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Using Artificial Neural Networks to Estimate the Equivalent Resistivity from typical Transmission Line Towers Grounding Arrangement in a Two-Layer Soil

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***Abstract*—This paper presents a procedure to estimate a homogeneous equivalent resistivity for typical transmission line tower ground arrangements that are immersed in a stratified soil model. This technique is based on artificial neural network training due to a dataset developed in a numerical routine to compute grounding resistance. The results obtained from Levemberg-Marquadt algorithm and Bayesian regularization show good accuracy compared to the applied dataset and to the measurement data from a 230 kV transmission line, a practical case analyzed. We note medians lower than 5% and acceptable values of standard deviation for practical cases, which suggests that the proposed procedure can be used for real-world conditions.**

Keywords*—Artifical neural networks, electric resistivity, grounding, modeling.

I. Introduction

Transmission line (TL) towers have grounding arrangement with the aim to provide a low impedance way for different types of electric system disturbances, such as those resultants from lightning. They are usually composed by horizontal electrodes arranged in a radial form, also known as counterpoise wires, as illustrated in Fig. 1.

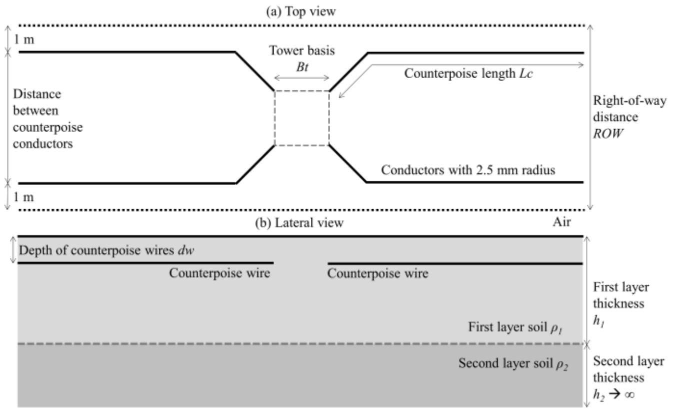

Fig. 1. Typycial TL tower grounding arrangement for a two-layer soil model.

To analyze TL transients, as the electric potential between the terminals of an insulator chain in order to preview the occurrence of backflashover, the computational model requires to consider the tower grounding arrangement.

Procedures based on Maxwell full-form equations, which tend to be more rigorous in a physical point-of-view, are reported in literature – called electromagnetic (EM) methods. Many of them analyze the transient behavior of grounding configurations for homogenous soils, such as [1,2]. However, soils are commonly better represented by stratified approximations of the medium as a function of their electrical resistivity at the grounding evaluation step [3]. Thus, due to the advances of computing power, a recent increase of works that analyze the transient characteristic of grounding arrangements in two or more layered soils are reported [4,5].

For techniques based on TL-theory, electrostatic and magnetostatic hypotheses are assumed, which tends to lead to significant errors at high frequencies due to the voltage drop at the conductor surface and the magnitude increase of displacement current, in addition to the relation of the electrode length with the wavelength [6]. In such condition, the so-called quasi-transverse electromagnetic (TEM) mode becomes a bad approximation to the problem.

However, considering the frequency spectrum of lightning, whose maximum values are of the order of 200 kHz and 1 MHz [7], respectively, for first and subsequent discharges, the solution obtained using TL theory can become a good approximation for grounding parameters, such as impulse impedance, in practical conditions [8-10]. Furthermore, more advantageous features in relation to the EM model are reached using TL technique, such as an easily implementation of the numerical routines and a much lower computational cost associated with an often-shorter time simulation required for the task of estimate the impulse grounding characteristic.

To compute harmonic grounding impedance based on TL-theory for arrangement composed by counterpoise wires, approximations can be used to estimate an equivalent resistivity ρ_{eq} to obtain a homogenous soil analogue to the stratified [8,9]. Such procedure is directly related to the selected way to compute the horizontal dimension of the arrangement, which does not have a specific or a more appropriate practice to its realization.

