TWO-PHASE SHORT-CIRCUIT FAULT DETECTIONS FOR TRANSMISSION LINE USING WAVELET TRANSFORM AND NEURAL NETWORK

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SUMMARY

Short-circuit is one of the most popular defects on the power transmission lines. Due to the presence of different types of short-circuit fault, in this paper we'll consider only the two-phase short-circuit fault type on a three-phase transmission line. The model use a transmission line at 220kV, 200 km long, frequency at 50Hz with different positions of the failure and different failure short-circuit resistances to test the proposed solutions. The input signals are only the voltages and currents at the beginning one-terminal of the transmission line. The math tool selected for this task is the decomposition algorithms by using Daubechies wavelets and MultiLayer Perceptron neural network (MLP). The numerical results will show the effectiveness of the proposed method.

Keywords: *Fault location, Transmission lines modeling, Reverse problem, short-circuit fault, Wavelet decomposition*

INTRODUCTION

The problem of short-circuit fault detection and its parameters estimation is one of the important tasks in a power transmission system. An accurate location of the fault will allow a faster repair and a faster system restoration. That will also lower the cost of operation of the system. For each short-circuit fault, we often need to estimate three parameters: the moment of the fault, the position of the fault and the shortage resistance.

In this paper, we present the idea and the results of a new method, which will use only the signals measured at the sending ends of the lines to detect and locate the two-phase short circuit happened on the line. This method will greatly reduce the number of hardware devices to be used. But we need to develop more complicate signal processing algorithms in order to be able to get the correct results.

The mathematical tool used to process the data is the signal decomposition by using Daubechies wavelets. The wavelet solutions outperform the classical Fourrier decomposition method because they can give not only the information about the harmonic frequencies in the signals but also the information about the moment that a specific frequency starts in a signal [4,5,6,7]. This advantage fits very well with the fault detection problems because when a fault occurs, there will be abrupt changes in signals on the lines, and as the consequence there will be some high frequencies newly appear in the signals.

The signals (currents and voltages) of the three lines will be used to generate the feature vector for the detection and estimation blocks, which use the MLP (Multi Layer Perceptron) - one of the most popular artificial neural networks - to process the data. The numerical results will validate the proposed ideas.

WAVELETS AND APPLICATIONS IN SIGNAL TIME- FREQUENCY ANALYSIS

Wavelet is called an advancer development of signal decomposition than the classical Fourier method. In the Fourier method, a signal is decomposed into sinusoidal functions as the base functions [6,7]. Because the basis sinusoidal functions have "unlimited" domain (i.e. the range in which we may have function values greater than small ε is unlimited). Hence when a frequency appears in the Fourier decomposition results we can say that the

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frequency exists all the time. The method quality is significantly reduced [1,3] for nonstationary signals, in which the components appear only for a part of the time range of the signal. Let's consider the following example, in which a signal contains the different amplitude frequencies and they appear at different moments:

$$f(t)=\begin{cases}2\sin(2\pi\cdot 2t) & \text{for } t<0,3\\ 0,5\sin(2\pi\cdot 10t) & \text{for } 0,3\le t<0,7\\ \sin(2\pi\cdot 20t) & \text{for } t\ge 0,7\end{cases} \quad (1)$$

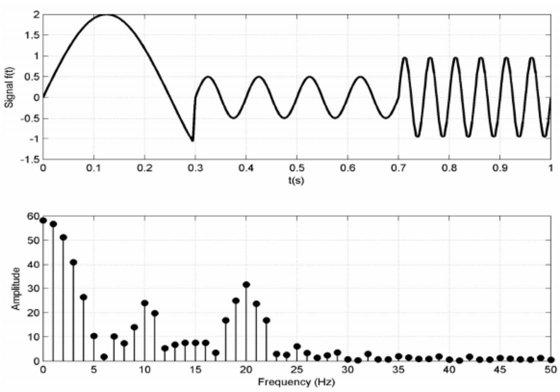

Figure 1. *The Fourier decomposition of a non-stationary signal (top: Original signal, bottom: Amplitude spectrum)*

