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Support vector machines applied to uniaxial compressive strength prediction of jet grouting columns

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ABSTRACT

Learning from data is a very attractive alternative to "manually" learning. Therefore, in the last decade the use of machine learning has spread rapidly throughout computer science and beyond. This approach, supported on advanced statistics analysis, is usually known as Data Mining (DM) and has been applied successfully in different knowledge domains. In the present study, we show that DM can make a great contribution in solving complex problems in civil engineering, namely in the field of geotechnical engineering. Particularly, the high learning capabilities of Support Vector Machines (SVMs) algorithm, characterized by it flexibility and non-linear capabilities, were applied in the prediction of the Uniaxial Compressive Strength (UCS) of Jet Grouting (JG) samples directly extracted from JG columns, usually known as *soilcrete*. JG technology is a soft-soil improvement method worldwide applied, extremely versatile and economically attractive when compared with other methods. However, even after many years of experience still lacks of accurate methods for JG columns design. Accordingly, in the present paper a novel approach (based on SVM algorithm) for UCS prediction of *soilcrete* mixtures is proposed supported on 472 results collected from different geotechnical works. Furthermore, a global sensitivity analysis is applied in order to explain and extract understandable knowledge from the proposed model. Such analysis allows one to identify the key variables in UCS prediction and to measure its effect. Finally, a tentative step toward a development of UCS prediction based on laboratory studies is presented and discussed.

1. Introduction and background

We are always trying to improve our knowledge of the world and to find solutions to complex problems. To this end, new and more powerful tools are constantly being developed and applied in order to satisfy the most ambitious goals and solve more efficiently complex problems. A good example is the development and the use of advanced statistical analysis to solve real problems characterized by high dimensionality. These tools are usually known as Data Mining (DM) techniques, and they present a very attractive alternative to the traditional statistical analysis. Indeed, in the last decade these tools have spread rapidly throughout computer science and beyond.

The goal of DM is to use computational tools to extract useful knowledge from raw data [1]. Therefore, as more data becomes available, more ambitious problems can be tackled.

As mentioned above, DM techniques are being applied to solve real complex problems, particularly where conventional approaches work poorly. Indeed, the best way to assess the real potential and usefulness of such tools is measuring performance when applied to real-world problems. By searching in the bibliography, a wide range of successful applications of DM techniques in different knowledge domains can be found. A few examples are its application in web search, spam filters, recommender systems, and fraud detection [2]. Also, in the field of civil engineering some successful examples can be found. For example, Support Vector Machines (SVMs) and Artificial Neural Networks (ANNs), two of the interesting supervised learning DM algorithms characterized by their flexibility and non-linear learning capabilities, have been applied to solving both classification and regression DM tasks in the geotechnics field [3–5]. Lai and Serra [6] applied ANNs to predict the compressive strength of cement conglomerates. Prasad et al. [7] proposed an ANN to predict the 28-day compressive strength of a normal- and a high-strength self-compacting concrete and high performance concrete with high volume fly ash. Miranda et al. [8] proposed a new alternative regression model using ANNs for the analytical calculation of strength and deformability parameters of rock masses. Goh and Goh [9] used SVMs to assess seismic liquefaction. Ezrin [10] studied the relationship between the swell pressure and soil suction behavior in specimens of Bentonite–Kaolinite clay mixtures with varying soil properties using ANNs.

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Tinoco et al. [11] applied SVMs and ANNs to predict deformability properties of Jet Grouting (JG) laboratory formulations over time. Additionally to this SVM application there are many other examples that can be found in the literature. SVMs have the potential to produce high quality predictions in several classification or regression tasks. Particularly, in the civil engineering field, SVMs have been applied in seismic reliability assessment [12], in reliability analysis [13] or in soil type classification [14].

In the present work, we applied a SVM to predict the Uniaxial Compressive Strength (UCS) of JG samples directly extracted from real JG columns.

JG technology is a soft-soil improvement method widely applied all over the world [15,16], aiming to yield the best results when we are forced to built under soft-soils characterized by high porosity, plasticity, compressibility and low strength [17]. The Yamakoda brothers introduced this technology in 1960's decade and since then, it has aroused interest within the geotechnical community due to it great versatility [18]. With JG technology it is possible to improve the mechanical and physical properties of different soil types (ranging from fine- to coarse-grained soils) and to obtain different geometries shapes (columns, panels, etc.). Additionally, to carried out the treatment there are minimal equipment needs and, when compared with similar methods JG is economically attractive.

