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High-impedance fault identification and classification using a discrete wavelet transform and artificial neural networks

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Abstract. Identification and classification of high-impedance faults (HIFs) in electric-power distribution systems (EPDSs) represent some of the most significant challenges faced by the distribution system operators (DSOs). The recent advances in signal processing and changes in the EPDS regulatory framework have prompted acceleration in the development of advanced methods used for fault identification and classification in EPDS. The paper presents a method for identification and classification of HIFs in medium-voltage (MV) EPDSs, based on the Discrete Wavelet Transform and Artificial Neural Networks. The method was tested on generated signals based on a real EPDS and it was demonstrated that it is capable to accurately detect and classify HIFs in EPDS. The paper contributes to the existing research by developing and testing, on a real EPDS, a HIF-identification and classification method which offers a better performance compared to the currently installed protection devices.

Keywords: Distribution system, faults, neural network, protection, wavelet transform

Identifikacija in klasifikacija visokoohmskih okvar z uporabo diskretne valjčne transformacije in nevronskih mrež

Identifikacija in klasifikacija visokoohmskih okvar v elektrodistribucijskih sistemih je pomemben izziv za operaterje elektroenergetskih omrežij. Napredek na področju obdelave signalov in spremembe pri regulativi elektrodistribucijskih omrežij so spodbudili razvoj naprednih metod za identifikacijo in klasifikacijo napak v elektroenergetskih omrežjih. V prispevku je predstavljena metoda za identifikacijo in klasifikacijo visokoohmskih okvar v srednjenapetostnem distribucijskem omrežju. Metoda temelji na uporabi diskretne valjčne transformacije in nevronskih mrež. Metodo smo preverili s signali na osnovi resničnih elektroenergetskih omrežij. Eksperimentalni rezultati potrjujejo, da lahko s predlagano metodo natančno in učinkovito ugotovimo visokoohmsko okvaro v elektrodistribucijskem omrežju.

1 INTRODUCTION

In the recent years, there have been historical changes in the power-system structure, organisation and management, driven by the process of market liberation and energy transition from the conventional to the renewable energy generation paradigm. As a consequence, the management and operation of the electric-power distribution systems (EPDS) have also changed. Distribution system operators (DSOs) are constantly scrutinised by regulators and customers in terms of service reliability and quality parameters [1]. Two of the major practical challenges faced by DSO are power-system fault detection and classification. In particular, fault detection and classification are very important for DSO in order to take appropriate actions and ensure that the system continues to operate safely and efficiently.

Unfortunately, many faults remain undetected due to complex physical properties of the voltage and current waveforms and lack of appropriate detection technologies which are capable to provide fast and accurate fault classification. This is particularly true in the case of high-impedance faults (HIFs), which present a special challenge. In the past, there has been an increase in the number of reported fault-detection methods, but an ideal detection and classification are still an open question and continue to be a subject of scholar efforts [2], [3]. Therefore, HIFs present a serious problem since they cannot be easily detected. For these reasons, there is a need for an ongoing investigation of new methods for the EPDS fault identification and classification, which makes this topic a vibrant research area.

The paper contributes to these efforts by presenting a new method for identification and classification of HIFs in medium-voltage (MV) EPDS based on a combination of Discrete Wavelet Transform (DWT) and Artificial Neural Networks (ANNs). The aim of the paper is to experimentally verify the new method which represents an improvement compared to operational capabilities of the protection systems currently deployed in EPDS. The method is expected to solve one of the major operational challenges faced by DSO. The paper is a part of an ongoing research into advanced power-system

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protection, with a particular focus on HIF detection in EPDS ([1], [3] and [4]).

2 Literature Review

The EPDS faults can be broadly classified in two categories, based on the fault resistance. The resistances in the first category are mostly below a few hundreds of Ohms. In order to clear this type of faults, it is necessary to isolate the faulted section of the system and to trip the circuit-breaker. For this type of faults, the distance protection scheme is feasible. The resistances in the second category are very high the neutral potential is very low [4].