The signal and its Fourier decomposition are shown on the Fig. 1. It can be seen clearly that the performance is not good, the detected frequencies are not clear and the relative amplitudes are also very unsatisfied. This weakness of the Fourier method can be improved by applying the Fourier decomposition for a series of short-time windows of the signal. This solution is call the STFT *(Short-Time Fourier Transform)* [1] and it has some major disadvantages: the number of mathematical operations is high, the quality strongly depends on the width of the window (a wide window has a lower of signal resolution so that the moment detection is weak, a narrow window cannot find accurately the frequencies components).

In those cases the wavelet methods come as an alternative for such non-stationary signals. The Daubechies wavelets $\psi(x)$ [3,4,5,6] are defined by:

$$\psi(x)=\sqrt{2}\sum_{k=0}^{2N-1}(-1)^k h_{2N-1-k}\varphi(2x-k) \quad (2)$$

where N is the wavelets order, $h_0,...,h_{2N-1}$ are the filter coefficients, which satisfy following conditions:

$$1.\ \sum_{k=0}^{N-1}h_{2k}=\frac{1}{\sqrt{2}}=\sum_{k=0}^{N-1}h_{2k+1} \quad (3)$$

$$2.\ \sum_{k=2l}^{2N-1+2l}h_k h_{k-2l}=\begin{cases}1 & \text{for } l=0\\ 0 & \text{for } l\ne 0\end{cases} \quad \forall l=0,1,N\text{-}1 \quad (4)$$

and functions $\varphi(x)$ are called mother wavelets and are calculated according to the recurrent formula:

$$\varphi(x)=0 \quad \forall x\in \mathbf{R}\setminus[0,2N\text{-}1] \quad (5)$$

$$\varphi(x)=\sqrt{2}\sum_{k=0}^{2N-1}h_k\varphi(2x-k) \quad (6)$$

The coefficients h_i are estimated from (5), (6) with the additional conditions on orthonormality of the set of wavelets and mother wavelets [4,6,7]. For example, for N=1, we have $[h_0,h_1]=\left[1/\sqrt{2},1/\sqrt{2}\right]$, and for N=2 we have: $[h_0,h_1,h_2,h_3]=\left[-0,183,-0,317,1,183,-0,683\right]$. From the above wavelets we can form a set of orthonormal functions $\psi_{j,k}(x)=2^{j/2}\psi(2^j x-k)$ for indices $j,k\in\mathbf{Z}$.

The base wavelet functions have a major different when comparing with the basis sinusoidal. All of them have a limited range of domain [3,4,5], in which the values of the functions are greater than a threshold $\varepsilon > 0$. With these wavelets, a time function can be decomposed into its components by using the next formula:

$$f(x)\to w_{a.b}(f)=\frac{1}{\sqrt{a}}\int_{-\infty}^{\infty}f(x)\psi\left(\frac{x-b}{a}\right)dx \quad (7)$$

where a is the scaling coefficient and b is the shift coefficient. For big values of a, the wavelet changes its values faster. It means that the given wavelet can be used better to approximate the higher frequencies.

Analogically, a wavelet with smaller *a* can be used to approximate the lower frequencies. By changing the values of the shift coefficient *b* we can estimate the moment a given frequency appear in the signal. Due to that not only we can find different frequencies but also their moments of appearance. As an example, let's consider the above example for the signal from (1) with Daubechies wavelet of orders less or equal 4. The results are presented on Fig. 2.

