(f)) = -\beta(f)L + \sum_{k=0}^{N-1} \theta_k \delta\left(f - \frac{k}{N} f_e\right)$

We transmit message on the sequence of the phases  $\{\theta_k\}$ . Then, the receiver estimates the sent sequence:  $\theta_{k_{est}} = (\arg(Y(f)) - \arg(Y_0(f))) \cdot G_k(f)$

$$G_k(f) = \begin{cases} 1, & \text{if } f = \left(\frac{k}{N} + n\right) f_e \\ 0, & \text{elsewhere} \end{cases}$$



### III-Remove interferences between concurrent sensors

To remove the interference noise, we propose a new method called OD-MCTDR (Orthogonal Distributed MCTDR). It consists in generating an MCTDR signal including subcarriers orthogonal to each other, and allocating a portion of available subcarriers to each sensor. Two signals  $S_n(t)$  and  $S_l(t)$  are orthogonal if they satisfy:  $\int_0^{T_s} S_n(t) S_l^*(t) dt = 0 \Rightarrow \int_0^{T_s} S_n e^{j2\pi n f_n t} S_l e^{-j2\pi n f_l t} dt = 0 \Rightarrow B = N\Delta f = N \frac{1}{T_s}$

The MCTDR signal reaching the reception sensor is written as follows:

$$y(t) = \sum_{k=1}^{N-1} c_k e^{j\theta_k} e^{j2\pi(f_0 + k\Delta f)t} \cdot H_k(t). \text{ The demodulation is performed as follows: } \frac{1}{T_s} \int_0^{T_s} y(t) e^{-j2\pi n \Delta f t} dt = \frac{1}{T_s} \sum_{k=0}^{N-1} \int_0^{T_s} c_k H_k e^{j2\pi(k-n)\Delta f t} dt = c_i H_i.$$

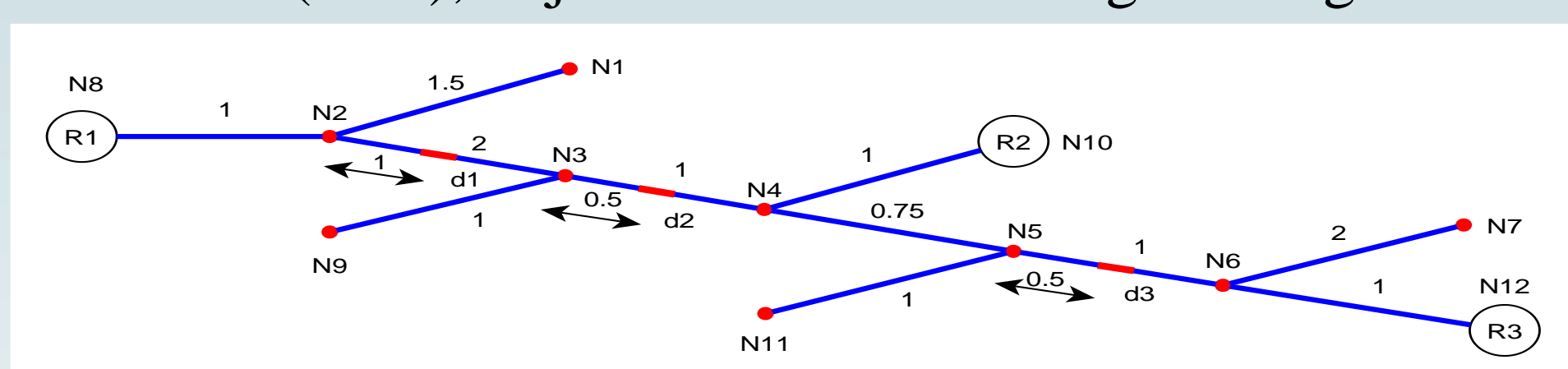
### B- Bayesian fusion

Each reflectometer  $R_j$  gives a probability of the presence of the fault on the branch  $B_k$ , that we will note  $P_{B_k}^{R_j}$ . This probability is obtained by measuring the amplitude of the fault peak in the reflectogram. The set of probability can be represented in a matrix  $m$ . After that, we combine the data between different sensors on the column vectors of the matrix. The combination will be done into a unique probability noted  $p(D_{B_k}/R_1, \dots, R_{N_s})$  by using Independent Opinion Pool (IOP) formula:  $p(D_{B_k}/R_1, R_2) = \frac{p_1 p_2}{p_1 p_2 + (1-p_1)(1-p_2)}$