With several computational routines to compute the low frequency grounding characteristic, i.e., the grounding resistance R_T, with significant precision reported by literature, it is possible to use one of them for simulations that consider stratified soils to find ρ_{eq} from a homogenous medium that results in the same R_T value. If we collect a series of data, it is possible to use them to train an artificial neural network (ANN) in order to estimate ρ_{eq} from the desired input data: geometry information and electrodes position from the arrangement composed by counterpoise wires, and the stratified soil parameters, in a similar procedure to that presented in [11]: to develop a dataset followed by ANN training.

This work presents the development of a trained ANN to estimate ρ_{eq} from an equivalent homogenous medium for typical groundings from TL towers buried in a two-layered soil. Two techniques for the ANN training step are used and their results compared to all the expected outputs from the developed dataset through a rigorous computational routine, which is based on EM theory, implemented to compute R_T from such arrangements. Furthermore, a practical case is realized to evaluate the ANN response to measurements from a TL.

II. Theoretical Review and Tooling Used

A. A numerical routine to compute grounding resistance from generic arrangements

A rigorous procedure to estimate the grounding resistance of arrangements in a two-layered soil is presented in [12]. In this work, the conductors are discretized and considered as spherical current sources, which are supposed to have the same electrical potential, i.e., a constant potential approximation.

As R_T is equal to the ratio of the conductor electric potential with the injected current in the arrangement, a matrix system composed by current and electrical potential vectors, besides the resistance matrix $\boldsymbol{R}$, is developed. The self-resistances R_{self} of each mesh segment are denoted inside the matrix $\boldsymbol{R}$, positioned in its main diagonal, by Heppe's expression [13]:

$$R_{self} = \frac{\rho}{2\pi L^2} \cdot \left\{ \begin{aligned} & L \ln\left(\frac{L+\sqrt{L^2+r^2}}{a} \cdot \frac{L+\sqrt{L^2+r^2+4D^2}}{\sqrt{r^2+4D^2}} \right) \\ & + r + \sqrt{r^2+4D^2} - \sqrt{L^2+r^2} - \sqrt{L^2+r^2+4D^2} \end{aligned} \right\}, \tag{1}$$

where ρ is the soil electric resistivity, L is the length and r the segment radius, and D is the depth where the current source is located.

For the case of mutual resistances R_{mutual}, positioned outside the main diagonal of $\boldsymbol{R}$, four expressions that depend on the positioning of each source and receiver current segment within a two-layered soil are indicated by [12]. The Method of Images is applied to consider the multiple reflections defined by the interfaces between the air and the soil in addition to that from the first and second layers of the medium [14]. Reflection and transmission coefficients are incorporated to R_{mutual} and the procedure accuracy is shown in [12] for meshes composed by lattices, typical of that applied to substations.

A numerical routine was implemented in MATLAB, considering the previous procedure, and its results were verified with solutions provided by [11] and other works from literature, as [12]. After the validation of the implemented algorithm, the developed code was used to develop a dataset, which is described in the next topic.

B. Dataset developed

In a similar way to [11], a dataset composed by 86400 entities was developed for ANN training, testing and validation steps. A radius of 2.5 mm was considered for grounding arrangement conductors, which is similar to that presented by [15].

Table I shows the range value applied to each input parameter from grounding arrangement, as the same designation used in Fig. 1, to develop the dataset, which is the same provided by [11].

TABLE I. Input parameters range of the developed dataset

Input parameter	***Range value***
First-layer soil electric resistivity ρ_1 (Ωm)	100 to 10000
Second-layer soil electric resistivity ρ_2 (Ωm)	90 to 10100
First-layer soil thickness h_1 (m)	0.3 to 10
Counterpoise cable length L_c (m)	20 to 90
Tower basis width B_t (m)	6 to 18
Counterpoise cables depth d_w (cm)	20 to 80
TL right-of-way *ROW* (m)	10 to 50

The chosen entities number to dataset was arbitrary and the values within the range of each input parameter was obtained randomly by *rand* function from MATLAB.

C. ANN and algorithms to their training step

The usage of ANN allows the development of a mathematical expression with the main goal of this work: obtain ρ_{eq} of a typical grounding arrangement from TL towers in a two-layer soil model.

