Comparison between python and matlab algorithms for the evaluation of the corrosion grade in guyed transmission towers using artificial neural networks and machine committees

Comparação entre algoritmos em python e matlab na avaliação do grau de corrosão em torres de transmissão estaiadas utilização comitês de máquina de redes neurais artificiais

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RESUMO

Nesse artigo são descritos dois comitês de máquinas baseados em redes neurais artificiais (RNAs) criados para avaliação de corrosão em estais de torres de transmissão. Os dados utilizados para treinamento das redes neurais foram coletados experimentalmente e descritos em artigo previamente publicado. Aqui foram complementados pela coleta de dados referentes a resistividade do solo. Um dos comitês foi implementado em Python com utilização da biblioteca Keras Tensorflow e foi composto por 3 RNAs. O outro foi elaborado em MATLAB e consistiu em 8 RNAs. Nos diferentes comitês de máquinas foram utilizadas arquiteturas distintas, sendo a diferença mais notável nos números de neurônios e camadas escondidas utilizados em cada modelo. Ambos os comitês apresentaram resultados satisfatórios para classificação quanto ao grau de corrosão dos estais. Um foco especial foi dado para o caso onde graus de corrosão elevados ocorriam, sendo necessário garantir alto grau de precisão, evitando que fossem apontadas classes leves de corrosão quando na realidade o grau é elevado. O comitê desenvolvido em MATLAB apresentou número significativamente menor de neurônios, o que possibilita implementação mais rápida e maior velocidade no processamento dos dados. Além disso, a correlação obtida foi de 96.70% para o comitê elaborado em MATLAB e de 95.17% para o comitê elaborado em Python ao passo que o anterior havia sido de 80%.

Palavras chave: Redes neurais artificiais, Comitê de máquinas, Torre de transmissão estaiada, Grau de corrosão, Hastes de âncora.

ABSTRACT

In this study two machine committees based on artificial neural networks (ANN), created with the purpose of evaluating the corrosion rates in guyed transmission towers, are described. The data used in the training process was gathered experimentally and were described in a previously publicized paper. In this paper soil resistivity results were added to the database. One of the committees was built in Python with the use of the Keras Tensorflow library and consisted of 3 ANN. The other was implemented in MATLAB from the ground up, consisting of 8 ANN. Distinct architectures were used on the committees, with the main difference being the number of neurons and hidden layers of each committee. Both models presented satisfactory results on the classification of corrosion rates. Special focus was given to cases with high corrosion rates, where a greater precision was required in order to avoid mistaken classification as low corrosion when, in reality, the levels are high. The machine committee developed in MATLAB used considerably less neurons, which allowed for a faster implementation. The total correlation obtained from the MATLAB machine committee was of 96.70% and from the Python committee was of 95.17% when the total correlation obtained previously was of 80%.

Keywords: Artificial neural networks, Machine committee, Guyed transmission tower, Corrosion rate, Anchor rods.

1 INTRODUCTION

The use of guyed towers in electric power transmission lines (TL) has increased significantly due to high economic viability when compared to standard towers. The corrosion in the anchor rods in these TL is a high cost for maintenance of the asset because mainly the methods used are destructible: it must be unburied, cracked the concrete, checked visually the condition of the rod and then, once again rebuild the concrete protection and reburied the anchor rod. The companies accountable for these maintenances are willing to develop further non-destructive methods for the assessment of the corrosion condition of the anchor rods before starting the proper maintenance [1-2].

The application of Artificial Neural Networks (ANN) has been widely spread over several different areas of knowledge to predict data as well as for pattern recognition.

Virgens et al. [3] evaluated the kinetics of the slow pyrolysis of the powder obtained from the fruit peel of Pachira aquatica Aubl. to determine the kinetic parameters for the pseudo-cellulose component. The authors concluded that the applied neural network was efficient in the prediction of the thermal data, obtaining similar thermogravimetric profiles when compared to experimental ones and high determination values. An ANN, using the Levenberg-Marquardt optimization algorithm method, was used by [4] for the monitoring of the propylene glycol production process ($C3H8O2$), with results indicating better ANN performance when compared to a semi-empirical model. Mariano et. al [5] proposed to estimate the nitrogen-corrected metabolizable energy values of the energetic and protein concentrate feedstuffs for broilers. In their work, it was studied values of error for the Machine Committee formed with different numbers of ANN. They propose to use at least 300 ANN combined to decrease error. Barzegar et al [6] compared different machine learning models to estimate uniaxial compressive strength in rocks to support the prediction of the rock failure, achieving the best result with machine committee model rather than standalone ANN models.

