

EXPLOITING THE IMPULSE RESPONSE OF GROUNDING SYSTEMS FOR AUTOMATIC CLASSIFICATION OF GROUNDING TOPOLOGIES

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Abstract - This work presents a system for automatic detection of grounding systems topologies which are already mounted into the soil. Such system can be of valuable help while inspecting already deployed grounding systems, to check whether they are arranged properly or not. The architecture of the proposed system is composed by four main subsystems: an excitation, a data acquisition, a feature extraction and a machine learning based model subsystems. To evaluate the proposed system, three topologies are considered to be detected in the experimental part. These topologies are two, three and four horizontal rods/electrodes with 2,5 meters length and separated in intervals of 3 meters buried into the soil. The results demonstrate that the proposed system (excitation, data acquisition, feature extraction and machine learning based model subsystems) can distinguish with an acceptable rate of accuracy among these three topologies.

1 - INTRODUCTION

It is far know that grounding systems play a vital role in electrical supply systems [1]. The correct design of the grounding systems are of vital importance for safety and protection of personnel, equipment and facilities, as well to the correct operation of the electricity supply network, to ensure good power quality, etc. The grounding systems topologies (GST) can be composed by one or more horizontal or vertical rods, buried or driven into the soil.

After selecting the correct structure of the earth system, its installation should be properly implemented. However, in some cases, this does not happen, mainly because of errors during the execution of the project, such as installing an incorrect number of rods (usually less than specified) and/or by forgetting to properly connecting the rods. This problem can be minimized by manually inspecting the grounding system after its installation. However, there is the possibility that the grounding system have already been covered or cemented, thereby precluding a visual inspection of the installed system. Under this kind of situation, it would be beneficial to have a method to check whether the configuration of grounding system is arranged properly or not. However, no method in literature exists for such an approach.

In this work, for the first time, a method based on machine learning for determining the topology of grounding systems is proposed. The proposed system performs the determination of the grounding topology based on an intelligent analysis of the impulse response of grounding systems. The use of impulse response is

motivated by the fact that at power frequency the soil behaves as a pure resistor, and at high frequency (when excited by an impulse voltage) it has resistive (R), inductive (L) and capacitive (C) characteristics. Moreover, it is already known that different topologies have different transient responses when excited by an impulse voltage. The geometry and the number of electrodes are the most remarkable variables that influence these different responses.

Traditionally, at low frequencies a grounding system composed by a single rod (Fig. 1a) can be described as a single resistor (Fig. 1b) and at a high frequency by a lumped R-L-C circuit (Fig. 1c).

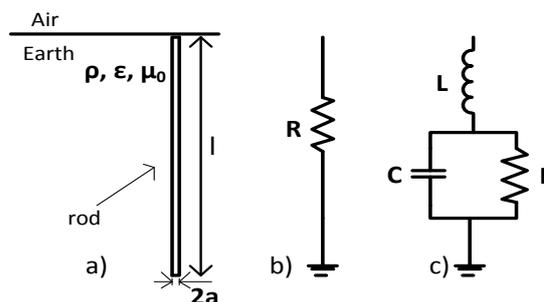


Figure 1 – a) Physical representation of a ground rod; b) equivalent circuit of ground rod at low frequency; c) a representation of equivalent circuit of ground rod at high frequency.

For example, in the reference work of Rudenberg [2], the parameters R, L and C are given by:

$$R = \frac{\rho}{2\pi l} \log \frac{2l}{a} (\Omega) , \quad (1)$$

$$C = 2\pi\epsilon l \left(\log \frac{2l}{a} \right)^{-1} (F) , \quad (2)$$

$$L = \frac{\mu_0 l}{2\pi} \log \frac{2l}{a} (H) , \quad (3)$$

From (1), (2) and (3), it is possible to note the dependence of the parameters R, L and C on the rod parameters, a and l . In [3, 4], the authors have used different formulas to design the R, L and C parameters, but it is still possible to see the dependence on the rod parameters. However, [5] reported that the formulas given by [2, 3, 4] are the not an exact representation of the response of the ground rod, and that it generally fails

