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Estimation of Grounding Resistance of Transmission Line Towers based on Artificial Neural Networks: A Practical Analysis based on a developed Android App

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***Abstract*—This work presents a practical evaluation of an Android app developed for grounding resistance estimation of typical transmission line (TL) towers arrangement. Such arrangements, composed by counterpoise cables, are evaluated for a two-layered soil model by a trained artificial neural network (ANN), which derives in a significative low computational cost for the solution problem. The developed algorithm is evaluated with measurements made in TL towers and compared to the solution provided by a rigorous numerical routine. The results indicate a good accuracy, with median and standard deviation lower than 7%, of the developed app for conditions where the input parameters have values within the range used to training ANN. Values outside the specified range can reach significative errors up to 5 and 17 times, respectively, for median and standard deviation.**

***Keywords*—Android app, counterpoise cables, grounding resistance, transmission line.**

I. INTRODUCTION

Called GroundingApp [1], an app to compute the grounding resistance of typical arrangement of TL towers was developed for the Android platform, i.e., runs in any mobile that uses this operating system, and is available on Play Store. The grounding problem is modelled considering a two-layered soil model and a TL tower arrangement composed by counterpoise cables.

Considering lightning as the main cause of TL interruptions, the grounding improvement is usually the choice for a higher performance of the line due to these phenomena. The disposal of the grounding conductors is usually standardized by electric power utilities in parameters such as right-of-way (ROW), length, electrode and geometry [2]. For fast surges like lightning, impedance tends to better represent the behaviour of grounding, but resistance remains as the main parameter in practice due to its diffusion among engineers and ease of simulation and measurement [3].

A lot of numerical routines for grounding resistance computation are proposed, but usually don't benefit from the popularization and recent significative advancement of mobile devices. Although grounding project is an activity commonly linked to environments such as offices, the possibility of estimate its resistance anywhere and anytime, even if approximately, is interesting due to practicality and simplicity. Another advantage is related to teaching, since it is very common for a student to use a cell phone or tablet to study.

This work is an extension of [4], with the main purpose of testing the developed app for conditions of real-world, such as measurements from TL towers. Although it has a friendly interface and is free, the app depends on a good performance for practical problems to justify its use by other users. Even the addition of other functionalities to the app demands this analysis to support such developments.

II. DEVELOPMENT STAGES OF THE APP ALGORITHM

A. A numerical routine to compute grounding resistances of generic TL towers arrangement

The first step to develop the app is the implementation of a rigorous numerical technique to compute the grounding resistance of generic arrangements. The chosen method is similar to [5], where the grounding electrodes are discretized as spherical current sources immersed in soil. A constant potential approach is considered, i.e., the electrical potential is considered uniform along all the conductors that composes the grounding configuration. Due to this, the current distribution is a derived parameter from this procedure and inferred by:

$$\boldsymbol{I} = \boldsymbol{R}^{-1}\boldsymbol{V} = \boldsymbol{G}\boldsymbol{V}, \tag{1}$$

where $\boldsymbol{G}$ denotes the conductance matrix referred to the soil conductor losses and equals to the inverse of the resistance matrix $\boldsymbol{R}$, $\boldsymbol{V}$ is the electrical potential vector at the surface of the N segments of the electrodes and $\boldsymbol{I}$ is the current distribution along the conductors. The $\boldsymbol{R}$ matrix, denoted by:

$$\boldsymbol{R} = \begin{bmatrix} R_{11} & R_{12} & \cdots & R_{1N} \\ R_{21} & R_{22} & \cdots & R_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ R_{N1} & R_{N2} & \cdots & R_{NN} \end{bmatrix}, \tag{2}$$

is composed by diagonal, their self-resistances, and non-diagonal elements – mutual resistances.