Corrosion has been the focus of some studies involving ANN. A corrosion prediction model for carbon steel in methyldiethanolamine (MDEA)-based binary mixtures with monoethanolamine (MEA), diethanolamine (DEA), or piperazine (PZ) at various concentrations using ANN was developed by [7]. Experimental studies of Q345R steel were performed, corrosion rates were obtained and used to create a database for training and testing an ANN. The same corrosion rate database was used to develop a support vector machine (SVM) model, in which optimal model values were used. The authors noted that the performance in both training and testing of the ANN model outperformed the SVM model. Ahuja et al. [8] presented a computer vision-based approach in combination with deep learning for corrosion classification. The results' evaluation shows an unbiased model with values in an acceptable range, similar to visual inspection. The approach proposed by the authors resulted in 93.4% accuracy for corrosion grade identification in four defined categories.

The current work builds upon the results obtained on a previous paper [9], which presented a method consisting of a machine committee based on ANN with the objective of substituting the current use of visual inspection, that is highly costly and requires the transportation of machines and equipment to remote locations. In order to evaluate the problem several characteristics of the focused upon TL were measured both in situ and with laboratory assessments. Among the variables analyzed were the resistivity, redox potential, pH, humidity, concentrations of chlorides and sulfates, total acidity, and several other parameters. A principal component analysis (PCA) was carried out and the number of inputs was reduced to 6 variables, which included the concentration of chlorides and sulfates and the alternated current measured in each of the 4 guys of the structure. The machine committee achieved a correlation of 80% when compared to visual inspection of the corrosion on the guys. In this work previous paper, the original variables available to evaluate the problem before applying PCA did not include the resistivity of the soil, which is one of the variables wide used in models developed to evaluate the corrosion level of the soil using the soil properties [10] and also, easier to collect and measure in the field compared to the concentration of chlorides and sulfates.

The objective of this study was to propose the diagnosis and classification of the corrosion degree of guyed towers using machine committee with artificial neural networks, replacing the concentration of the chlorides and sulfates by the soil resistivity due to the simplification to collect such variable in the field allowing a faster and cheaper method for assessing the corrosion grade. Two separate machine committees were developed with different approaches and compared in this paper. One was implemented in MATLAB R2014a from the ground up using the 4 fundamentals error-backpropagation equations to train artificial neural networks and the other was implemented in Python using machine learning libraries. The methods used to build each machine committee are discussed and compared as are the results obtained from both.

2 MATERIALS AND METHODS

In this item, the ANN models that formed two distinct machine committees, implement in Python and in MATLAB R2014a, are described along with the techniques and considerations made in each. The database used was the same as the one in [9] with the addition of the soil resistivity measurements made in the field. The number of samples was 269 towers. The total correlation between the machine committees was taken as the rate between hits and misses when comparing the committees' classification with the actual expected results.

2.1 MACHINE COMMITTEE DEVELOPED IN PYTHON

The machine learning model developed aims to qualitatively classify the degree of corrosion of the towers into low, medium, or critical based on the input data collected of resistivity and alternating current measured at each guy anchor. For this purpose, a committee of machines was elaborated, composed of 3 different artificial neural networks.

For this machine committee the employed networks were implemented with the same architecture and structure, varying only their training conditions. For the definition of the best network structure, optimization of the number of layers and neurons was carried out in the model, where an optimal configuration of network architecture was achieved with the use of 2 dense hidden layers with 250 connected neurons each.

The final diagnosis of the data is processed by 3 different neural networks through a committee of machines, which will calculate the final classification based on the arithmetic mean of the individual responses of each network in probabilistic terms, being the class with the highest probability the final answer for the corrosion degree of the data under analysis.