to represent the circuit in very high frequencies. In [5] the author concluded that the distributed parameters circuit is the best way to represent the equivalent circuit of a rod when subjected to a high frequency signal. However, the intend of this discussion it is not to define the best way to describe the high frequency equivalent circuit of grounding systems, but instead is to shown that the response of grounding systems is dependent not only on the soil parameters (ϵ , μ_0 , ρ), but also on the rods parameters (a and l) in a very complex way. Moreover, when it comes to more complex arrangements, the equivalent electrical circuit becomes more complex and difficult to describe. Then, the use of the transient response of grounding system seems to be a viable alternative to discriminate among different topologies, since it carries information about the rods parameters (a and l).

The architecture of the proposed system is composed by four main subsystems: an excitation, a data acquisition, a feature extraction and a machine learning based model subsystems. The excitation system injects a signal that simulates a lightning stroke. After the signal response is acquired, a feature vector is extracted from the transient response in order to perform the classification stage. The features are characteristics of the signal in the frequency domain (through fast Fourier transform (FFT) decomposition), it was generated a total of a total of 250 features. As said before, the system proposed here uses a machine learning based model to classify the different topologies. The model selected to perform the classification stage was the support vector machine model (SVM) [6], the state of art in classification systems. As it is a multiclass classification problem, the SVM model was combined using the strategy called min-wins rule [7]. This approach has shown to make the proposed system "free of classification error". However, under the drawback that some topologies are undetermined (i.e. it is not possible to identify them). Then, in such cases it is necessary to appeal to the other ways to determine if the grounding topology is arranged properly or not.

When applying the proposed architecture in real scenarios, it is necessary to acquire the transient response of one rod (with the same characteristics of the other rods) on the soil under study and then use this information when evaluating the topology to be determined. This is necessary to reduce the influence of the soil on the extracted FFT features. From now on, this one rod will be called as the reference rod.

In the experimental part, the proposed approach was evaluated by considering three topologies: two, three and four horizontal rods/electrodes with 2,5 meters length and separated in intervals of 3 meters buried into the soil. The data was acquired at different days and different locations. The results demonstrate that is possible to achieve an acceptable rate of accuracy while discriminating the different topologies.

This paper is organized as follows. Section 2 presents the architecture of the proposed system. Section 2.1 and 2.2 present the excitation and data acquisition system. Section 2.3 described the features extracted from the impulse signal response. Section 2.4 describes the machine learning model used, the SVM model, used to classify the different topologies. Section 3 presents the

experimental results. Finally, section 4 gives the conclusion remarks.

2 – AUTOMATIC CLASSIFICATION OF GROUDDING TOPOLOGIES SYSTEM

The proposed system is depicted in Fig. 2. It can be summarized as follows. First the voltage impulse generator is applied in the grounding system, then the response of voltage and current is acquired by the data acquisition system, after that the FFT features are extracted from the transient part of these signals. At the end, these FFT features (extracted taking into consideration the information of reference rod) are entered into the SVM model that determines the grounding system topology.

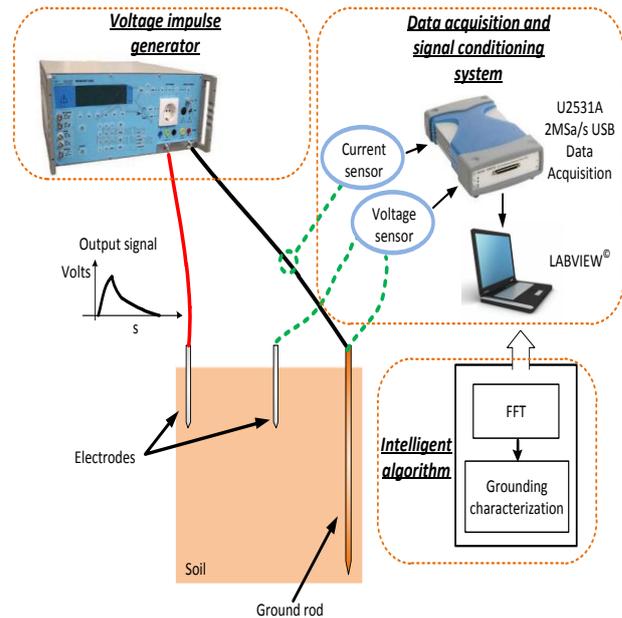


Figure 2 – Architecture of proposed system.

