# PREDICTION OF ELASTIC YOUNG MODULUS OVER TIME OF JET GROUTING LABORATORY FORMULATIONS BY APPLICATION OF DATA MINING TECHNIQUES

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### **KEYWORDS**

Soil improvement, Jet Grouting, Data Mining.

# EXTENDED ABSTRACT

The work present in this paper was developed under the PhD thesis entitled "Application of Data Mining Techniques to the Design of Jet Grouting Columns". The main goals of this study are the developing of analytical model, by application of Data Mining (DM) techniques, able to estimate the mechanical and physical properties of Jet Grouting (JG) material, namely the evolution of uniaxial compressive strength and elastic Yong modulus over time, as well as the diameter of JG columns. Thus, in this paper, and as a part of the PhD study three Data Mining models, i.e. Artificial Neural Networks (ANN), Support Vector Machines (SVM) and Functional Networks (FN) were used to estimate the Elastic Young Modulus  $(E_0)$  of JG laboratory formulation over time. Furthermore, the results were compared with the Eurocode 2 analytical model.

Nowadays, there are several methods to improve the physical and mechanics properties of soil, mainly softsoils, where JG technology is highlight. However, at the design stage of JG, there are still uncertainties because there are no reliable methods that allow the prediction of the diameters and the mechanical properties of the soil-cement elements (Croce and Flora 2001). Thus, given the high potential of JG technology, there is need to develop more rigorous and accurate models of design. In many geotechnical structures advanced designs incorporates the serviceability design criteria. For this purpose, deformability properties of the improved soils are needed. In a non linear stress-strain relationship different moduli can be defined. For this work the initial modulus at very small strains was adopted since, is a laboratory parameter that can be compared with geophysical field test results. In the other hand, powerful tools have emerged that allow extract useful information from large data base (e.g. Data Mining techniques). Thus, we start by adapting the Eurocode 2 analytical model to JG material. Moreover, DM techniques were also applied, which allow to develop a novel predictive model of  $E_0$  over time.

During the training and validation process of the Data Mining (DM) models, data from huge JG laboratory formulations, prepared on University of Minho were used. The dataset includes 188 results, derived from 9 JG laboratory formulations and 8 input parameters, which are referred as the more relevant parameters in mechanical properties of soil-cement mixtures 2003). The parameters used were: (Shibazaki Water/Cement ratio – W/C; Age of the mixture – t; The relation between the mixture porosity and the volumetric content of cement –  $n/(C_{iv})^d$ ; Cement content of the mixture - %C; Percentage of sand - %Sand; Percentage of silt - %Silt; Percentage of clay - %Clay and Percentage of organic matter - %OM. The soils used in the preparation of JG laboratory formulations come from five field works in Portugal and Spain. While all of the soils were classified as fine soil they have different percentages of sand, silt, clay and organic matter. All formulations were prepared with cement CEM I 42.5R. and CEM II 42.5R.

The Eurocode 2 analytical model (EC2) is widely used in the estimation of  $E_0$  of concrete over time. So, we adapted its analytical expression to JG material (EC2<sub>adapted</sub>). According to EC2, the evolution of the  $E_0$  over time just depends of the age of the mixture (t), the cement type used (s) and the Yong Modulus of each formulation at 28 days of time cure  $(E_{cm})$ .

Artificial Neural Networks (ANN) mimics some basic aspects of brain functions, which processes information by means of interaction among several neurons. We adopted the most popular model, the multilayer perceptron that contains only feedforward connections, with one hidden layer with H processing units. To chose the best value of H we used a grid search  $\{2, 4, ..., 10\}$ (Hastie et al. 2001). The Support Vector Machines (SVM) was initially proposed for classification tasks. After the introduction of the  $\varepsilon$ -insensitive loss function, it was possible to apply SVM to regression tasks (Smola and Scholkopf 2004). SVM has theoretical advantages over ANN, such as the absence of local minima in the learning phase. The main idea of the SVM is to transform the input data into a high-dimensional feature space by using a nonlinear mapping. For this propose, we used the popular Gaussian kernel. Functional Networks (FN) are a general framework useful for solving a wide range of problems, where the functions of the neurons can be multivariate, multi-argument and it is also possible to use different learnable functions, instead of fixed functions. When compared with ANNs, there are some advantages (Zhou et al. 2005).

To evaluate the predictive performance of the models, we calculate the Mean Absolute Error (MAD), Root Mean Absolute Error (RMSE) and Coefficient of determination (R<sup>2</sup>). We adopted the Leave-One-Out scheme for measuring the predictive capability of each model, where sequentially one example is used to test the model and the remaining data is used for fitting the model.

### MAINLY RESULTS AND CONCLUSIONS

The EC2 analytical model, after adapted its coefficients to JG material, showed a good performance in  $E_0$  prediction (see Table 1). However, some limitations were also identified. The main one is related with the need to carry out laboratory tests to obtain the young modulus of each formulation at 28 days, which difficult its application in early stages of a project level.

Table 1: Comparison of the Performance between the four Models: ANN, SVM, FN and EC2 models

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Metric	ANN	SVM	FN	EC2 <sub>adapted</sub>
MAD (GPa)	0,17	0,18	0,22	0,16
RMSE (GPa)	0,24	0,25	0.30	0,25
$R^2$	0,97	0,96	0,95	0,96

After we train the three DM models, i.e. ANN, SVM and FN, a high performance was reached, as demonstrated by metrics MAD, RMSE and  $R^2$  (see Table 1). The best result was obtained by ANN model, with an  $R^2 = 0.97$ . In Figure 1 we can see the excellent relation between the  $E_0$  measured and the predicted values by SVM model.

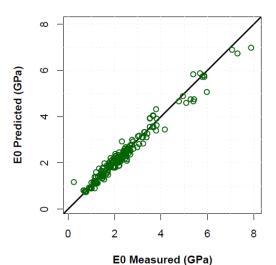


Figure 1: Predicted versus Measured  $E_0$  of JG Laboratory Formulations using the SVM Model

As a conclusion, we can say that the DM models previously exposed can give a valuable contribution in terms of improving the construction process of JG columns and reducing the costs of laboratory formulations. We also observed that the Data Mining techniques present a high potential to develop rational models to predict the mechanical and physical properties of JG material.

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## **AKNOWLWDGEMENTS**

The authors wish to thank to Portuguese Foundation for Science and Technology (FCT) the support given through the doctoral grant SFRH/BD/45781/2008.

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