The branch that represents the highest probability will be considered as the faulty branch.

### C- Graph theory

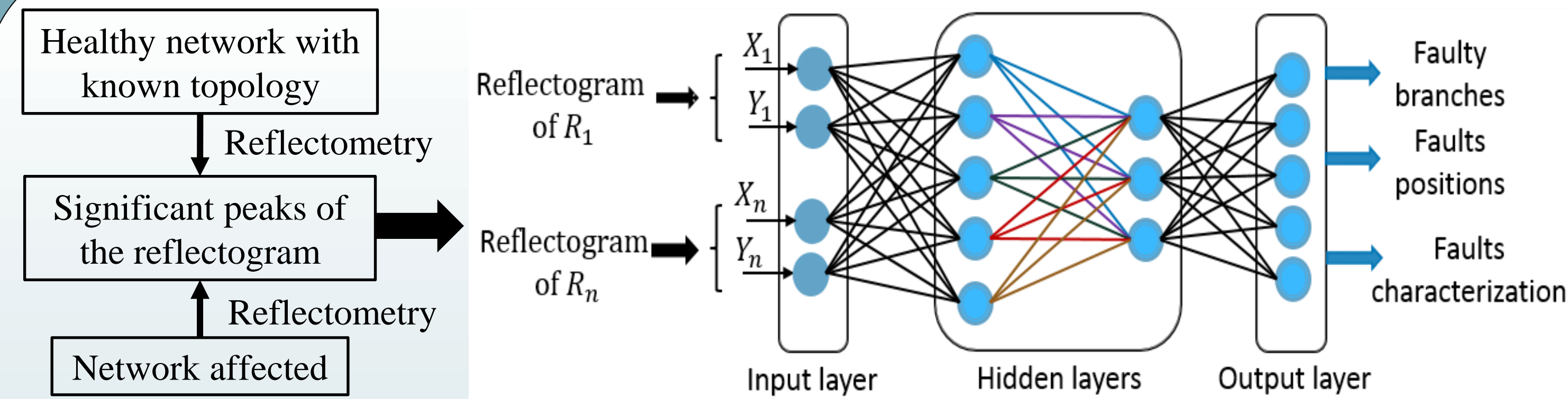
A complex wired network can be represented by a graph  $G = (V, E)$  with set of nodes  $V$  and Edges  $E$ . It can be modeled by the use of connection matrix  $m = \{a_{ij}\}$ . The fusion is performed by using MCTDR test signal combined with the graph theory to locate the soft faults. The fusion is performed using different graph theory algorithms such as: Breadth-first search (BFS), Dijkstra and nearest neighbor algorithm.



