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Determination of Corona Location from Audible Corona Noise by Using Artificial Neural Network

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Abstract

In this study, corona location is determined by neural network using corona sound samples as input data of the network. On an experimental set-up corona is produced by placing x-shaped strings on to a conductor which leads to produce corona noise. By applying 50 Hz AC high voltage to the conductor, corona sound data are acquired experimentally from a test set-up. Recorded sound data of corona (electrical discharge) and coordinates of the string are applied to an artificial neural network (ANN). During the application, linear prediction coefficients are used to analyze corona sound. It is shown that, following the proposed method can be used for the determination of corona location problem.

1. Introduction

If the electric field is uniform, a gradual increase in voltage across a gap produces a breakdown of the gap in the form of a spark without any preliminary discharges. On the other hand, if the field is non-uniform, an increase in voltage will first cause a discharge in the insulation to appear at points with highest electric field intensity. This form of discharge is called a corona discharge [1]. The electrical discharge can be characterized by not only from its current impulses, voltage impulses and electromagnetic field propagation but also from its heat, light, sound emissions and produced smell. This phenomenon is accompanied by a hissing noise. Acoustic and optic methods can be used for the discharge detection and location [2]. To use its sound, light, heat i.e. instead of voltage of the discharge is very important part of fault detection, diagnostics and long term system monitoring and evaluation studies especially for high voltages which are very difficult to measure directly.

In this study, by means of artificial neural networks (ANN) a new approach has been presented that the sound recordings of corona (electrical discharge) are used to determine the location of the electrical discharge [3-4]. The data that is used to determine the corona location from audible corona noise using the neural networks have been collected from a high-voltage line model installed in a high-voltage laboratory. The model has been arranged to produce corona when high voltage applied. In order to produce corona, x-shaped strings (as sharp points) has been placed on the line model. The corona noise has been recorded around the line model by using a capacitive microphone which is compatible with the standards. In order to apply the sound recordings to the neural network, the sound data has been analyzed by linear prediction coding (LPC) technique.

2. Linear Prediction Coding (LPC)

Linear prediction coding or analysis is a way to obtain a smooth approximation of the sound spectrum. The objective of this method is to design a filter which resembles the spectrum of the signal that is desired to obtain frequency response [3]. The spectrum is modeled with an all-pole function, which concentrates on spectral peaks.

In the classical forward linear prediction, an estimate for the next sample $\hat{y}(n)$ of a linear discrete-time system is obtained as a linear combination of p previous output samples.

$$\hat{y}(n) = \sum_{i=1}^{p} a_i y(n-i) \tag{1}$$

where a_i denotes the linear prediction (LP) coefficients. They are fixed coefficients of a predictor all-pole filter, whose transfer function is

$$H(z) = \frac{1}{A(z)} = 1 \big/ \left(1 - \sum\nolimits_{i=1}^{p} a_i z^{-i}\right) \tag{2}$$

The goal of the linear prediction is to find the set of the linear prediction coefficients $\{a_1, a_2, ..., a_p\}$ that minimize the short-time mean-squared prediction error

$$e = E\left\{\left|y(n) - \sum_{i=1}^{p} a_i y(n-i)\right|\right\} \approx \sum_{n=-\infty}^{\infty}\left|y(n) - \sum_{i=1}^{p} a_i y(n-i)\right|^2 \quad (3)$$

where $E\{.\}$ denotes expectation. By definition, e is also the prediction error power [4]. Several algorithms exist for minimizing e and solving the linear prediction coefficients a_i. In this study autocorrelation method is used for minimization. To solve the minimization problem, the Levinson-Durbin algorithm which is a well-known algorithm, is used in this study. Detailed explanations can be found in [5-7].

3. Artificial Neural Networks

An artificial neural network is a method that consists of a set of processing elements called neurons that interact by sending signal to one another along weighted connections. The connection weights, which can be determined adaptively, specify the precise knowledge representation. Connection weights are usually determined by a learning procedure. By using the weights which can be determined by different learning procedure one can reach the result knowledge [8].

