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TECHNICAL PAPER

Advanced tools and techniques to add value to soil stabilization practice

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Abstract The aim of this paper is to demonstrate the advanced tools and techniques used for adding value to the soil stabilization practice. The tools presented involve advanced laboratory tests and modeling using codes and soft computing to evaluate the mechanical behavior of stabilized soils with cement, ranging from short-term to long-term behavior. More precisely, these tools are able to: 1. Predict the mechanical behavior of the stabilized soils over time from data obtained in the early ages saving time in laboratory tests; 2. Predict the mechanical behavior of the stabilized soils over time based on basic parameters of soil type and binder using historical accurate data, avoiding mechanical laboratory tests. 3. Incorporate the serviceability limit state concept in a novel proposal to estimate the design modulus in function of the uniaxial compressive strength and the strain level, making more economic and sustainable geotechnical solutions.

Keywords Soil stabilization · Design modulus · Soft computing · Eurocode 2 · Service limit state

Introduction

Soil stabilization works require laboratory testing to obtain the best dosage of binder necessary to achieve hydraulic and mechanical properties associated with the service limit state of the geotechnical structure. The laboratory studies are time consuming and consequently affecting the delivery time of the project since in general the mechanical properties are obtained for at least 28 days [1]. To overcome this problem the design engineer can use available empirical rules, codes, and actually more advanced tools and techniques such as data mining.

Concerning the empirical rules, most of the available ones are very conservative for mechanical property predictions since the laboratory techniques available at the time they were established did not use advanced laboratory tests using local strain measurements and/or wave propagation techniques [2, 3]. In this work this will be addressed and a novel proposal will be presented.

In what concerns the use of codes, a paper presented by authors adapts the Eurocode 2 for prediction of the mechanical properties of soil–cement mixtures and this will be reported in this paper to decrease the time in mechanical laboratory testing [4, 5]. In this context, a recent test method named EMM-ARM will be presented allowing the possibility to predict stiffness of stabilized soil from the early ages [6].

Alternative advanced techniques using soft computing are also nowadays available with predictive capacities when a huge amount of historical data is available. This is our case for results of laboratory soil–cement tests were these techniques are also applied. In fact, these soft computing techniques are powerful tools for analyzing and extracting information from raw data, enabling the identification of complex relationships between several input variables and the target output. Indeed, there are several successful cases where these tools were used to solve complex problems in different knowledge areas, including this one related to soil stabilization using jet grouting technology [7–9].

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In summary this paper will cover these two different approaches for laboratory formulations of soil stabilization with cement. Furthermore, an insight into design application is gained through a novel proposal allowing the prediction of the design modulus in function of the uniaxial compressive strength for the level of strain of the material corresponding to the serviceability limit design of the structure.

Mechanical property prediction

Mechanical propriety prediction of soil–cement mixtures is a key issue in soil stabilization projects. To accomplish this task, a current practice in the framework of soil stabilization projects, such as in jet grouting (JG) or cutter soil mixing (CSM) is to prepare and test some laboratory formulations, using the same soil and binder to be applied during the in situ treatment. However, these formulations can represent by itself an important cost to the project. Thus, to minimize the number of formulations to prepare and consequently the final cost of the project, it is useful to have an available numerical model able to accurately predict its mechanical properties (strength and stiffness) over time [10].

Nowadays, there are some empirical models available that can give a valuable help during the design stage. However, due to the high number of variables involved (treatment parameters, binder, soil properties, etc.) as well as the heterogeneity of the soils, most of the existing approaches present important applicability limitations. Hence, in last years several attempts have been made to overcome this limitation. In this paper, two different approaches are summarized, which have shown to be very effective in mechanical property estimation of soil–cement mixtures.

EC2-modified approach

One reference approach that already proved to be of great efficiency [5] in uniaxial compressive strength (UCS) and elastic Young modulus (E_0) prediction of soil–cement mixtures is the analytical expression proposed in the Eurocode 2 (EC2) [11] for both strength and stiffness prediction of concrete. According to this approach, mechanical properties of soil–cement mixtures can be estimated over time based on its characteristics at 28 days time of cure. However, this delay in testing of soil–cement seriously limits the design study as well as the control during production and quality assurance at early ages. Thus, to overcome this drawback of EC2 approach, a modified version was proposed, using reference data tested at early ages instead of the conventional 28 days time of cure [4]. The achieved results allow us to balance the model prediction accuracy and time consumption in the final project and construction work costs, by comparing model performance using reference data tested at 3, 7, 14, and 28 days time of cure.