### D- Neural network

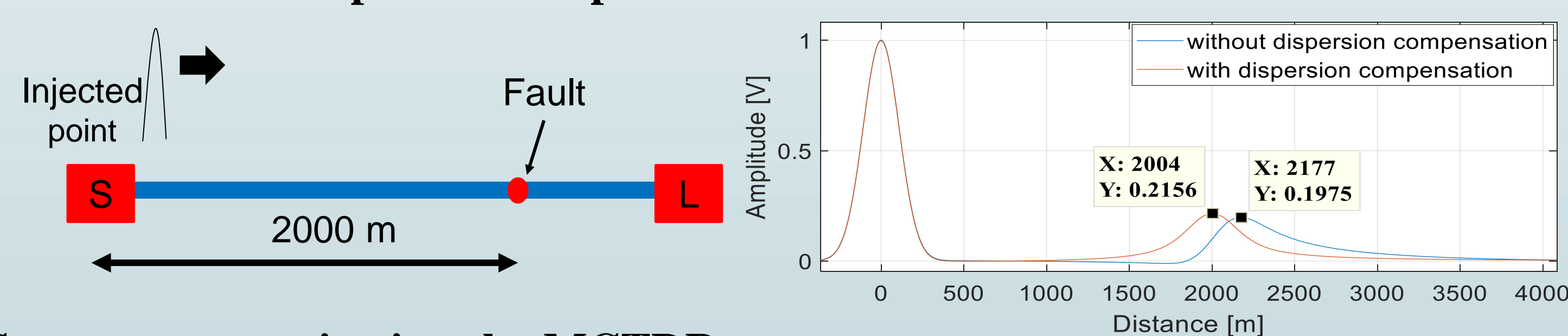
The fusion of data is performed by combining MCTDR method with multilayer-perceptron neural network (MLP-NN). This method provides powerful tools for detecting, locating and characterizing the soft faults in complex wired networks. The required datasets for training and testing the MLP-NN are obtained from the simulation of soft-faults in various scenarios (fault locations and fault resistance).

|          | $N_1$ | $N_2$ | $N_3$ | $N_4$ | $N_5$ | $N_6$ | $N_7$ | $N_8$ | $N_9$ | $N_{10}$ | $N_{11}$ | $N_{12}$ |
|----------|-------|-------|-------|-------|-------|-------|-------|-------|-------|----------|----------|----------|
| $N_1$    | 0     | 1.5   | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0        | 0        | 0        |
| $N_2$    | 1.5   | 0     | 2     | 0     | 0     | 0     | 0     | 0     | 1     | 0        | 0        | 0        |
| $N_3$    | 0     | 2     | 0     | 1     | 0     | 0     | 0     | 0     | 0     | 1        | 0        | 0        |
| $N_4$    | 0     | 0     | 1     | 0     | 0.75  | 0     | 0     | 0     | 0     | 0        | 1        | 0        |
| $N_5$    | 0     | 0     | 0     | 0.75  | 0     | 1     | 0     | 0     | 0     | 0        | 0        | 1        |
| $N_6$    | 0     | 0     | 0     | 0     | 1     | 0     | 2     | 0     | 0     | 0        | 0        | 1        |
| $N_7$    | 0     | 0     | 0     | 0     | 0     | 2     | 0     | 0     | 0     | 0        | 0        | 0        |
| $N_8$    | 0     | 1     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0        | 0        | 0        |
| $N_9$    | 0     | 0     | 1     | 0     | 0     | 0     | 0     | 0     | 0     | 0        | 0        | 0        |
| $N_{10}$ | 0     | 0     | 0     | 1     | 0     | 0     | 0     | 0     | 0     | 0        | 0        | 0        |
| $N_{11}$ | 0     | 0     | 0     | 0     | 1     | 0     | 0     | 0     | 0     | 0        | 0        | 0        |
| $N_{12}$ | 0     | 0     | 0     | 0     | 0     | 1     | 0     | 0     | 0     | 0        | 0        | 0        |