Two algorithms were considered to accelerate multilayer Perceptron (MLP) ANN convergence: Levemberg-Marquadt (LM) and Bayesian regularization method (RB), all available by the function fitting-tooling from MATLAB: *nftool*.

To minimize the squared-error between ANN and the data used to its training, a recursive weight update routine through the epochs is considered, as presented in [16]:

$$w^{k+1}(i,j) = w^k(i,j) - \eta\delta^k(i)a^{k-1}(j), \tag{2}$$

$$\underline{\delta}^k = F'^k\left(net^k\right)\left[W^{k+1}\right]^{\boldsymbol{T}} \underline{\delta}^{k+1}, \tag{3}$$

$$b^{k+1}(i,j) = b^k(i,j) - \eta\delta^k(i), \tag{4}$$

where w^{k+1} is the weight applied to kth input a^k from activation function, b^{k+1} is a biased function, η is the learning rate and δ^k is the index sensibility in relation to input i at hidden layer k, besides $F'^k(\underline{net}^k)$ represents a diagonal matrix composed by partial derivatives from activation function related to each layer net.

The LM algorithm updates each weight by approaching the Jacobian matrix from the error vector. Such procedure results in a significative performance gain, since the Hessian matrix does not need to be computed in its directly form [17]. In this situation, (2) can be rewritten in its matrix form as:

$$\boldsymbol{w}^{k+1} = \boldsymbol{w}^k - \left[\boldsymbol{J}^T\boldsymbol{J} + \mu\boldsymbol{I}\right]\boldsymbol{J}^T\boldsymbol{e} \quad (5)$$

where $\boldsymbol{J}$ is Jacobian matrix with first-order derivative related to weights and bias, $\boldsymbol{I}$ is identity matrix and $\boldsymbol{e}$ is the error vector. The scalar μ is not null, since LM is part of Quasi-Newton methods, and varies through each epoch, following the increase or decrease of weight gradient. Thus, besides it maintains the estimated weights in a called trusted-region, it tends to accelerate the training convergence [18].

For RB method, a regularization is made inside the LM algorithm at backpropagation process moment [19]. We need to minimize a functional $\boldsymbol{F}$ composed by squared errors sum and a cost function:

$$\boldsymbol{F} = \beta\boldsymbol{E_D} + \alpha\boldsymbol{E_W} \quad (6)$$

$$\boldsymbol{J} = \boldsymbol{E_D} + \lambda\boldsymbol{E_S} \quad (7)$$

where $\boldsymbol{E_W}$ is the net squared errors sum, α, β and λ are regularization parameters, $\boldsymbol{E_D}$ is a term from standard error and $\boldsymbol{E_S}$ from regularization error.

As presented by [20], BR method aims the search for solutions with a significantly generalization capacity by Bayesian inference, which evaluates hypotheses by a statistic procedure by means of maximum likelihood.

To help the comprehension of the trained ANN in this work, Fig. 2 illustrates the desired inputs and outputs.

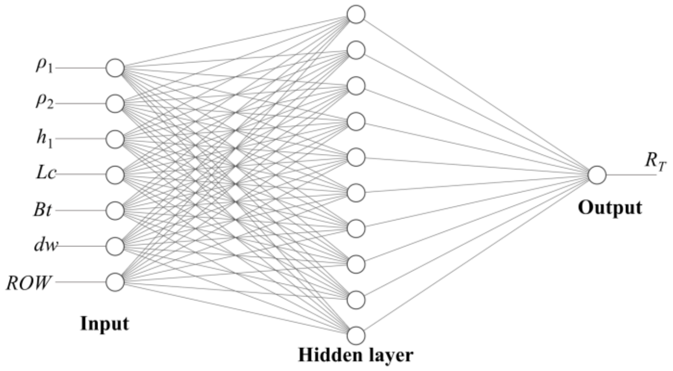

Fig. 2. Schematic of trained ANN with the inputs and outputs parameters.

