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Wavelet neural network methodology for ground resistance forecasting

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ABSTRACT

Motivated by the need of engineers for a flexible and reliable tool for estimating and predicting grounding systems behavior, this study developed a model that accurately describes and forecasts the dynamics of ground resistance variation. It is well-known that grounding systems are a key of high importance for the safe operation of electrical facilities, substations, transmission lines and, generally, electric power systems. Yet, in most cases, during the design stage, electrical engineers and researchers have limited information regarding the terrain's soil resistivity variation. Moreover, the periodic measurement of ground resistance is hindered, very often, by the residence and building infrastructure. The model, developed in the present study, consists of a nonlinear, nonparametric wavelet neural network (WNN), trained in field measurements of soil resistivity and rainfall height, observed the past four years. The proposed framework is tested in five (5) different grounding systems with different ground enhancing compounds, so that can be used for the evaluation of the behavior of several ground enhancing compounds, frequently used in grounding practice. The research results indicate that the WNN can constitute an accurate model for ground resistance forecasting and can be a useful tool in the disposal of electrical engineers. Therefore, this paper introduces the wavelet analysis in the field of ground resistance evaluation and endeavors to take advantage of the benefits of computational intelligence.

1. Introduction

Grounding systems are an integral part of the protection system for electrical facilities and electric power systems against lightning and power frequency fault currents, as they are designed to dissipate high magnitude fault currents into the earth through a safe passage in the shortest possible time. Their purpose is to keep at minimum the ground potential rise (GPR), consequence of a discharging fault current, so as to ensure the safety of people and equipment from electric shock. Nevertheless, the assumption that any grounded object can be safely touched is not always correct. Under fault conditions, the ground potential rise could reach hazardous levels that may well lead to human losses and equipment destruction. Thus, for a well-designed grounding system in order to provide constant and full protection, technical measures are necessary to ensure a good and consistent behavior of the system throughout its lifecycle.

As far as the power frequency resistance is concerned, a grounding system must maintain a low resistance in respect to remote earth during its service. In this way, the decline in potential rise can restrain the high values of step and touch voltages in the facility and its vicinity, which are able to jeopardize human lives. International standards [1–3] highlight the variation of ground resistance value under the effect of soil structure and soil moisture. Therefore, for safety reasons, regular measurement of ground resistance in grounding systems is recommended [1–3].

However, in most cases, an electrical engineer has to cope with confined spaces for the construction of an effective grounding system, or with the large cost which often may be inhibitive for the construction. Furthermore, soil resistivity of the upper layer is subjected to seasonal variation due to weather conditions, such as rainfall, ice and air temperature, which mainly effect on soil

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humidity, while the dissolved salts percentage and the soil structure play a major role in soil resistivity value [4–6]. In the last decades the usage of ground enhancing compounds for soil alleviation and decreasing the ground resistance value becomes more and more popular in engineering field.

Despite the recommendations of the standards, the periodic measurement of ground resistance is hindered, very often, by the residence and building infrastructure. Moreover, many times it is essential for engineers to have an estimation of the behavior of constructed or, in design stage, grounding systems over time. This work endeavors to develop a novel tool for estimating and forecasting the ground resistance values of several grounding systems, based on soil resistivity measurements at the location of interest and on local rainfall data, using WNN.

2. Wavelet neural networks

2.1. General description

Wavelet neural networks or, simply wavelet networks (WNs), are a new class of networks that combine the classic sigmoid neural networks (NNs) and the wavelet analysis (WA). WNNs have been used with great success in a wide range of applications. Wavelet analysis has proved to be a valuable tool for analyzing a wide range of time-series and has already been used with success in image processing, signal de-noising, density estimation, signal and image compression and time-scale decomposition. It is often regarded as a "microscope" in mathematics [7] and it is a powerful tool for representing nonlinearities [8]. However, WA is suitable for applications of small input dimension, since the construction of a wavelet basis is computationally expensive when the dimensionality of the input vector is relatively high [9].

Wavelet analysis decomposes a general function or signal into a series of (orthogonal) basis functions called *wavelets*, which have different frequency and time locations. More precisely, wavelet analysis decomposes time-series and images into component waves of varying durations called wavelets, which are localized variations of a signal [10,11]. As illustrated by Donoho and Johnstone [12], the wavelet approach is very flexible in handling very irregular data series. Ramsey [13] also comments that wavelet analysis has the ability to represent highly complex structures without knowing the underlying functional form, which is of great benefit in economic and financial research. A particular feature of the signal analyzed can be identified with the positions of the wavelets into which it is decomposed.

