Wavelet Neural Network for Ground Resistance Estimation

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Abstract: **This paper presents the results of a computational approach for the ground resistance of grounding systems, used for the safe operation of electrical installations, substations and power transmission lines and aspires to build a forecasting model for the ground resistance values. The proposed model consists of a Wavelet Neural Network, which has been trained and validated by field measurements, performed for the last three years. Several grounding rods, encased in ground enhancing compounds and natural soil, have been tested, so that a wide data set for the training of the network can be obtained, covering various soil conditions. The input variables of the network are the soil resistivity within various depths of the tested field, varying with respect to time and the rainfall height during the year. This work introduces the wavelet analysis in the field of ground resistance estimation and attempts to take advantage of the benefits of artificial intelligence.**

I. INTRODUCTION

Grounding systems are an essential part of the protection system of electrical installations and power systems against lightning and fault currents, as they are designed to dissipate high magnitude fault currents to earth, providing safety to personnel working in and to people living or passing by near power system installations. International standards point out the influence of moisture content, temperature and soil compaction on the soil resistivity and they recommend the periodic measurement of the ground resistance for the control of its values [1–2].

However, most of the cases of electrical installations are characterized either by lack of space for the installation of the grounding systems, or the huge cost which often maybe prohibitive 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 humidity, whereas the dissolved salts percentage and the soil consistency play a major role in soil resistivity value [3–5]. 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.

On the other hand, the periodic measurements of ground resistance is very often impeded by the residence and building infrastructure, as well as many times it is essential for engineers to have an estimation of the behavior of constructed or in design phase grounding systems over time. This work aims 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 wavelet neural networks.

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). WNs 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 suitable for applications of small input dimension because the construction of a wavelet basis is computationally expensive when the dimensionality of the input vector is relatively high [6]. WNs were proposed by Zhang and Benveniste [7] 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. [8] 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. Finally, a complete theoretical background on wavelets and wavelet analysis is given in [9–11].

II. Experimental Setup and Measurements

In this work, three grounding rods, *St/e-Cu* type A, dimensioned 17x1500mm, with a minimum copper thickness 254μm, were evaluated in field conditions. The first one has been driven in natural soil, while the rest have been immersed in ground enhancing compounds (see [12] for the details of installation). The electrodes were tagged as follows: G_1: natural soil, G_2: conductive concrete and G_3: chemical compound A. The measurements performed at the experimental field, for over three years, are [12]: i) Soil resistivity, ii) Ground resistance of grounding rods R_{g1}, R_{g2}, R_{g3} and iii) Rainfall height. A representative sample of the field measurements is the graph of Fig. 1, where the experimental results of ground resistance measurement are illustrated:

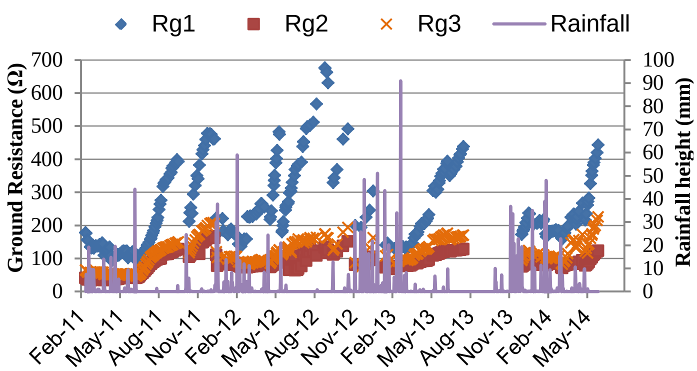

Figure 1. Ground resistance of grounding rods versus time and rainfall

III. Proposed Wavelet Neural Network Methodology for the Estimation of Ground Resistance

A. WN Architecture

In this study, a multidimensional wavelet network with a linear connection between the 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. 2.

