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Fault detection on the transmission lines using fuzzy neural network

Duong Hoa An, Nguyen Thanh Thuy, Truong Tuan Anh

Abstract - **The faults can happen to transmission lines at any time, any places and caused by different reasons. An accurate and fast solution to detect, locate and isolate the faults will improve the quality of the power systems' performance. The Time-Domain Reflectometry (TDR) method has been used to detect the fault location based on the time a pulse signal need to travel from the begin of the lines to the fault location and back. But due to the presence of non-resistance elements and nonlinear elements on the lines, the reflected impulse was deformed, which in turn reduces the accuracy of the travelling time calculation. In this paper, a Neuro-fuzzy network was used to improve the fault location detetion based on the analysis of reflected waveforms on the transmission lines after sending the pulse into the line. This paper presents the numerical results using Matlab-Simulink models to show the high quality of the proposed method.**

Index Terms **—fault detection, time domain reflectometry, TSK neural network.**

I. Introduction

The electric system is a complex system in both structure and operation so the faults of any element in the system will affect the power supply reliability, power quality. Some fault can be serious and may cause massive economic damage.

Therefore, the identification and fast fix of faults on transmission lines to reduce the economic losses and to improve the reliability and quality of electricity supply to the consumers is very necessary.

When the faults have happened, the protection element acted to isolate the faults. Later we need to locate the position of the fault. One of the proposed methods is the time domain reflectometry (TDR). This method will use a pulse generator circuit (voltage/current) to apply at the beginning of the transmission line. After sending the pulse into the line, we will track and record the reflected signal. The analysis of reflected waveforms on the transmission lines to detect the fault location and to estimate the fault resistance and the load characteristics. Due the presence of non-resistance and non linear elements on the lines, the reflected waveform is deformed, which causes error when estimating the moment the reflected wave gets back to the beginning of the line.

This paper uses a TSK neuron-fuzzy network to process the reflected signal to increase the accuracy of estimation of the reflected moment to further accurately calculate the location of faults on the transmission lines.

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II. TSK NEURAL NETWORK

A. *TSK fuzzy neural network model*

TSK (Takagi –Sugeno- Kang) fuzzy neural network model is built with learning algorithm to adjust the network parameters to fit a given sample data sets [2]. This network is characteristic in parallel processing of a set of inference rules.

The TSK model uses fuzzy logic rules as:

$$\textbf{if } \mathbf{x} \approx \mathrm{A} \textbf{ then } y \approx f(\mathbf{x}) = q_{i0} + \sum_{i=1}^{N} q_{ij} x_i$$

where: q_{ij} arelinear constants, $\mathbf{x}$ is the input vector $\mathbf{x} = [x_1, x_2, \ldots, x_N]$.

On Fig. 1, TSK network structure is presented based on three main parameters (N, M, K), where: N - number of inputs (the number of elements of the input vector **x**), M- number of inference rules, K- number of outputs. There are 5 layers contained in a TSK network:

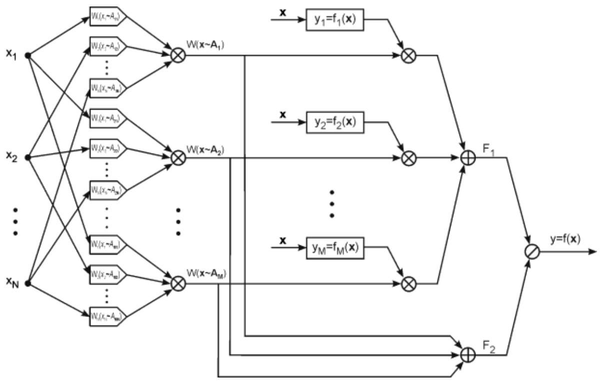

Fig. 1. TSK fuzzy neural network

Layer 1: Fuzzy fying layer to calculate the condition value of each input component $W(x_i \approx A_i)$.

Layer 2: Calculate the fuzzy logic condition value for the whole input vector $W(\mathbf{x} \approx \mathbf{A})$.

Layer 3: Calculating the value of TSK functions $f_i(\mathbf{x})$.

Layer 4: Calculate the weighted values F_1 and F_2 of the inference rules.

Layer 5: Calculate the output value: $y = \frac{F_1}{F_2}$

To build a TSK network for a task, first the centers $\mathbf{A}_i$ need to be initialized. A good initialization would help to avoid bad local minima of the cost function and to speed up the learning process. In this paper we used the so called subtractive clustering method for this purpose.

