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Estimation of Voltage Magnitude from DC Corona Noise Using Neural Network

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Abstract

In this study, measuring positive DC corona voltage without any contact with the voltage source by using only recorded sound data of corona (electrical discharge) and utilizing generalized regression neural network (GRNN) was presented. The recorded positive DC corona sound data were acquired experimentally from a test set-up. The test set-up was used for producing corona sound by applying different levels of positive DC high-voltage. Recordings and the voltage magnitudes which causes corona have been used in training and validation sets of the neural network. The main objective of this study is developing a model to measure voltage magnitude by only analyzing the recorded corona sound data. During the application of algorithmic method, linear prediction coefficients were used to pre-process the sound data for feature extraction. It is shown that, by means of measuring voltage magnitude, reasonable results can be obtained by following the proposed method.

1. Introduction

The electrical partial discharge occurring at the points of highly concentrated electric fields is known as corona. It is a self-sustained electrical gas discharge which consists of a high-field active electrode surrounded by an ionization region where the free charges are produced. Corona is very distinctive in nature. It has many effects such as, electric current, energy loss, radio interference, mechanical vibrations, chemical reactions, visible light, and audible noise [1-4]. This study, mainly concerns about audible noise of positive DC corona.

Acoustic methods can be used for discharge detection and location, fault detection, diagnostics and long term system monitoring and evaluation studies. Detecting and locating partial discharges within power transformers [5] and finding radio inference sites caused by discharges associated with high voltage power lines [6] are some studies in the literature using acoustic methods. More recently, acoustic methods have been used to detect discharges in high voltage compressed gas insulated transmission systems [7], monitor discharges at high voltage capacitors, detecting faulty insulation in high voltage insulators [8], and the feasibility of detecting discharges during testing of spacecraft apparatus at low pressure and vacuum has been established [9, 10]. Using sound of a discharge is a very important progress for measurement techniques especially for high voltages which are very difficult to measure directly [11].

The electrical discharge depends on many variables such as, medium temperature, air pressure, humidity, material type, dimensions, geometry, homogeneity, duration and type of the applied voltage [1-2]. For that reason, using audible noise of DC corona in order to measure the voltage which generates corona is not a common study. However, it is now considered as an interesting measurement technique by the developments of computer skills and improvements on the signal processing, measurement and evaluation techniques.

This paper presents a new approach for voltage measurements which is essential to power system control, protection and monitoring without any contact with the line. This method is cost effective and less complex in terms of installation maintenance than the traditional measuring methods [12].

In this study, a new approach is presented that the sound recordings of positive DC corona (electrical discharge) are used to determine the voltage magnitude by means of generalized regression neural networks (GRNN) [13, 14]. The sound data have been collected from a high-voltage line model installed in a high-voltage laboratory. Different levels of positive DC voltages are applied to the line model in order to produce corona which causes audible noise. After obtaining sound recordings of positive DC corona, a signal processing routine is applied to the sound data. This procedure called as feature extraction, which is pre-processing the original data. It is used for simplify the data when the problem has much data but not much information. The sound recordings of

DC corona have been analyzed by linear predictive coding (LPC) technique. Calculated LP coefficients are then applied to a neural network in order to determine the line voltage.

2. Feature Extraction

Basically, feature extraction is simplifying the amount of resources required to describe a large set of data accurately. Using big amount of data is one of the major problems when performing analysis of complex data. Analysis with a large number of variables generally requires a large amount of memory and computation power or a classification algorithm which overfits the training sample and generalizes poorly to new samples. Feature extraction is a general term for methods of constructing combinations of the variables describing the data with sufficient accuracy without these problems.

Common denominator of all recognition systems is the signal processing front-end, which converts the acoustic waveform to some of type of parametric representation. This parametric representation is then used for further analysis and processing. In this study, linear predictive coding (LPC) is used for feature extraction of the positive DC corona sound data.

2.1. Linear Predictive Coding (LPC)

Linear predictive coding (LPC) is a tool used for representing the spectral envelope of a digital signal in compressed form, using the information of a linear predictive model. It is one of the most useful methods for encoding good quality sound at a low bit rate and provides extremely accurate estimates of sound parameters. It 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 [15]. The spectrum is modeled with an all-pole function, which concentrates on spectral peaks. In this study, LPC is used for feature extraction

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. The predicted signal value can be expressed as,

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

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

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

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

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

where $E\{.\}$ is the expected value. By definition, e is also the prediction error power [16]. The most common choice in optimization of parameters a_i is the root mean square (RMS) criterion which is also called autocorrelation. In this method the expected value of the square error is minimized. To solve the minimization problem, the Levinson-Durbin algorithm was used in this study. Detailed explanations can be found in [17-19].

