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Estimation of Corona Voltage from Corona Sound Using Wavelet and Neural Network

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Abstract

This study presents determination of magnitude of voltage applied on a HV line by neural network using corona sound data as input of the network. Corona sound data used in this study are acquired from an experimental set-up when is applying 50 Hz AC high voltage at different levels to the line conductor. Recorded sound data of corona (electrical discharge) and the knowing voltage magnitudes are applied to an artificial neural network (ANN). To analyze corona sound, linear prediction coefficients are used. It is shown from the results that the proposed method can be used for the measuring voltage magnitude.

1. Introduction

One of the fractal properties of electrical discharges such as corona, sparks, lightning is their audible sound. High voltage sparks in air produces acoustic emissions similar to lightning but on a much reduced scale. Similarly, acoustic emissions from an electrical discharge (corona) on a high voltage transmission line could be heard by ear. Hence, it is very important to have information about electrical discharges in order to find their location, effects, and properties and to design systems of good quality [1].

Electrical discharge sound is one of the non-electrical quantities of an electrical discharge. Using a non-electrical quantity to determine the magnitude of voltage which generates corona is not a common study. Acoustical measuring methods are now considered as an interesting measurement technique by the developments of computer skills and improvements on the signal processing, measurement and evaluation techniques. Using sound of a discharge instead of voltage of the discharge is now considered as 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.

Acoustical methods are used for detecting and locating partial discharges within power transformers [2] and finding radio inference sites caused by discharges associated with high voltage power lines [3]. More recently, acoustic methods have been used to detect discharges in high voltage compressed gas insulated transmission systems [4], monitor discharges in high voltage capacitors, detecting faulty insulation in high voltage insulators [5], and the feasibility of detecting discharges during testing of spacecraft apparatus at low pressure and vacuum has been established [6-7].

In this study, by means of generalized regression neural networks (GRNN) a new approach is presented that the sound recordings of corona are used to measure the line voltage, which causes the corona [8-9]. The data that are used to determine the voltage from audible corona noise using the ANN have been collected from a high-voltage line model installed in a high-voltage laboratory. Acquired data have been processed by wavelet de-noising technique to limit environmental noises and applied to an ANN. In order to apply the sound recordings to the ANN, the sound data has been analyzed by linear prediction coding (LPC) technique.

2. Linear prediction coding (LPC)

Linear prediction coding 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 [10]. 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

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

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

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

where $E\{.\}$ denotes expectation. In this study autocorrelation method is used for minimization. To solve the minimization problem, the Levinson-Durbin algorithm is used in this study [10-12].

3. De-noising sound data

In order to determine the voltage magnitude from audible sound data of corona by using ANN properly, the sound signal should be cleared from environmental noises. Traditionally, the noise removal or de-noising is based upon filtering, which assumes that the signal and the noise spectra do not overlap. However, if these spectra overlap, depending on the amount of overlap, some details in the underlying signal would be lost. To overcome this problem, the noise can be filtered out not based entirely on their frequency spectrum, but also on their amplitude. Wavelet de-noising technique operates as this principle. The procedure works out by decomposing the signal containing noise into wavelet coefficients, setting to zero some wavelet coefficients below a certain threshold and then taking the inverse wavelet transform on the remaining coefficients to reconstruct the original signal without noise. In this process, it is assumed that the wavelet coefficients lying below the selected threshold are only due to the noise presents with the signal [13-17].

3.1. Wavelet coefficients

In one-dimensional discrete wavelet transform (DWT), the wavelet coefficients are obtained by expressing the signal as a summation of finite number of scaled and time-shifted wavelet basis function which is often referred to as the mother wavelet. This summation is repeated for different scales of the mother wavelet to obtain a map of the wavelet coefficients for the whole duration of the signal. A wavelet coefficient is an indicator of the similarity or the correlation between the different sections of the signal and the scaled mother wavelet. Therefore, if the approximate shape of the analyzed signal is known beforehand, an appropriate mother wavelet could be selected for the decomposition to give high valued wavelet coefficients [15].

At lower scales of the mother wavelet, the wavelet is more compressed, and therefore, capable of more precisely representing high frequency details of the signal. On the other hand, at higher scales the wavelet is more stretched, and is capable of representing the low frequency portions of the signal more accurately.

Signal ‘S’ is applied to two filters in parallel. The outputs of these filters are down sampled by a factor of two to give the approximate coefficients ‘*cA*’ with low pass filter (LPF) and the detail coefficients ‘*cD*’ with high pass filter (HPF). A multiple level decomposition will repeat the above procedure on the approximate coefficients at each level.