B. Application of subtractive clustering method to initialize the network centers before learning

In order for the learning algorithms of the TSK network to converge faster, in this paper, the clustering subtraction method was used as a preprocessor for determining the initial locations for fuzzy if-then rules. Consider a data set with p samples $\{\mathbf{x}_i\}_{i=1,2,...,p}$, the candidates for cluster centers were selected from the data input points themself. First, a density measure at data point $\mathbf{x}_i$ is defined as:

$$P_i = \sum_{j=1}^{p} e^{-\frac{4}{r_a^2}\|\mathbf{x}_i - \mathbf{x}_j\|^2} \quad (1)$$

where: r_a is a positive constant representing a neighborhood radius, $\|\mathbf{x}_i - \mathbf{x}_j\|^2$ – the Euclidean distance between data points. Hence, a data point will have a high density value if it has many neighboring data points.

The first cluster center x_1^* is chosen as the point having the largest density value P_1^*.

$$P_1^* = \max_{i=1}^{p} P_i \quad (2)$$

Next, the density measure of each data point $\mathbf{x}_i$ is updated as follows:

$$P_i = P_i - P_1^* \cdot e^{-\frac{4}{r_b^2}\|\mathbf{x}_i - \mathbf{x}_1\|^2} \quad ; i = 1,...n \quad (3)$$

Where: r_b – a positive constant which defines a neighborhood that has measurable reductions in density measure. Therefore, the data points near the first cluster center x_1^* will have significantly reduced density measure.

After revising the density function, the next cluster center is selected as the point having the highest density value.

$$P_i = P_i - P_k^* \cdot e^{-\frac{4}{r_b^2}\|\mathbf{x}_i - \mathbf{x}_k\|^2} \quad ; i = 1,...,n \quad (4)$$

This process continues until a sufficient number of clusters are obtained.

C. The role of the TSK neural network

For each from the considered m cases, the j-th short circuit signal is obtained $\mathbf{y}_j = [y_{j0}, y_{j1}, \ldots, y_{jN}, ...]$, where j = 1,...,m is the received signal when active pulse is transmitted to the beginning of the line, $s_j = t_{rj} - t_{cj}$ is the estimated error, where: t_{rj} and t_{cj} are actual times and times calculated according to the feedback wave from the point of failure to the beginning of the line. The starting point of the signal $\mathbf{y}_j$ was t_{cj}, which was determined by using wavelet decomposition as presented in [3]. The TSK network was trained to estimate the error, so that the final time of arrival of the pulse is calculated as $t_{cj} + TSK(\mathbf{y}_j)$.

III. SIMULATION MODELS USING MATLAB SIMULINK

This paper uses Matlab –Simulink to build models which simulate the wave propagation on the lines. The parameters of the simulation line are: $l = 60km$ – the length of the line; $L_0 = 0.9337\ mH/km$ – the inductance per unit; $R_0 = 12.73\ \text{m}\Omega/km$ – the resistance per unit length, and $C_0 = 12.74\ \mu F/km$ – the capacitance per unit length.

- The model line without fault is presented in Figure 2.
- The fault model line is shown in Figure 3 with the fault at distance of 20 km.

When the line has faults, consider the following assumptions:

- The fault is isolated there by cutting power and the line is removed from source and load. Simulation model shows in Fig.4 with fault at different positions.
- In case of fault occurence, protection system only cut power source and the line is still connected to the load.

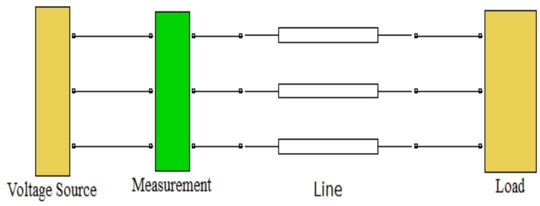

Fig. 2. Simulation model to find the incoming wave and the reflected wave of a faul-free 3-phase transmission line

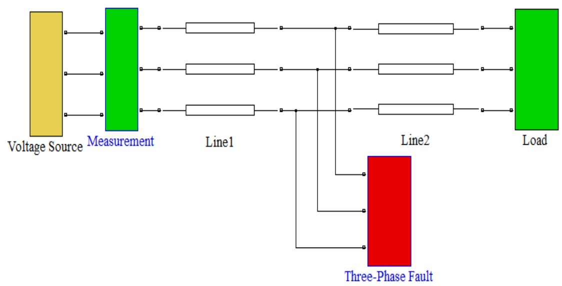

Fig. 3. Simulation model to find the incoming wave and the reflected wave of a faulty 3-phase transmission

