NEURAL NETWORKS RECOGNITION OF WEAK POINTS IN POWER SYSTEMS BASED ON WAVELET FEATURES

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SUMMARY

Early locating and identifying basic weak-points (sharp-edge corona, polluted-insulator "baby arcs" and loose contact arcing) in electrical power systems significantly decrease the imminent failure, outage time and supply interruption. We previously introduced a method for detecting the basic weak-points based on sound/waveform patterns and frequency analysis of their ultrasonic emissions. However, non-stationary patterns of the basic weak-points' emitted signals and background noise frequently led to confusing discrimination. Therefore, this paper develops an effective pattern recognition scheme, employing wavelet feature extraction and Artificial Neural Network (ANN) classification, to identify the basic weak-points and two weak-point combinations (polluted insulator stressed by a transmission line with a sharp-edge and multiple sharp-edges on the same line), based on their modulated ultrasonic emissions. Extensive testing proved that the proposed scheme achieved average recognition rate of 98% when tested using weak-points underneath 33-kV and 132-kV transmission lines with 2-second detected signals. Moreover, increasing the acquisition time (>30 seconds) and classifying the weak-points based on majority voting over the ANN's responses of multiple (15) consecutive sections, consistently led to 100% successful recognition of the considered weak-points.

INTRODUCTION

Electrical transmission lines and insulators are widely used in electrical power transmission and distribution networks that have been serving for many years. The insulation deteriorates under normal operating conditions, and this deterioration is accelerated due to short or long term overloads, lightning or switching surges, moisture condensation, and vibration or other climatic and mechanical stresses. These factors also may lead to other serious weak points such as poor/loose connections with subsequent arcing and micro roughness over line conductors. Hence, the basic weak points in electrical power networks are sharp-edges corona, polluted-insulators *"baby arcs"* and loose-contacts arcing [1]. Early locating and identifying such weak-points in electrical power systems significantly decrease the imminent failure, outage time and supply interruption that critically reflect the operability and reliability of the electrical power networks/systems [1-7].

In general, the basic weak points (sharp-edges, baby-arcs and loose-contacts) generate audio noise, radio interference complaints and/or ultrasonic noise emissions. Therefore, there are several types of sensors to detect and locate them [2-4]. The ability to locate and identify the weak points guides the maintenance staff to take a proper action such as hot washing of lines and insulators, short-circuiting the gaps by better bonding or tightening the connections, and by smoothening the coronating points to suppress corona activity. Thus, major reduction in the outage time, impending failure, equipment damage and supply interruption can be attained.

Several techniques for partial discharge identification [5] using artificial neural network (ANN) , in case of various power components, have been proposed based on various feature extraction methods such a segmented time domain data compression [6] and short duration Fourier transform [7]. Alternatively, the wavelet transform (WT) [8], a mathematical tool developed in the 1980s, has been recently applied to many problems in power systems, such as analysis and visualization of electrical transients [9].

Previously, we introduced a method for detecting the three basic weak-points based on sound/waveform patterns and frequency analysis of their ultrasonic emissions [4]. However, non-stationary patterns of the basic weak-points' emitted signals and background noise frequently led to confusing discrimination/misclassification that was a strong motivation to automate the discrimination process. Hence, this paper develops an efficient pattern recognition scheme, employing wavelet feature extraction and ANN classification, to identify not only the basic weak-points but also two weak point combinations (polluted insulator stressed by a transmission line with a sharp-edge and multiple sharp-edges on the same line), based on their modulated ultrasonic emissions.

The rest of the paper is organized as follows: Background on the WT and ANN is first presented. Next, the proposed methodology is introduced. Then, details on the experimental set-up and data assembly are given. Next, the design of the ANN used is presented. The detailed results and discussion are presented and finally followed by the conclusion.