The decomposition of the approximate coefficient at any level j, (cj) into the approximate and detail coefficients ($cj + 1$ and $dj + 1$) at next higher level ($j + 1$) can be mathematically expressed using two fundamental equations

$$cA_{j+1} = \sum_{m} h(m-2k)cA_j(m) \quad (4)$$

$$cD_{j+1} = \sum_{m} g(m-2k)cA_j(m) \quad (5)$$

where, $h(k)$ and $g(k)$ are two decomposition filters. Theoretically, the decomposition process can continue up to infinite number of levels. However, at each successive level the bandwidth of the low pass filter halves, thus eliminating part of the signal spectra. As the process continues, at one level it would become apparent that further decomposition beyond that level is ineffective. Assuming that the signal components corresponding to the approximate coefficients are denoted by Aj’s and those corresponding to the detail coefficients are denoted by Dj’s (for example, at level 1, the signal components are A_1 and D_1), the signal S can then be expressed by equation (15).

$$S = A_j + D_1 + D_2 + D_3 + ... + D_j \quad (6)$$

3.2. De-noising procedure

The first step for noise reduction is to select a suitable wavelet (mother wavelet) for the decomposition. There are several families of wavelets. In this study, Daubechies wavelets are used. db5 is a reasonable candidate as the mother wavelet, because the db5 is very similar to the sample corona sound signal. The next step is to select a suitable level for the decomposition. Decomposition of the noisy signal using the chosen wavelet to the desired level is then carried out. This produces a series of approximate and detail coefficients. Noise, which normally contains high frequency components, is contained in the detail coefficients.

Following the wavelet selection and determination of the decomposition levels, the wavelet transform would be carried out. The next step is to threshold the detail coefficients to remove the noise leaving the high frequency details of the intact signal. Finally, the signal is reconstructed using the inverse DWT on the remaining non-zero coefficients to obtain the de-noised signal [15].

Wavelet reconstruction is computed by using the original approximation coefficients of level N and the thresholded detail coefficients of levels from 1 to N. If the number of decomposition level is small, the approximation will contain more features of the signal including the external noise. By choosing the right number of scales at analysis promising results can be obtained in the de-noising of measurement data acquired from the field [13-17].

4. 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 [18].

4.1. 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 [18-22] in the network.

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

$$y_k = \frac{1}{\delta} \sum_{j=1}^{n_h} \omega_{j,k} h_j \tag{7}$$

where:

$$\delta = \sum_{k=1}^{n_0} \sum_{j=1}^{n_h} \omega_{j,k} h_j \tag{8}$$

$$\omega_j = \left[\omega_{j,1}, \omega_{j,2}, \ldots, \omega_{j,n_0}\right]^T \tag{9}$$

$$h_j = f\left(x, c_j, \sigma_j\right) = exp\left(-\frac{\|x-c\|_2^2}{2\sigma_j^2}\right) \tag{10}$$

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 [18].

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 [21]. 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 [18].

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

$$d(x) = \left(\delta_1, \delta_2, \ldots, \delta_{n_0}\right)$$
$$\delta_j = \begin{cases} 1 & if\ x\ belongs\ to\ the\ class\ corresponding\ to\ y_k \\ 0 & otherwise \end{cases} \tag{11}$$

when the RBF h_j is assigned for, with utilizing the special property of GRNNs, $\omega_j = d(x)$, the entire network becomes topologically equivalent to the network with a decision unit [18, 21].

5. Experimental data acquisition

In this study, the audible corona sound was acquired from a high voltage transmission line model setup in a laboratory in order to measure the applied voltage by only using the recorded sound data as an input. In the line model with that purpose, for producing corona 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 4. As 27 kV is the corona inception voltage, nine different constant alternating voltage levels above 27 kV in effective values (rms) which are 30 kV, 35 kV, 40 kV, 45 kV, 50 kV, 55 kV, 60 kV, 65 kV and 70 kV having 50 Hz frequency audible to the human ear were applied to the wire from a 0.220/100 kV, 5 kVA high voltage test transformer [8, 9].

The experiment was repeated for each above given voltage level 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 corona discharge sound was recorded for each voltage level via an ordinary computer multimedia microphone. The experiment was carried out in electromagnetic shielded laboratory at the air pressure of 1.00725 ×

10^5 Pa (755.5 mmHg) and room temperature of 18 °C at a relatively quiet ambient. GRNN was used for determining the voltage magnitude from audible corona sound [8, 9].