3.1. Generalized Regression Neural Network

GRNN is a multilayer feedforward network which is a special case of a Radial Basis Function (RBF) ANN. The network structure of GRNN consists of a radial basis layer and a linear layer. Detailed schematic of the GRNN is given in Figure 1 with n_i input neurons, n_h radial basis functions and n_o output neurons [8-12].

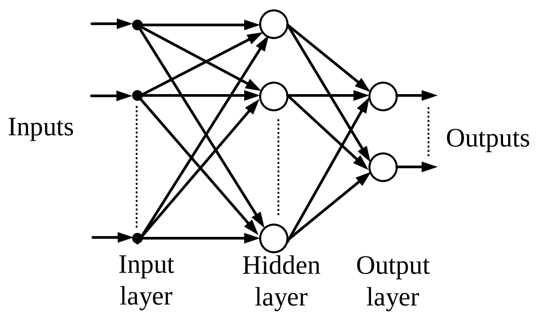

Figure 1. Schematic diagram of GRNN

Each input neuron x_i ($i = 1, 2, \ldots, n_i$) corresponds to the element in the input vector $x = [x_1, x_2, \ldots, x_{ni}]^T$, h_j ($j = 1, 2, \ldots, n_h$) is the radial basis function where n_h is varied. Output of each neuron y_k is calculated as

$$y_k = \frac{1}{\delta}\sum_{j=1}^{n_h} \omega_{j,k} h_j \quad (4)$$

where:

$$\delta = \sum_{k=1}^{n_0}\sum_{j=1}^{n_h} \omega_{j,k} h_j \quad (5)$$

$$\omega_j = \left[\omega_{j,1}, \omega_{j,2}, \ldots, \omega_{j,n_0}\right]^T \quad (6)$$

$$h_j = f\left(x, c_j, \sigma_j\right) = exp\left(-\frac{\|x-c\|_2^2}{2\sigma_j^2}\right) \quad (7)$$

where c_j is called the centroid vector, σ_j is the radius of RBF which is also known as smoothing parameter, and w_j denotes the weight vector between the j^{th} RBF and the output neurons [8].

As shown in Figure 1, the structure of a GRNN is similar to the well-known multilayered perceptron neural network (MLP-NN) except that RBFs are used in the hidden layer and linear functions in the output layer [11]. In comparison with the conventional RBF-NNs, the GRNNs have a special property, namely that no iterative training of the weight vectors is required. That is, like other RBF-NNs, any input-output mapping is possible, by simply assigning the input vectors to the centroid vectors and fixing the weight vectors between the RBFs and outputs identical to the corresponding target vectors. This is quite attractive, since conventional MLP-NNs with back-propagation type weight adaptation involve long and iterative training, and there even may be a danger of their being stuck in local minima (this is serious as the size of the training set becomes large) [8].

Moreover, the special property of GRNNs enables us to flexibly configure the network depending on the tasks given, which is considered to be beneficial to real hardware implementation, with only two parameters, c_j and σ_j, to be adjusted. The only disadvantage of GRNNs in comparison with MLP-ANNs seems to be, due to the memory-based architecture, the need for storing all the centroid vectors into memory space, which can sometimes be exhaustive for on-line data processing, and hence, the utility is slow in the reference mode (i.e., the testing phase). Nevertheless, with the flexible configuration property, the GRNNs can be exploited for interpretation of the notions relevant to actual brain, such as "intuition," or other psychological functions.

In Figure 1, when the target vector d(x) corresponding to the input pattern vector x is given as a vector of indicator functions

$$d(x) = \left(\delta_1, \delta_2, \ldots, \delta_{n_0}\right) \quad (8)$$

$$\delta_j = \begin{cases} 1 & if\ x\ belongs\ to\ the\ class\ corresponding\ to\ y_k \\ 0 & otherwise \end{cases}$$

when the RBF h_j is assigned for, with utilizing the special property of GRNNs, $w_j = d(x)$, the entire network becomes topologically equivalent to the network with a decision unit [8, 11].