2.1 – VOLTAGE IMPULSE GENERATOR

The objective of the excitation system is to create an excitation system that simulates a lightning stroke. The lightning stroke waveform is a double exponential that can be described by the following formula:

$$v(t) = V_0 \cdot (e^{-\alpha \cdot t} - e^{-\beta \cdot t}), \quad (4)$$

where V_0 is the peak value, and α and β defines the rise time and pulse width, respectively, by the following formulas:

$$t_r \approx \frac{1}{\beta} \quad (5)$$

$$t_p \approx \frac{1}{\alpha} \quad (6)$$

According to [8], the transient of surge voltage, due the lightning strokes, have a rise time of approximately 0,5 to $10\mu s$ and its peak value decay to 50% after 30 to $200\mu s$. The circuit responsible to generating the excitation signal is shown in Fig. 3. The system of Fig. 3 can be described by two main steps. In the first step, the gate S_1 is closed

and S_2 is kept open, the gates S_1 and S_2 are MOSFETs. Then, the parallel transformers TR_1 and TR_2 boost the voltage from $220V_{rms}$ to $640V_{rms}$, approximately. Then, the voltage is rectified, by the bridge rectifier composed by the diodes D_{R1} , D_{R2} , D_{R3} , D_{R4} and capacitor C , so that the series capacitors C_1 , C_2 and C_3 are charged, the role of resistor R_1 is to limit the current to the capacitors. In the second step, the gate S_1 is opened and gate S_2 is closed, then the series capacitors C_1 , C_2 and C_3 (charged before in the first step), will generate an impulse voltage over the grounding system through the gate S_2 that is closed.

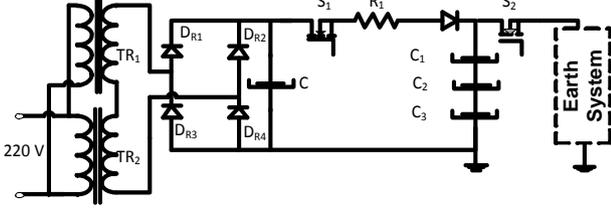


Figure 3 – Architecture of excitation system.

The behavior of the excitation system in Fig. 3, has a quite similar behavior of a double exponential. The voltage applied to the grounding system is in the order of 1kV.

2.2 – DATA ACQUISITION

The voltage and current are acquired by the data acquisition system. The voltage and current probes are distant of 12,5m and the current 20m, respectively from the grounding system. They are acquired at a sample rate of 2M/s.

After the excitation system injects the impulse signal in the grounding system, the voltage and current responses are collected by the data acquisition system. The system used for data acquisition is the system U2531A from Agilent, which has a maximum sample rate of 2M/s. This sample rate is sufficient enough to capture data samples in the order of micro seconds (us). The voltage sensor, from LEM, has frequency response up to 500 kHz (+-2dB).

2.3 – FEATURE EXTRACTION

After the voltage and current signals are acquired by the data acquisition, its features are extracted as follows. First, the transient response is isolated (the first 250 samples are considered as the transient signal) it corresponds to $125\mu s$ after the excitation signal has been applied. Then, the FFT, a popular signal processing approach, is used to transform the data of voltage and current from time to frequency domain. The first 125 components of FFT signal were considered as features of classification model. Then, 125 FFT features are extracted from the transient of voltage and 125 FFT features are extracted from the transient of current, generating a total of 250 features. The FFT features of voltage and current are then subtracted by the FFT features of voltage and current of the reference rod.

2.4 –SVM CLASSIFICATION MODEL

The SVM model is the state of art in machine learning for classification. It works by identifying the best separating hyperplane (the plane with maximum margins) between

the two classes of the training samples within the feature space [6]. It works as follows.