All of the 3 non-stationary components were perfectly detected. The 2sin(2π.2t) component is detected and included in $\mathbf{a_4}$, the 0,5sin(2π.10t) component is detected and included in $\mathbf{d_4}$ and the sin(2π.20t) component is included in $\mathbf{d_2}$ and $\mathbf{d_3}$. And the moments of changes are also clearly indicated as the sudden change of amplitudes on the $\mathbf{a_4}$, $\mathbf{d_2}$ and $\mathbf{d_1}$. For non-stationary signals, the performance of the wavelet methods is much great improved and it outstands the classical Fourier method.

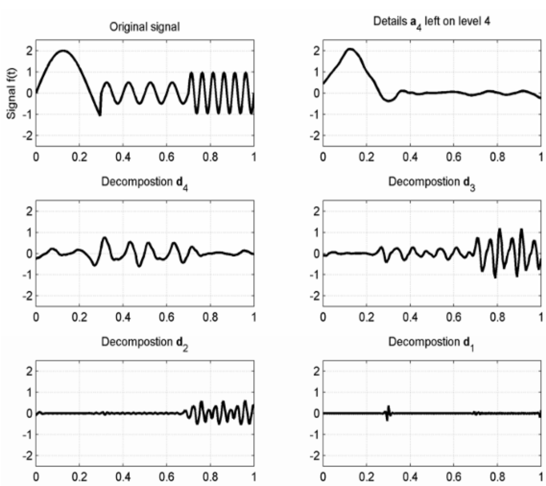

Figure 2. *The decomposition of a non-stationary signal by using 4th order Daubechies wavelets (top-left: original, others: decomposed components)*

THE MLP AND ITS APPLICATION IN ESTIMATION OF THE FAULT PARAMETERS

As mentioned above, the MLP will play the role of the reverse model as seen on Fig. 3.

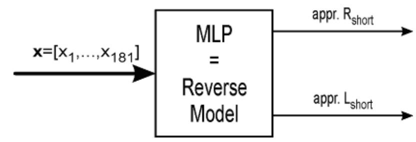

Figure 3. *The reverse model using MLP to estimate the fault parameters*

Having the given 183-component input vectors, the MLP should calculate two desired outputs: d_1 - the approximated value of the fault resistance of the fault and d_2 - the approximated distance from the beginning of the lines to the fault.

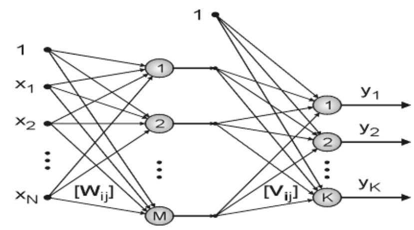

Figure 4. *The structure of the MLP with one hidden layer*

The MLP [2] with one hidden layer of neurons is a nonlinear model and has the structure as shown on Fig. 4. Its can described by the triple (N, M, K), where N is the number of inputs signals, M is the number of hidden neurons, K is the number of output signals. Once those numbers are selected as well as the transfer functions for hidden and output layers, the MLP still have the connection weights that should be trained in order to fit the output signals of MLP to the desired values. Let the weights between input layer and hidden layer be noted as W_{ij} and the weights between hidden and output layers be noted as V_{ij}. Let the transfer function of neurons in the hidden layer is f_1, the transfer function of neurons in the output layer is f_2. The output signals from MLP can be derived with following feed forward steps:

The total input of each hidden neuron: $u_i = \sum_{j=0}^{N} x_j \cdot W_{ij}$ for $i = 1, 2, \ldots, M$.

The output of each hidden neuron: $v_i = f_1(u_i)$ for $i = 1, 2, \ldots, M$.

The total input of each output neuron: $g_i = \sum_{j=0}^{M} v_j \cdot V_{ij}$ for $i = 1, 2, \ldots, K$.

The output of MLP network: $y_i = f_2(v_i)$ for $i = 1, 2, \dots, K$.

The cost function to be minimized during the training process is defined as the sum squared of errors for all data samples:

$$E = \sum_{i=1}^{p} \|\mathbf{y}_i - \mathbf{d}_i\|^2$$

where p is the number of data samples (i.e. 851 in this paper), $\|.\|$ is the Euclidean distance between the output of the MLP network and the desired output from the samples set.