III. Results

A. Evaluation of ANN as a function of neuron number inside the hidden layer

Simulations were realized considering LM algorithm and RB method to evaluate ANN response as a function of neuron number n_h that composes the hidden layer. We opted to use 80% of dataset to ANN training and 10% for test and validation steps, besides a range value for n_h of 20 to 30. To reach certain statistical variability, each evaluation with certain n_h value and LM or RB algorithms was repeated twenty times.

Although the mean squared error (MSE) is commonly applied to evaluate the ANN response, we opted by the mean relative error (MRE) due to its simplicity to interpret in addition to the big dataset used at ANN training step. To comprehend the error distribution for each n_h, cases where ANN diverges more than 100% from reference data were registered. Also, due to the input parameters number and significative entities number, we verified MRE from ANN trained related to all the original developed dataset.

Respectively, Fig. 3 and 4 shows EMR from ANN as a function of n_h parameter, and the rate cases where the error is higher than 100% for LM and RB algorithm by box plots.

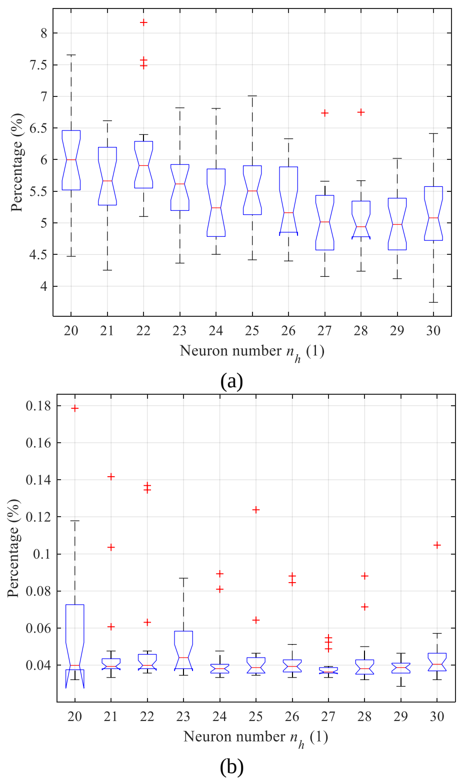

Fig. 3. Varying n_h for LM algorithm: (a) MRE related to complete dataset and (b) rate cases with error higher than 100%.

EMR between 5 and 6% for LM and 4.5 and 5.5% for RB method are reported in Fig. 3 and 4. There is a tendency of EMR reducing with n_h increasing, which is expected. The main problem associated with very high n_h is overfitting, which diminishes the response generality from ANN for the problem.

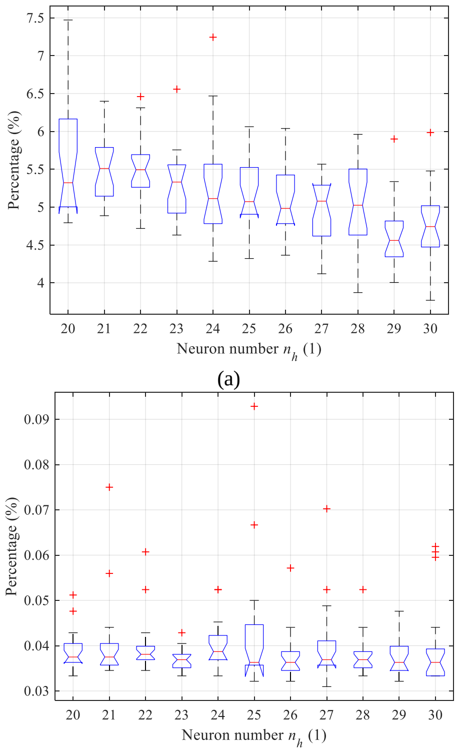

Fig. 4. Varying n_h for RB algorithm: (a) MRE related to complete dataset and (b) rate cases with error higher than 100%.

Due to the MRE ANN order observed in Fig. 3 and 4, apparently no overfitting characteristics are presented in trained ANN. Five outliers are reported to RB method, less than that seven found for LM algorithm.