For training and test purposes, a set of soil–cement formulations for JG and CSM technologies were used, performing a total of 342 records for UCS study and 188 records for E_0 study. These records contemplate formulations prepared with soils collected from different sites, with different water cement ratios (W/C), cement content (kg/m^3) and type (coefficient s), which were tested at different ages (t). For a detailed characterization of the different formulations considered please see [4].

Following the EC2 approach [11], strength and stiffness prediction of concrete over time can be performed according to the following equations, respectively:

$$f_{cm}(t) = e^{\left(s\cdot\left[1-\left(\frac{28}{t}\right)^{a}\right]\right)} \cdot f_{cm} \tag{1}$$

$$E_{cm}(t) = \left(e^{\left(s\cdot\left[1-\left(\frac{28}{t}\right)^{b}\right]\right)}\right)^{c} \cdot E_{cm} \tag{2}$$

In the above equations, t is the age of the mixture, s is a coefficient related with the cement type defined in EC2 [11], a, b, and c are coefficients to be adjusted using laboratory soil–cement mixtures test results, f_{cm} and E_{cm} represent, respectively, the strength and stiffness of each formulation at 28 days time of cure (reference data), and $f_{cm}(t)$ and $E_{cm}(t)$ are, respectively, the strength and stiffness of the mixture at the age t.

To adapt Eqs. 1 and 2 to JG laboratory formulations (JGLG) and CSM laboratory formulations (CSMLF) and

Table 1 Coefficients a, b, and c of Eqs. (1) and (2) [4]

Model	a	b	c
3 days			
UCS —JGLF	0.04	–	–
UCS —CSMLF	−28.47	–	–
E_0—JGLF	–	$2.42E^{-4}$	$1.14E^{2}$
7 days			
UCS —JGLF	0.37	–	–
UCS —CSMLF	0.26	–	–
E_0— JGLF	–	$2.24E^{-4}$	$8.62E^{2}$
14 days			
UCS —JGLF	0.50	–	–
UCS —CSMLF	0.42	–	–
E_0— JGLF	–	$4.30E^{-4}$	$1.978E^{3}$
28 days			
UCS —JGLF	0.67	–	–
UCS —CSMLF	0.56	–	–
E_0—JGLF	–	$1.61E^{-3}$	$6.909E^{2}$

assess its performance when applied to unseen data, both datasets (strength and stiffness studies) were split into two subsets. One, with 2/3 of the records, for training model purposes (i.e., to adjust the coefficients a, b, and c of Eqs. 1 and 2, respectively), and another one, with the remaining records, to test model accuracy.

To check if it is possible to use reference data tested at early ages instead of the conventional 28 days, Eq. (1) was trained with UCS data from JGLG and CSMLF, and Eq. (2) with E_0 data from JGLF. In each one of these experiences, the parameters f_{cm} and E_{cm} that represent in the original EC2 approach the 28-day strength and stiffness of each formulation, respectively, were iteratively replaced by the equivalent information at 3, 7, 14, and 28 days time of cure. Table 1 summarizes the optimized values of coefficients a, b, and c for each one of the three situations described above.

Figure 1 illustrates the relationship between experimental data versus predicted by EC2 approach adapted/modified to JGLF considering reference data tested at 3 days time of cure (Fig. 1a) and 14 days time of cure (Fig. 1b). As expected, when considering reference data tested at very early ages (e.g., 3 days of cure) the achieved performance is poor. On the other hand, using reference data tested at more advanced ages (e.g., 14 days time of cure) the EC2 model performance increases