The details about MLP structure, its parameters and training algorithms can be founded in [2]. The default training algorithm for MLP in Matlab Neural Network Toolbox is the Levenberg - Marquardt algorithm [2].

SIMULATION OF TWO-PHASE SHORT-CIRCUIT FAULT ON A THREE -PHASE TRANSMISSION LINE

By using the SimPower Toolbox of Matlab, the three-phase transmission line model was built as seen on Fig. 5.

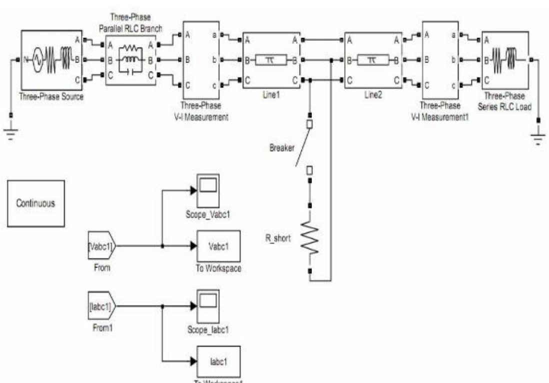

Figure 5. *The model to simulate a three-phase transmission line with two-phase short-circuit fault (between phase B and phase C)*

In this paper, the transmission line is modeled by using following "static" parameters:

Voltage source Vs(t): symmetric, Y-connected with $V_a(t) = 220\sqrt{2}\sin(314t)\ kV$. Internal impedance of each phase source is simulated by a resistance $R_a = 0.893\Omega$ connected in serial with an impedance $L_a = 16.58mH$.

Equivalent impedances of source and load connected between the transmission line (3 elements are in parallel): $R = 180\Omega$; $L = 25mH$ and $C = 120\mu F$.

Characteristic parameters of the transmission line:

$$[R_1, R_0] = [0.01273, 0.3864]\Omega / km;$$
$$[L_1, L_0] = [0.9337, 4.1264]mH / km;$$
$$[C_1, C_0] = [12.74, 7.751]nF / km.$$

The length of the line: $l = 200km$.

Number of sections: 10 (that makes the length of each section equal 20km).

The equivalent load connected to the end of the line is defined as $Q_L = 110MW; P = Q_L / 300$ at $|V_a| = 220kV$.

The two-phase short-circuit fault event is simulated by closing down a switch connecting two phases. To have a database of different cases of faults, we set 3 parameters of each fault:

The location of the fault (defined by l_{short} - the distance from the beginning of the lines to the fault location): 9 different places on the line $l_{short} \in [20, 40, ..., 180]km$. The fault resistance: 6 different values $R_{short} \in [0, 50, 100, 150, 200, 250]\Omega$.

The time moment of the short-circuit fault: 21 time moments during one period $\Delta T_0 \in [0, 1, \dots, 20]ms$ (every 1ms during 1 period of 20ms).

All possible combinations of those 3 parameters will give $9 \times 6 \times 21 = 1134$ cases of simulations and data samples. For each case, we get the instantaneous phase current signals at the start of the line $i_a(t), i_b(t), i_c(t)$ sampled at 1 kHz frequency.

The examples of generated signals are given in Fig. 5. From those samples, 851 samples (~75% of the set) were used to train the reverse model, the rest 283 (~25% of the set) samples were used to test the trained model.

The testing samples were uniformly selected from the database (it means the cases number 4, 8, …, 1132 were selected).

SIMULATION RESULTS

Using Wavelet decompositions to detect the fault moment

For each case, the values of 3 input currents are input into the Daubechies' wavelet decomposition block to detect the moment of sudden changes in those signals. As the current signals are discrete sampled with the frequency 1kHz, if the expected accuracy is about milisecond then we need the ability to detect the changes in 1 sampling period. For this purpose, we will apply the wavelet up to 9^{th} order [3,4,5].