The network output is given by the following expression:

$$g_{\lambda}(\mathbf{x};\mathbf{w}) = \hat{y}(\mathbf{x}) = w_{\lambda+1}^{[2]} + \sum_{j=1}^{\lambda} w_j^{[2]} \cdot \Psi_j(\mathbf{x}) + \sum_{i=1}^{m} w_i^{[0]} \cdot x_i \qquad (1)$$

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:

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

where ψ is the mother wavelet and

$$z_{ij} = \frac{x_i - w_{(\xi)ij}^{[1]}}{w_{(\zeta)ij}^{[1]}} \qquad (3)$$

In the above expression, i=1,…m, j=1,…λ+1 and the weights w correspond to the translation $(w_{(\xi)ij}^{[1]})$ and the dilation $(w_{(\zeta)ij}^{[1]})$ factors. The complete vector of the network parameters comprises $w = \left(w_i^{[0]}, w_j^{[2]}, w_{\lambda+1}^{[2]}, w_{(\xi)ij}^{[1]}, w_{(\zeta)ij}^{[1]}\right)$. 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 [13–15]

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

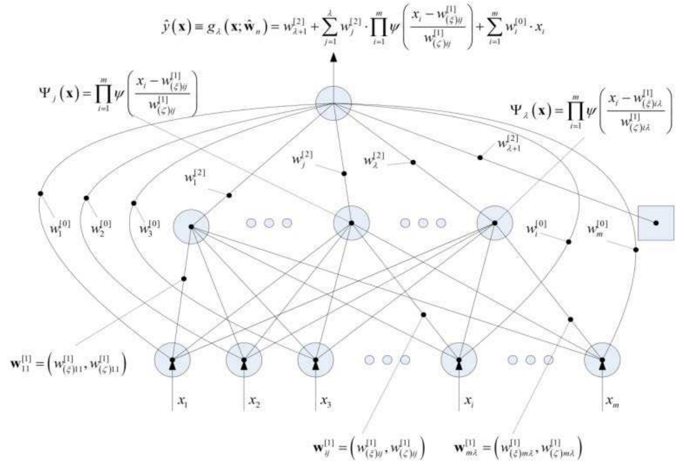

Figure 2. A Feedforward Wavelet Neural Network

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 to less iterations in the training phase of the network and to training algorithms that will avoid local minima of the loss function in the training phase. In the present network the Backward Elimination (BE) method [6, 15] is used for the initialization of the network parameters. The BE starts the regression by selecting all the available wavelets from the wavelet library. Then the wavelet that contributes the least in the fitting of the training data is repeatedly eliminated. The drawback of BE is that it is computationally expensive but it is considered to have good efficiency.

After the initialization phase, the network is further trained in order to obtain the vector of the parameters $w = \hat{\mathbf{w}}_n$ which minimizes the loss function. The ordinary back-propagation algorithm (BP) is used for the training of the WN, as it is probably the most popular algorithm used for training WNs. BP is less fast but also less prone to sensitivity to initial conditions than higher order alternatives. According to this algorithm the weights of the network are trained to minimize the mean squared error function (or loss function), which is given by the following formula:

$$L_n = \frac{1}{n}\sum_{p=1}^{n} E_p = \frac{1}{2n}\sum_{p=1}^{n} e_p^2 = \frac{1}{2n}\sum_{p=1}^{n}\left(y_p - \hat{y}_p\right)^2 \qquad (5)$$

where, y_p is the target value, $\hat{y}_p$ the network output and n the number of the patterns in the training set.