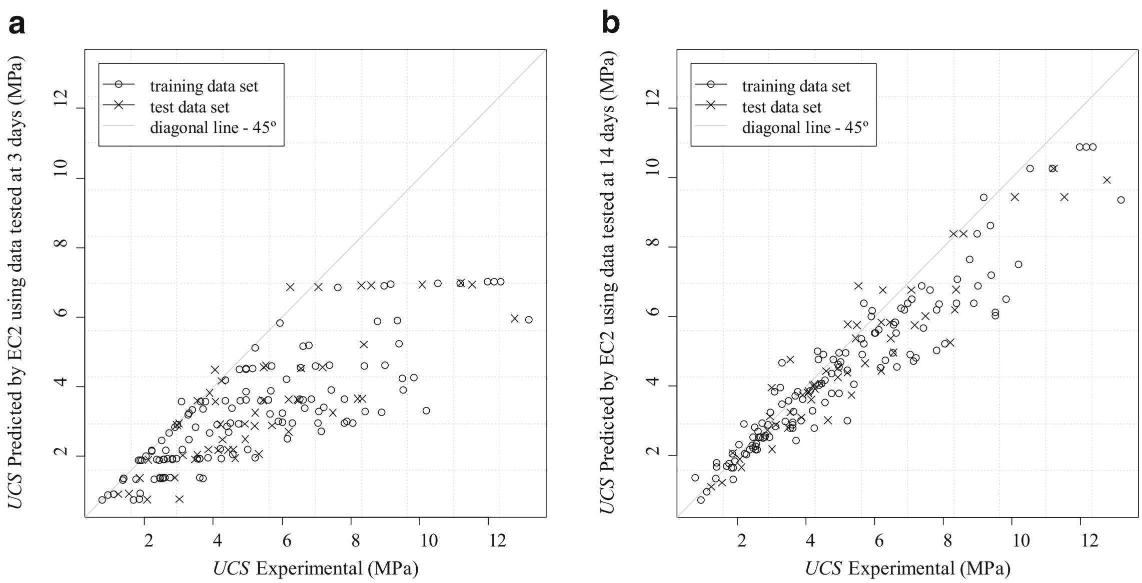


Fig. 1 *Scatterplot* of UCS experimental versus predicted by EC2-modified approach using JGLF [4]: **a** reference data tested at 3 days; **b** reference data tested at 14 days

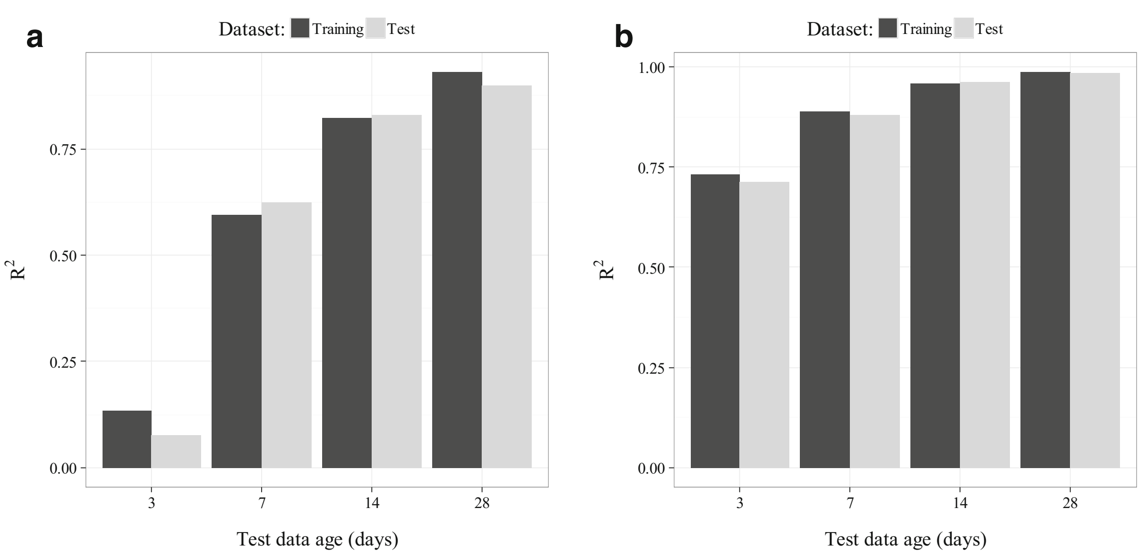


Fig. 2 EC2-modified approach performance in UCS prediction as a function of the reference data age; **a** using JGLF; **b** using CSMLF

Table 2 EC2-modified approach performance based on MAD, RMSE, and R^2 [4]

Model	MAD		RMSE		R^2	
	Training set	Test set	Training set	Test set	Training set	Test set
3 days						
UCS—JG	1.93	1.96	2.60	2.45	0.13	0.08
UCS—CSM	0.39	0.48	0.63	0.70	0.73	0.71
E_0—JG	0.70	0.79	0.98	1.05	0.49	0.45
7 days						
UCS—JG	1.30	1.23	1.78	1.56	0.60	0.62
UCS—CSM	0.29	0.32	0.41	0.45	0.89	0.88
E_0—JG	0.56	0.58	0.82	0.83	0.61	0.61
14 days						
UCS—JG	0.81	0.78	1.17	1.04	0.83	0.83
UCS—CSM	0.16	0.18	0.25	0.26	0.96	0.96
E_0—JG	0.36	0.39	0.47	0.48	0.87	0.87
28 days						
UCS—JG	0.50	0.57	0.73	0.80	0.93	0.90
UCS—CSM	0.10	0.11	0.14	0.15	0.99	0.99
E_0—JG	0.29	0.26	0.38	0.35	0.92	0.93