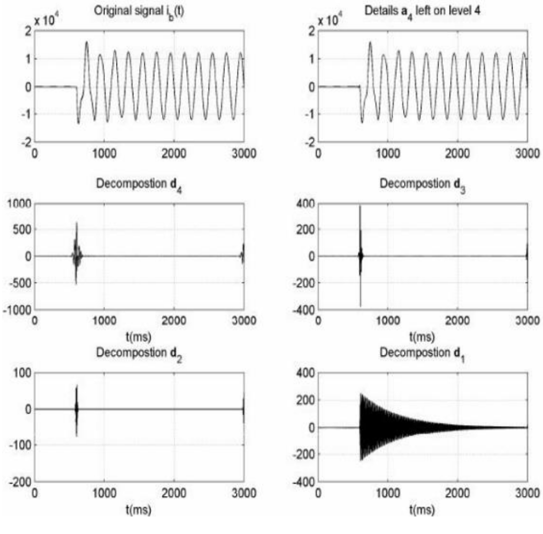

Figure 6. *The decomposition of the current signal of phase B from Fig. 9 into 9^{th} order Daubechies wavelets*

Figure 6 presents an example of current signal decomposition (for phase B) by using the 9^{th} order Daubechies wavelet. First of all, the $\mathbf{d_1}$ component was extracted [3,4,5,6] from the original signal $\mathbf{u_1} = u_1(t)$ and the rest $\mathbf{a_1} = \mathbf{u_1} - \mathbf{d_1}$ was used for next step. Recursively, the $\mathbf{d_2}$ component was extracted from $\mathbf{a_1}$ and the rest $\mathbf{a_2} = \mathbf{a_1} - \mathbf{d_2}$ was to be used next,… After 4 steps of decomposition we received 4 components $\mathbf{d_1},...,\mathbf{d_4}$ and the rest of the signal $\mathbf{a_4}$. We can observe the tendency that the higher the index i the lower of their frequency of detected signal in $\mathbf{d_i}$. According to that, the fastest changes should be included in $\mathbf{d_1}$.

This observation will lead to the algorithm for detection of the fault moment, which will be discussed in the next session.

For a better explanation of the algorithm, the component $\mathbf{d_1}$ is redrawn on the Fig. 7 with greater zoom in. There are two clearly visible transient states on $\mathbf{d_1}$. Let's omit the first transient (corresponded to 20 samples at the sampling frequency was 1kHz), which was caused by the window effect.

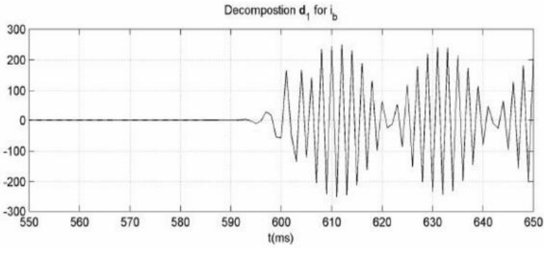

Figure 7. *The zoomed – in $\mathbf{d_1}$ for phase **B** from Fig. 6*

During the fault-free state, the values of $\mathbf{d_1}$ signal are very small, so let's define a threshold value equals five times of the maximum value of $\mathbf{d_1}$ from this period:

$$\text{threshold} = 5 \cdot \max_{t \in [20ms, 40ms]} \left(\left| d_1(t) \right| \right) \tag{8}$$

When the instant values of $\mathbf{d_1}$ start to vary, we find the moment when it crosses the threshold

$$t_1 = \min_t \left(\left| d_1(t) \right| \right) > \text{threshold} \tag{9}$$

After that, we look forward in the neighborhood of t_1 (it was selected as the range $[t_1-10,\ t_1+20]$). At the sampling frequency 1kHz this range is equivalent to 1 period after t_1 and half period before t_1. The moment of the fault will be assigned to the maximum of the value $\mathbf{d_1}$ in the range.

$$T_{short} : \left| d_1\left(T_{short}\right) \right| = \max_{t \in [t_1 - 10, t_1 + 20]} \left(\left| d_1(t) \right| \right) \tag{10}$$

This search algorithm is performed for all three phases independently and the earliest moment among the 3 estimated values is used as the fault moment.

