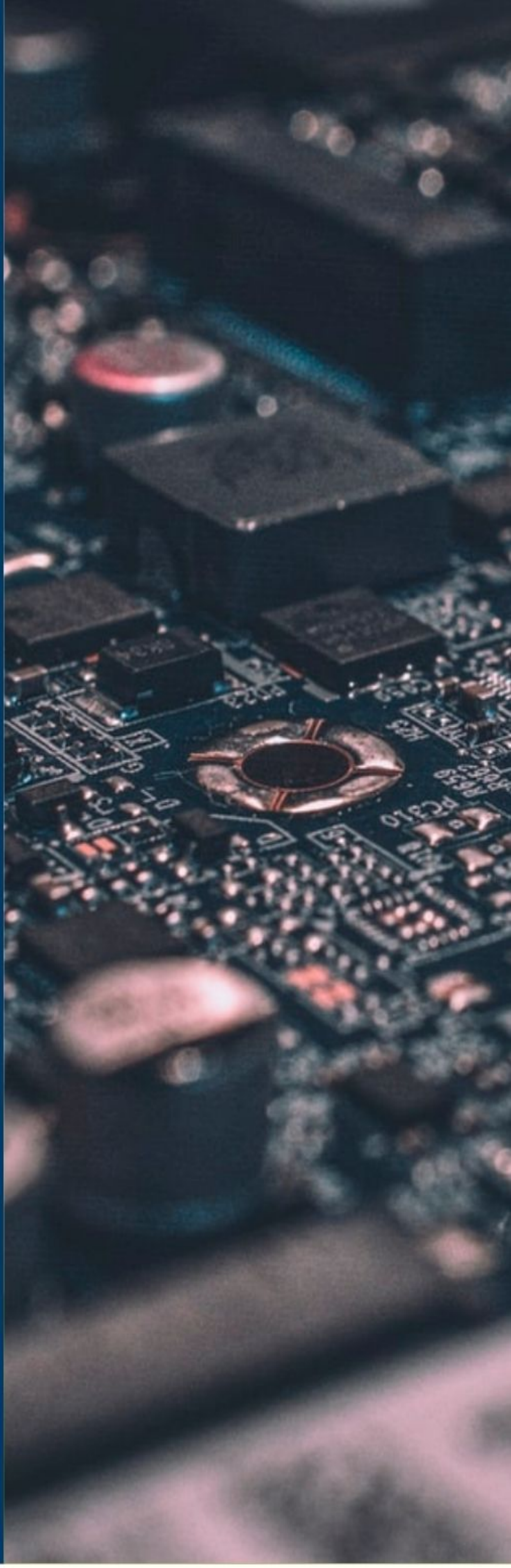

Localisation of faults in wiring networks using time domain reflectometry and adaptive neuro-fuzzy inference system

A. Laib✉, M. Melit, B. Nekhoul, H. Boudjefdjouf and H. Bouchekara

The aim the present research is to develop a new approach for the localisation of faults in wiring networks based on adaptive neuro fuzzy inference system (ANFIS) and time domain reflectometry (TDR). In this approach a forward model has been developed and validated with measurements in order to generate a TDR response of any wiring network then the inverse problem is solved using ANFIS. The developed approach has been tested using a complex configuration that is YY-shaped network. The results show the efficiency and accuracy of the proposed approach.

Introduction: Modern electric power networks are able to handle more and more complicated tasks where their main functions are to transfer energy and information where they are needed. In order to guarantee the performance such systems, safety is of paramount importance. Therefore, an accurate and efficient diagnosis is needed. Time domain reflectometry (TDR) is commonly used to detect and localise faults in wiring networks; where a specific signal is injected into the wiring network at an injection point (this can be the origin point) and collect the reflected signals. However, TDR technique, when it used alone, might not be able to give complete information about the wiring network under test, especially in the case of complex networks. In [1], TDR is combined with an artificial neural network to detect and locate faults, this approach is efficient to detect and locate faults in complex networks but it has a major disadvantage that it needs big data for training. Recently, alternative approaches using TDR and iterative-based optimisation methods such as genetic algorithm [2, 3], electromagnetism-like mechanism [4], particle swarm optimisation [5, 3], teaching–learning-based optimisation [6], backtracking search algorithm [7], and black hole [8] are used to detect, locate and characterise faults in wiring networks. However, the major drawback of these methods is that they are computationally expensive and therefore, they need a long time to converge. To overcome the above mentioned drawbacks of exiting methods, i.e. small data for training, the ability to perform an online diagnosis, a new approach based on TDR and adaptive neuro fuzzy inference system (ANFIS) is proposed in this Letter. In this approach, the TDR response of the wiring network under test is calculated using the finite difference time domain (FDTD) method then ANFIS is applied to solve the inverse problem for localising faults in complex wiring networks.