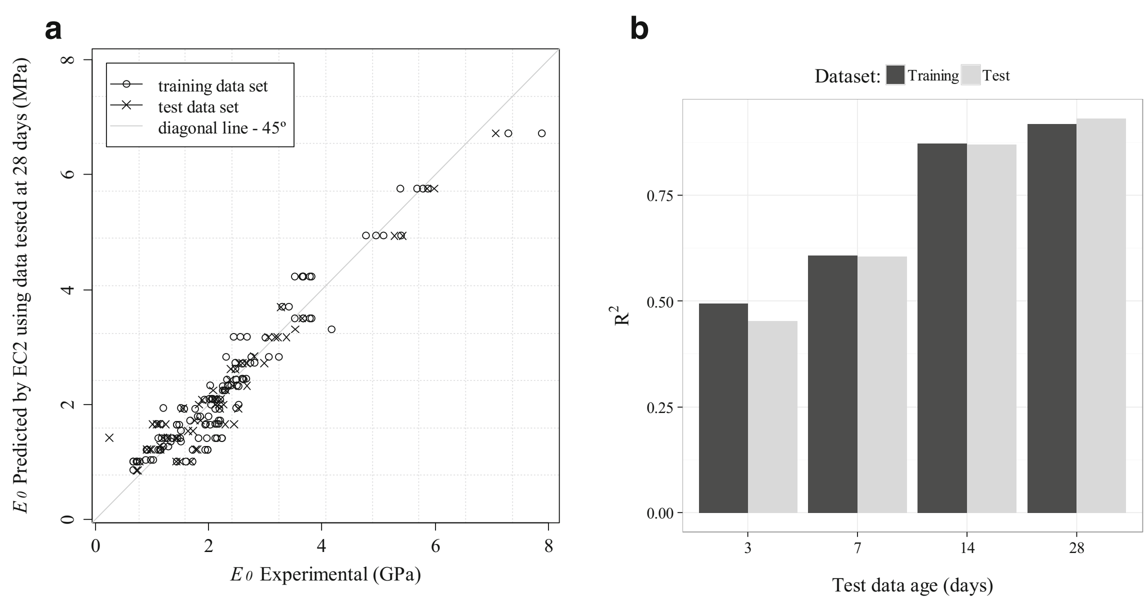


Fig. 3 EC2-modified approach adapted to JGLF for E_0 prediction: **a** *scatterplot* of E_0 experimental versus predicted by EC2-modified approach using reference data tested at 28 days [4]; **b** EC2-modified approach performance as a function of the test data age

significantly. Indeed, when considering reference data tested at 28 days, a very high performance is achieved (R^2 around 0.9), as depicted in Fig. 2a, which compares EC2-modified approach performance based on R^2, when reference data tested from 3 to 28 days are used. Table 2 compares EC2-modified approach for each one of these situations, based on MAD, RMSE, and R^2 metrics [4]. From this analysis the influence of the age of the reference data is clear. It is also observed that there is just a small difference between EC2-modified approach performance, when reference data tested at 14 or 28 days are considered. This observation shows that in some situations it may be advantageous to use reference data tested at 14 days, instead of waiting twice as long to achieve just a small better prediction confidence. In the case of UCS prediction of CSMLF, the influence of the reference data age is not so significant (see Fig. 2b). Indeed, an excellent performance was achieved (R^2 very close to 1) when using reference data tested at 28 days. Moreover, even when reference data tested from early ages are used (e.g., 7 days time of cure)

Table 3 Comparison of models' performance in UCS and E_0 prediction, based on MAD, RMSE, and R^2 metrics, according to MR, ANN, and SVM algorithms [13]