The presented algorithm above was applied for all 1134 cases, which have been generated. The results are shown on Fig. 8.

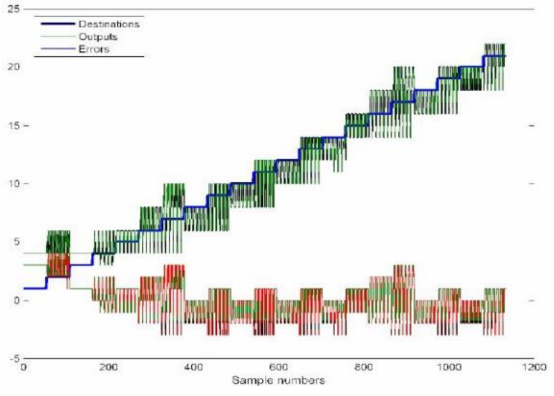

Figure 8. *The results for 1134 samples*

We can observed that the maximum error was:

$$E_{max} = \max_{i=1\div1134} |y_i - d_i| = 4(ms) \qquad (11)$$

and the average value of errors is calculated as

$$E_{average} = \frac{\sum_{i=1}^{1134} |y_i - d_i|}{1134} = 1{,}35(ms) \qquad (12)$$

where d_i is the real (expected) moment of the fault, y_i is the moment estimated by using the proposed method.

Using Neural network (MLP) for the estimation of fault location and fault resistance

By using the method of trial-and-error, the MLP had 183 inputs, 10 hidden neurons (with tangent hyperbolic transfer function) and 2 outputs (with linear transfer function). The network was trained with the Levenberg-Marquardt algorithm for 200 iterations, during which the sum-squared error defined in (3) was greatly reduced as seen on the Fig. 9.

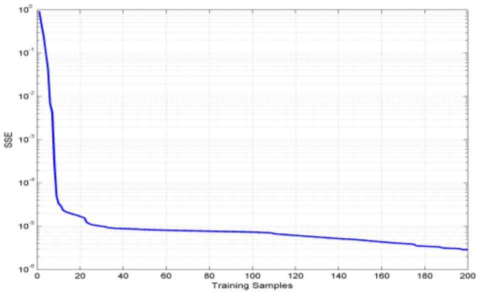

Figure 9. *The change of the cost function during the learning process of the designed MLP network*

From the start value of 0,929 (when the weights were initiated with random values), the final value SSE was only $2{,}86.10^{-6}$, which practically can be assumed to be 0. After that, the MLP was tested with 283 new data. We can see on Fig. 10 and Fig. 11 the expected outputs for the testing samples. The real outputs from the MLP and the error between the MLP outputs and the desired values are presented on Fig. 12 and Fig. 13. As it can be seen, the testing results are also very good. For the estimation of fault resistance (Fig. 12), the mean value of error was only 0,69Ω (compare to the range of 250Ω) and the maximum value of error was only 5,57Ω.

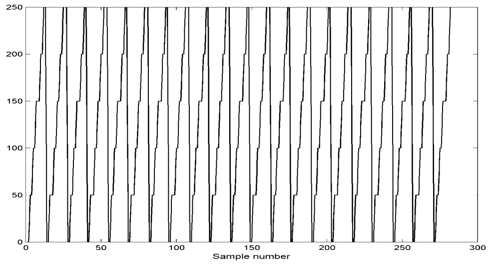

Figure 10. *The desired values of of fault resistance of the fault for testing data*