If we consider unitary elements for $\boldsymbol{V}$ and the total current I_T injected into the soil as the sum of all elements forming the $\boldsymbol{I}$ vector, the grounding resistance R_T can be estimated by:

$$R_T = \frac{V_1}{I_T} = \frac{1}{I_T}. \tag{3}$$

The Method of Images, defined in [6], is applied to compute the infinite current source images inside the ground due to the boundary conditions between the soil and the air and from the first- and second-layer soil interface. Thus, computing the mutual resistances of $\boldsymbol{R}$ for a two-layer soil model requires expressions for four possible conditions:

1. Source and receptor segments are inside the first-layer of the soil;

2. Source and receptor segments are inside the second-layer of the soil;

3. Source segment is inside the first-layer, while the receptor segment is immersed in the second-layer of the soil;

4. Source segment is inside the second-layer, while the receptor segment is immersed in the first-layer of the soil.

The expressions for each condition, respectively, are described in [5] using the Method of Images:

$$R_{mutual} = \frac{\rho_1}{4\pi L_j L_m}\left\{\begin{array}{l} \dfrac{1}{\sqrt{{r_{xy}}^2+\left(z-h_i\right)^2}}+\dfrac{1}{\sqrt{{r_{xy}}^2+\left(z+h_i\right)^2}} \\ +\displaystyle\sum_{n=1}^{\infty} k_{12}^n \left[\begin{array}{l} \dfrac{1}{\sqrt{{r_{xy}}^2+\left(z-2nh_1+h_i\right)^2}}+ \\ \dfrac{1}{\sqrt{{r_{xy}}^2+\left(z-2nh_1-h_i\right)^2}} \\ +\dfrac{1}{\sqrt{{r_{xy}}^2+\left(z+2nh_1-h_i\right)^2}}+ \\ \dfrac{1}{\sqrt{{r_{xy}}^2+\left(z+2nh_1+h_i\right)^2}} \end{array}\right] \end{array}\right\}, \tag{4}$$

$$R_{mutual} = \frac{\rho_2}{4\pi L_j L_m}\left\{\begin{array}{l} \dfrac{1}{\sqrt{{r_{xy}}^2+\left(z-h_i\right)^2}}+\dfrac{k_{21}}{\sqrt{{r_{xy}}^2+\left(z+2h_1+h_i\right)^2}} \\ +k_{21}^{'}k_{12}^{'}\displaystyle\sum_{n=0}^{\infty} k_{12}^n \left[\dfrac{1}{\sqrt{{r_{xy}}^2+\left(z-2nh_1+h_i\right)^2}}\right] \end{array}\right\}, \tag{5}$$

$$R_{mutual} = \frac{k_{12}^{'}\rho_2}{4\pi L_j L_m}\left\{\begin{array}{l} \dfrac{1}{\sqrt{{r_{xy}}^2+\left(z-h_i\right)^2}}+\dfrac{1}{\sqrt{{r_{xy}}^2+\left(z+h_i\right)^2}} \\ +\displaystyle\sum_{n=1}^{\infty} k_{12}^n \left[\begin{array}{l} \dfrac{1}{\sqrt{{r_{xy}}^2+\left(z-2nh_1+h_i\right)^2}}+ \\ \dfrac{1}{\sqrt{{r_{xy}}^2+\left(z-2nh_1-h_i\right)^2}} \end{array}\right] \end{array}\right\}, \tag{6}$$

$$R_{mutual} = \frac{k_{21}^{'}\rho_1}{4\pi L_j L_m}\left\{\begin{array}{l} \dfrac{1}{\sqrt{{r_{xy}}^2+\left(z-h_i\right)^2}}+\dfrac{1}{\sqrt{{r_{xy}}^2+\left(z+h_i\right)^2}} \\ +\displaystyle\sum_{n=1}^{\infty} k_{12}^n \left[\begin{array}{l} \dfrac{1}{\sqrt{{r_{xy}}^2+\left(z+2nh_1-h_i\right)^2}}+ \\ \dfrac{1}{\sqrt{{r_{xy}}^2+\left(z-2nh_1+h_i\right)^2}} \end{array}\right] \end{array}\right\}, \tag{7}$$

where h_1 is the thickness of the first-layer soil, h_i is the depth of the current source segment immersed in the ground, r_{xy} is the xy-distance of the source from the receptor segment, ρ_1 and ρ_2 are the electric resistivity of the first- and second-layer of the soil, L_j is the length of the current source segment and L_m from the receptor segment, k and k' are, respectively, the reflection and transmission constants given by:

$$k_{12} = \frac{\rho_2-\rho_1}{\rho_2+\rho_1},\ k_{12}^{'} = \frac{2\rho_1}{\rho_2+\rho_1}, \tag{8}$$

$$k_{21} = \frac{\rho_1-\rho_2}{\rho_2+\rho_1},\ k_{21}^{'} = \frac{2\rho_2}{\rho_2+\rho_1}. \tag{9}$$