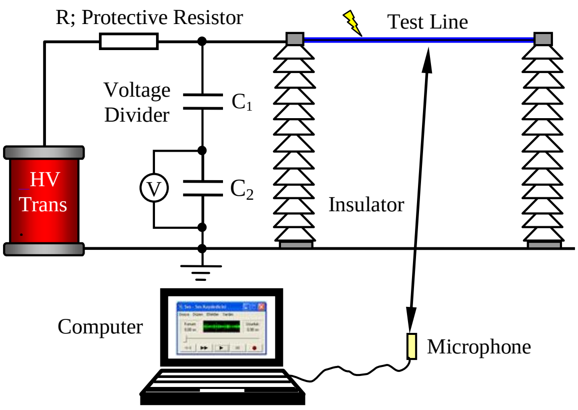

Figure 1. Experimental setup

6. Application

Corona sound data at each voltage level are acquired for the duration of 180 seconds. The sound samples which have 22050 Hz sampling frequency and resolution of 16 bits are recorded by using MATLAB packet program.

The measured signals have noisy components. For that reason, sound signals are cleaned by the wavelet de-noising technique in order to limit the external noise. The signals are de-noised by using the db5 mother wavelet in wavelet transform. As a general rule, the studies show that, choosing a mother wavelet similar in shape to the original signal to be analyzed gives better results in the de-noising applications. The measured sound signals have high frequency noise. During the wavelet de-noising process 5 level decomposition is used.

After cleaning the noisy sound samples, the linear prediction coefficients are computed for each frame having the length of 20 ms during a second. Computed frames are not overlapped. After LP coefficients are computed for each frame, the average value of all LP coefficients is computed. Each one-second sound sample is represented by its average LP coefficient value. 20th degree LP coefficients are computed for all the recordings. Since there are nine different applied voltage levels, per second for 180 seconds produces 1620 sound samples and the LP coefficients.

The training and validation sets for the GRNN are obtained from these 1620 data. In the study, all data set is divided into two subsets consisting 810 patterns. The 1st subset is used for training the GRNN and the 2nd subset is used for validation. Following that procedure, the LP coefficients of de-noised sound data is applied to a GRNN and errors of the network are 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 absolute relative error. The formula used for computation of errors is given below:

$$ARError = \frac{1}{Nn_o}\sum_{j=1}^{N}\sum_{k=1}^{n_o}\frac{|d_{jk} - y_{jk}|}{y_{jk}} \qquad (12)$$

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, 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 voltage magnitude of corona using corona sound sample.

Table 1. Training and validation sets errors

σ	Training set ARError [%]	Validation set ARError [%]
0.05	4.6536	4.8855
0.04	4.2101	4.4345
0.03	3.7364	3.9883
0.02	3.0725	3.4101
0.01	1.4347	2.4009
0.009	1.1365	2.2656
0.008	0.8202	2.1242
0.007	0.5142	1.9786
0.006	0.2621	1.8402
0.005	0.0910	1.7161
0.004	0.0248	1.7403

As seen from the Table 1, for the spread value of 0.005, the corona sound data can be used for determining the voltage magnitude with an acceptable error. If the sigma value is smaller than that, the model will over fit the data, because each training point will have too much influence.

7. Conclusion

In this study, measuring the line voltage by using the sound data produced at that voltage level was presented. For that purpose, the recorded sound data was first cleaned from the external noises, than analyzed by the linear prediction coding. The coded sound information was applied to the GRNN for the de-noised data. Consequently, the magnitude of the voltage was determined by using the recorded corona sound signals.

Performance of the identification of corona voltage depends on perception and recording of the sound data. Discharge sound heavily depends on the geometry, dimensions, cleanliness, dryness, and smoothness of the line (or electrode system) 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, 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. 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 preferable for corona measurements, because it is difficult to distinguish between the environmental noise and the corona noise. Therefore, the corona sounds are usually measured at frequencies higher than 15 kHz, which are called ultrasonic. In this study, the corona sounds are measured within the sonic frequency range. Therefore, the environmental noises became very dominant. In order to limit the effects of external noises, the sound data should be cleaned. In this study, wavelet de-noising technique is preferred to clean the sound data from environmental noises. The application results of the GRNN show that, using the de-noised data, measuring voltage magnitude by using sound samples gives acceptable results.

In order to analyze the sound data, it is possible to use different methods. In this study, linear prediction 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.

9. References

[1] P. S. Maruvada, *Corona Performance of High-Voltage Transmission Lines*, Research Studies Press, Hertfordshire, England, 2000.

[2] R. A. Jongen, P. Morshuis, S. Meijer, J. J. Smit, "Identification of partial discharge defects in transformer oil", *Conf. on Electrical Insul. and Dielectric Phenomena, CEIDP '05*, 16-19 Oct. 2005, pp. 565 – 568.