Conceptually, JG technology intends to mix the natural soil with cement slurry, which is directly injected into the subsoil. The new material obtained, also known as *soilcrete* will be characterized by enhanced resistance, compressibility, and permeability. To produce this improved mass of soil, a rod is driven into the subsoil to the intended depth. After that, grout is injected, with or without other fluids (air and/or water), at high pressure and velocity through small nozzles placed at the end of the rod, which is continually rotated and slowly withdrawn. The high cinematic energy of the injected fluids cuts the soil and mixes them with the injected grout. According to the number of fluids injected, three systems are currently in use [18]. Using the *single fluid system*, grout only is injected at high pressure and velocity. The *double fluid system* is very similar to the single system but with the addition of an air shrouding to the nozzle. Finally, the *triple fluid system* combines conceptually the single and double fluid systems: that is, the erosion of the ground is carried out by a high-pressure water jet shrouded with air and an additional low-pressure grout line is responsible to mix the eroded soil with the cement slurry injected. Depending on the system applied, several parameters need to be controlled. Generally, the most important variables that affect the design of JG columns are soil type, mixture influx between soil and grout, exiting jet energy from the nozzle, grout flow rate, and rotating and lifting speed [19].

JG technology has been applied for different purposes. Padura et al. [20] describe a case study where JG was adopted to consolidate the ground in the restoration of the emblematic building La Normal in Granada. This technology also has been used to improve foundation soils, slope stabilization, and underpinning [21]. Furthermore, JG was also used as a method of performing block stabilization of contaminated soils, as well as for the formation of barriers for the control of contaminant migration in the environmental field [22].

Although the technology has been widely applied over many years, there are still important limitations to overcome. One of the most relevant involves the absence of reliable approaches for JG physical and mechanical properties design. Indeed, even in large-scale works, JG design is essentially based on empirical methods [23,24] and supported by JG companies' know-how. Fig. 1 shows schematically the quality control process currently used in JG design. The soil heterogeneity and the high number of variables involved in the JG process, sometimes with complex relationships between them, are the main factors for such scenarios. Since the empirical approaches currently applied are often too conservative and have limited applicability, the economy and the quality of the treatment can be affected. Hence, and bearing in mind the high versatility of JG technology and its role in important geotechnical works, the need to develop new and more reliable methods to accurately estimate the effects of the different variables involved in the JG process on physical and mechanical properties of JG material is evident.

Supported by case studies, some mathematical expressions have been proposed to predict JG mechanical properties [26,27,19]. However, since such expressions have been based on traditional statistics approaches and use only data from particular conditions, they are unable to give an adequate answer when applied to unseen data, leading to poor results.

In order to help to overcome JG columns design complexity, the use of advanced statistical analysis can be seen as a promising alternative. Hence, the application of DM techniques to data from past projects, mainly from large geotechnical works, can provide a strong framework to help to support decisions in future projects, namely in small-scale works where information is scarce.

In previous work [28], the performance and learning capabilities of DM tools were successful tested using data from JG laboratory formulations. This was the first time that such tools were applied in the study of JG mechanical properties, particularly to predict UCS of JG laboratory formulations. In the present paper, we analyse and discuss DM techniques' performance when applied to the prediction of UCS of JG samples collected directly from JG columns. Particularly, an SVM is trained and tested with JG data collected from different JG columns (built under different soil types and with different JG parameters) in order to estimate its UCS over time based on soil and mixtures properties. The main results are here described and interpreted. Furthermore, in order to overcome the main criticism of DM algorithms, that is, their lack of understandable results [9], a novel visualization approach [29] is applied, based on a sensitivity analysis method. Such approach enables the identification of the most important input parameters and their average influence in UCS prediction, allowing a better understanding about what was learned by the model. In addition, based on a two-dimensional (2-D) Global Sensitivity Analysis (GSA), the iteration between input variables is also measured and interpreted. With this paper, an update of preliminary results depicted at [30], where JG data from just one case study were analysed, is made. Furthermore, the sensitivity analysis performed and described at [31] is here improved.

2. Support vector machines algorithm

The present study focuses on adapting the SVM algorithm [32] to predicting the UCS of JG samples over time. Following is presented a brief description about the SVM algorithm.

SVM performs a supervised learning, where the model is adjusted to a dataset of examples that map I inputs (independent variables) into a given target (the dependent variable). SVM are a very specific class of algorithms, which is characterized by use of kernels, absence of local minima during the learning phase, sparseness of the solution and capacity control obtained by acting on the margin or on number of support vectors. When compared with other types of base learners, such as the widely used multilayer perceptron (also known as back-propagation ANN), SVM represents a significant enhancement in functionality, since it always achieves the optimal learning convergence, while ANNs might get stuck in local minima. By using a non-linear kernel, the SVM implicitly maps the input space into high-dimensional feature space (see Fig. 2). In this feature space, the algorithm finds the best