It can be observed that (4) to (7) are similar to those expressions showed by Heppe [7], which considers the self-resistances of $\boldsymbol{R}$ matrix, as in this work, described by:

$$R_{self} = \frac{\rho}{2\pi L^2}\cdot \left\{\begin{array}{l} L\ln\left(\dfrac{L+\sqrt{L^2+a^2}}{a}\cdot\dfrac{L+\sqrt{L^2+a^2+4D^2}}{\sqrt{a^2+4D^2}}\right) \\ +a+\sqrt{a^2+4D^2}-\sqrt{L^2+a^2}-\sqrt{L^2+a^2+4D^2} \end{array}\right\}, \tag{10}$$

where the source segment has length L, radius a and is immersed into a depth D.

The implemented numerical routine is capable to estimate the grounding resistance of generic geometries, such as those typical from TL towers, as desired in this work. In the next topic, the computational routine is used to develop a dataset composed by some geometric and soil parameters, beyond the grounding resistance, that will be applied to train and test an ANN.

B. Developing a dataset and defining the input and output parameters for the app algorithm

Using the implemented numerical routine presented in the last topic, a dataset is developed for the desired grounding configuration, as illustrated in Fig. 1. The conductors are supposed to have a 2.5 mm radius [8] and a distance of 1 m is considered to the ROW delimitations. Furthermore, the input parameters range are presented in Table I, which output parameters is always the estimated grounding resistance by the automated computational routine described in the last topic.

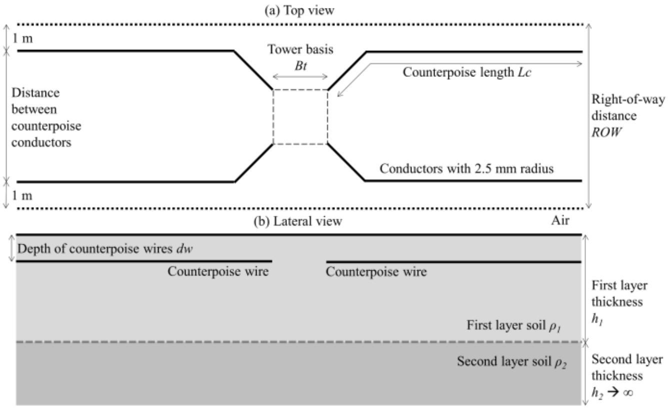

Fig. 1. TL tower grounding arrangement considered for a two-layered soil.

TABLE I. INPUT PARAMETERS RANGE OF THE DEVELOPED DATASET

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

A total of 86400 samples were used to develop the final dataset, with the goal of traversing values within the extensive range considered for the input parameters, as showed in Table I. As reported by [4], the validity of the dataset is only reached due to the standardized of the grounding arrangements of TL towers. Other geometries will require a new dataset, which can involve other input parameters for its formation.

C. ANN Train and Test using the developed dataset

The training process considers multilayer Perceptron (MLP) ANN with the Levemberg-Marquadt (LM) as a convergence accelerator algorithm, which is used from the MATLAB's fitting toolbox: *nftool*.

The stage of training considers the minimization of mean squared error (MSE) between target and output through the epochs by weight updating [9]:

$$w^{k+1}(i,j) = w^k(i,j) - \eta\delta^k(i)a^{k-1}(j), \tag{11}$$

$$\underline{\delta}^k = F'^k\left(net^k\right)\left[W^{k+1}\right]^T \underline{\delta}^{k+1}, \tag{12}$$

$$b^{k+1}(i,j) = b^k(i,j) - \eta\delta^k(i), \tag{13}$$

where w^{k+1} is the weight applied to the k-th input a^k from activation function, b^{k+1} is a bias factor, η is the learning rate and δ^k is the sensitivity index relative to the input i in the hidden layer k. Also, $F'^k(\underline{net}^k)$ represents the diagonal matrix composed by partial derivatives of the activation function related to the net of each layer.