In relation to the rate cases with an error higher than 100% compared to dataset, again RB method tends to present a better result than LM algorithm: a rate of, approximately, 0.035% versus 0.04%. Such rates can be considered very small in relation to the entities number that composes dataset, since they vary from 30 to 35 cases in a set of 86400 elements. Even of only entities at training or validation step would result in errors higher than 100%, such proportion in a set of 17280 elements would vary between 0.17% to 0.2%, which is remarkable. Nineteen and seventeen outliers were identified in Fig. 3 (b) and 4 (b), which highlights the lower variability of RB method response compared to LM algorithm.

Although it was not presented in previous figures, the same behavior of lower rate cases with error higher than 50% in relation to the dataset is observed for RB algorithm. For this situation, a rate of 0.5% for RB and 0.6% for LM is calculated. For errors higher than 20%, the rate is lower for the LM algorithm than RB: 6 versus 9%. This characteristic suggests a higher capacity of generalization for RB method, since its error rate tends to be more spreader related to the dataset – something indicated at the algorithm description realized by [20].

B. *Case study for measurements made on a 230 kV TL*

Based on the results from previous section, we opted to choose two trained ANN from each algorithm: one with the lowest MRE related to the dataset and another with the lowest error rate greater than 100%. Table II presents their designations in this work, n_h value, MRE related to the dataset and the error rates greater than 20, 50 and 100%.

TABLE II. DESIGNATION FOR TRAINED ANN AND THEIR PERFORMANCE RELATED TO THE DATASET

Algorithm	***LM***		***RB***	
Designation	LM1	LM2	RB1	RB2
n_h	30	29	30	27
MRE related to the dataset	3.74%	4.62%	3.77%	4.57%
Error rate higher than 20%	2.95%	4.07%	7.33%	8.27%
Error rate higher than 50%	0.19%	0.37%	0.25%	0.35%
Error rate higher than 100%	0.03%	0.03%	0.04%	0.03%

The evaluation of LM1, LM2, RB1 and RB2 is realized from measurement data provided by a 230 kV TL [21]. Resistivity measurements from 95 TL towers are considered and some considerations for grounding arrangements are assumed: Lc = 30, 60 or 90 m (depending of soil characteristic around the TL tower), r = 2.5 mm, ROW = 38 m, d_w = 60 cm and B_t = 10 m.

With values for ρ_1, h_1, ρ_2 and the arrangement configuration, we calculate R_T by the numerical routine from Section 2.1 and by its equivalent resistivity ρ_{eq}, that generates the same grounding resistance value, by a simple, but efficient procedure: a Rule of Three. If ρ_{eq} is the desired resistivity to be estimated, considering $R_{T100\Omega m}$ as the grounding resistance for a homogenous soil with a resistivity $\rho_{100\Omega m}$ = 100 Ωm, we have:

$$\rho_{eq} = \left(R_T \cdot \rho_{100\Omega m}\right) / R_{T100\Omega m} \tag{8}$$

The equivalent resistivity from (8) is compared to that estimated by the ANN from Table II, aiming to compute the precision of each technique. Table III presents the performance parameters for the considered ANN.

TABLE III. TRAINED ANN PERFORMANCE RELATED TO ALL MEASUREMENT DATA OF A 230 KV TL

Algorithm	***LM***		***RB***	
Designation	LM1	LM2	RB1	RB2
n_h	30	29	30	27
MRE related to the data	16.0%	7.32%	10.1%	12.0%
Median related to the data	3.65%	4.29%	3.12%	4.03%
Standard deviation	54.4%	15.2%	19.8%	56.2%
Error rate higher than 20%	10.5%	4.21%	12.6%	6.32%
Error rate higher than 50%	7.37%	2.11%	5.26%	3.16%
Error rate higher than 100%	3.16%	1.05%	1.05%	1.05%

The results shown ANN medians lower than 5%, an interesting value if we consider the changes through the year due to climate variations for soil resistivity. The option by a specific ANN can be realized based on the lowest value of median, condition of RB1, or the solution that presents the lowest error rates that are higher than 20, 50 and 100%, simultaneously – in this situation, LM2 tends to be a more suitable option.