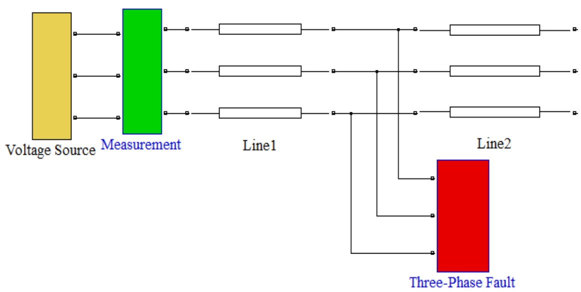

Fig. 4. Simulation model to find the incoming wave and the reflected wave of a faul-free load –free 3-phase transmission line

Using the model in Fig.2 to simulate the load in cases R, R series L, R parallel C, we get the results as shown in Figs. 5, 6, 7 and 8.

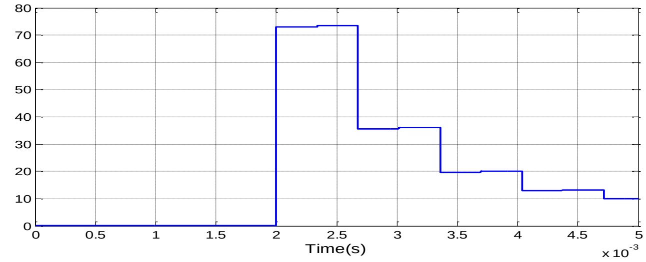

Fig. 5. The form of the voltage at the beginning of the line when the load is purely resistance

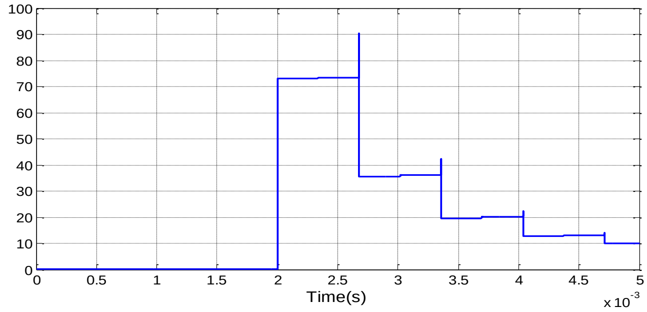

Fig. 6. The form of the voltage at the beginning of the line when the load is series R-L

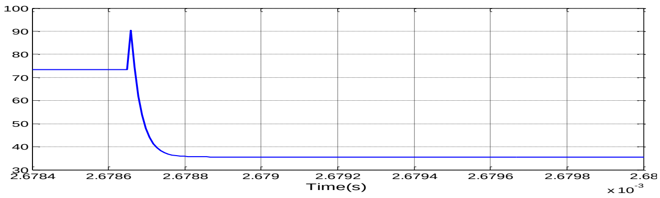

Fig. 7. Zoomed in signal from Fig.8 at the 1st reflection

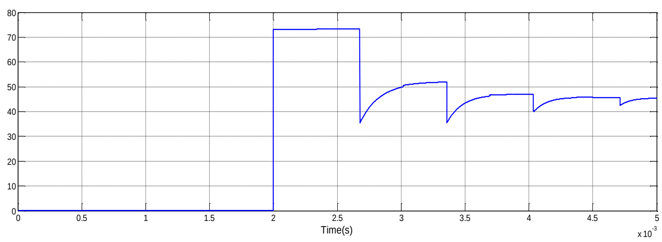

Fig. 8. The form of the voltage at the beginning of the line when the load is parallel R-C

Figures 5-8 show the measured signal which has two sudden times very clearly at t ~ 2 ms and 2,678 ms. The 1st moment was the time when the voltage source is turned on to the line and the later moment was when the reflected signal from the end of the line arrived back. If we can calculate exactly the arrival/appearance time, from Eq. (3) we will estimate the speed of wave propagation on the line and analysis the reflected waveforms on the transmission lines to detect the load characteristics.

Specifically, if the reflected signal is a squared wave, we have resistive loads. If the reflected signal is a damping with positive signs, the load is a R in series with a L and when it is negative, the load is a R in parallel with a C.

When the line has no fault, the time of wave spreads from beginning to end of line is calculated as in the following formula:

$$\Delta t = t_2 - t_l = \frac{2 \cdot l}{v} \qquad (5)$$

Where, t_1 is point time of closing voltage and t_2 is the time point of reflected signal from the end of the line.