Metric	MR		ANN		SVM	
	UCS	E_0	UCS	E_0	UCS	E_0
MAD	0.78 ± 0.00	0.34 ± 0.00	0.32 ± 0.00	0.15 ± 0.00	0.33 ± 0.00	0.17 ± 0.00
RMSE	1.08 ± 0.00	0.48 ± 0.00	0.51 ± 0.00	0.21 ± 0.00	0.52 ± 0.00	0.25 ± 0.01
R^2	0.85 ± 0.00	0.87 ± 0.00	0.97 ± 0.00	0.97 ± 0.00	0.97 ± 0.00	0.96 ± 0.00

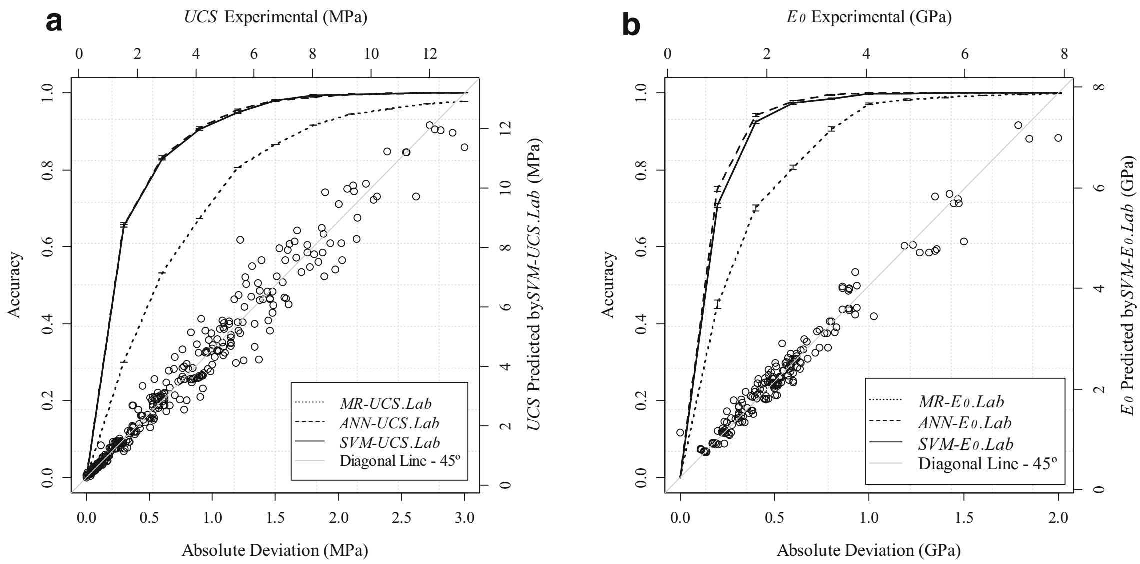


Fig. 4 REC *curves* and *scatterplot* of UCS experimental versus predicted by: **a** *SVM-UCS.Lab* [13]; **b** *SVM-E_0.Lab* [24]

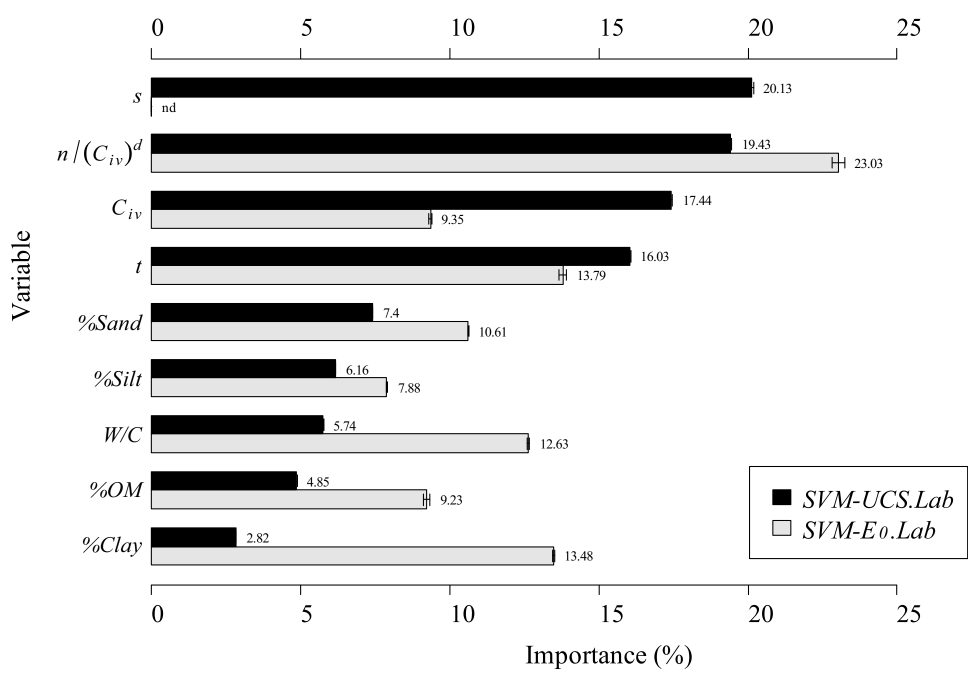


Fig. 5 Relative importance of each input variable quantified by 1-D SA, according to *SVM-UCS.Lab* and *SVM-E_0.Lab* models (adapted from [7, 13])

