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Soft Fault Identification in Electrical Network using Time Domaine Reflectometry and Adaptive Neuro-Fuzzy Inference Systeme

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Abstract*—the main purpose of this work is to implement a new and accurate approach based on Time Domain Reflectometry (TDR) combined with Adaptive Neuro-Fuzzy Inference System (ANFIS) to solve the problem of soft faults detection and localization on complex wiring electric network. Firstly, the response of the transmission line is given by applying the Finite Difference Time Domain method (FDTD) on the transmission line equations. Then, the ANFIS method is used to solve the inverse problem which permits to detect and localize the soft fault. Finally, very acceptable results are obtained and many problems are solved at the same time as: defining the exact position and exact resistance values of the fault, defining the state of electrical network in the real time.

***Keywords*— soft fault; electric network; identification; transmission line; reflectometry. Adaptive Neuro-Fuzzy Inference System**

I. Introduction

The most modern electric systems are composed by wiring networks like as transportation systems, nuclear facilities, buildings, power distribution systems, industrial machinery...etc where the transmission of information and energy is decisive for their appropriate functioning, for this reason the security of this modern systems requires exigency of the wire diagnosis to detect and locate electric faults, Time Domain Reflectometry (TDR) is the most used technique for wire fault identification, their basic idea is to inject a signal in the network and analyze the reflected signal, this last includes information about the faults, different methods of reflectometry are developed like as Time-Frequency Domain Reflectometry (TFDR), Spectrum Time Domain Reflectometry (STDR) [1]□[2] . Although known Reflectometry is an efficient method to diagnose simple topologies, it remains limited in the case of complex multi branch networks, in [3] TDR is combined with adaptive neuro-fuzzy inference system in order to locate the hard faults in complex electrical network ,also in [4] TDR is combined with wavelet and Neural Network in order to detect and locate hard faults .However, although known Reflectometry methods are efficient in the case of hard faults (open and short circuits) that produce important reflection but they are not able to detect and localize the soft faults like as frays or chafes that produce small anomalies, several works like as presented in [5] use the baseline method where output signal of the faulty wiring is compared with the output of the healthy wiring to detect and locate soft faults, this approach is efficient to find soft faults, but it is not capable to define the nature of faults by giving the exact resistance values, also TDR is combined with Neural Network (NN) in [6] to detect and localize faults, where NN is trained with data includes information about wiring network topology offline and use it online if required, this method is efficient to detect and localize faults in complex network but the main inconvenient of this last is necessity to a big data for training which is very difficult to create it, in alternative approach (Genetic Algorithm (GA) [7]-[8], Particle Swarm Optimization (PSO) [8], is to use a direct model in iterative procedure, where each one from previously methods is applied to the inverse process after generated TDR response and compared with measured one, however the inconvenient of these methods is computationally expensive where they need very long time for diagnosis, for solving these two problem (detect and localize of soft faults with a small data for training, diagnosis online) the combination of the time Domain Reflectometry (TDR) and the Adaptive Neuro Fuzzy Inference System (ANFIS) method is proposed, where the response of the transmission line is obtained using the Finite Difference Time Domain method (FDTD) applied to transmission line equations, and the adaptive ANFIS method is applied to solve the inverse problem for identifying the soft faults.

II. RLCG Model of Transmission Line

The propagation in Multiconductor Transmission Line (MTL) is modeled by RLCG circuit model where the differential equation is defining by:

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

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

And R, L, C and G: are the per-unit-length parameters, respectively, the series resistance, the series inductance, the shunt capacitance and the shunt conductance [9]. Finite Difference Time-Domain (FDTD) method is used to determinate the time-domain analysis of the MTL. This method converted the differential equations into recursive finite difference equations, and discretized the space variable (line axis) in Δz increments also the time variable t is discretized in Δt increments, the derivatives in MTL equations is approximated by the finite differences. In this work the length of the spatial cell size Δz and the sampling interval Δt are chosen by verifying the stability condition $\Delta t = \Delta z/v$.