So, the weights $w_i^{[0]}$, $w_j^{[2]}$ and the parameters $w_{(\xi)ij}^{[1]}$ and $w_{(\zeta)ij}^{[1]}$ are trained during the learning phase for approximating the target function. A key decision related to the training of a WN is when the weight adjustment should end. Under the assumption that the WN contains the number of wavelets that minimizes the prediction risk, the training is stopped when one of the following criteria is met: the cost function reaches a fixed lower bound or the variations of the gradient or the variations of the parameters reaches a lower bound. These stopping criteria can be mathematically expressed as:

$$\left|L_n(ep) - L_n(ep-1)\right| \le \text{limit}_1 \qquad (6)$$

$$\left|\frac{\partial L_n(ep)}{\partial w_t} - \frac{\partial L_n(ep-1)}{\partial w_t}\right| \le \text{limit}_2 \qquad (7)$$

Afterwards, one of the most crucial steps is to identify the correct topology of the network. A desired WN architecture should contain as few HUs as necessary while at the same time it should explain as much variability of the training data as possible. The Minimum Prediction Risk (MPR) principle can be applied as the most suitable measure of the generalization ability of the network. The idea behind MPR is to estimate the out-of-sample performance of incrementally growing networks. More precisely, the prediction risk of a network $g_\lambda(\mathbf{x};\hat{\mathbf{w}}_n)$ is the expected performance of the network on new data that have not been introduced during the training phase and is given by:

$$P_\lambda = E\left[\frac{1}{n}\sum_{p=1}^{n}\left(y_p^* - \hat{y}_p^*\right)^2\right] \qquad (8)$$

In order to estimate the prediction risk and to find the network with the best predicting ability, a series of information criteria has been developed. In this case, the Bayesian Information Criterion (BIC) is considered to be the most appropriate among the other criteria for the WN construction, as its little computational burden doesn't affect the precision on estimations. First the WN is constructed with zero HUs. Then, the corresponding information criterion is estimated. Next, one HU is added to the network and the procedure is repeated until the network contains a predefined maximum number of HUs. The number of HUs that produces the minimum prediction risk is the number of the appropriate wavelets for the construction of WN. The BIC is expressed as:

$$J_{BIC} = \frac{1}{n}\sum_{p=1}^{n}(y_p - \hat{y}_p)^2 + \frac{k\hat{\sigma}^2 \ln(n)}{n} \qquad (9)$$

where, k is the number of the parameters of the network, n the number of the training patterns and σ^2 the noise variance estimator.

Finally, a variable selection algorithm is applied during the WN construction, aiming to determine the most significant input variables for the network output. In real problems it is important to determine correctly the independent variables. In most problems there is a little information about the relationship of any explanatory variable with the dependent variable. As a result, unnecessary independent variables are included in the model reducing its predictive power. Among various sensitivity criteria and model fitness criteria the Sensitivity Based Pruning (SBP) [16] is chosen for the variable selection of the examined architecture. The SBP method quantifies a variable's relevance to the model by the effect on the empirical loss of the replacement of that variable by its mean and is given by:

$$SBP(x_j) = L_n(\mathbf{x};\hat{\mathbf{w}}_n) - L_n(\bar{\mathbf{x}}^{(j)};\hat{\mathbf{w}}_n) \qquad (10)$$

where, $\bar{\mathbf{x}}^{(j)} = \left(x_{1,t}, x_{2,t}, ..., \bar{x}_j, ..., x_{m,t}\right)$ and $\bar{x}_j = \frac{1}{n}\sum_{t=1}^{n} x_{j,t}$