an interesting performance is reached (R^2 around 0.6). In addition, just a very small difference is observed in EC2-modified approach performance when considering reference data tested at 14 or 28 days time of cure.

Based on the above results, it is observed that EC2-modified approach performs better in strength prediction of CSMLF. Comparing JGLF and CSMLF used in this study, the main difference is related with the way how the cement

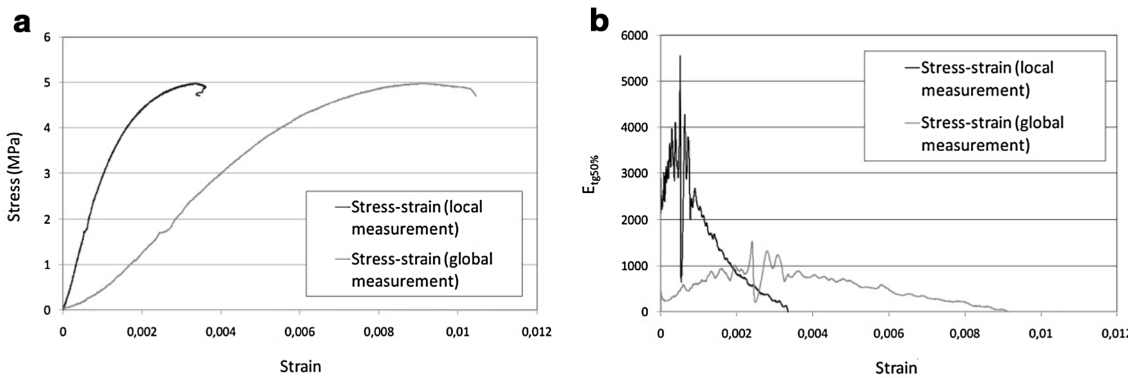


Fig. 6 Comparison of the stress–strain and modulus-strain *curves* for a fresh sample [25]

was mixed with the soil. While in JGLF, such mixture was made through a cement grout, in CSMLF the cement was mixed in powder state. Accordingly, based on this observation, we can conclude that EC2 approach works better with soil–cement mixtures prepared with powder cement than with a cement grout.

Analyzing the result of EC2-modified approach for stiffness prediction of JGLF, we can see that the achieved performance is very similar to those in UCS study. As shown in Fig. 3a, EC2-modified approach is able to accurately predict E_0 over time, particularly when reference data tested at advanced ages (i.e., 28 days time of cure) are used. In addition, a clear influence of the reference data age in EC2-approach performance is observed, as illustrated in Fig. 3b. This means that when reference data tested at early ages are used, EC2 performance is low, increasing significantly when fed with reference data tested at more advanced ages (higher than 14 days time of cure).

Recently, a novel approach known as EMM-ARM (elasticity modulus measurement through ambient response method) has been explored to apply it to soil mixtures [12]. Although such technique has been originally designed to test concrete, it can be quickly extended to other materials such as mortar, cement paste, stabilized soils, and even epoxy resins [6]. EMM-ARM is based on the identification of the resonant frequency of the testing mould, which evolves along time due to the hardening process of the tested material, and then the E modulus of the tested material can be inferred with basis on the dynamic equations of motion of the testing system. So, this recent laboratory test method can be used to obtain the E modulus at early ages and then used as an input value in EC2 approach.

Soft computing techniques

Three different DM algorithms, namely multiple regression (MR), artificial neural network (ANN), and support vector machines (SVM), where applied in the development of predictive models for UCS and E_0 of laboratory soil–cement mixtures [13]. For a detailed description of the parameters adopted for each technique, particularly for ANN and SVM, please see Tinoco et al. [7] and Tinoco et al. [13]. The overall generalization performance of the trained model was assessed using 20 runs under a leave-one-out approach [14], where successively one example is used to test the model and the remaining are used to fit the model [7]. All experiments were conducted in the R tool [15] and supported by rminer library [16].