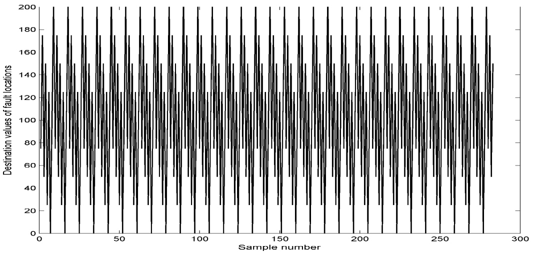

Figure 11. *The desired values of location of the fault for testing data*

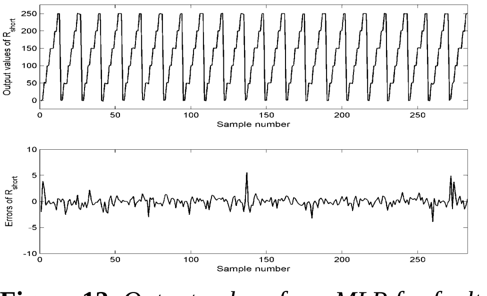

Figure 12. *Output values from MLP for fault resistance estimation of the fault (top) and the estimation errors (bottom)*

For the estimation of fault location (Fig. 13), the mean value of error was only 155,6m (compare to the range of 200km) and the maximum value of error was 905,7m. Those results are quite good for practical applications and they can help to prove the quality of the proposed solution.

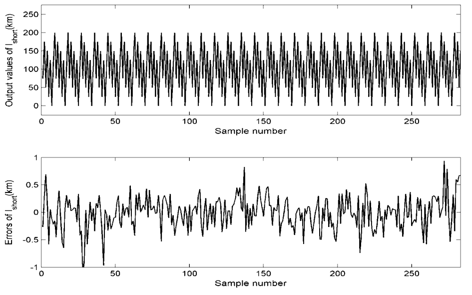

Figure 13. *Output values from MLP for location estimation of the fault (top) and the estimation errors (bottom)*

CONCLUSION AND FURTHER DEVELOPMENT

The paper has proposed a new approach to detect and locate the two-phase short-circuit fault on the three-phase transmission lines. The proposed method uses the Daubechies wavelet decompositions of the phase currents signals from the beginning of the transmission line only. For the selected configuration of the line, the achieved average error was less than 1,35ms and the maximum error was 4ms. The proposed model can identify the location of the fault and the resistance at the fault point very accurate. The average error for location was less than 160m for the 200km lines, the average error for fault resistance was less than 1Ω.

This method can be extended and tested with other type of faults or switching events on the transmission lines, such as phase-to-ground short circuit, single phase interruptions,…

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TÓM TẮT

ỨNG DỤNG BIẾN ĐỔI WAVELET VÀ MẠNG NƠRON NHÂN TẠO PHÁT HIỆN SỰ CỐ NGẮN MẠCH 2 PHA TRÊN ĐƯỜNG DÂY TẢI ĐIỆN

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Ngắn mạch là một trong những lỗi phổ biến trên các đường dây truyền tải. Do có nhiều dạng sự cố ngắn mạch khác nhau, trong bài báo này chỉ xét khi xảy ra sự cố ngắn mạch 2 pha trên đường dây truyền tải 3 pha. Đường dây được sử dụng có cấp điện áp 220kV, chiều dài 200km tần số 50Hz với các vị trí khác nhau của sự cố và điện trở sự cố để thử nghiệm các giải pháp đề xuất. Các tín hiệu đầu vào là các điện áp và dòng điện ở một đầu đường dây. Các công cụ toán học được lựa chọn cho nhiệm vụ này là các thuật toán phân tích sử dụng wavelets Daubechies và mạng nơ-ron MLP. Các kết quả cho thấy hiệu quả của phương pháp đề xuất.
Từ khóa: *Vị trí sự cố, Mô hình đường dây truyền tải, bài toán ngược, sự cố ngắn mạch, phân tích Wavelet*

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