HIFs can generally be defined as faults with current values in the range from 0 to 75 A in an effectively grounded EPDS [5]. Their detection and classification continue to be a major challenge for DSO and is becoming even more difficult with the increase in the EPDS complexity. The existing EPDS protection systems are not completely adequate for HIF detection due to various issues such as sensitivity, selectivity and diversity [6]. The harmonic component in the zero-sequence current has been typically used in the existing detection methods [5]. Nowadays, the research into HIF detection continues to attract new interests [7], [5] and [8].

In particular, the combination of DWT and ANN appears to be a promising approach for HIF detection, because the wavelet transform (WT), which maps the time-domain signals into the time-scale domain, is capable to describe both the frequency information and the location of the frequency components. This unique feature of WT makes it a very popular method for HIF detection [8]. Further, ANNs have been tested in various engineering applications and are regarded as a fast and accurate method for classification with powerful prediction capabilities. For these reasons, DWT and ANNs are often used together in HIF identification and classification applications [8] and [9]. In conclusion, HIF identification and classification continue to be a relevant research topic and a combination of DWT and ANNs is a promising approach to an improvement of the existing EPDS protection systems.

3 Theoretical Basics

WT is used in numerous engineering applications. It is regarded as a mathematical tool which has numerous advantages when compared with traditional methods in a stochastic signal-processing application, mainly because waveform analysis is performed in a time scale region [10]. WT of a signal $f\ (t) \in L^2(R)$, where L^2 is the Lebesgue vector space, is defined by the inner-product between $\Psi_{ab}(t)$ and $f(t)$ as [10]:

$$WT\ (f,a,b) = \frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} f(t)\,\Psi\left(\frac{t-b}{a}\right)dt \qquad (1)$$

where a and b are the scaling (dilation) and translation (time shift) constants, respectively, and Ψ is the wavelet function which may not be real as assumed in the above equation for simplicity [10]. The Wavelet transform of the sampled waveforms is obtained by implementing DWT given by [10]:

$$DWT\ (f,m,n) = \frac{1}{\sqrt{a_0^m}}\sum_k f(t)\,\Psi\left(\frac{n-ka_0^m}{a_0^m}\right) \qquad (2)$$

where a and b from equation (1) are replaced by a_0^m and ka_0^m, k and m being integer variables. In a standard DWT, the coefficients are sampled from a continuous WT on a dyadic grid, $a_0 = 2$ and $b_0 = 1$, yielding $a_0^0 = 1$, $a_0^{-1} = 2^{-1}$, etc. [10].

In the Back propagation neural network (BPNN), the output is a feedback to the input to calculate the change in the values of weights [11]. The weights of the back-error-propagation algorithm for the neural network are chosen randomly to prevent a bias toward any particular output. The first step in the BPNN algorithm is a forward propagation [11]:

$$a_j = \sum_i^m w_{ji}^{(1)} x_i \qquad (3)$$

$$z_j = f(a_j) \qquad (4)$$

$$y_j = \sum_i^M w_{kj}^{(2)} z_j \qquad (5)$$

where a_j represents the weighted sum of the inputs, w_{ij} is the weight associated with the connection, x_i are the inputs, z_j is the activation unit of (input) that sends a connection to unit *j* and y_i is the i-th output.

The second step is calculation of the output difference [11]:

$$\delta_k = y_k - t_k \qquad (6)$$

where δ_k represents the derivative of the error at a k-th neuron, y_k is the activation output of unit *k* and t_k is the corresponding target of the input.

The next step is back propagation for hidden layers [11]:

$$\delta_j = (1 - z_j^2)\sum_{k=1}^K w_{kj}\delta_k \qquad (7)$$

where δ_j is the derivative of error w_{kj} to a_j.

Afterwards, the gradient of the error with respect to the first- and the second-layer weights is calculated, and the previous weights are updated. MSE for each output in each iteration is calculated by [11]:

$$MSE = \frac{1}{N}\sum_{1}^{N}(E_i - E_o)^2 \tag{8}$$

where N is number of iterations, E_i is the actual output and E_o is the output of the model.

After each step, the weights are updated with the new ones and the process is repeated for the entire set of input-output combinations available in the training-data set, and this process is repeated until the network converges for the given values of the targets for a predefined value of the error tolerance [11].