Table 3 shows and compares the performance of the models based on MAD, RMSE, and R^2. As shown, ANN

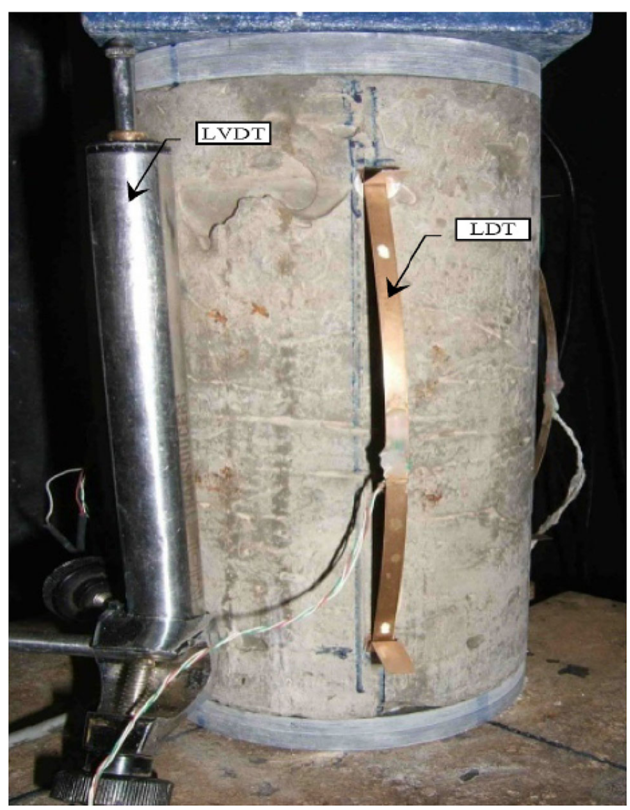


Fig. 7 Laboratory specimen instrumented with LDT and LVDT [1]

and SVM algorithms evidence a high performance in both UCS and E_0 prediction of laboratory soil–cement mixtures, with an R^2 higher than 0.96. Such high performance is plotted in Fig. 4, which depicts the relationship between experimental and predicted values (read on top and right axis) according to SVM algorithms (*SVM-UCS.Lab* and *SVM-E_0.Lab* models), overlapped by regression error characteristic (REC) curves [17] (read on button and left axis). Observing REC curves, we can see that both ANN and SVM models present a very similar performance, which is significantly better than MR models.

Aiming a better assessment and interpretation of the data-driven models for both UCS and E_0 prediction, the relative importance of each input variable was calculated based on a sensitivity analysis (SA) as described by Tinoco et al. [7], and Cortez and Embrechts [18]. Figure 5, which plots the relative importance of each input variable according to SVM predictive models of UCS (*SVM-UCS.Lab*) and E_0 (*SVM-E_0.Lab*), illustrates that the relation

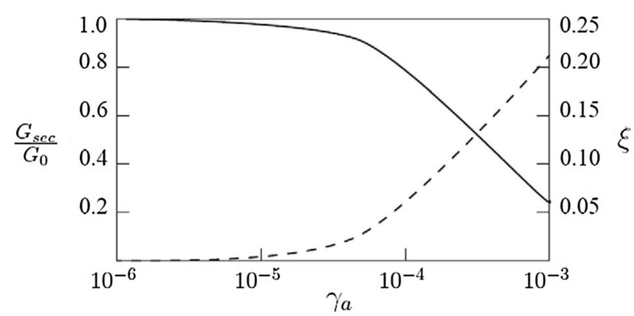


Fig. 8 Typical soil variation of stiffness (*full*) and damping (*dashed*) with shear strain [25]

$n/(C_{iv})^d$ is the key variable in both mechanical property prediction of laboratory soil–cement mixtures. Moreover, in the UCS study the t, C_{iv}, and s also have a strong influence in UCS development. On the other hand, it is also observed that the soil properties are apparently more relevant in stiffness prediction of laboratory soil–cement mixtures than in strength study.