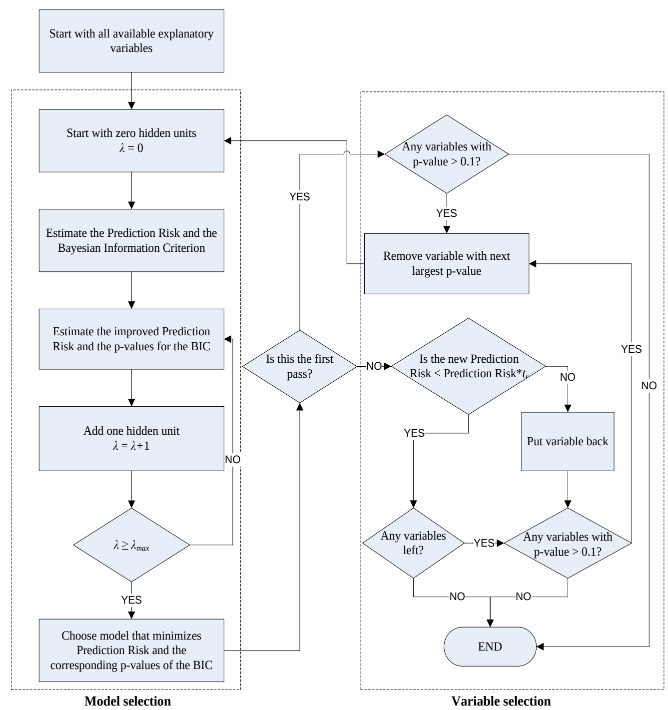

Figure 3. Flowchart of the proposed WN methodology

The proposed methodology for the estimation of ground resistance value of each rod can be concisely illustrated in the flowchart of Fig. 3.

B. *Application of WN*

For the problem of ground resistance estimation a multidimensional wavelet network with a linear connection between the wavelons and the output is applied. The nodes of the input layer are the daily value of soil resistivity at the depth of 1m, 2m, 4m, 6m and 8m on the day of measurement (ρ_{id}), the mean weekly value of soil resistivity at the same depths (ρ_{iw}), the mean monthly value of soil resistivity at depths of 1m and 2m (ρ_{im}) and the total rainfall height of the day of the measurement (r_d), of the previous week (r_w) and of the previous month (r_m). It is noted that i = 1, 2, 4, 6, 8m in depth. The output variable is the ground resistance of each tested grounding system, thus a separate network for each one of the rods is constructed.

The initialization of the network parameters is performed by the BE method, starting the regression by selecting all the available wavelets from the wavelet library. Then the wavelet that contributes the least in the fitting of the training data is repeatedly eliminated. In Fig. 4 the initialization method for the rod G_1 is illustrated. A closer inspection of Fig. 4 reveals that the initialization is very good. The WN starts its training very close to the target function significantly reducing the required training time.

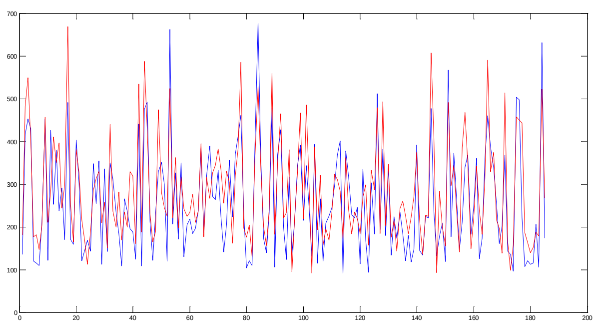

Figure 4. Initialization of the WN parameters

The experimental data set, which comprises 265 input-output patterns, is divided randomly into two sets:

- The training set (185 patterns) is used until the network has learned the relationship between the inputs and the output.
- The validation set (80 patterns) is used for the initialization of the WN parameters, for the model and variable selection, as well as for the evaluation of the learning and generalization ability.

The WN is trained with the use of Batch mode with constant learning rate η = 0.1 and zero momentum term. The maximum number of epochs is set to 100,000 indicatively but the training never reaches even the half of it. The second derivative of the Gaussian, i.e. "Mexican Hat" wavelet, given by (4), is used as an activation function.