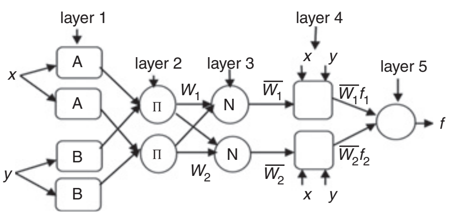

Fig. 1 *First order Sugeno ANFIS architecture (Type-3 ANFIS)*

Adaptive neuro-fuzzy inference systems: An ANFIS works by applying neural learning rules to identify and adjust the parameters and structure of a fuzzy inference system (FIS) [9]. The attractive features of an ANFIS based only on the available data include: excellent explanation facilities through fuzzy rules easy to implement, fast and accurate learning, strong generalisation abilities, and easy to incorporate both linguistic and numeric knowledge for problem solving [10]. We assume that the examined FIS has two inputs and one output. For a first-order Sugeno fuzzy model, a typical rule set with two fuzzy 'if then' rules can be expressed as follows:

$$\text{If } x \text{ is } A_1 \text{ AND } y \text{ is } B_2 \text{ THEN } y_1 = f_1(x, y) = p_1 x + q_1 y + r_1$$
$$\text{If } x \text{ is } A_2 \text{ AND } y \text{ is } B_2 \text{ THEN } y_1 = f_2(x, y) = p_2 x + q_2 y + r_2$$

The ANFIS system has a total of five layers [9] as shows in (Fig. 1).

ANFIS uses two sets of parameters: a set of premise parameters and a set of consequent parameters where the premise parameters are the membership function parameters and the consequent parameters are the first order Sugeno rule parameters (*pi*, *qi*, *ri*). ANFIS uses a hybrid learning algorithm to update the parameters of the network, where back propagation gradient descent methods and the least-squares are used for training FIS membership function parameters and the first order Sugeno rule parameters (*pi*, *qi*, *ri*) to model a given set of input/output data. More details about ANFIS architecture, rules, layers, and functions are available in [9–11].

Forward model: The forward model is used in order to get the TDR response of any wired network. The propagation in Network Transmission Line (NTL) can be modelled using a RLCG circuit model [12], the corresponding equations are:

$$\frac{\partial}{\partial z} v(z, t) = -R \cdot i(z, t) - L \cdot \frac{\partial}{\partial t} i(z, t) \tag{1}$$

$$\frac{\partial}{\partial z} i(z, t) = -G \cdot v(z, t) - C \cdot \frac{\partial}{\partial t} v(z, t) \tag{2}$$

where R, L, C and G: are the per-unit-length parameters, the series resistance, the series inductance, the shunt capacitance and the shunt conductance, respectively [12]. The time-domain analysis of the MTL is determined by the FDTD method [12]. The length of the spatial cell size Δz and sampling interval Δt is chosen by insurance of the stability condition on the time stepping algorithm $\Delta t = \Delta z / v$, with v is the propagation velocity.

Validation of the developed forward model: The RG58 CU coaxial cable shown in Fig. 2 has been used for this network where the distributed parameters L, and C, R, G can be calculated based on the formulation given in [13] and is evaluated as follows: $C = 100 \times 10^{-12}$ F/m, $L = 250 \times 10^{-9}$, $G = 2w \times 10^{-13}$ S/m, $r = 0.02\,\Omega$/m. The YY-shaped network used here is sketched in Fig. 3, this network is composed of five branches that are L1 = 1 m, L2 = 4 m, and L3 = 1 m, L4 = 0.5 m and L5 = 1.5 m. The network is affected with one a hard fault (short circuit) in branch L2 at a distance of 2.4 m form the origin.