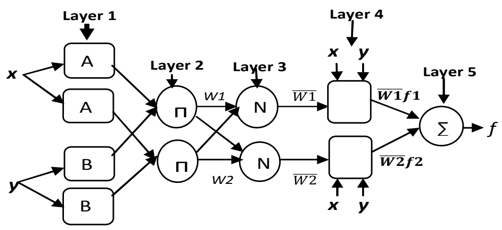
III. Adaptive Neuro-Fuzzy Inference System (ANFIS)

The Adaptive Neuro-Fuzzy Inference System (ANFIS) is a hybrid model which combines the Neural Network (NN) adaptive capability and the Fuzzy Logic (FL) qualitative approach [10]. Took both advantages Jang [10] combining the two techniques, and proposed the (ANFIS) where is a hybrid intelligent system which he implements a Sugeno fuzzy inference system for a systematic approach to generating fuzzy rules from a given input output dataset. We assume that the rule base contains for fuzzy if-then rules of a Takagi and Sugeno's type:

$$If\ x\ is\ A_1\ AND\ y\ is\ \ B_2\ THEN\ \ f_1(x,y) = p_1x + q_1y + r_1$$

$$If\ x\ is\ A_2\ AND\ y\ is\ \ B_2\ THEN\ \ f_2(x,y) = p_2x + q_2y + r_2$$

The ANFIS architecture contains a five-layer as shown in Fig.1 [10].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 the least-squares and back propagation gradient descent methods are used for training Fuzzy Inference Systems FIS (membership function parameters and the first order Sugeno rule parameters (pi, qi, ri))to model a given set of input/output data[10].



IV. Proposed Approach

A. Hybrid TDR_ANFIS

First, the signal of voltage difference between healthy and faulty response of network is used from the input of electrical network to extract two groups of candidate features, fig 2 based on TDR difference signal where the max amplitude is selected with it corresponding time appearance, the first group of candidate is the time appearance (t) of the max voltage magnitude which is used to localize the fault, the second group of candidate is the value of max voltage magnitude where used to define the nature of faults by given the corresponding resistance value. The inverse problem is used by applying Adaptive Neuro-Fuzzy Inference System (ANFIS) to detect and localize faults in electrical network. the combination of least-squares and back propagation gradient descent methods is used for training FIS premise and consequent parameters.

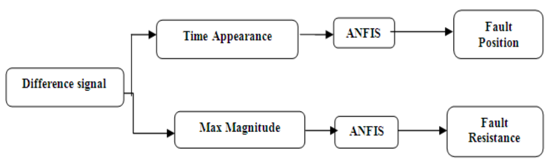


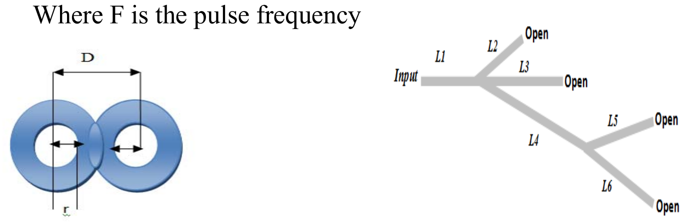
Figure 2.Diagram of the proposed algorithm

V. Simulations Results

*A. Validation:*Our MTL model is validated with published results in [7], the configuration illustrated in Fig 3.b has been considered, where network consists of cable with cross section shown in Fig 3.a, the conductor radius r = $0.5e^{-3}$ m and separation D = $2.06e^{-3}$ m. The distributed parameters L, and C, R, G can be calculated based on formulation in [11]. The complex network includes six branches: L1 = 1 m, L2 = 0.60m, L3 = 2.25 m, L4 = 4.25m, L5 = 1.75m, and L6 = 1m, the type of termination of the branches is indicated at the end of the branch. The source signal is a raised cosine pulse as follow:

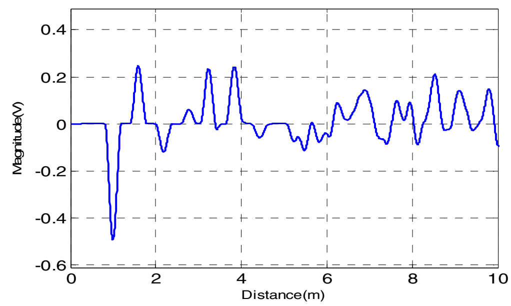
$$e(t) = \begin{cases} 0.5(1-\cos(2\pi Ft)) & 0 < t < \frac{1}{F} \\ 0 & otherwise \end{cases} \quad (3)$$

Where F is the pulse frequency

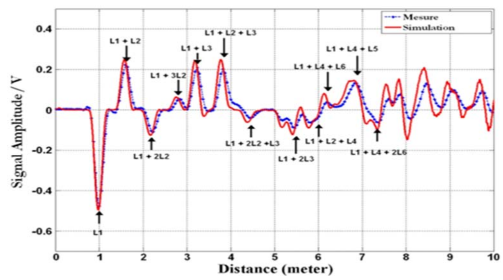


(a). Cross-section of used cable (b) .Configuration of network under study

Figure 3. Network under study



(a) .Network reflectometry response,



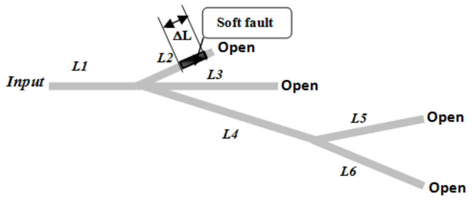
(b) .Published results by [7].