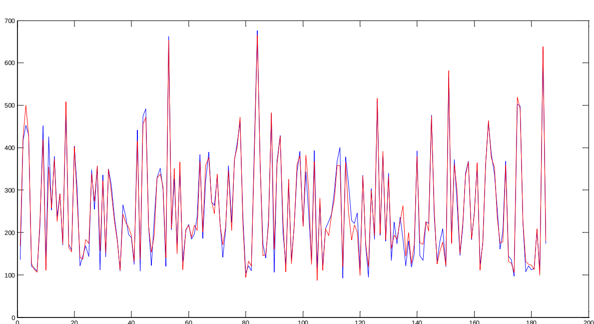

Figure 5. Training of the WN

For the model and the variable selection the BIC method and the SBP algorithm are applied respectively. The algorithm running is carried out for two scenarios. In the first one, the SBP method is applied and the optimum number of significant variables, that the method produces, is used for the network training, while in the second one no variable selection is applied and all the input variables of the data set are used. The results from the application of the training algorithm for the validation set are presented in Table I.

TABLE I
INDICES FOR THE TRAINING AND VALIDATION SET FOR BOTH SCENARIOS OF ALL GROUNDING RODS

		Training	Validation	Training	Validation
R_{g1}		Variables: r_d, r_m, ρ_{2d}, ρ_{16d}, ρ_{12w} HU: 11		Variables: All HU: 8	
	NMSE	0.0077	0.0846	0.0989	0.2554
	SMAPE %	2.00	5.65	5.07	7.77
	R^2	0.996	0.958	0.955	0.877
	R^2 adjusted	0.992	0.916	0.912	0.770
R_{g2}		Variables: r_d, r_m, ρ_{2d}, ρ_{4d}, ρ_{8d}, ρ_{12d}, ρ_{4w} HU: 12		Variables: All HU: 1	
	NMSE	0.0085	0.0631	0.2864	0.3785
	SMAPE %	0.97	3.19	8.96	11.75
	R^2	0.996	0.971	0.845	0.793
	R^2 adjusted	0.992	0.941	0.714	0.622
R_{g3}		Variables: r_d, r_m, ρ_{2d}, ρ_{4d}, ρ_{8d}, ρ_{12d} HU: 14		Variables: All HU: 3	
	NMSE	0.003	0.1155	0.053	0.0951
	SMAPE %	0.74	3.64	2.66	3.63
	R^2	0.999	0.942	0.973	0.952
	R^2 adjusted	0.997	0.885	0.947	0.905

NMSE: normalized mean squared error
SMAPE: symmetric mean absolute percentage error
R^2: determination coefficient

Moreover, Fig. 5 shows the training phase for the rod G_1, while the fitting results of the validation set for the three electrodes are illustrated in Figs. 6–8. The horizontal axis represents the serial number of the values of the validation set. It is clear that when the variable selection scheme is applied, the WN can approximate very accurately the real data.

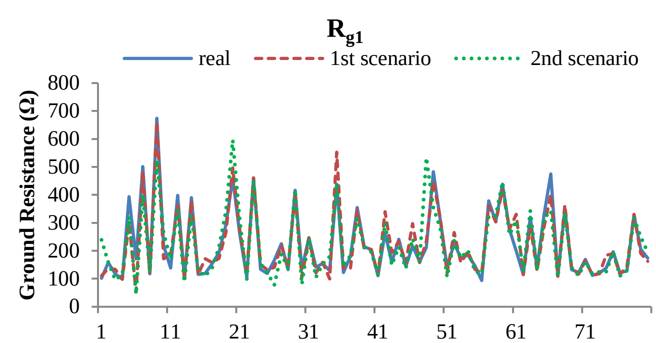

Figure 6. Real and estimated values of ground resistance for grounding system G_1 (validation set)

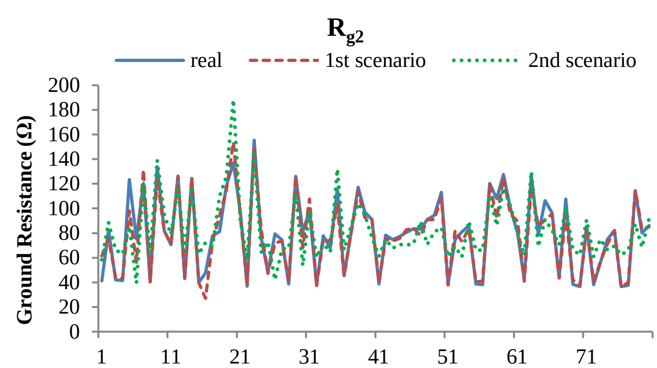

Figure 7. Real and estimated values of ground resistance for grounding system G_2 (validation set)