The LM algorithm updates each weight by an approximation of the Jacobian matrix from the error vector. This results in a significantly gain performance because the Hessian matrix doesn't need to be direct computed [10]. So, (11) is rewritten in its matrix notation:

$$\boldsymbol{w}^{k+1} = \boldsymbol{w}^k - \left[\boldsymbol{J}^T\boldsymbol{J} + \mu\boldsymbol{1}\right]\boldsymbol{J}^T\boldsymbol{e}, \tag{14}$$

where $\boldsymbol{J}$ is the Jacobian matrix, $\boldsymbol{e}$ is the error vector and $\boldsymbol{1}$ is the identity matrix. As LM a Quasi-Newton method, the scalar μ isn't null and varies through the epochs in relation to the increase or reduction of the weight gradient, what results in an acceleration of training convergence and keep the results in a trusted-region.

To illustrate the trained ANN, Fig. 2 presents the input parameters and the desired output considered in this work. The nomenclature of the input data is similar to that adopted by Fig. 1.

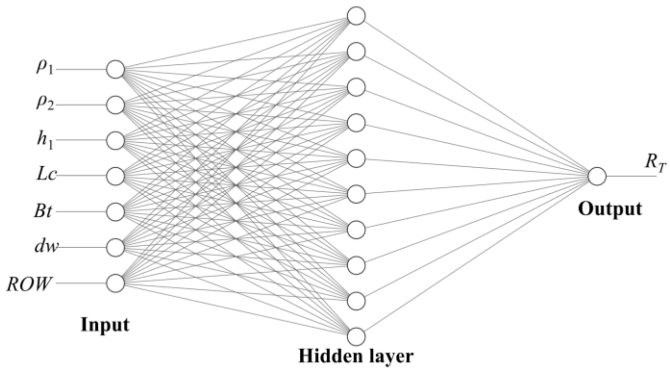

Fig. 2. Schematic of the trained ANN with the input and output data.

As presented in [4], 80% of the dataset was used to train and 20% to test the ANN, considering a n_h range of 10 to 30, where n_h is the neuron number that forms the hidden layer. To reach certain statistic variability, each n_h was simulated ten times and the iteration limit number for LM algorithm of 1500 was considered.

The main results, as presented in Fig. 3 using all the dataset for analysis, related to the mean relative error (MRE) show that this parameter tends to reduce up to n_h = 25, where the MRE starts to be almost constant. The outliers are less recurrent for higher n_h values, range where the output rate has an error higher than 100% compared to the target are of the order of 0.1%. The same output rate is lower than 0.2% and the median are lower than 10% for all the dataset for condition with n_h > 13. Furthermore, the boxplots don't show a behavior of overfitting, probably due to the significative number of input parameters at the training step of ANN.

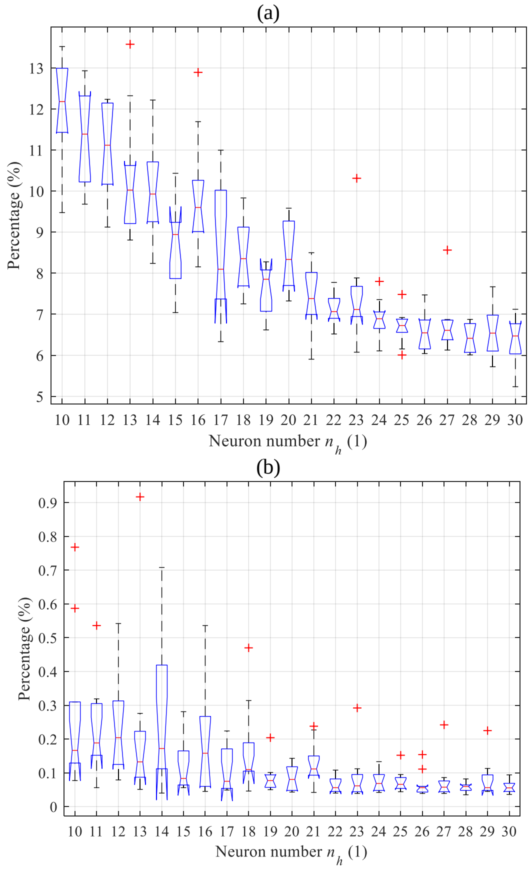

Fig. 3. (a) MRE for trained ANN for the entire dataset and (b) the cases rate where the output has a diference higher than 100% related to the dataset output target – adapted from [4].