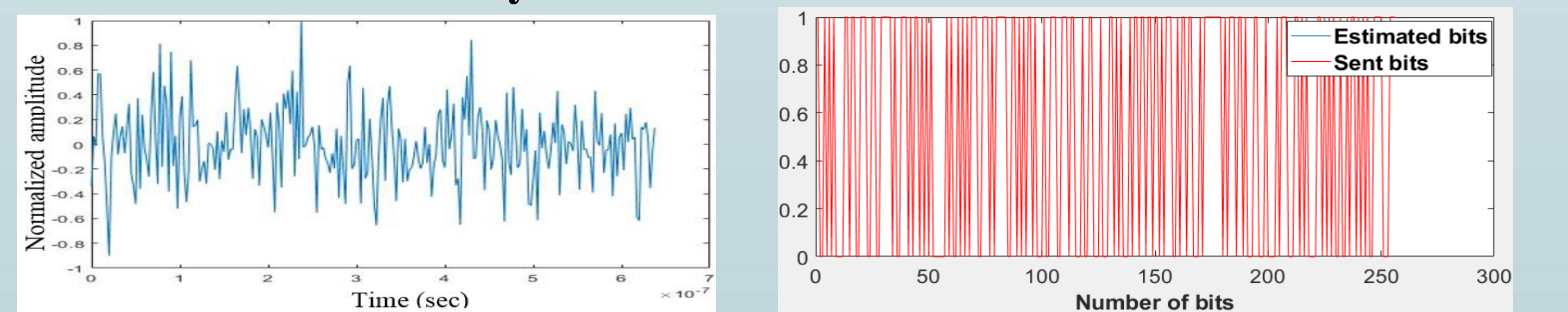


## Results

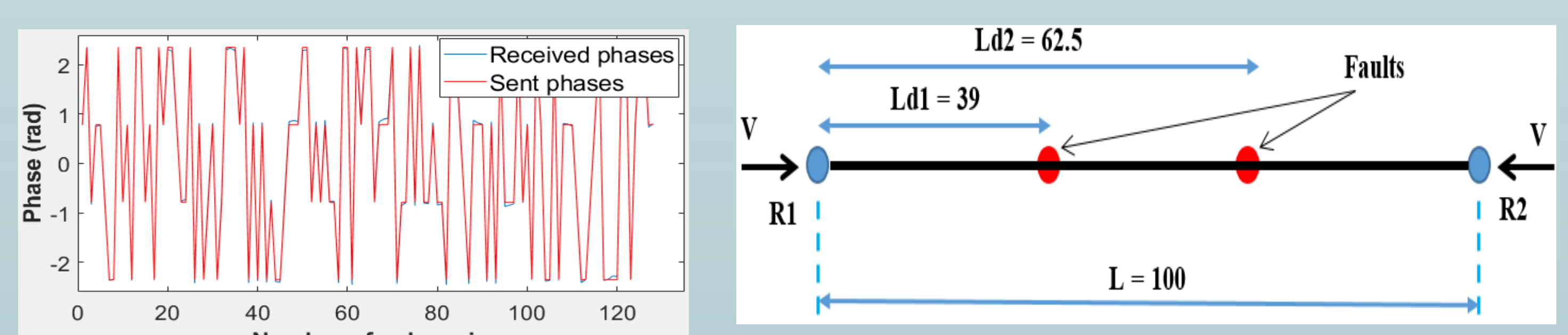
### New method of dispersion compensation