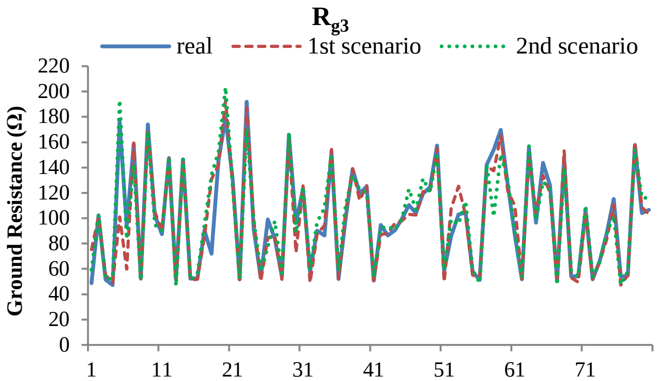

Figure 8. Real and estimated values of ground resistance for grounding system G_3 (validation set)

IV. Discussion – Conclusions

A WN based on back-propagation algorithm with batch training method and learning rate has been developed, trained and validated in order to predict the variation of ground resistance of several grounding systems during the year. This work is an attempt to apply WNs on ground resistance estimation and forecasting; more specifically for estimating the behavior of ground enhancing compounds, which are widely used in grounding systems all over the world. It is a continuation of previous research work on ANN application on grounding systems [17]. The proposed WN includes an extensive input vector with a lot of input variables derived from the field measurements of soil resistivity and rainfall height in specific time intervals. These input variables are used either in their entirety, or a few of them according to the variable selection procedure, for the training of the network. Hence, two scenarios have been elaborated for the training and the validation of the WN and its performance has been evaluated in each one of them.

Referring to the results of Table I, the values predicted by the proposed WN were more than satisfactory in all cases. Regarding the R^2 and adjusted R^2 coefficients one could notice that the variable selection method yields significantly better results and better convergence to the real values of ground resistance in the case of G_1 and G_2 rods with values 0.958, 0.916 and 0.971, 0.941 respectively. The SMAPE of the first scenario also presents evidently lower value than that of the second scenario, as it is 5.65% against 7.77% for G_1 and 3.19% against 11.75% for G_2. This fact validates the need of variable selection in order to keep the variables of major importance that contribute the most to the output modulation. For the G_3 case the performance of both approaches is similar. A closer inspection of Table I reveals almost the same SMAPE while the adjusted R^2 is only 2% higher for the full model. However, using the full model the training time was significantly increased. The highest convergence between experimental and estimated ground resistance values has been achieved for G_2 grounding system, with the SMAPE of validation set reaching the value of 3.19% and the R^2 coefficient reaching the value of 0.971. In general, the estimation results of the proposed WN for the ground resistance value of all the rods are quite encouraging, as the R^2 and adjusted R^2 coefficients of the validation set for the first scenario is higher than 0.9 and the SMAPE values are relatively low. Besides, this allegation is confirmed in the Figs. 6–8, where the success in convergence of the WN model is illustrated, and the predominance of the first scenario is quite obvious.

Further work on the architecture and the training of the WN may be done. The different grounding systems can constitute the outputs of a single network, instead of constructing single networks for each system. Moreover, the calculation of the leverage of each input value may lead to discarding those values that influence excessively on the network output. This will result in a faster and better training of the network.

In conclusion, it can be stated that another step for the development of forecasting methods for ground enhancing compounds and, generally for grounding systems performance, has been done with promising results on grounding field.

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