From a practical point-of-view, LM2 probably would be a more reasonable choice, since it presents a median little higher than the others, but compensates it with an error rate much lower and consistent compared to the other approximations. Also, LM2 has the lowest standard deviation value observed in this analysis.

C. *Specific study for measurements of a 230 kV TL within the input parameters range used to train ANN*

From 95 TL towers measurements, a total of 52 are totally within the range values from input parameters used to training the ANN. As this procedure is a more reasonable condition to use ANN due to its training domain, a last evaluation is realized to this specific group.

Table IV shows the performance of each ANN evaluated.

TABLE IV. TRAINED ANN PERFORMANCE RELATED TO 52 MEASUREMENTS OF A 230 KV TL THAT ARE WITHIN THE RANGE VALUE OF INPUT PARAMETERS

Algorithm	***LM***		***RB***	
Designation	LM1	LM2	RB1	RB2
n_h	30	29	30	27
MRE related to the data	20.4%	4.69%	6.46%	4.45%
Median related to the data	2.96%	4.23%	3.04%	4.37%
Standard deviation	71.5%	3.77%	9.55%	2.96%
Error rate higher than 20%	9.62%	0.00%	7.69%	0.00%
Error rate higher than 50%	5.77%	0.00%	0.00%	0.00%
Error rate higher than 100%	5.77%	0.00%	0.00%	0.00%

LM1 clearly presents the worse response in this evaluation, despite the lowest median, as can be noted by its high standard deviation value.

The best ANN for this condition are LM2 and RB2, which do not have cases with errors higher than 20, 50 and/or 100%. A slightly better response is noted for RB2, if we consider the very similar median, MRE values and a higher standard deviation for LM2. However, considering the entire 95 TL tower measurements a much more critical condition for ANN, LM2 remains the most reasonable choice to be applied in relation to the data evaluated in this work.

IV. CONCLUSIONS

This work presented the training of ANN to estimate the equivalent resistivity of a grounding resistance related to typical TL towers arrangement in a two-layered soil model. Two algorithms, LM and RB, were applied to train, after the development of a dataset by simulations derived from a rigorous numerical routine. The input and output parameters were defined to training all ANN.

After the training, validation and test steps of ANN as a function of the dataset, a practical case was performed considering measurements of a 230 kV TL. All data and a part of it, that is within the range values of the trained input parameters for ANN, were analyzed.

In general, the results indicate a suitability of the procedure to estimate ρ_{eq}, which can be used to calculate harmonic grounding impedance in techniques based on TL-theory or EM models that contemplates only homogenous soils, such as [2]. Medians lower than 5% were reported for dataset analysis and the practical condition from 230 kV TL. For LM2, error rates higher than 20% of the order of 4% were noted. If we consider only the range values of input parameters used at training step for ANN, it was not observed a case with an error rate higher than 20%, a remarkable result.

A comparative study with similar techniques related in literature is indicated, as [22], and an implementation of this procedure on GroundingApp [23], a free Android app with focus on grounding, will be the next steps of this research.

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REFERENCES

[1] L. Grcev, and F. Dawalibi, “An electromagnetic model for transients in grounding systems,” *IEEE Transactions on Power Delivery*, Vol. 5, Iss. 4, pp. 1773-1781, October 1990.

[2] S. Visacro, and A. Soares, “HEM: a model for simulation of lightning-related engineering problems,” *IEEE Transactions on Power Delivery*, Vol. 20, Iss. 2, pp. 1206-1208, April 2005.

[3] S. Visacro, Aterramentos elétricos. São Paulo, SP: Artliber, 2002.

[4] V. Toseva, L. Grcev, and K. El Khamlichi Drissi, High frequency performance of ground rod in two-layer soil, in *Proc. IEEE EUROCON 2017 -17th International Conference on Smart Technologies*, Ohrid, Macedonia, pp. 914-918, July 2017.

[5] H. Karami, and K. Sheshyekani, “Harmonic impedance of grounding electrodes buried in a horizontally stratified multilayer ground: A full-wave approach,” *IEEE Transactions on Electromagnetic Compatibility*, Vol. 60, Iss. 4, pp. 899-906, August 2018.