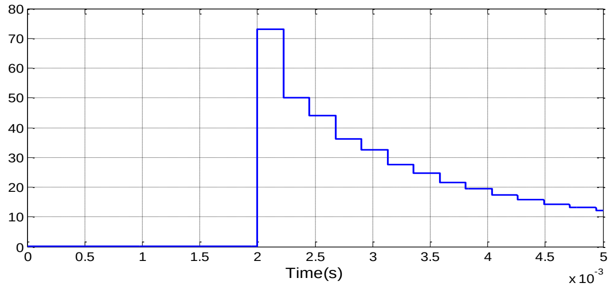

Fig. 9. Form of the reflected voltage signal at the beginning of the lines when there is a 3-phase resistive fault at 20km (the load resistance is Rload=100Ω)

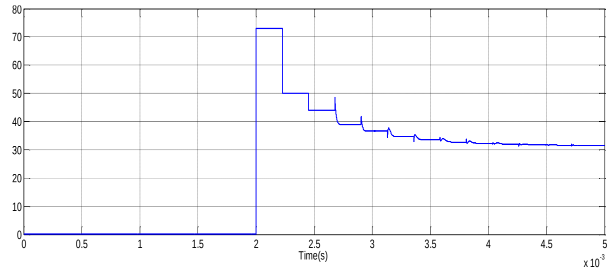

Fig. 10. Form of the reflected voltage signal at the beginning of the lines when there is a 3-phase fault at 20km (the load is a R_{load}=100Ω in series with a L_{load}=1 mH).

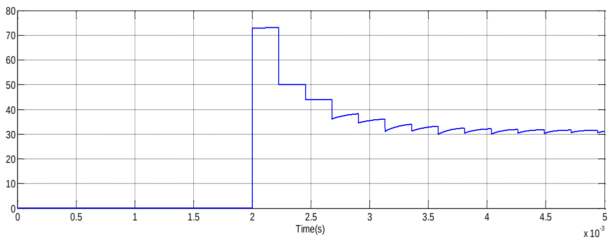

Fig. 11. Form of the reflected voltage signal at the beginning of the lines when there is a 3-phase fault at 20km (the load is a R_{load}=100Ω in paralle with a C_{load}=1μF).

In Figures 9-11 the measured signals at first line when the line was been faults are shown. In this paper, we consider parameters of the fault is purely resistive. So reflected waves from fault point is always square and reflected waves from the end of the line shown in Figure 9, 10 and 11.

We can see in Figure 9, 10 and 11 that has more many point time when voltage change suddenly. Because it added components reflected from fault point (more reflected waves appear earlier than cases without fault). If we define exactly the time point of reflected signal, we will define exactly wave propagation time on the line thereby determining the fault location. We can determine the shape of the load and the load parameters when comparison the voltage of reflected signal before and after.

Thus, the analysis reflected signal consists of two main steps:

1. Determine the time of arrival back of the reflected waves
2. Calculated the fault distance from the arrival time of the reflected waves.

In this paper, we reuse the method presented in [3] using wavelet analysis to determinethe time of arrival of the reflected signal on transmission lines. The method from [3] was quite accurate (the errors were [3]), but in order to further improve, this paper uses the TSK to correct the estimation of the arrival time.

With the arrival time estimated as in [3], we extracted asection of the reflected voltage signal at the beginning of the lines is $y_j = \left[y_{j0}, y_{j1}, \dots, y_{jN} \right]$ with the sampling time $h = 1(\mu s)$ where $y_{jk} = t_{cj} + k \cdot h;\quad k = 0,1,\dots,19$ corresponding to 20 values.

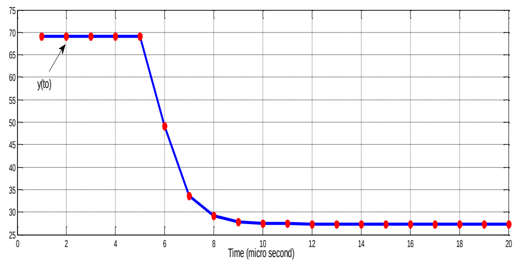

Fig. 12. Example of sampling 20 probes starting from the beginning of the signal

This vector of 20 values will form the input into the TSK network. The output of the network is the correction amount to adjust the starting point, i.e. the final time of arrival of the reflected signal is calculated as $t_{cj} + TSK(\mathbf{y}_j)$. The network was trained using a hybrid algorithm described in [2].