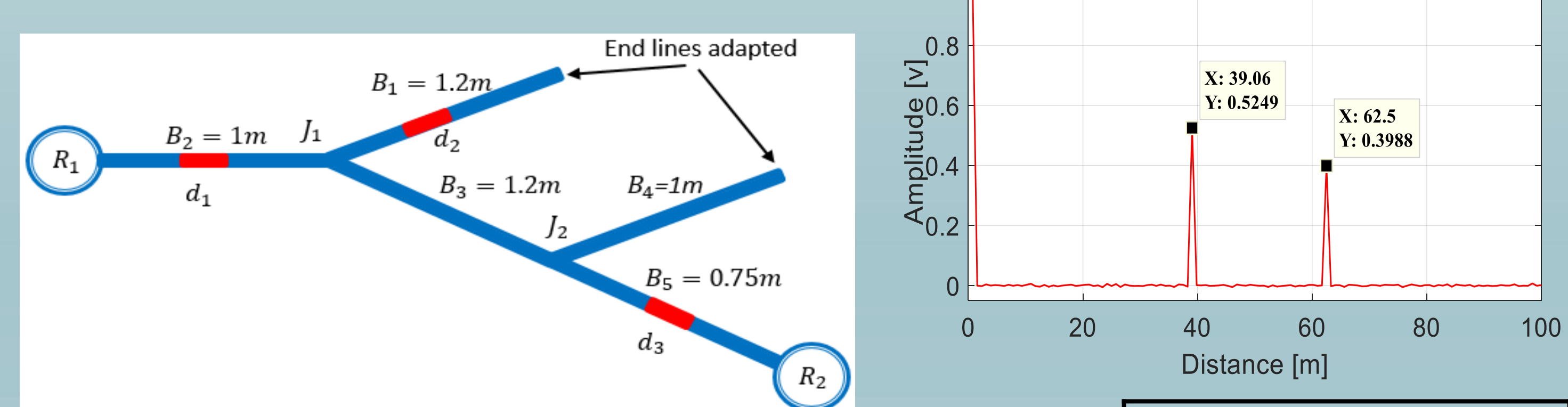
### Sensors communications by MCTDR



### Remove interferences between concurrent sensors



### D- Neural network



| Amplitude [V]  | Distance [m] | Neural Network |          |                  |
|--|--------------|----------------|----------|------------------|
|  |              | Branch         | Position | Z                |
| Soft fault on branch $B_1$ at 0.5 m, $\Delta Z = 15,95\%$<br>$\Delta Z + Z_c = 120 + 13.29 = 133,29\Omega$ |              | 1              | 0.5044   | 133.16 $\Omega$  |
|  |              |                |          |                  |
| Amplitude [V]  | Distance [m] | Neural Network |          |                  |
|  |              | Branch         | Position | Z                |
| Soft fault on branch $B_2$ at 0.5 m, $\Delta Z = 18,7\%$<br>$\Delta Z + Z_c = 120 + 15.59 = 135,59\Omega$  |              | 2              | 0.4947   | 135.683 $\Omega$ |
|  |              |                |          |                  |
| Amplitude [V]  | Distance [m] | Neural Network |          |                  |
|  |              | Branch         | Position | Z                |
| Soft fault on branch $B_5$ at 0.5m, $\Delta Z = 18,2\%$<br>$\Delta Z + Z_c = 120 + 15.18 = 135,18\Omega$   |              | 5              | 0.503    | 135.619 $\Omega$ |
|  |              |                |          |                  |

## Conclusions

Distributed reflectometry, where several sensors are placed at different points of the network, seems like a good solution to overcome the fault location ambiguity. In this work we propose methods for canceling the interference noise and ensuring the communication between the sensors. We propose also several methods to ensure data fusion between the sensors. Neural network method seems to be the fastest and most efficient method, which allows to detect, locate and characterize multiple soft faults in complex wired networks. In future works, we aim to demonstrate the accuracy of proposed methods by experimental measurements.

## Bibliography

1. A. Lelong, M. Carrion, "On line wire diagnosis using multicarrier time domain reflectometry for fault location," In Sensors, 2009 IEEE 751-754, October 2009.
2. W. Ben Hassen, F. Auzanneau, "On-line diagnosis using Orthogonal Multi-Tone Time Domain Reflectometry in a lossy cable," in Proceedings of the 10th International Multi-Conference on Systems, Signals and Devices (SSD '13), pp. 1-6, March 2013.
3. N. Ravot and F. Auzanneau, "Defects detection and localization in complex topology wired networks," Ann. Telecommun., vol. 62, nos. 1-2, pp. 193-213, Jan. 2007.
4. W. Ben Hassen, F. Auzanneau, F. Peres, and A. Tchangan, "Diagnosis Sensor Fusion for Wire Fault Location in CAN Bus Systems," in IEEE SENSORS, Nov 2013, pp. 1.
5. A. Lelong, L. Sommervogel, N. Ravot, and M. Olivas, "Distributed Reflectometry Method for Wire Fault Location Using Selective Average," IEEE Sensors Journal, vol. 10, no. 2, pp. 300-310, February 2010.