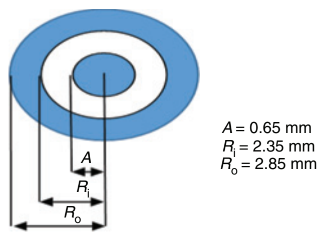

Fig. 2 *Cross section of the used cable*

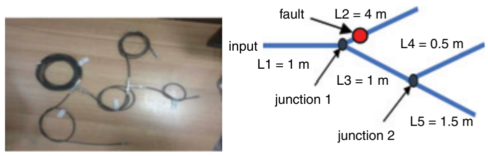

Fig. 3 *YY-shaped network used for the validation of the forward model*

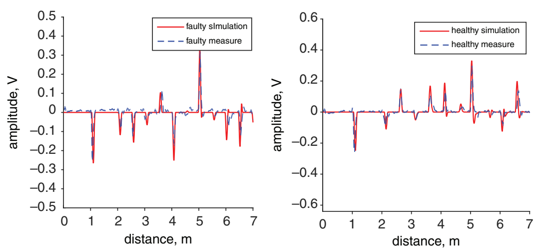

Fig. 4 *Comparison between measured and simulated TDR responses of the healthy and faulty Y Y-shaped network*

Fig. 4 shows a comparison between the TDR response obtained using measurement and the one obtained using the developed forward model for the two cases of healthy and faulty network wiring network. It can be seen from this figure that there is a good agreement between measured and simulated TDR responses. The small differences between the simulated and measured values may be due to variation between the ideal and actual characteristic impedance of the cable.

Inversion result: In this case the faulty YY-shaped network investigated in the previous section is considered. The inverse problem is solved by applying the ANFIS method where the difference between the voltage signals of healthy and faulty networks is used. Once this difference is calculated, the maximum value of this difference and its corresponding time i.e. the appearance time (t) are identified. This time is used than for the localisation of faults. The diagram of the proposed approach is shown in Fig. 5.

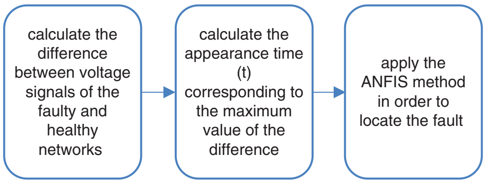

Fig. 5 *Diagram of proposed approach based on ANFIS*

Wang *et al.* [14] restricts the size of the training data to be about 5 times the number of modifiable parameters (premise parameters and consequent parameters), where these parameters depends on fuzzy ‘if then’ rules of a Takagi and Surgeon’s type. Modifiable parameters are the number of premise parameters plus the number of consequent parameters. The efficiency of the ANFIS method is improved by changing the number of rules from two to six as illustrated in Table 1. The obtained results using ANFIS method are tabulated in this Table 1. The generalization capability of the ANFIS is examined using the RMS error obtained on the test set which contains input/output data not contained in the previous set, The ANFIS training time, is about 2 min and 10 s using a PC equipped with Intel(R) Core (TM) i3-2310M Processor and 4 Gb of RAM. It is worth mentioning that, the creation of the needed databases and the training of the ANFIS can be performed offline. It can be noted from Table 1 that, the ANFIS method is very efficient for the localisation of the hard faults affecting the YY-shaped wiring network. This can be justified by the small value of error found. Furthermore, the computational time is very low (<1 s), this offers the ANFIS method the ability to be applicable online. Moreover, it is shown that the number of examples used for both training and validation is low (about 120 examples in the case of two rules and about 360 examples in the case of six rules) and this number is sufficient to train and validate the ANFIS architecture.

Table 1: Efficiency of the ANFIS method for the localisation of faults for the YY-shaped network

Number of rules	2	3	4	5	6
Number of modifiable parameters	12	18	24	30	36
Length of training data $5 \times$ total number of parameter	60	90	120	150	180
Length of validation data $5 \times$ total number of parameter	60	90	120	150	180
Length of testing data	1960	1900	1840	1780	1720
Length of total data	2080	2080	2080	2080	2080
Localisation error (m)	3.11×10^{-4}	2.04×10^{-4}	2.54×10^{-4}	2.02×10^{-4}	1.87×10^{-4}
Computational time (s)	0.274	0.224	0.217	0.228	0.227

Conclusion: In this Letter a new approach based on ANFIS is proposed for the localisation of faults in wiring networks based on time domain reflectometry. The wiring network has been modelled using MTL approach where the transmission line equations have been resolved using FDTD method. The developed forward model has been validated using measurements. A complex configuration that is the YY-shaped networks have been investigated. The obtained results for the localisation of faults are very accurate based on the small value of error found. It has been demonstrated that the ANFIS method doesn’t need big data for training.

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One or more of the Figures in this Letter are available in colour online.

A. Laib, M. Melit and B. Nekhoul (*LAMEL Laboratory, University of Jijel, BP 98 Ouled Aissa, 18000 Jijel, Algeria*)

✉ E-mail: abderrzaklaib@yahoo.fr

H. Boudjefdjouf and H. Bouchekara (*Constantine Electrical Engineering Laboratory, LEC, Department of Electrical Engineering, University of Freres Mentouri Constantine, 25000 Constantine, Algeria*)

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