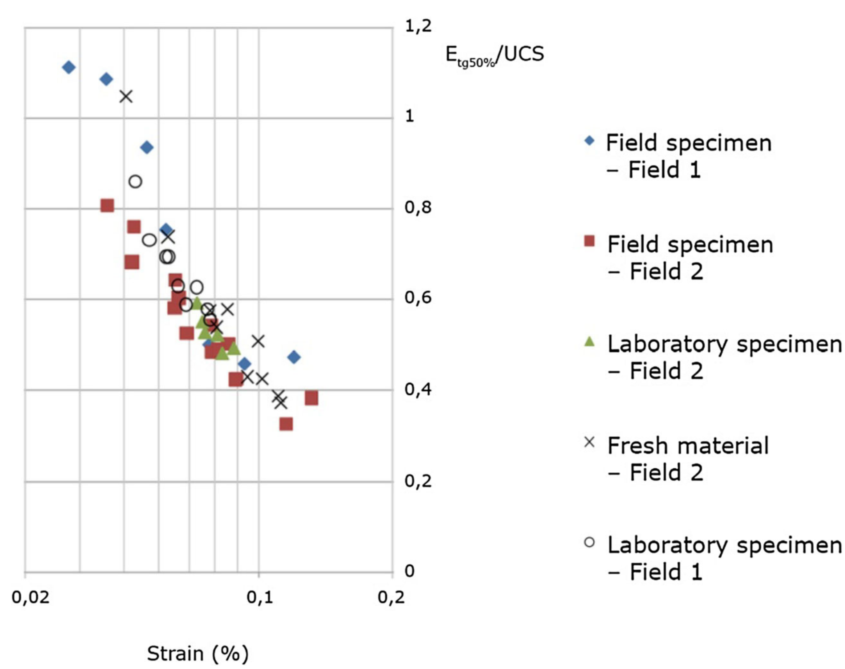
Novel proposal for application in design

For design purposes, UCS and $E_{tg50\%}$ (tangent deformability modulus at 50% of the maximum stress) are those properties currently required. Due to time and cost concerns, usually only compression tests without strain measurement are carried out. Therefore, for $E_{tg50\%}$ quantification a relation between $E_{tg50\%}$ and UCS ($E_{tg50\%}$/UCS) can be very useful.

In the past, and based on experimental results, some relations have been proposed. However, since the local deformation measurement techniques were not applied, a big scatter was observed and also the modulus was underestimated. Then, it is fundamental to update $E_{tg50\%}$/UCS relation considering new experimental results for which local deformation was measured.

Indeed, previous investigations, dating from the 1980s [19–22], show the imprecision of evaluating moduli by the use of external measurement of the deformation of samples. This fact is addressed in Fig. 6, where the result of the modulus tangent to 50% of the ultimate strength ($E_{tg50\%}$) is very distinct when the stress–strain and modulus-strain curves are plotted with local and external measurements of

Fig. 9 Correlation between the ratio $E_{tg50\%}$/UCS as a function of the strain



the sample deformation. For the example shown, the ultimate strain obtained with the external measurement device is about three times as high as the local measurement and the $E_{tg50\%}$ determined with the local measurement is about three times as high as the $E_{tg50\%}$ determined with the external measurement.

Figure 7 illustrates how local measurements can be measured using LDTs (Local Deformation Transducers, [23]).

On the other hand, it is known that soil moduli are dependent on the applied level of strain. This relation is depicted in Fig. 8, which illustrates a typical soil variation of stiffness (full line) with shear strain.

As a final step we need to know how to correlate $E_{tg50\%}$ and UCS as a function of the applied strain level. Based on Fig. 9, we can see that there is a well-defined trend between the strain and the relation of $E_{tg50\%}$/UCS, for 28 days. This novel proposal was established based on laboratory and field data which give more reliability in its use. With this proposal, the design engineer can easily predict the $E_{tg50\%}$ for the design strain level based on the conventional uniaxial compressive strength test results.

Conclusions

The findings presented in this paper are an added value for the soil stabilization practice. Despite the results presented for one type of binder, the cement, it is believed that the same methodology can be adapted for other type of binders too. The results presented show that the approach proposed in EC2 for mechanical property prediction over time can be adapted for stabilized soils using mechanical test results obtained at early ages. In this context and in what concerns the moduli, advanced laboratory tests with local strain measurements (on sample measurements) are necessary and the recent EMM-ARM (elasticity modulus measurement through ambient response method) can be very useful.

It is also demonstrated how soft computing techniques can be used as a powerful tool for predictive purposes of mechanical properties over time when a historical database is available.

Finally, a novel proposal is presented for the prediction of design modulus based on the results of conventional uniaxial compressive strength tests. This modulus is a function of the strain level of the stabilized material mobilized for the serviceability state of the structure.

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