IV. NUMERICAL TESTS AND RESULTS

In this paper, we use the transmission lines model described in Fig. 3 when changing some input parameters to generate the data sets as:

- Fault location: N = 8 positions (5, 10, 15, 20, 25, 30, 35, 40km).
- Fault resistance R_{sc}: K = 3 values (1,5,10Ω).
- Fault types: P = 4 types (single phase shortage, double phase shortage, double phase grounded shortage, triple phase shortage).
- Fault inductance: Q = 5 cases (0; 0,1; 1; 1.5 ; 2 mH)

The total number of simulations with to the fault location, fault resistor, fault type: $N \cdot K \cdot P \cdot Q = 8 \cdot 3 \cdot 4 \cdot 5 = 480$ cases. With a sample dataset of M = 480 simulated samples, in this paper, we will randomly take 360 samples to learnand 120 random to check the quality of the network built from the original dataset.

With the given data set, the TSK network had 20 inputs (corresponding to 20 values in the extracted signal $y_j = \left[y_{j0}, y_{j1}, \dots, y_{jN} \right]$) and one input is the arrival time error generated by the method described in [3]. The results of the learning process are shown in F and 14. Where: Figure 14 is the output from the TSK network and the expected values. Figure 14 shows the error between the output response and the learning result. Figure 15 is the shape of the output response of the TSK network

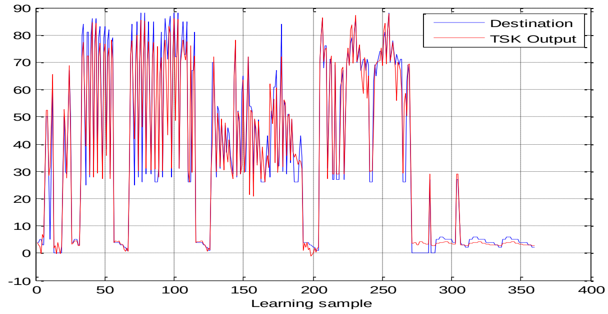

Fig. 13. The output from the TSK network and the expected values

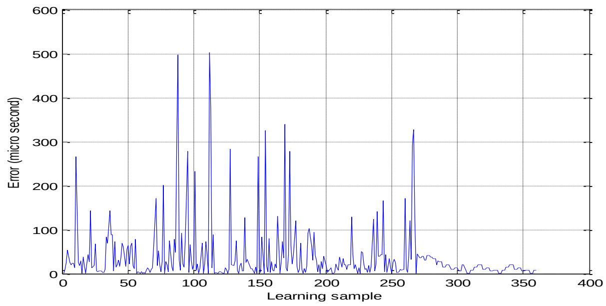

Fig. 14. Graph of errors between learning results and input data

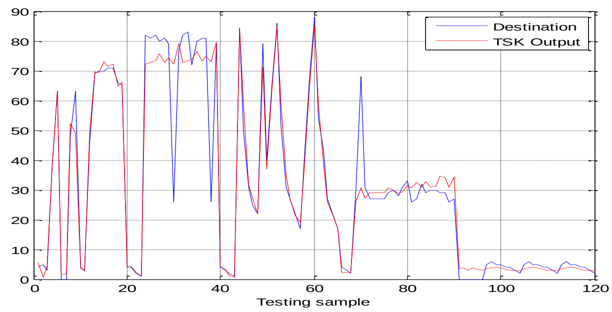

Fig. 15. Graph of test output response of TSK network

The average error over the whole data sets is calculated by the formula (where n – the number of samples pairs):

$$E_t = \sqrt{\frac{\sum_{k=1}^{n} (y_k - d_k)^2}{n}}$$

The average error of the total 360 sets of data sets is: 0,37891µs with the largest learning error of 5,0218 µs.

The test results are shown in Figures 15. The average total error of the 120 test data sets is: 0.3559 µs with the largest error of the test results is 4.6895 µs. With the average error of calculating the time of the feedback wave to the beginning of the line is nearly 0.38 µs, the average error location estimation error is: $l_s = v * \mathrm{E}_t \approx 90$ (m). Where v is the wave velocity on the transmission line v = 235,468 km / s.

V. CONCLUSION

This paper presented a new model combining wavelet analysis with TSK fuzzy logic neural network to locate the fault. Which wavelet is used to analyze the feedback signal from the beginning of the line. Based on the analyzed signal, the instant signals will be extracted to put into the neural network to determine the location of the fault. Simulation results show that the solution has quite high accuracy. Future work will consider branched transmission lines.

ACKNOWLEDGMENT

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