The training algorithm of the neural networks was implemented in Python with the TensorFlowKeras library [10], defining the loss function sparse categorical cross-entropy using the L1 and L2 regularization methods, the Adam optimization algorithm, with sigmoid as the activation function for the hidden layers, softmax as the activation function for the output layer and the use of an early stopping feature to monitor the accuracy presented by the neural network throughout the training in order to avoid the occurrence of overfitting.

The training and validation datasets of the networks were defined by using base experimental data collected in the field. The data was artificially expanded by linear interpolation between two data sampling points. The training and testing data sets were implemented under different conditions for each neural network, with 20% of the test data in two ANNs and 30% in the other. The division of the data to be trained and tested was performed randomly.

2.2 MACHINE COMMITTEE DEVELOPED IN MATLAB

In this step, the neural network training algorithm was programmed in MATLAB based on 4 fundamental error-backpropagation equations [11], considering a regularized cross-entropy cost function and sigmoidal transfer function for the hidden layers, given their better performance in neural network training for problems of classification and choice [12-14]. The weights and biases were initiated by a heuristic technique, creating a normal distribution with the mean equal to zero and standard deviation equal to $1/nn^{l-1}$, where nn^{l-1} is the number of neurons in the immediately preceding layer. In the last layer, the softmax function was used to generate a probability distribution of the activation of neurons by the neural network. The first layer of the network, the input layer, was constructed with *n* neurons, each representing one of the variables. The number of neurons in the hidden layers was fluctuating from 8 up to 16. The last layer has 8 neurons, each representing a classification of grade. The basic typology defined in this stage was used to train 2100 neural networks, varying the learning rate η from 0.008 to 0.500, the number of hidden layers from 1 to 3 and the regularization factor λ from 0 up to 20%*η in the cost function. A routine of early stopping was programmed using 'non-improvement in 20' technique, to avoid overfitting during the ANN training. The networks were evaluated for accuracy, which consists of predicting the validation data that were not used during training, and the hit rate, which consists of how well the network represents the data used for training. The best ANN trained in this step were combined in Machine Committee using the average of the output layer as combinator operator.

3 RESULTS AND DISCUSSIONS

The proposed MATLAB R2014a ANN committee was a result of 8 different ANNs, chosen throughout the topology optimization. As a result, Table 1 shows the architecture of the networks.

Table 1 - Architectures of the 8 ANNs built for the MATLAB machine committee

Network	Hidden Layers	Neurons by hidden layer	Learning Rate
1	2	9	0.100
2	2	13	0.500
3	2	13	0.400
4	3	13	0.400
5	2	14	0.400
6	3	14	0.300
7	2	15	0.500
8	3	15	0.300

After testing the networks, two important results were highlighted. The accuracy and the hit rate. These results for each network are shown in Table 2.

Table 2 - Precision on validation and total dataset

Network	Accuracy [%]	Hit rate [%]
1	80.49%	78.44%
2	65.85%	89.96%
3	75.61%	88.10%
4	80.49%	86.25%
5	80.49%	86.99%
6	70.73%	89.59%
7	70.73%	88.48%
8	65.85%	87.36%

It is observed in Table 2 that each network on its own might lack precision, even reaching close to 35% error on the validation data, therefore justifying the use of a machine committee to improve accuracy and hit rate [15]. With this solution it was possible to improve the results, reaching precision on total data of 96.7%, as indicated in Table 3. The precision on the classification of high corrosion rate was one of the main points on which errors could lead to critical results, once the maintenance of the anchor rods will be performed according to the classification and, in these cases, the machine committee points to low corrosion when the rods are actually highly corroded. Thus, this was one of the parameters used to classify the ANNs according to their performance.

Table 3 - Precisions observed on low corrosion data, high corrosion data and total data for the machine committee built in MATLAB

Number of samples	Correlation on classification of low corrosion rate data	Correlation on classification of high corrosion rate data	Total correlation
269	99.51%	87.27%	96.70%

The results presented in Table 3 show that although the total precision is remarkably high, there is still relatively high error when classifying the high corrosion rate data. This indicates the need for special attention when using this machine committee, because when the transmission tower is in a critical corrosion state there is a 12.73% chance of this system implying the tower is in a safer condition.