The chosen ANN has n_h = 30, MRE = 5.64% for entire dataset and cases rate with error higher than 20, 50 and 100% compared to the output target from dataset equal to 0.03%, 0.43% and 6.14%. Furthermore, for the entire dataset a median of 2.46% and a standard deviation of 8.81% is observed for the ANN implemented on the app.

III. Evaluation of the App for a Practical Condition

A. Basic considerations for the TL towers measurements

A case with 95 TL towers measurements is considered to evaluate the app for a real-world condition. For this condition, we define a tower basis width equals to 10 m, 60 cm for counterpoise cables depth and a ROW of 38 m. Three options of counterpoise cables length are analyzed: 30, 60 and 90 m – each one depends of the soil characteristics.

From such measurements, 43 of 95 cases have some input parameter outside the recommended range value for the app, that corresponds to the same range value used in training and/or testing ANN steps – this is equivalent to 45.3% of the TL measurements. Within these measurements, some were clearly wrong due to the values measured by Wenner four-pin method presented in report [11]. A few numbers of measured distances are observed in some towers and some apparent resistivities outside the measuring range of the used device.

Due to such observations, the measurements are divided in two groups. The first group englobes the conditions which values are within the acceptable range for using the trained ANN: 52 measurements. The second, composed by 43 cases, consists of conditions that are outside the range values defined in the training step of ANN. The main analysis must be made for the first group, but the second set indicates how the ANN performs for conditions that are not indicated for its use.

B. Group 1:measurements with values within the range values indicated for the trained ANN use

The 52 TL towers measurements that are within the range values for the trained ANN have their characteristic exhibited in Fig. 5, which shows histogram for their main input parameters. Also, Table II presents a summary statistics for group 1 using the trained ANN.

As observed in Table II, a median of 6.47% is calculated with a standard deviation of 6.69%. These results show a coherence of using the ANN to estimate grounding resistance for this type of measurements, i.e., the app tends to compute good approximations for a practical condition if the trained range values for the input parameters were respected. Cases where the error of ANN and the grounding resistance for Group 1 is higher than 20% are equal to only 3. Furthermore, no cases were observed with an error higher than 50% and 100%, which is a desirable result. The highest error observed in such analysis is equal to 24.63% for a case with ρ_1 = 515 Ωm, ρ_2 = 226 Ωm and h_1 = 1.24 m.

C. Group 2:measurements with values outside the range values indicated for the trained ANN use

Group 2 contemplates 43 TL towers with input parameters values outside from the indicated range for using the trained ANN. Their characteristics are illustrated by histograms in Fig. 6 and a summary statistics is presented in Table III.

The results from Table III support the advice of using the trained ANN only within the input parameter range values due to their significative error. We observe a median of 29.1% and a standard deviation of 111.1%, what are, respectively, almost 5 and 17 times the presented for Group 1. More than half of Group 2 implies in an error higher than 20%, 11.6% and 2.33% are superior than 50% and 100%, what is remarkable. The most significative error observed in Group 2, equals to 744.7%, is related to a case with ρ_1 = 53 Ωm, ρ_2 = 13311 Ωm and h_1 = 9.26 m. For this situation, if we suppose ρ_2 equals to ρ_1 = 53 Ωm due to h_1 significative value, the error turns to 47.0%, what is still a bad approximation.