Figure 4. Reflectometry response

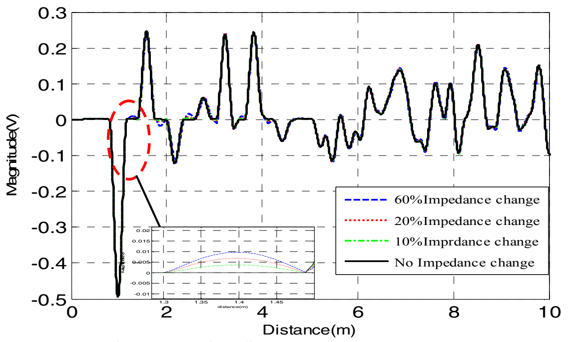
The comparison between our numerical results and measurements published by [7] is carried fig 4 . It is shown that our simulation results based on resolving transmission line equations by FDTD is comparable with the measured result in [7]. This fact confirms the efficiency of our proposed approach and permit to use our model to make a detailed investigation.

B. Parametric Study

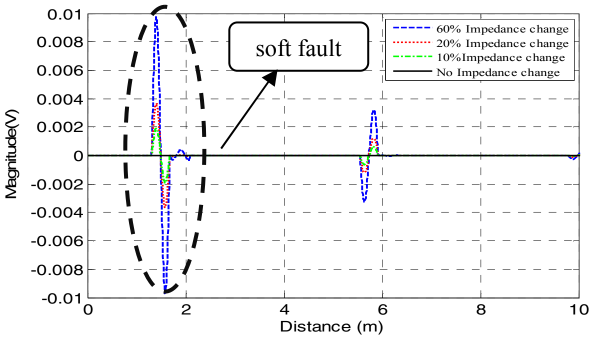
The configuration illustrated in fig 3.b has been studied .the wiring network affected by one soft fault in the branch L2 at 1.4 m from the input (Fig.5.a). The length of the soft fault is ΔL = 2 cm where a local change in impedance of: 10%, 20%, 60% respectively from characteristic impedance (Zc=78.92).



(a). Configuration under study



(b). Network reflectometry response



(c). difference signal between healthy and faulty network,

Figure 5. Results of network affected in branch L2

It is shown in Fig.5.b that the reflectometry response of the network, the soft fault generate small variation in the signal, in this case it is very difficult to detect and localize the fault unlike this variation is very clear when we use the difference signal between healthy reflectometry and faulty reflectometry Fig.5 .

C. Inversion Results

The inverse problem is used by four ANFIS for the two cases Fig.6. The first $ANFIS_P$ is used for localizing faults in electrical network and we use the last three $ANFIS_r$ for defining the fault's resistance. The number of $ANFIS_r$ used to defining the faults are selected because of the junctions, the distributed $ANFIS_r$ is describes as follow: the first $ANFIS_r1$ is used to characterize the faults situated before junction J1, the second $ANFIS_r2$ is used to characterize the faults situated between junction J1 and junction J2 and the third $ANFIS_r3$ is used to characterize the faults situated after junction J2. The datasets are constituted of examples linking the time appearance (t) of max amplitude to the position of the fault and the max voltage amplitude to it corresponding fault resistance.

Wang and Al. [12] shows that the size of the training data can be reduced to about 5 times the number of modifiable parameters (both premise and consequent parameters). In our work the number of examples input/output database is 1580 examples for each $ANFIS_r$: training set (13% of all samples), validation set (13% of all samples) and testing set (74 % of all samples), where the number of total parameter is 36, and about 1215 examples for $ANFIS_p$, training set (10% of all samples) , validation set (10% of all samples) and testing set (80 % of all samples) where the number of total parameter is 24.

The table I represent the length of data used for training validation and testing both of $ANFIS_p$ and $ANFIS_r$.

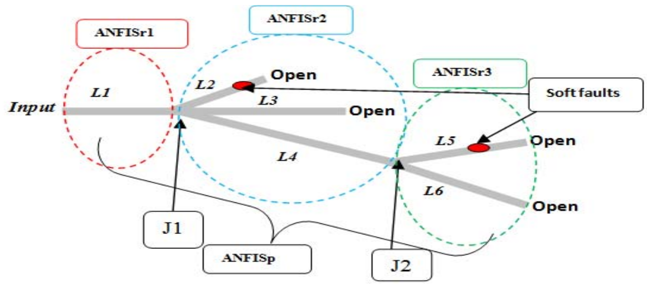


Figure 6. Distributed ANFIS

TABLE .I. The length of training, validation and testing data used.