[6] C. Paul, Analysis of multiconductor transmission lines. Hoboken, NJ: John Wiley & Sons, 2007.

[7] S. Visacro, W.L.F. Pinto, F.S. Almeida, M.H.M. Vale, and G. Rosado, Experimental evaluation of soil parameter behavior in the frequency range associated to lightning currents, in *Proc. 2008 29th International Conference on Lightning Protection (ICLP)*, Uppsala, Sweden, pp. 1-5, June 2008.

[8] C.E.F. Caetano, R. Batista, J.O.S. Paulino, W.C. Boaventura, I.J.S. Lopes, and E.N. Cardoso, A simplified method for calculating the impedance of vertical grounding electrodes buried in a horizontally stratified multilayer ground, in *Proc. 2018 34th International Conference on Lightning Protection (ICLP)*, Rzeszow, Poland, pp. 1-7, September 2018.

[9] R. Batista, C.E.F. Caetano, J.O.S. Paulino, W.C. Boaventura, I.J.S. Lopes, and E.N. Cardoso, “A study of grounding arrangements composed by vertical electrodes in two-layer stratified soils,” *to be published in Electric Power Systems Research*, 2019.

[10] R. Batista, and J.O.S. Paulino, “A practical approach to estimate grounding impedance of a vertical rod in a two-layer soil,” *to be published in Electric Power Systems Research*, 2019.

[11] R. Batista, and M.R. de Araújo, Estimação da resistência de malhas de aterramnto típicas de estruturas de linhas de transmissão por meio de aplicativo para Android, in *Proc. XVIII Encontro Regional Íbero-Americano do Cigré (ERIAC)*, Foz do Iguaçu, Brazil, May 2019.

[12] L.M.R. Raggi, "Projeto de malhas de aterramento: Contribuição ao cômputo da estratificação do solo," M.S. thesis, Graduate Program in electrical Engineering, Federal University of Minas Gerais, Belo Horizonte, 2009.

[13] R.J. Heppe, "Computation of potential at surface above an energized grid or other electrode, allowing for non-uniform current distribution," *IEEE Transactions on Power Apparatus and Systems*, Vol. PAS-98, Iss. 6, 1978-1989, November 1979.

[14] J.C. Maxwell, A treatise on electricity & magnetism. New York, NY: Dover, 1954.

[15] CEMIG, "Instrução para aterramento de estruturas de linhas de transmissão de 69 a 500 kV – 30.000-ER/LT-3368a," CEMIG, pp. 1-27, July 2003, https://www.cemig.com.br

[16] S. Haykin, Neural networks: A comprehensive foundation. Upper Sadle River, NJ: Prentice-Hall, 1998.

[17] M.T. Hagan, and M.B. Menhaj, "Training feedforward networks with the Marquadt algorithm," *IEEE Transactions on Neural Networks*, Vol. 5, Iss. 6, pp. 989-993, November 1994.

[18] R. Battiti, "First- and second-order methods for learning: between steepest descent and newton's method," *Neural Computation*, Vol. 4, Iss. 2, pp. 141-166, 1992.

[19] D. MacKay, "Bayesian Interpolation," *Neural Computation*, Vol. 4, Iss. 3, pp. 415-447, 1992.

[20] T.H. Medeiros, Treinamento de redes neurais artificiais com otimização multi-objetivo e regularização Bayesiana: um estudo comparativo," M.S. thesis, Graduate Program in electrical Engineering, Federal University of Minas Gerais, Belo Horizonte, 2004.

[21] Transirapé, "Estudos de desempenho de linha de transmissão quanto a surtos atmosféricos e avaliação de risco à 60 hz: LT 230 kV Irapé-Araçuaí 2," Technical report, pp. 1-79, August 2007.

[22] J. Endrenyi, "Evaluation or resistivity tests for design of station grounds in nonuniform soil," *IEEE Transactions on Power Apparatus and Systems*, vol. 82, no. 69, pp. 966-970, Dec. 1963.

[23] R. Batista, "GroundingApp", BR512019000270-9, INPI – National Institute of Industrial Property, 2019.