BACKGROUND

In pattern recognition, the extracted features should preserve as much of the original information of the signal of interest as possible while eliminating redundant and irrelevant information that could cause extraneous noise [10]. Given a zero-mean, finite energy wavelet mother function $h(t)$, a set of functions $h_{s,\tau}(t)$ can be generated from the single wavelet mother function by dilations and translations. The functions $h_{s,\tau}(t)$, for all possible scales s and shifts τ, are referred to as the wavelets. The continuous

WT of a signal *f(t)* decomposes the signal *f(t)* into frequency components using the wavelets $h_{s,\tau}(t)$. In wavelet analysis, the signal *f(t)* looks like as a signal passing through 2 perfect reconstruction quadrature mirror filters, low pass and high pass filters, followed by down sampling by a factor of 2 [8]. Multiple levels of the WT involves successively decomposing the low pass band only at each level. Alternatively, decomposing both the low and high bands of the transformed signal at all levels of the wavelet tree, results in the wavelet packets (WP) [8,11] that allows higher resolution at high frequencies.

Inspired by biological nervous systems, ANNs are composed of interconnected simple processing elements (artificial neurons). A weighted sum of the neuron's inputs subjected to a linear or nonlinear (typically sigmoid-shaped) activation function constitutes an artificial neuron. ANNs are trained to perform pattern recognition tasks by adjusting the (synaptic) weights of the connections [10] using a representative training set of input feature vectors and their corresponding target vectors. The generalization capability of a neural network is evaluated by its ability to recognize patterns that were not encountered during the training stage. The common advantages of using ANN in pattern recognition (compared to statistical methods) are its capability of implementing much more complex partitioning of the feature space and amenability to parallel processing.

The multi-layer perceptron (MLP) is a feed-forward ANN (FFANN) with one input layer, one or more hidden layers and one output layer. The power of MLPs, rather than 1-layer multi-linear perceptron, comes from the theory that states: 2-layer FFANN with sufficiently many neurons in the single hidden layer is sufficient to classify linearly non-separable sets [10,12,13].

PROPOSED METHODOLOGY

An ANN pattern recognition scheme is developed to identify the basic weak points based on WP features. So, the proposed methodology consists of three main stages: Sensing of weak points and preprocessing, feature extraction using wavelet packets and weak point discrimination using ANN.

The set used for sensing weak points in power systems is the ultraprobe2000 set, which detects ultrasonic frequencies between 20kHz and 100kHz. The optimum frequency corresponds to the maximum reading is 32kHz [14]. To provide more reliable and robust features to the classification stage, the sections of the detected signal are preprocessed. Each 16384-sample windowed section x of the sensed signals is preprocessed as follows:

1- Elimination of any DC distortion in the processed section x, to get a zero-mean signal x_1.

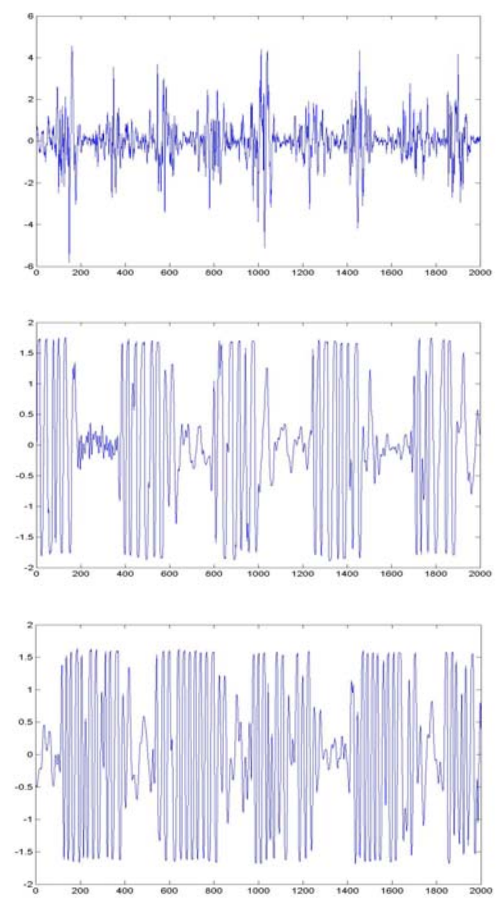
2- Low pass filtering followed by down sampling x_1 using a half-band low pass filter to obtain a smoothed signal x_2.