Data length	$ANFIS_p$	$ANFIS_r$
Training data (5 * Total number of parameter)	**122**	**182**
Validation data (5 * Total number of parameter)	**122**	**182**
Testing data	**971**	**1216**
Total data	**1215**	**1580**

The table II shows the efficiency of distributed (ANFIS) method on identification and localization of soft faults.

TABLE.II. Identification of two different soft faults using ANFIS

	ΔZ = 10 % **ΔZ + Zc = 86.49 Ω**	**ΔZ = 20 %** **ΔZ + Zc = 94.34 Ω**	**ΔZ = 60 %** **ΔZ + Zc = 125.8 Ω**
soft fault at 1.4 m	**86.49086 Ω**	**94.34946 Ω**	**125.7996 Ω**
	1.39862 m	**1. 39862 m**	**1. 39862 m**
soft fault at 6 m	**86.48959 Ω**	**94.34956 Ω**	**125.80009 Ω**
	6.0015 m	**6.0015 m**	**6.0015 m**

Table II Confirm the efficiency of distributed (ANFIS) method on identification and localization of the soft faults, it is shown

that soft fault has been carefully appointed with small error both on localization and identification

TABLE.III. Comparison of the fault identification using with Genetic Algorithm [6] and the our new approach based on ANFIS

		ΔZ = 10 % ΔZ+Zc = 86.49 Ω	ΔZ = 20 % ΔZ+Zc = 94.34 Ω	ΔZ = 60 % ΔZ + Zc = 125.8 Ω
GA [7]		**85.52 Ω**	**96.13 Ω**	**124.25 Ω**
		5.96 m	**6.03 m**	**5.91 m**
ANFIS		**86.48959 Ω**	**94.34956 Ω**	**125.80009 Ω**
		6.0015 m	**6.0015 m**	**6.0015 m**

The results parented in Table III confirm the efficiency of ANFIS in the identification of soft fault. It is shown that GA technique used in [7] occurs some error both on the localization and the identification, we notice that the fault is situated at 6 m with different values of impedance (ΔZ = 10%, 20% and 60%), this proved that GA technique is not very efficient to detect and characterize the fault, we can see that the ANFIS method can solve this problem; we see that the soft fault resistance has been accurately determined, either the soft fault is localizing with exact precision (Table II).

TABLE IV. Comparison of Computational time diagnosis obtained with published results and the new approach based on ANFIS

	Error (m)	Computational time
Genetic Algorithm (GA) published results by [8]	**$5.75*10^{-4}$**	**94.60 mn**
Particle Swarm Optimization (PSO) published results by [8]	**$4.75*10^{-4}$**	**26.36 mn**
Adaptive Neuro-Fuzzy Inference System (ANFIS)	**$1,17*10^{-3}$ for ANFISp $5.98*10^{-4}$ for ANFISr**	**Less 1 second**

Table IV demonstrate the efficiency of our proposed approach in computational time diagnosis where the inversion carried out with this method is very fast (less than 1 s with $1.17*10^{-3}$ m error for fault localization and error about $5.98*10^{-4}$ Ω for fault identification) in addition that can be achieved "online". On the contrary, an iterative method (Genetic Algorithm; GA), requires 94.60 min with an error $5.75*10^{-4}$m and 26.36 min with error $4.75*10^{-4}$ m in the case of Particle Swarm Optimization (PSO) to find the state of configuration in [7].

TABLE V. Comparison of data used to training Neural Network and our proposed approach based on Adaptive Neuro-Fuzzy Inference System (ANFIS)

	Number of data used for training
Neural network published results by [6]	**21000**
Adaptive Neuro-Fuzzy Inference System (ANFIS)	**122 for $ANFIS_p$;219 for $ANFIS_r$**

Table V shows that ANFIS does not need a huge data for training. In fact, only 122 examples is sufficient for training ANFISp which is used to localize the fault and not more than 219 examples for training ANFISr which use to define the resistance of the fault. In the other side, Neural Network need to big data for training (21000 examples to train it).

VI. CONCLUSION

A new method has been proposed in this paper, it is based on TDR and ANFIS techniques. The electrical network is modeled using MTL approach where the transmission line equations are resolved using FDTD method. Our MTL model is validated by comparison with [7] and satisfactory results are obtained. The inverse problem is applied by ANFIS method; very acceptable results are obtained where the soft fault has been accurately determined. Unlike GA where occurs some errors both on localization of soft fault and definition of it corresponding resistance value [7], also the state of the network is defined on line where our approach is compared with published results in [6], also the efficient of ANFIS method is proved; we are demonstrate that our proposed approach need a relatively small data for training compared to published work [6].

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