The results obtained with neural networks developed in Python were initially not satisfactory, several network structures were tested with the use of 8 to 15 neurons hidden layers which failed in the attempt to predict the data associated with critical corrosion classification degree. It was found that this prediction difficulty was related to the small amount of data and the low incidence of data classified with a critical corrosion degree, representing only 20% of the total data.

In an attempt to solve this problem, the construction of a specialist network was tested, which focused on the task of classifying the data associated with the critical corrosion rate. This network was trained with a balanced dataset, in which all original data classified as critical corrosion was maintained, in order to obtain a distribution of 50% classified as critical corrosion and 50% as non-critical. Using this technique, the incidence of errors in the classification of data associated with a critical corrosion rate was reduced by 45%.

However, since the model's accuracy in forecasting this data category is the main analysis parameter to be maximized, several other network structures and regularization resources were tested using the Keras Tuner library Random Search feature. As a result of this approach, the best neural network configurations were found as shown in Table 4, which used all the collected base data, without balancing, and surpassed the accuracy in the classification of critical corrosion degree data from the specialist network. This is explained by the use of the regularization resources L1 and L2 which amplified the precision of neural networks in training and especially in testing, since it is a technique that prevents the effects of overfitting and consequently improves the generalization capacity of the model.

Table 4 - Parameters used on the 3 ANNs for the Python machine committee.

ANN	Optimizer	Learning rate	L1 Regularization factor	L2 Regularization factor	% test data	Hidden layer activation function	Output layer activation function	Early Stopping
1	Adam	0.001	1.00E-05	1.00E-04	20	Sigmoid	Softmax	Yes
2	Adam	0.001	1.00E-05	1.00E-04	20	Sigmoid	Softmax	Yes
3	Adam	0.001	1.00E-05	1.00E-04	30	Sigmoid	Softmax	Yes

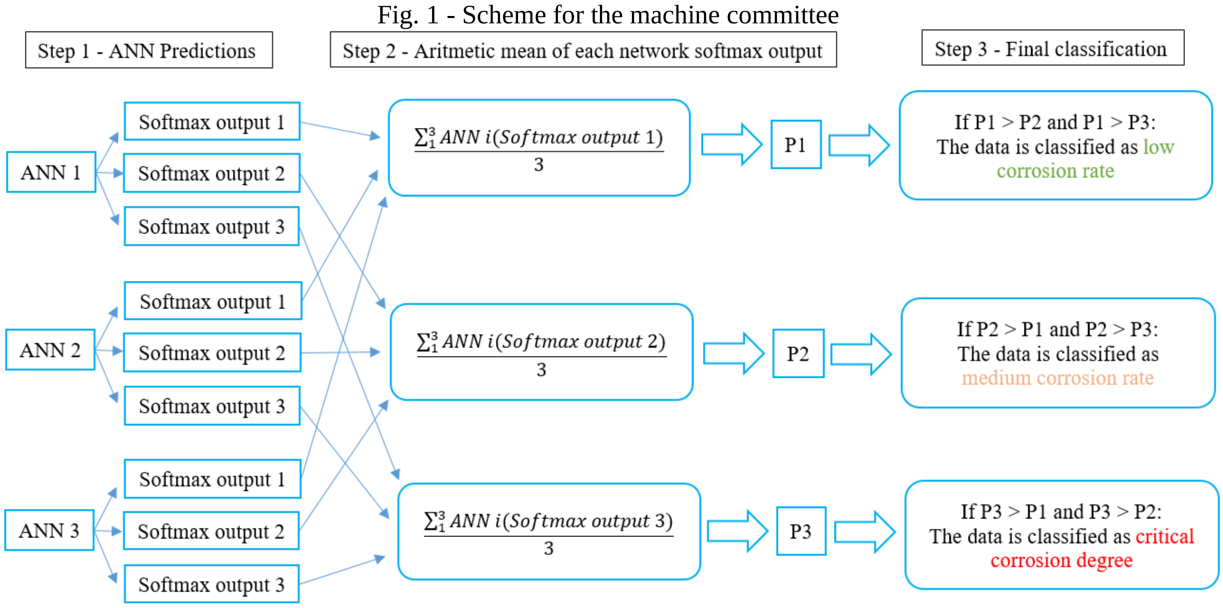
The individual results of these models are shown in Table 4 when evaluated with the entire data set:

Table 5 - Individual ANN precision scores

Network	Correlation on classification of high corrosion rate data	Correlation on Validation Data	Total correlation
ANN 1	81.82%	98.15%	94.42%
ANN 2	85.45%	85.19%	91.08%
ANN 3	89.10%	97.53%	96.28%

Finally, the final diagnosis will be processed by a machine committee composed of those 3 ANN's, as shown in Fig.1 the final classification prediction follows 3 steps:

Fig. 1 - Scheme for the machine committee



The first step is the calculation of the softmax activation function output which provides a probability distribution over predicted output classes. The second step is defined by the arithmetic mean calculation of each network softmax output value. That individual output value is related to a classification probability over one output class. In the last step, a final prediction about the data corrosion rate is made by taking the highest value obtained in the second step. The results obtained with that method is show in Table 6.

Table 6 - Results obtained for the machine committee built in Python

Machine Committee	Correlation on classification of high corrosion rate data	Total correlation
	89.10%	95.17%

We can see from Table 6 that the accuracy decreased when compared to the ANN 3 as shown in Table 5, this is completely expected once the machine committee computes the mean response over the 3 ANN's. The advantage of this procedure is the superposition that occurs between these neural networks preventing overfitting and improving the generalization capacity of the model.

4 ANN MODELS COMPARISON

Comparing the results obtained with both ANN machine committeess one can infer that individually the networks with a higher number of neurons reached a better precision on the total dataset. More neurons in the hidden layers increase the processing capacity of the network, facilitating the convergence of the cost function minimization algorithm, resulting in a higher hit rate, however, the use of excess neurons can cause a vanishing gradient on the model, due to the impossibility of training and validating the weights of the neural network throughout the training. However, as described in Section 2 of this paper due to the early stopping feature and regularization techniques the model's test accuracy was monitored, besides that, the test accuracy on all these networks was high and close to the training values, avoiding the occurrence of overfitting.

It is important to note a very similar precision verified when comparing the machine committee results, from Table 3 and Table 5 is possible to determine a difference of only 1.53% in the accuracy of total data and 1.83% in the accuracy on the classification of high corrosion rate data. Therefore, when combining each ANN's predictions through a machine committee, the final response obtained by any of the methods described in this paper will be likely similar.

It is also relevant to emphasize that due to the use of fewer neurons in the hidden layers and a greater number of networks in the composition of the machinery committee, the proposed MATLAB R2014a ANNs are more suitable for real applications in an attempt to predict the degree of corrosion of cable-stayed towers, due to its better ability to generalize and adapt in relation to the models developed with the use of a greater number of neurons in the hidden layers.

5 CONCLUSIONS

It was possible to substitute chloride and sulfate ions as parameters by the soil resistivity while improving the classification capabilities of the machine committee by increasing the number of training data. The use of resistivity rather than chloride and sulfate ions allows for a much faster evaluation process by the maintenance team, once there is no necessity to collect samples and perform laboratory analyses, since resistivity can be measured in the field, as can the alternate currents on the guys.

The machine committee built-in MATLAB, with ANN with 1 to 3 hidden layers and 9 to 16 neurons by hidden layer, showed an overall higher correlation (96.70%) when compared to the committee built in Python with the Keras Tensorflow library (95.17%), that used 2 hidden layers and 250 neurons on each layer. When it comes to high corrosion rates being classified as low, both committees presented good results 87.27% and 89.19% for the MATLAB and Python committees respectively.

The application of specialized ANN trained with proportional data distributed on classifications of high and low corrosion rates allowed for the reduction of the number of wrongly classified high corrosion as low corrosion rates. However, overall the reduction was not significant when compared to that achieved by uniting several ANN in machine committees. The use of the regularization resources L1 and L2 allowed for higher precision both in training and, especially, in testing. Along with early stopping the regularization technique allowed for the prevention of overfitting and, consequently, improved the generalization capacity of the neural network and, in turn, of the machine committee.

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