Another evident behaviour observed outside the indicated range is the incoherence of ANN for grounding resistance estimation. Increase the counterpoise length outside the specified range can increase too grounding resistance, what is unrealistic with the problem. This aspect, while with a much lower chance, can happen within the indicated range, although was not observed in preliminary tests. The ANN can be view as

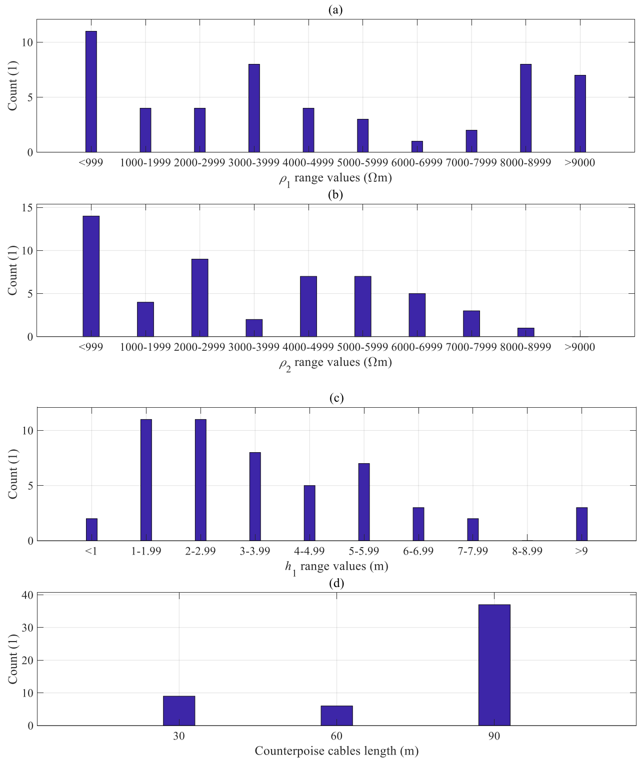

Fig. 4. Histograms with the count of group 1 input parameters range values for (a) ρ_1, (b) ρ_2, (c) h_1 and (d) counterpoise cables length.

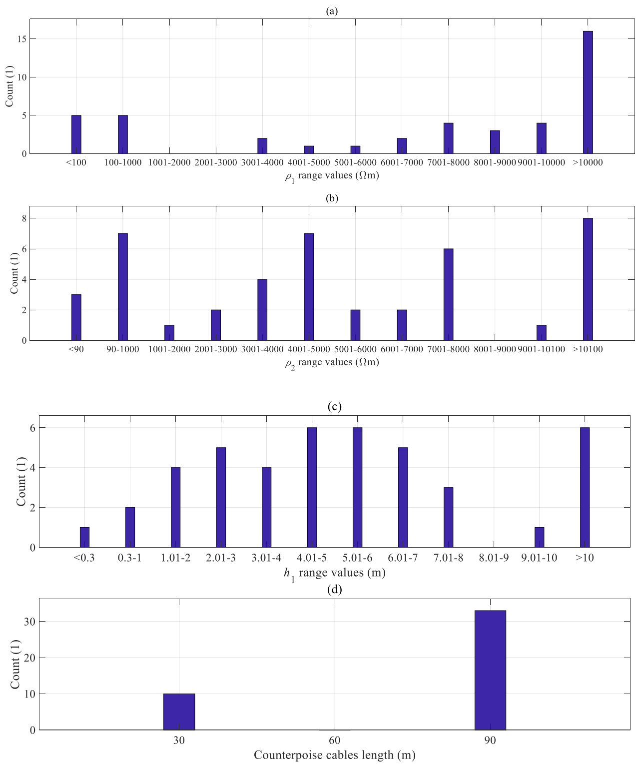

Fig. 5. Histograms with the count of group 2 input parameters range values for (a) ρ_1, (b) ρ_2, (c) h_1 and (d) counterpoise cables length.

TABLE II. ANN OUTPUT PERFORMANCE FOR GROUP 1

Summary statistics	***Value***
Median (%)	6.47%
Mean (%)	8.27%
Standard deviation (%)	6.69%
Rate cases with an error superior than 20% (%)	5.77%
Rate cases with an error superior than 50% (%)	0.00%
Rate cases with an error superior than 100% (%)	0.00%

TABLE III. ANN OUTPUT PERFORMANCE FOR GROUP 2

Summary statistics	***Value***
Median (%)	29.1%
Mean (%)	42.3%
Standard deviation (%)	111.1%
Rate cases with an error superior than 20% (%)	58.1%
Rate cases with an error superior than 50% (%)	11.6%
Rate cases with an error superior than 100% (%)	2.33%

as an equivalent mathematical formulation that share characteristics with used dataset for the training and test steps.