4 Results, Discussion and Future Work

This section of the paper presents results of the proposed algorithm application to the problem of HIF identification and classification in MV EPDS. In order to demonstrate the practical relevance of the proposed algorithm, it is applied to a real 10 kV MV EPDS currently used in Bosnia and Herzegovina. First the EPDS test system is described, followed by an outline of the computational procedure. Next, results of the proposed method are presented and discussed. Finally, the future research directions are given.

4.1 The test system

As the MV and low-voltage (LV) distribution systems mostly operate as radial systems, the proposed algorithm is tested in a radial EPDS.

The test system developed for the purpose of algorithm testing represents a part of a real MV distribution system operating in the area of the City of Mostar (Bosnia and Herzegovina) which is similar to typical distribution systems used throughout Europe.

The MV customers are supplied from a 35/10 kV main transformer via 10 kV feeders. The LV customers are supplied via 10/0.4 kV substations. The test 10 kV network supplies electricity in an urban area and mostly consists of underground cables. Detailed test system parameters are given in Table 1.

Table 1. Power-system parameters.

Component	Parameters
System voltages	V_{MV1} = 35 kV, V_{MV2}=10 kV, V_{LV}=0.4 kV f = 50 Hz
Transmission lines	$length_{L1}$= 5.87 km, $length_{L2}$= 0.95 km, $length_{L3}$= 4.47 km, $length_{L4}$= 1.47 km, $length_{L5}$= 5.34 km, $length_{L6}$= 6.63 km, $length_{L7}$= 3.11 km Z_{L1}= Z_{L2}= Z_{L3}= Z_{L4}= Z_{L5}= Z_{L6}= Z_{L7} R_1= 0.206 Ω/km, R_0= 0.96 Ω/km L_1= 0.359x10^{-3} H/km, L_0= 1.178x10^{-3} H/km C_1= 0.254x10^{-6} F/km, C_0= 0.118x10^{-6} F/km
Transformers 35/10 kV	P_n=8 MVA, R_1=0.0802 Ω, L_1=4.028x10^{-4} H, R_2=19.64x10^{-3} Ω, L_2=9.866x10^{-5} H
Transformers 10/0.4 kV	P_n=630 kVA, R_1=0.2495 Ω, L_1=4.873x10^{-5} H, R_2=1.33x10^{-4} Ω, L_2=2.598x10^{-8} H

The simulation model is developed in MATLAB/Simulink software and presents a three-phase model of the part of the Mostar EPDS fed from two parallel 35/10 kV transformers. A schematic representation of the test system is shown in Fig. 1.

The faults and measurements are performed on a 10 kV underground cable that feeds the entire consumption area. Faults are simulated for different fault resistances (in the range from 20 Ω to 600 Ω) and at different fault locations. The simulated faults are phase A to the ground fault (AG), phase A to phase B to the ground fault (ABG) and phase A to phase B to phase C to the ground fault (ABCG).