In summary, the network configuration by means of a GRNN is simply achieved as in the following.

Network Growing: Set $c_j = x$ and fix σ_j, then add the term $w_{jk}h_j$ in equation (2). The target vector d(x) is thus used as a class "label" indicating the sub-network number to which the RBF belongs.

Network Shrinking: Delete the term $w_{jk}h_j$ from equation (2).

4. Experimental study

In this study, the audible corona noise was acquired from a high voltage transmission line set up in a laboratory in order to determine the corona location by only using the recorded sound data as an input. In the transmission line with that purpose, for producing discharge sounds, 5 m long having circular cross-section area of 2.5 mm^2, smooth, clean, dry copper wire was laid at a height of 220 cm above from the ground between two support insulators as a part of the experimental setup. A simplified diagram of the experimental setup is given in Figure 2. As 27 kV is the corona inception voltage, a constant alternating voltage level above 27 kV in effective values (rms) which is 30 kV, having 50 Hz frequency audible to the human ear were applied to the wire from a 0.220/100 kV, 5 kVA, single phase high voltage test transformer [4].

X-shaped strings have been attached at different coordinates to generate sharp points on the wire in order to produce corona when high voltage is applied. Each test has been carried out for one sharp point at a voltage of 30 kV. The location of the sharp point was shifted 20 cm away from the previous location and test repeated for twenty one different coordinates of the x-shaped strings. Corona sound was recorded throughout 180 seconds for each sharp point coordinates. The microphone was located at 1 m above from the ground and at a horizontal distance of 1 m away from the midpoint of the wire. The corona discharge sound was recorded via a capacitive microphone. The experiment was carried out in electromagnetic shielded laboratory at the air pressure of 755.5 mmHg and room temperature of 17.5 °C at a relatively quiet ambient. Generalized regression neural network (GRNN) was used for the determination of the corona location in terms of the audible corona noise [2].

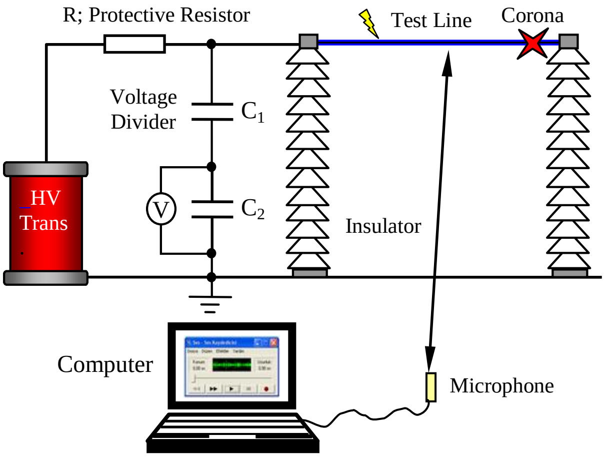

Figure 2. Experimental setup

5. Application

As explained in section 4, electrical discharge (corona) sound samples at 30 kV are acquired for the duration of 180 seconds for 21 different sharp point coordinates on the line model. The sound samples which have 22050 Hz sampling frequency and resolution of 16 bits are recorded by using MATLAB packet program. The linear prediction coefficients are computed for each frame having the length of 20 ms during a second on the recorded sound samples and those frames are not overlapped. After LP coefficients are computed for each frame, the average value of all LP coefficients is computed. 20th degree LP coefficients are computed for all the recordings. Each one-second sound sample is represented by its 20 average LP coefficients. Since there are twenty-one different coordinates, per second for 180 seconds produces 3780 sound. The training and test sets for the GRNN are obtained from these 3780 data. The first 2520×20 LP data which are computed from the first 120 seconds of sound data recorded at each sharp point location are used as the training set; the remaining data are used as the test set. Following that procedure, the analyzed sound data is applied to a GRNN and test errors are determined. The input vector of the GRNN is the LP coefficients of sound data and the output vector of the GRNN is the coordinates of the sharp points on the wire at which the sound samples are recorded.