Assume a set of training data $D = \{(x_i, y_i); i = 1, \dots, n\}$, where $x_i \in R^D$ and $y_i = \{1, -1\}$ representing two classes. The optimal separation plane between hyperplanes is determined by maximizing the distance between the hyperplane and the nearest point of each class. The hyperplane is determined by minimizing the following function:

$$\min \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n \xi_i \quad (7)$$

subject to:

$$y_i [w^T \cdot \phi(x_i) + b] \geq 1 - \xi_i \quad (8)$$

where w , b and ξ_i are the weight vector, bias and slack variable, respectively. In Eq. (8), $\phi(x_i)$ is a nonlinear function that maps the input data onto a high dimensional feature space, where the data is linearly separable. Locating the optimal hyperplane is a quadratic programming problem that is solved by the construction of a Lagrange multiplier and by considering the boundaries conditions. Considering both constraints, the dual quadratic optimization problem is obtained:

$$\max \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{j=1}^n \alpha_j y_j K(x_i, x_j) \quad (9)$$

subject to:

$$\sum_{i=1}^n \alpha_i y_i = 0 \quad (10)$$

$$0 \leq \alpha_i \leq C, i = 1, \dots, n \quad (11)$$

where $K(x_i, x_j) = \phi^T(x_i)\phi^T(x_j)$ is the kernel function and α_i are the Lagrange multipliers. By solving (9), subjected to (10) and (11), where the decision function is:

$$f = \text{sign}(b + \sum_{SV} \alpha_i y_i K(x_i, x_j)) \quad (12)$$

Where SV denotes the support vectors for which the corresponding Lagrange multipliers are positive. In this work, a Gaussian RBF kernel is used as the kernel function:

$$K(x_i, x_j) = -\gamma \cdot \|x_i - x_j\|^2 \quad (13)$$

When using the SVM algorithm and the RBF kernel function, only the parameters C and γ should be set. In this work the parameters were selected by considering the classification error in a leave one out cross validation scheme.

The SVM was primary designed to deal with binary classification problems. Its implementation in multiclass problems can be done by using the method proposed in [7], called as min-wins rule. This rule together with the SVM model work as follows. For example, assume that the problem has three classes, defined as c_1, c_2, c_3 . Then a pairwise SVM model (M_{12}) is constructed to discriminate c_1, c_2 another pairwise SVM model (M_{13}) to discriminate c_1, c_3 and another pairwise SVM model (M_{23}) to discriminate c_2, c_3 . Then, for a test sample x_i , all pairwise outputs are combined to form a 3-class decision. Then, the class which the sample x_i belongs is the class that wins the most pairwise comparisons. If there is draw in the pairwise comparisons, then the class can be identified.

3 – EXPERIMENTAL RESULTS

The results presented come from real data acquired in different days and distinct places/terrains. A total of nine assays were conducted. Figs. 4 and 5 show the transient response of voltage and current of one the terrains with one, two, three and four horizontal rods, as the grounding system.

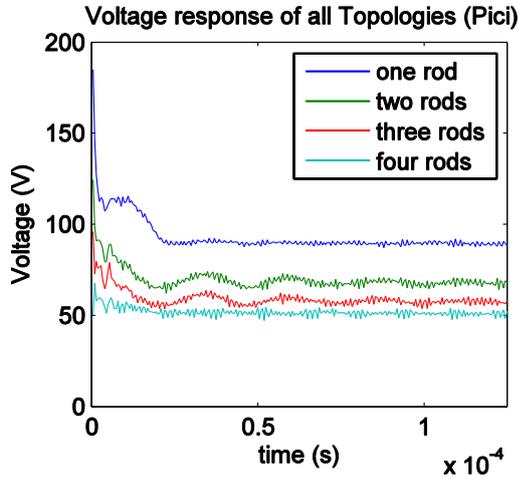


Figure 4 – Voltage response of grounding system composed of one, two, three and four parallel rods.