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 the relation between input – output is characterized [20].

3.1. Generalized regression neural network

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. n_i denotes input neurons, n_h denotes radial basis functions and n_o denotes output neurons [20-24] in the network.

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

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

where:

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

$$\omega_j = \left[\omega_{j,1}, \omega_{j,2}, \dots, \omega_{j,n_0}\right]^T \tag{6}$$

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

where c_j is called the centroid vector, σ_j is the radius of RBF which is also known as smoothing parameter, and ω_j

denotes the weight vector between the j^{th} RBF and the output neurons [20].

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 [23]. The GRNNs have 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 [20].

Moreover, the special property of GRNNs enables the designer 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.

When the target vector d(x) corresponding to the input pattern vector x is given as a vector of indicator functions

$$d(x) = (\delta_1, \delta_2, \dots, \delta_{n_0})$$

$$\delta_j = \begin{cases} 1 & \text{if } x \text{ belongs to the class corresponding to } y_k \\ 0 & \text{otherwise} \end{cases} \quad (8)$$

when the RBF h_j is assigned for, with utilizing the special property of GRNNs, ω_j = d(x), the entire network becomes topologically equivalent to the network with a decision unit [20, 23].

4. Experimental Study

In this study, in a high voltage laboratory, a high voltage transmission line model was installed for intentionally producing corona. In the line model 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. The simple diagram of the experimental set-up is shown in Figure 1. Thirteen different positive DC voltages which are 40 kV, 45 kV, 50 kV, 55 kV, 60 kV, 65 kV, 70 kV, 75 kV, 80 kV, 85 kV, 90 kV, 95 kV and 100 kV were applied to the wire, respectively [13, 14].

The experiment was repeated for each above given voltage levels and the corona sound was recorded throughout 180 seconds in each test. The microphone was located at 1.5 m above from the ground and at a horizontal distance of 1 m away from the midpoint of the wire. The positive DC corona discharge sound was recorded for each voltage level via an ordinary microphone.

The laboratory at which the experiment was carried out was electromagnetically shielded. The ambient conditions are 1019 Pa (765 mmHg) air pressure and 19 °C room temperature. After obtaining sound data, generalized regression neural network was used for the estimation applied DC voltage from corona sound [13, 14].

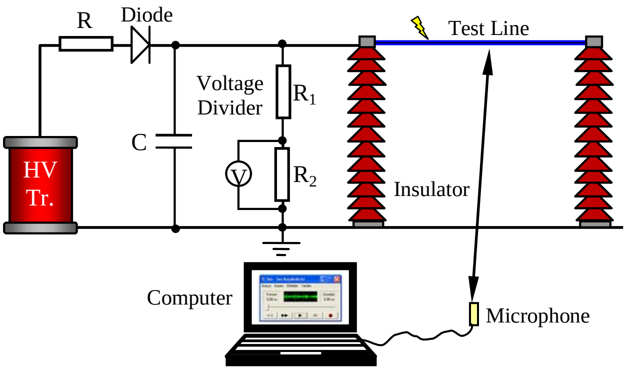

Fig. 1. Experimental Set-up

Corona discharges appear at a lower magnitude for negative voltages than for positive voltages. This is because the secondary processes that occur at the cathode for negative corona are delayed for positive corona, as the cathode is isolated from the ionization region by the drift region [12]. For that reason, positive DC voltages are applied to the wire in this study.

5. Application

As mentioned before, electrical discharge (corona) sound samples at each voltage level were acquired for the duration of 180 seconds. The sound samples which have 22050 Hz sampling frequency and resolution of 16 bits were recorded by using MATLAB packet program.

First 22050 data of the sound sample which represent one second at 50 kV DC voltage is shown in Figure 2. Each recording from seven different DC voltage levels has an impulse noise at the beginning of the signal.