[3] C. Larsson, B. Hallberg, S. Israelsson, "Long-term audible noise and radio noise performance from an operating 400 kV transmission line", *IEEE Trans. on Power Delivery,* Vol. 3, No. 4, Oct. 1988, pp. 1842–1846.

[4] C. P. Suwarno, P. Anita, "Partial discharge diagnosis of Gas Insulated Station (GIS) using acoustic method", *Int. Conf. on Electrical Engineering and Informatics, 2009. ICEEI '09*, Vol. 02, 5-7, Aug. 2009, pp. 667 - 671.

[5] R. Tadeusiewicz, T. Wszolek, A. Izworski, W. Wszolek, "Recognition of defects in high voltage transmission lines using the acoustic signal of corona effect" *Proc. of the 2000 IEEE Signal Processing Society Workshop, Neural Networks for Signal Processing,* Vol. 2, 11-13 December 2000, pp. 869 – 875 **.**

[6] G. M. Spirov, V. D. Selemir, A. S. Kravchenko, S. I. Gerasimov, "High-power pulsed light and possibilities of their application", *Pulsed Power Plasma Science PPPS-2001, Digest of Technical Papers*, Vol. 2, 7-22 June 2001, pp. 1162 - 1165.

[7] A. S. Kravchenko, G. M. Spirov, V. D. Selemir, S. I. Gerasimov, "High-power pulsed light and acoustic radiation and possibilities of their application", *IEEE Conference Record - Abstracts Pulsed Power Plasma Science*, 17-22 June 2001, pp. 320.

[8] Ö. Kalenderli, B. Bolat, S. Bolat, "Determination of voltage level from electrical discharge sound by probabilistic neural network," *SIU 2006 the IEEE 14th Signal Processing, Communication and Applications Conf.*, Antalya, Turkey, 2006.

[9] S. B. Sert, Ö. Kalenderli, "Determination of source voltage from audible corona noise by neural networks" *IEEE Trans. on Dielectrics and Electrical Insulation,* Vol. 16, No. 1, Feb. 2009, pp. 224-231.

[10] A. Eronen, "Automatic Musical Instrument Recognition", Master of Science Thesis, Tampere University of Technology, 2001.

[11] L. Rabiner, B. Juang, *Fundamentals of Speech Recognition*, Prentice Hall, New York, 1993.

[12] J. O. Smith, "Viewpoints on the history of digital synthesis", Proc. of the ICMC, Helsinki, Oct. 1991.

[13] M. Lenz, K. Feser, "Wavelet transform application during impulse tests of power transformers", *13th Int. Symp. on High Voltage Engineering,* Delft, Netherlands, 25-29 Aug. 2003, pp. 534.

[14] C. Zhou, X. Ma, I. J. Kemp, "Optimal algorithms for wavelet-based denoising in PD measurement,*" 13th Int. Symp. on High Voltage Engineering*, Delft, Netherlands 25-29 Aug. 2003, pp. 349.

[15] S. N. Hettiwatte, Z. D. Wang, P. A. Crossley, P. Jarman, G. Edwards, A. Darwin, "De-noising of partial discharge signals detected at a 400 kV power transformer," *13th Int. Symp. High Voltage Engineering*, Delft, Netherlands, 25-29 Aug. 2003, pp. 501.

[16] L. Satish, B. I. Gururaj, "Wavelet analysis for estimation of mean-curve of impulse waveforms superimposed by noise, oscillations and overshoot," IEEE Trans. on Power Delivery, Vol. 16, 2001, pp. 116-121.

[17] B. Quak, E. Gulski, F. J. Wester, P. N. Seitz, "Wavelet analysis of PD in power cables," 13th Int. Symp. High Voltage Engineering, Delft, Netherlands, 25-29 Aug. 2003, pp. 293.

[18] S. Haykin, *Neural Networks: a Comprehensive Foundation*, Upper Saddle River, N.J., Prentice Hall, 1999.

[19] D. F. Spetch, "General regression neural network", *IEEE Trans. on Neural Networks,* Vol. 2, No. 6, 1991, pp. 568-576.

[20] L. Rutkowski, "Generalized regression neural networks in time-varying environment", *IEEE Trans. on Neural Networks,* Vol. 15, No. 3, 2004, pp. 576-596.

[21] T. Hoya, "Notions of intuition and attention modeled by a hierarchically arranged generalized regression neural network", *IEEE Trans.* on Systems, Man, and Cybernetics-Part B: Cybernetics, Vol. 34, No. 1, 2004, pp. 200-209.

[22] T. Hoya, J. A. Chambers, "Heuristic pattern correction scheme using adaptively trained generalized regression neural networks", *IEEE Trans. on Neural Networks,* Vol. 12, No. 1, 2001, pp. 91-100.