WNNs were proposed by Zhang and Benveniste [14] as an alternative to feedforward neural networks. The wavelet networks are a generalization of radial basis function networks. They are one hidden-layer networks that use a wavelet as an activation function, instead of the classic sigmoidal family. It is important to mention here that the multidimensional wavelets preserve the "universal approximation" property that characterizes neural networks. The nodes (or wavelons) of the hidden layer are the wavelet coefficients of the function expansion that have a significant value. In Bernard et al. [15] various reasons were presented explaining why wavelets should be used instead of other transfer functions. In particular, firstly, wavelets have high compression abilities and, secondly, computing the value at a single point or updating the function estimate from a new local measure, involves only a small subset of coefficients.

2.2. Proposed WNN methodology and architecture for ground resistance forecasting

In this study, a multidimensional WNN with a linear connection between the hidden units (wavelons) and the output is implemented. Moreover, in order for the model to perform well in the presence of linearity, direct connections from the input layer to the output layer are established. The structure of a single hidden-layer feedforward wavelet network is given in Fig. 1. The network output is given by the following expression:

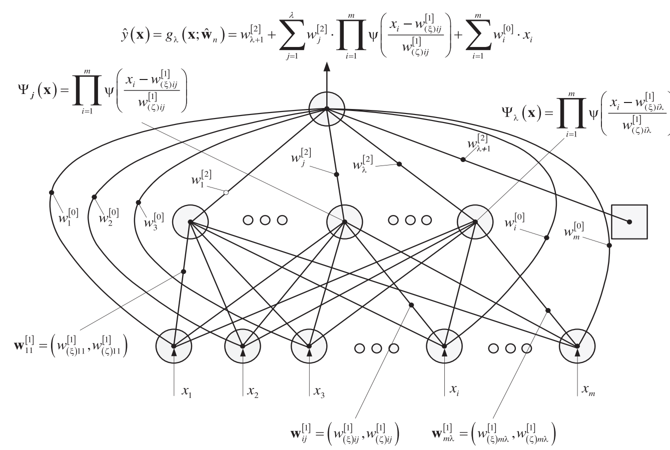

Fig. 1. Structure of a feedforward WNN [21].

$$g_\lambda(\mathbf{x};\mathbf{w}) = \hat{y}(\mathbf{x}) = w^{[2]}_{\lambda+1} + \sum_{j=1}^{\lambda} w^{[2]}_j \cdot \Psi_j(\mathbf{x}) + \sum_{i=1}^{m} w^{[0]}_i \cdot x_i \quad (1)$$

In the above expression, $\Psi_j(\mathbf{x})$ is a multidimensional wavelet which is constructed by the product of m scalar wavelets, $\mathbf{x}$ is the input vector, m is the number of network inputs, λ is the number of hidden units (HUs) and w stands for a network weight. The multidimensional wavelets are computed as follows:

$$\Psi_j(x) = \prod_{i=1}^{m} \psi(z_{ij}) \quad (2)$$

where ψ is the mother wavelet and

$$z_{ij} = \frac{x_i - w^{[1]}_{(\xi)ij}}{w^{[1]}_{(\zeta)ij}} \quad (3)$$

In the above expression, $i = 1, \ldots, m$, $j = 1, \ldots, \lambda + 1$ and the weights w correspond to the translation ($w^{[1]}_{(\xi)ij}$) and the dilation ($w^{[1]}_{(\zeta)ij}$) factors. The complete vector of the network parameters comprises $w = (w^{[0]}_i, w^{[2]}_j, w^{[2]}_{\lambda+1}, w^{[1]}_{(\xi)ij}, w^{[1]}_{(\zeta)ij})$. These parameters are adjusted during the training phase. Furthermore, the second derivative of the Gaussian, the so-called "Mexican Hat" wavelet is used which proved to be useful and to work satisfactorily in various applications [18–20]:

$$\psi(z_{ij}) = (1 - z^2_{ij}) e^{-\frac{1}{2} z^2_{ij}} \quad (4)$$

A wavelet is a waveform of effectively limited duration that has an average value of zero and localized properties. Hence, a random initialization may lead to wavelons with a value of zero, affect the speed of training and lead to a local minimum of the loss function. Utilizing the information that can be extracted by the WA from the input dataset, the initial values of the parameters w of the network can be selected in an efficient way. Efficient initialization will result in less iterations in the training phase of the network and in training algorithms that will avoid local minima of the loss function in the training phase. In the present network the Backward Elimination (BE) method [9,20] is used for the initialization of the network parameters. The BE starts the regression by selecting all