The only parameter that has been used in the GRNN is spread value, given by σ. The optimum spread value of the GRNN is determined by using trial-by-error process in the studies. The σ value is the spread of radial basis functions used in the GRNN. A larger spread leads to a large area around the input vector where layer 1 neurons will respond with significant outputs. Therefore if spread is small the radial basis function is very steep, so that the neuron with the weight vector closest to the input will have a much larger output than other neurons. The network tends to respond with the target vector associated with the nearest design input vector. As spread becomes larger the radial basis function's slope becomes smoother and several neurons can respond to an input vector. The network then acts as if it is taking a weighted average between target vectors whose design input vectors are closest to the new input vector. As spread becomes larger more and more neurons contribute to the average, with the result that the network function becomes smoother [13].

In Table 1, change of training and validation errors with respect to the spread value for the sound signal are shown. All the recorded data is used in the problem in order to determine the determination of corona location using corona sound sample.

Table 1. Errors of training and validation sets

	RMS Errors (%)	
σ	**Training**	**Validation**
0.1	1.8658	2.6282
0.09	1.7616	2.4842
0.08	1.6294	2.3080
0.05	0.9292	1.5582
0.03	0.1147	1.0826
0.025	0.0256	1.0845
0.02	0.0025	1.1435
0.019	0.0014	1.1720
0.018	0.0007	1.1852
0.01	3.6779e-008	2.1174

It is to be noted here that in this study the errors in training and validation sets are represented by root mean squared error (rms). The formula used for computation of errors is given below:

$$rms = \sqrt{\frac{1}{Nn_o}\sum_{j=1}^{N}\sum_{k=1}^{n_o}\left(d_{jk} - y_{jk}\right)^2} \qquad (9)$$

where N denote the total number of patterns contained in the training or validation set, n_o is the number of output neurons.

For the spread value of 0.019, the corona sound data can be used for determining the corona location with an acceptable error. If the sigma value is smaller than 0.018, the model will over fit the data, because each training point will have too much influence.

6. Conclusion

In this study, determination of corona location with artificial neural network by using the sound data produced at a constant alternating voltage level is presented. For that purpose, the sound data is analyzed by the linear prediction coding. The coded sound information is applied to the generalized regression neural network. Consequently, the location of the corona is successively determined by using the recorded corona sound signals.

Performance of the identification depends on perception and recording of the sound data. Discharge sound heavily depends on the geometry, dimensions, cleanliness, dryness, and smoothness of the structure in which the discharge appears. If circular cross sectioned, clean, dry, and smooth wire is used, the possibility of the discharge around the wire diminishes. For that reason, x-shaped strings having a diameter smaller than the diameter of the wire is located on the wire in order to produce partial discharges. As the diameter of the string is small and the magnitude of voltage is high, electrical stress on the conductor is bigger than breakdown field of air surrounding the wire, which leads to a discharge phenomena. This partial electrical discharge which is called corona causes sounds that are results of ion movements around the conductor in the range of 15 Hz – 30 MHz frequencies.

Audible noises within the frequency range of human hearing (15 Hz – 15 kHz) are not very preferable for corona sound measurements, because it is difficult to distinguish between the environmental noise and the corona noise. Therefore, the corona sounds are usually measured at the frequencies higher than 15 kHz, which are called ultrasonic. In this study, the corona sounds are measured within the sonic frequency range, for that reason, the environmental noises became very dominant. The application results of the ANN can be optimized by using de-noised sound data.

In order to analyze the sound data, it is possible to use different methods. In this study, linear prediction coding is preferred. It has been seen that the results are appropriate for the data but different methods can be applied to the problem and compared to each other in order to determine the optimum method. It is obvious that algorithmic methods such as fuzzy logic and genetic algorithms can be also used for this study.

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