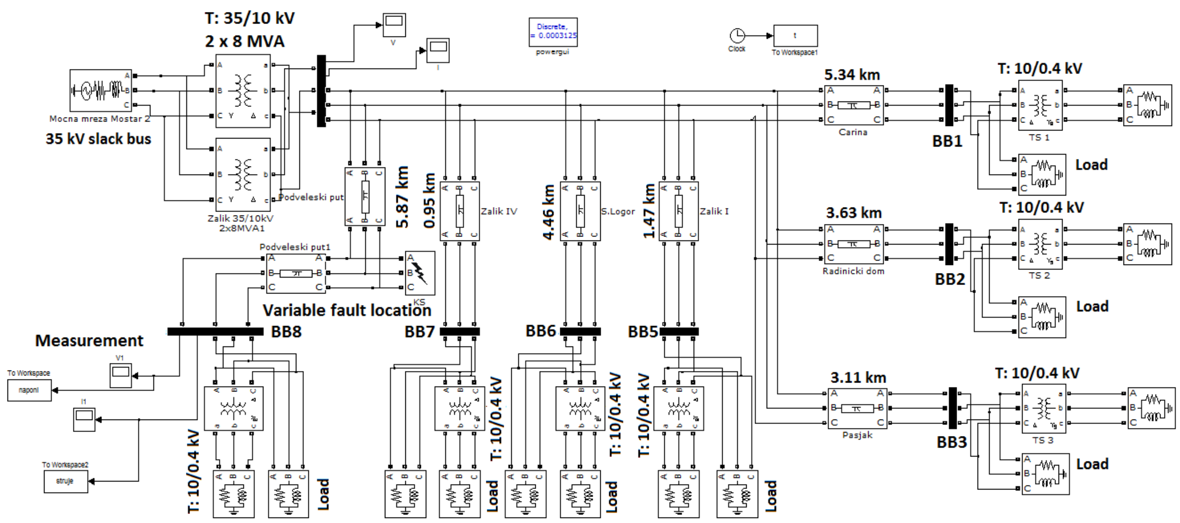


Figure 1. Test system developed in MATLAB/Simulink

The sampling frequency of the current protection relays and measuring equipment in the Bosnia and Herzegovina EPDS is 3.2 kHz. Since the existing equipment already operates with this sampling frequency, a logical upgrade would be to use this equipment coupled with the proposed algorithm. This fact is the reason for using the chosen sampling frequency.

For the proposed DWT-ANN algorithm, the condition with no fault and the conditions with three types of the fault are simulated for various resistance values and fault locations, giving a total of 1600 fault scenarios.

4.2 Computational procedure

The proposed method for fault identification and classification is based on a combination of DWT and ANN. It does not require current measurements and coefficient calculations because it performs with details and approximation waveforms rather than with calculated coefficients. The simulation model considers the fault resistance values for the unearthed MV network, based on [4].

After simulating all the possible fault scenarios, for each fault and different values of the fault location and resistance, the voltage waveforms are generated. The fault is simulated during the entire simulation interval, i.e. (0 – 0.08 s). When the voltage waveforms are generated, DWT is applied to these waveforms. A Daubechies 4 wavelet is used at a 3.2 kHz voltage signal, therefore one approximation and four details are obtained for each voltage. Four levels of decomposition are used in this paper in order to get the following frequency bands:

- First detail level - frequency band: [800, 1600] Hz,
- Second detail level - frequency band: [400, 800] Hz,
- Third detail level- frequency band: [200, 400] Hz,

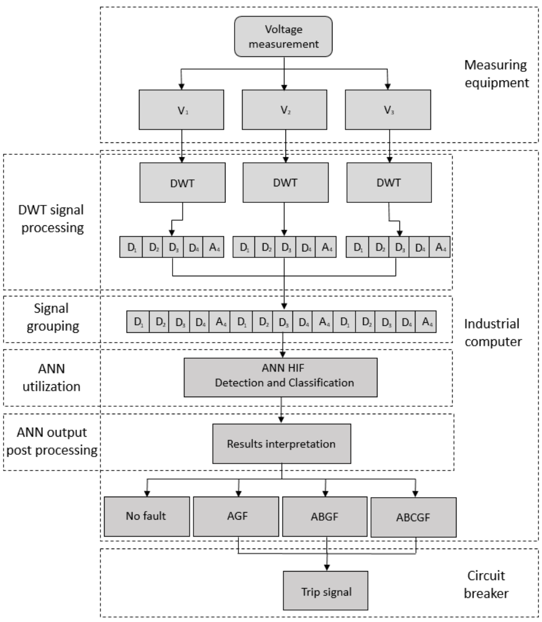


Figure 2. Algorithm of the proposed method.

- Fourth detail level - frequency band: [100, 200] Hz,
- Fourth approximation level - frequency band: [50, 100] Hz

The A4 waveform is a base sinusoidal wave and reflects the signal behaviour during each fault. The rest of the DWT waveforms are higher harmonic components of the voltage signal, and therefore they reflect a distinctive voltage behaviour during each fault type.

The algorithm is also tested by the Symlet 4 and Biorthogonal 4.4 wavelet families, and the output results are similar or the same. Therefore, it is not necessary to be particularly cautious regarding the choice of the wavelet family. The DWT signal components give a good insight into the system behaviour during fault conditions. For this reason, they are used as representative signals for each fault type. Afterwards, these DWT signals are combined and grouped and represent a unique „signature“ for each fault, which represents the input to ANN. After that, ANN is trained with a large set of this data, thus becoming capable to detect and identify the EPDS faults.