3- Power normalization of x_2 to get a unity power signal $x_n = x_2 / m_2(x_2)^{1/2}$, where $m_2(x_2)$ denotes the estimated 2nd order central moment of x_2, mainly to avoid the undesirable effects of parameters such as the applied voltage value, distance, sensitivity of the Ultraprobe set, orientation, relative position, ….etc. which may badly affect the classification decision.

Three-level WP decomposition with a Daubechies' mother function, has been applied to x_n. This chosen size of the wavelet tree was experimentally sufficient to result in discriminating features as illustrated later. The following features are used to constitute a 17×1 feature vector:

- The mean of the absolute value of x_n, i.e. $m_1(|x_n|)$. This feature mainly emphasizes the time diversity of weak point waveforms shown in Fig.1.
- The 2nd order central moments of the leaves' wavelets coefficients of the wavelet tree, providing information on the power distribution among the leaves of the tree.
- The 3rd order central moments of the wavelet coefficients of the leaves of the wavelet tree which are added to improve the classification as mentioned later.

Extracted features are initially used to train a 2-layer MLP using error back-propagation (BP) algorithm [10]. Then the trained ANN is used in weak points recognition.



Time normalized by the sampling interval

Fig. 1.: Time domain waveform of: a. Sharp-edge. b. Baby-arc. c. Loose-contact. The Y-axis gives the signal amplitude in voltage.

EXPERIMENTAL SET-UP AND DATA ASSEMBLY

The expected basic weak points in the high voltage power network, namely sharp-edges, polluted insulators and loose-contacts shown in Fig.2, were simulated and stressed in the laboratory by AC voltage. Precautions have been made to avoid the occurrence of partial discharge on high voltage connections. This is why all circuit connections were made from thick straight conductors with copper spheres at ends. In case of sharp-edge weak point, different sharp-edges with different edge diameters (for example 0.5mm, 1mm and 1.8mm) were used to make sure that the obtained neural network is more general irrespective of the sharpness of weak point. Two weak-point combinations, polluted insulator stressed by a transmission line with a sharp-edge and multiple sharp-edges on the same line, were also simulated. Different applied voltage values were attempted starting from 10kV until 105kV.

A total of 5100 data sections of each weak point type have been recorded (during a long period, over 10 months, and at various weather conditions: atmospheric temperature and humidity percentage) and preprocessed, and their 5100 17x1 feature vectors are computed as explained in the previous section.

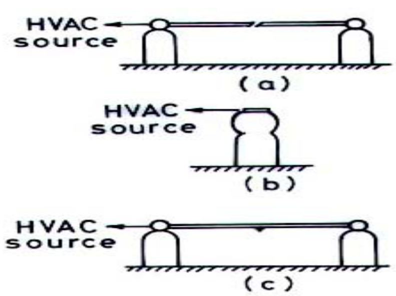


Fig. 2. Laboratory simulation of different weak points.
(a) Loose contact (b) Polluted insulator. (c) Sharp edge.

DESIGN OF NEURAL NETWORK STRUCTURE

To design a 2-layer FFANN having a 17-M-3 structure, i.e., 17 inputs, M hidden neurons and 3 output neurons, we first set the desired output (Target) corresponding to the various basic weak point types to be {+1 -1 -1}, {-1 +1 -1} and {-1 -1 +1} for sharp-edge, baby-arc, loose-contact weak points, respectively.