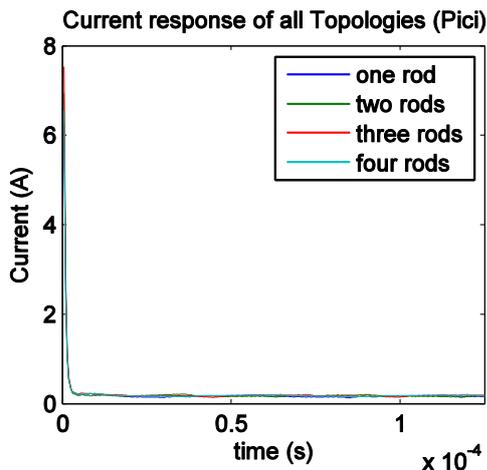


Figure 4 – Current response of grounding system composed of one, two, three and four parallel rods.

Three distinct topologies were considered to evaluate the capability of the proposed system. The first topology is composed by two rods, the third topology is composed by three rods, and the last topology is composed by four rods. All the rods have 2,5 meters length and are separated in intervals of 3 meters. Each configuration is considered as a class, where the label used for two, three and four rods are AP-01, AP-04 and AP-07, respectively.

The data acquired in all assays were conducted by using the methodology described in Section 2.1 and 2.2. The features were extracted by using the procedure described in Section 2.3. and the multiclass SVM was built using the max-wins rule described in Section 2.4.

The classification accuracy of the proposed system was achieved by training the SVM model using the features extracted from data acquired in eight assays and testing in the assay not used in the training phase. It was repeated in such way that all the assays were used for test.

The summary of results is shown in Table 1. The organization of the Table was done as follows. The top of Table indicate the number of assay used for test, which ranges from 1 to 9. The column of assay #1 indicates that experiment #1 was used for test, while the other experiments were used for training the SVM model, and so on. The first left column indicate the topology tested (i.e. the feature of such topology was entered in the classification model). The content of Table 1 indicates the outcome of the SVM model when using as input the features coming from the topology indicated in the left column. The label *NP* means “not possible” to determine.

As can be notice it was possible to determine the topology AP-01 in 55% of the cases tested, i.e. it was not possible to determine the topology in 4 terrains. For the topologies AP-04 and AP-07 it was possible to determine the topology in 44% of the presented cases (4 of 9). It is also possible to note that there is not any misclassified topology. This is due the fact of the strategy for combining the SVM binaries classifiers to perform multiclass classification, called mix-wins rule [7].

	Assay number								
	1	2	3	4	5	6	7	8	9
AP-01	AP-01	NP	NP	AP-01	AP-01	AP-01	NP	AP-01	NP
AP-04	AP-04	NP	NP	NP	AP-04	NP	AP-04	NP	AP-04
AP-07	NP	NP	AP-07	NP	AP-07	AP-07	NP	AP-07	NP

Table 1 – Results of classification system.

It was not possible to determine the topology in 51% of the cases (14 of 27). From the machine learning perspective, this is due the fact that only few numbers of samples were used for training the SVM classifier and also because the presence of a large number of input features 250 in total. By increasing the number of training samples, probably the number of *NP* results will decrease. This is an interesting challenge from machine learning perspective, work with few samples and a large number of input variables. Future works will address this issue.

4 - CONCLUSIONS

In this work a method for automatic classification of grounding systems topologies was presented. It is composed by four main subsystems: an excitation, acquisition, features extraction and classification subsystems. The proposed system was evaluated in real scenarios and has shown to provide satisfactory results in terms of classification rate.

This approach demonstrates that it is possible to determine the topologies under the soil in 49% of the tested cases, even with a small number of samples (only 9) for training. This is an attractive result since in most of the real cases the grounding system is not inspected due

after it is covered. By using this method, one can reduce the uncertainty about what is under the soil.

The major drawback of the proposed approach is the necessity of the reference rod. Future works will address this issue, by implementing a method that eliminates the reference rod.

Beyond the results of classification, this work has proposed an innovative work with original objectives. This innovative approach opens several gates and challenges for the grounding and earthing systems and also the machine learning community, since this can be seen as a multiclass problem with few numbers of samples and many input variables.

Future works will improve the steps of feature extraction and classification model, by considering different methods.

5 – ACKNOWLEDGES

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