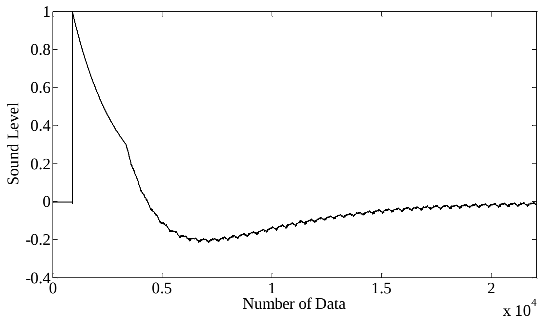

Fig. 2. The first 22050 data of the positive DC corona sound for 1 second at 50 kV.

In order to clear the sound signal from this noise, the first one second of the sound signal recorded for seven different voltage levels have been removed individually.

The linear prediction coefficients were computed for each frame having the length of 20 ms during a second on the recorded sound samples and those frames were not overlapped. After LP coefficients were computed for each frame, the average value of all LP coefficients was computed. Each one-second sound sample was represented by its average LP coefficient value. 10th degree LP coefficients were computed for all the recordings. Therefore, there are 179 data for each voltage level. Since there are seven different applied voltage levels, per second for 179 seconds produces 2327 sound samples and the LP coefficients.

The training and validation sets for the GRNN are obtained from these 2327 data. In the study, all dataset was divided into two subsets. The 1st subset is used for training the GRNN consisting 1164 patterns, and the 2nd subset was used for validation consisting 1163 patterns. Following that procedure, the LP coefficients of sound data were applied to a GRNN and errors of the network were determined. The input vector of the GRNN is the LP coefficients of sound data and the output vector of the GRNN is the voltage magnitude at which the sound samples are recorded.

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

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

$$ARError = \frac{1}{Nn_o}\sum_{j=1}^{N}\sum_{k=1}^{n_o}\frac{\left|d_{jk} - y_{jk}\right|}{y_{jk}} \tag{10}$$

where d is the desired value, y is the real value of the voltages, N denote the total number of patterns contained in the training or validation set, n_0 is the number of output neurons.

In Table 1, the change in errors of the network with respect to the spread value for thirteen different positive DC voltages is shown. All the recorded data are used in the decision making problem in order to determine the DC voltage magnitude of a given sound sample.

Table 1. The change of misclassification with respect to σ for the measured sound signal

	Training Set		**Validation Set**	
σ	**AR Error [%]**	**rms [%]**	**AR Error [%]**	**rms [%]**
0.05	3.597	10.613	3.558	10.466
0.04	2.804	8.595	2.786	8.491
0.03	2.017	6.564	2.025	6.530
0.02	1.319	4.740	1.393	4.865
0.015	0.975	3.784	1.137	4.206
0.01	0.473	2.184	0.915	3.809
0.009	0.339	1.695	0.885	3.828

The only parameter that has been tuned 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 network.

Tables 1 shows that as the spread value decreases, and errors in the training set decreases, too. However, the errors in the test set do not show a significant change after the sigma value of 0.01. As seen from the Table 1, for the spread value of 0.01, the corona sound data can be used for determining the voltage magnitude with an acceptable error of 0.9%. If the sigma value is smaller than that, the model will over fit the data, because each training point will have too much influence.

The accuracy of the measurements could be improved if the technique was to find commercial usage in substations. In order to improve the results, the sound samples can be cleaned by applying several signals processing procedure such as wavelet denoising procedure.

6. Conclusions

In this study, measuring the DC line voltage by using the sound data produced at that voltage level was presented. For that purpose, the DC corona sound data were analyzed by the linear predictive coding. The processed sound information was applied to a generalized regression neural network. Consequently, the magnitude of the DC voltage was determined by using the recorded corona sound signals.

Performance of the identification depends on perception and recording of the sound data. Corona discharges are significantly affected by atmospheric conditions and discharge sound heavily depends on the geometry, dimensions, cleanliness, dryness, and smoothness of the structure in which the discharge appears. For that reasons, as the diameter of the wire 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.

When the input data to an algorithm is too large to be processed and it is suspected to be notoriously redundant then the input data will be transformed into a reduced representation set of features. Transforming the input data into the set of features is called features extraction. If the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input. In order to pre-process the sound data, it is possible to use different methods. In this study, linear predictive coding was 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.

The absolute relative error of the test set is 0.9 %. The accuracy of the measurements can be improved by cleaning the sound recordings in order to limit the effects of external noises. The accuracy of measurements may improve with investments in new, calibrated equipment.

This study is an application for future studies of monitoring and evaluation in electrical systems and remote sensing and forecasting voltage magnitude using the corona sound that appears during a line fault without any physical connection to the line especially at high voltage levels.

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