Then, to properly size the hidden layer, we adopted a network growth procedure guided by both the network's training and validation performance (as a good estimate of it generalization capabilities). The procedure finds the experimentally optimum number of hidden neurons as follows: Disjoint training and validation sets constituting 50% and 20% of the overall data set, respectively, have been uniformly randomly selected. Then, starting with a small number (4 neurons), the number of hidden neurons has been successively incremented and each new network structure has been trained using error BP algorithm. To conditionally stop the training procedure, a training performance goal 0f 0.01 (mean square error) and 350 maximum number of epochs have been chosen. The rates of correctly classified validation patterns have been computed for the trained ANN. When the average rate of correct validation classification manifested no further improvement or even started going down, we stopped enlarging the size of the hidden layer. The procedure has been repeated 12 times. On the average, it has been experimentally found that learned networks with a number of hidden neurons > 15, did not significantly improve the rate of the correctly classified validation patterns. Consequently, 15 hidden neurons are used.

After optimally choosing the ANN structure (17-15-3), 66% of the data sections (10098 sections, 3366 for each weak point type and 16384 samples each) were uniformly randomly selected and used to train the selected structure.

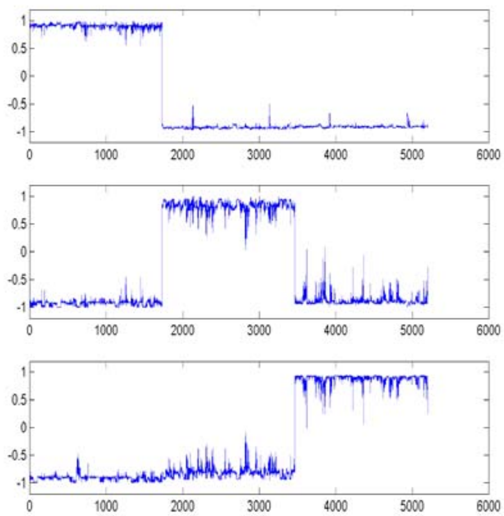
RESULTS AND DISCUSSION

Table I summarizes the average (over 10 random experiments, for both training and testing) testing results (±standard deviation) of successfully trained ANNs using a total of 5202 sections of basic weak-points' signals; 1734 representing sharp-edge weak points, 1734 representing baby-arc weak points and 1734 representing loose-contact weak points. Fig. 3 depicts the simulation results when concatenating the feature vectors of the three weak points and sequentially applying the 5202 17×1 feature vectors to the trained ANN. To get robust and more reliable network decisions, we considered the outputs laying in between -0.3 and 0.3 as zero, meaning that the ANN "cannot identify" the weak point type. In case of sharp-edge weak point, 97.23 % identification rate was obtained, indicating that 1686 out of 1734 were recognized correctly. In case of baby-arc weak point, 96.19 % identification rate was obtained, indicating that 1668 out of 1734 were recognized correctly. In case of loose-contact weak point, 96.42 % identification rate was obtained, indicating that 1672 out of 1734 were recognized correctly.

Table. I. The details of weak points data used for ANN training/testing and results of testing.

Weak point type		Sharp-edge	Baby-Arcs	Loose-contact
Total Data	Sections	5100	5100	5100
Training Data	Sections	3366	3366	3366
	%	66	66	66
Testing Data	Sections	1734	1734	1734
	%	34	34	34
Recognized Data	Sections	1686 ± 9.037	1668 ± 9.39	1672 ± 10.05
	%	97.23 ± 0.52	96.19 ± 0.54	96.42 ± 0.6
Error	%	0.39	2.51	2.87
Cannot be Identified	%	2.35	1.25	0.66

It should be mentioned that when the 3rd order central moments were excluded from the feature vector (i.e., using only 9×1 vectors) the generalization capabilities of the designed ANN markedly degraded with a ~15% drop in the average correct classification rate. On the other hand, the recognition rates for the basic weak points are improved and the average training time is reduced (by about 30%), in case of using zero-mean version of the rectified normalized signal $|x_n|$ instead of x_n as an input to the WP analysis stage. Specifically, the identification rate has increased to 98.56 % for sharp-edge weak points, 99.08 % for baby-arc weak points, and 99.08 % for loose-contact weak points.