The ANN output consists of a set of the values that are not discrete, do not indicate an exact fault type, and do not represent a fault possibility. By adding a modification to interpret results, it is possible to convert these outputs to 0% and 100% (probability of the absence and presence of each fault). The block *Results interpretation* in Fig. 2 simply finds the highest value for the each ANN output scenario and sets it to 100%, while setting all other outputs to 0%. With this modification it is possible to get an unambiguous fault type as the algorithm output.

Once trained, ANN is capable of fault detection and classification, according to the algorithm shown in Fig. 2. With the measuring equipment installed in EPDS, the voltage waveforms can be measured and sent to an installed industrial computer with a DWT-ANN algorithm software. In the case of a fault detection, an appropriate trip signal, depending on the fault type, can be sent to the circuit breaker.

4.3 Results

In order to use the proposed algorithm in a real PDS, ANN needs to be trained to all the possible scenarios in EPDS. Since the algorithm is planned to be used in the online mode to constantly monitor the system voltages, it can constantly improve and learn new possible EPDS operating scenarios.

For the beginning, the input data for ANN need to be created. In order to get a unique EPDS signature for every fault type, a signal that reflects this state needs to be created. For this purpose, 1600 simulations for three types of the fault and normal operating conditions, with various fault resistances and fault locations, are carried out. For each fault scenario, each phase voltage is measured and transformed with DWT. By combining the DWT signals of all phase voltages for each fault scenario, a group signal that reflects the system behaviour during each fault is created, as shown in Fig. 2.

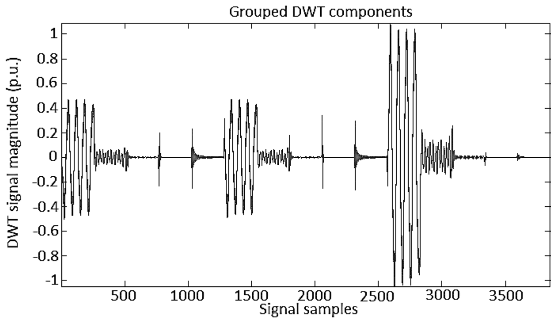
Grouped DWT signal is a signal that is built simply by adding the start of the next signal to the end of the previous signal using the details and approximation waveforms for each fault scenario in the system, i.e. this signal is composed from the DWT waveforms of the currently measured voltage signal. A grouped signal for 400 simulations for each fault type is shown in Fig. 4.

The differences between the created signals for a particular fault type are apparently negligible, but ANN is capable to classify them correctly. Higher harmonic components, which are important for the identification process, can be efficiently identified in the DWT filters of the corresponding frequency range. Generally, DWT is widely used for the noise-removal applications [12], [13]. Moreover, since the proposed algorithm is paired with ANNs, which are known to have a high accuracy in the pattern classification and noise removal ability, this issue is addressed even more effectively [7].

After this unique signal for each fault scenario is created, the input set of data for ANN training is ready. Designed ANN takes the input set of 1600 input vectors and 1600 corresponding outputs during a training process. After that, trained ANN has four possible outputs, where each output notes the normal operating condition and three types of PDS faults. It is important to note that the ANN outputs are numerical values, that don't clearly detect or classify the PDS faults.

Because of that, a modification to the ANN output will be introduced. This modification will take the ANN output vector and set the highest value to 100%, and all other output values to 0%. This will result in an unambiguous output that clearly notes the presence of a fault and identifies the fault type. The proposed DWT - ANN algorithm is capable to accurately detect the fault and distinguish between the three possible categories of faults, regardless of the fault-resistance value and fault location. After the training and testing process, the created ANN is perfectly capable to classify faults in the EPDS.