For a wide range values such as the studied problem in this work, added with seven input parameters, the dataset developed usually is insufficiently to cover all domain possible regions. Thus, such regions that were not well contemplated by the dataset typically derives in bad output approximations and change the value of input parameters can alter the grounding resistance with an inconsistent physical behaviour. This aspect is inherent with ANN and it should be seen not as a disadvantage, but as a premise of the method. ANN allows to express an output parameter as a function of other that do not necessarily need to have a direct or indirect relation. For this work, it is able to relate grounding resistance with interest parameters for the problem analysis, which makes it a very practical tool.

IV. CONCLUSIONS

This work presented an Android app to estimate the grounding resistance of usual TL towers arrangement. Using a rigorous computational routine to develop a dataset for practical conditions, ANN varying neuron numbers of the hidden layer were trained and tested considering MLP with LM algorithm to accelerates their convergence. Seven input parameters were considered for a one desired output: the grounding resistance.

For the chosen ANN, an app was developed in Android Studio and their performance was evaluated for a practical condition. With a median of 6.47% with a standard deviation of 6.69%, the results indicate that the algorithm appears to be suitable for use under practical conditions, since the range values for input parameters be respected. This can be observed for Group 2, whose results were much worse in terms of precision than that presented for Group 1.

Such conclusions allow a future improvement of the app with the introduction of analytical formulas for simpler geometries, such as horizontal and vertical electrodes. Also, app functions with standard-based tips for the procedure of measuring soil resistance and resistivity can be implemented. Other languages for the app are welcome, as French and German versions, to help the expansion of the tooling to new users.

Considering the analyzed problem in this work, wider range values for input parameters of usual TL towers arrangement can be evaluated for a better precision of the app.

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APPENDIX

The app was developed in Android Studio and, as showed in Fig. A-1, has three main functions. The command “Start to use” opens a new window with fields to inform values related to each input parameter for the estimation of the grounding resistance; “About the app” shows the app functions; and “How to use and recommendations” describes the soil model adopted and figures that illustrate to user how the app works.

As mentioned, GroundingApp is available for free on Play Store in three languages: Portuguese, English and Spanish. The English version of the app is used to illustrate Fig. A-1.

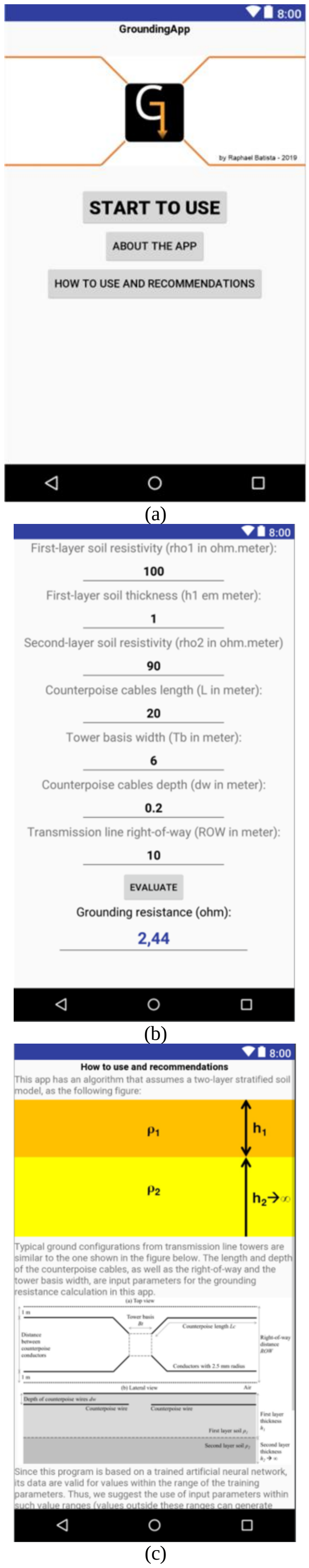

Fig. A-1. Images from GroundingApp: (a) home screen, (b) functions “Start to use” and (c) “How to use and recommendations”.