Index of the tested signal section

Fig. 3. ANN response for the basic weak-points.
Sharp-edge: 1 → 1734, Baby-arc: 1735 → 3468
Loose-contact: 3469 → 5202. From top to bottom, responses of the 1st, 2nd & 3rd o/p's.

Recognition of Basic and Combined Weak-Points

Two additional types of weak points, which may be found in real practice, are also discussed, a combination of the basic sharp-edge and the baby-arc weak points (i.e., polluted insulator is stressed by a transmission line with a sharp-edge) and two-basic sharp edges spaced along transmission line by 2 cm. The features has been extracted from these combined weak points and fed to the neural network for recognition. The so-far trained ANN (using the 3 basic weak points only) failed to identify the above-mentioned weak point combinations with acceptable recognition rates. This calls for re-training the ANN to identify all the considered weak-points, namely, the three basic weak points and the two combined weak points. The target is properly selected being {-1 1 1} for the first combined weak point and {1 –1 –1} for the second combined weak point (which is the same as that for the basic sharp-edge weak point). Such good selection for the target states increases the ANN recognition rates at minimum training time. The ANN was trained using a total of 4845 data sections with 969 sections of each type of the considered basic and combined weak-points and tested using a total of 2805 data sections with 561 sections of each type. Table II summarizes the average (over 10 random training and testing procedures) recognition rates (±standard deviation) of the successfully trained ANNs.

In general, it has been experimentally verified that increasing the acquisition time into ≥ 30sec. (i.e. > 14 consecutive sections), individually processing each section and then classifying the weak point based on majority voting over the ANN's responses of all sections, consistently resulted in 100% correct classifications.

Table II Recognized data by the trained ANN in case of the 5 weak points.

Weak-point type		Sharp-edge	Baby-arc	Loose-contact
Recognized Data	Sections	550 ± 9	505 ± 22	557 ± 2.2
	%	98.04 ± 1.6	90.02 ± 3.9	99.29 ± 0.39
Error	%	0.71	7.7	0.61
Cannot be identified	%	1.4	2.2	2.6
Weak-point type		Two-sharp Edge	Combined of Sharp-edge And baby-arc	
Recognized Data	Sections	547 ± 6.2	478 ± 20	
	%	97.5 ± 1.11	85.02 ± 3.5	
Error	%	0.42	11.7	
Cannot be identified	%	2.16	5.9	

Weak-Points on Full Scale Transmission Lines

Considering detection and classification of weak points encountered in case of full-scale overhead transmission lines, some problems may be faced such as the effect of surrounding noise due to wind and the long distance between the Ultraprobe and the transmission-line conductors. This is in addition to the measurement in uncontrolled conditions, which is different from that at controlled conditions in the laboratory. This part reports the results obtained using data recorded under transmission lines in the field and is considered as a real test to the proposed neural network after being trained.

The ultrasound emission was recorded at two locations along 33-kVand 132-kV transmission-line conductors. The first outdoors location was at the mid-span between transmission-line towers, where one basic point is expected, namely, the sharp-edge weak point. The second outdoors location was very close to the tower where line conductors are suspended by (already cleaned) insulators.

The proposed ANN, already trained using laboratory weak points, 98% succeeded to recognize these weak points as either sharp edges at the mid-span between transmission-line towers or loose contacts between line conductors and insulators (at locations very close to the towers). In addition, as previously mentioned, using an acquisition time ≥ 30 seconds and a majority voting over the ANN's responses of all the 15 individual 2-second sections, consistently resulted in 100% correct classifications of the considered weak points.

CONCLUSION

The proposed scheme, employing effective preprocessing, WP feature extraction and classification using the properly designed MLP ANN, has been proved to be very successful in achieving full recognition of the considered basic and combined weak points on laboratory-modeled and full-scale power transmission lines through their modulated ultrasound emissions.

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