In order to get a good insight into the algorithm efficiency, it is necessary to test it with new fault scenarios with new resistance values and different fault locations, i.e. fault scenarios that ANN is not trained to. For this purpose, new simulations with new parameters are carried out. Table 2 shows classifier results to this



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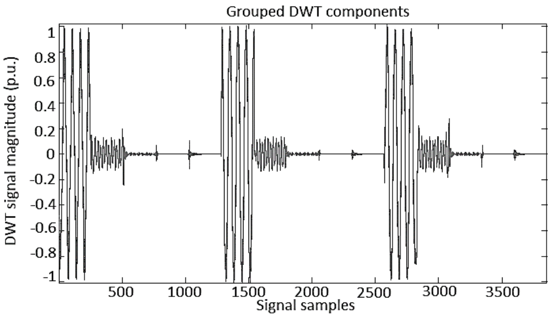

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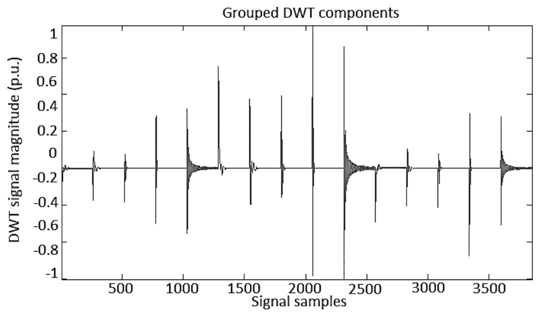

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Figure 4. Grouped DWT component signals:
(a) AG HIF fault, (b) ABG HIF fault, (c) ABCG HIF fault

fault scenarios, where column *Desired output* presents a simulated-fault type and column *Actual output* an evaluated fault type. The 0% or 100% values present the absence or presence of a specific fault. Column *Actual output* presents the ANN output for each fault scenario. The proposed DWT – ANN algorithm has a 100% accuracy in the range of 20 – 600 Ω for all fault locations.

The proposed algorithm is planned to be used in the online mode. The storage method is important since the grouped DWT components take a lot of storage. A present-day industrial computer with a somewhat larger

Table 2. Output of the DWT-ANN classifier for different fault resistances, fault locations and fault types.

Resistance (Ω)	**Fault location (% length)**	**Desired output (probability in %)**				**Actual output (probability in %)**			
		AGF	**ABGF**	**ABCGF**	**No fault**	**AGF**	**ABGF**	**ABCGF**	**No fault**
20	0.01	100	0	0	0	100	0	0	0
110	0.16	0	0	0	100	0	0	0	100
200	0.31	0	100	0	0	0	100	0	0
290	0.46	0	0	100	0	0	0	100	0
380	0.61	100	0	0	0	100	0	0	0
470	0.76	0	100	0	0	0	100	0	0
560	0.91	0	0	0	100	0	0	0	100

hard drive will be enough for online monitoring. Few minutes old data can be deleted if no disturbances are recorded. However, voltage waveforms can be saved for a later analysis. The ANN output modification contributes to the algorithm speed since the ANN output matrix now consists of zeros and ones, and hence does not consume much space and makes the matrix easier to operate with.

4.4 *Future research directions*

The list of the EPDS fault types is not exhausted by the faults included in this paper. However, this algorithm is applicable to new scenarios since it can be easily extended by an additional training of ANN. The proposed algorithm has a potential practical application in terms of its implementation on the EPDS protection-system devices. In order to achieve that, the algorithm robustness improvement is an important part of the future research in this area. Further, an extension in the number of the system components and scenarios that can lead to a false tripping signal should be considered. Finally, an agent-based modelling of complex systems is proposed as an interesting future direction in this area.

5 Conclusion

EPDS faults are undesirable events and remain a serious challenge for DSO. In particular, HIF identification and classification present a particularly complex task due to physical characteristics of HIF and shortcomings of the existing protection devices. For these reasons, this topic remains an open research area. The paper proposes a method to improve the existing algorithms for identification and classification of HIFs in MV EPDS, based on DWT and ANN. This study is a part of an ongoing research into advanced power-system protection algorithms concerned mainly with the HIF identification and classification. The proposed method has a practical significance since, as demonstrated, it can be applied to a real EPDS and it accurately identifies and classifies faults in the 20 – 600 Ω range of the fault resistance for various fault locations. The proposed algorithm is believed to be a promising approach to the future implementation of the power-system protection devices.

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