Revista Ingeniería de Construcción RIC
Vol 38 Nº3 2023
www.ricuc.cl
DOI: 10.7764/RIC.00080.21

ENGLISH VERSION

Influence of artificial intelligence on the optimization of the dosage of natural hydraulic lime, plastic and metallic fibers on the geological characteristics of a treated soil.

Influencia de la inteligencia artificial en la optimización de la dosificación de cal hidráulica natural, fibras plásticas y metálicas sobre las características geológicas de un suelo tratado.

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Fecha de Recepción: 17/03/2023
Fecha de Aceptación: 21/05/2023
Fecha de Publicación: 30/12/2023
PAG: 473-484

Abstract
This study was necessary because in Peru the application of resources such as artificial intelligence in the optimization of treatment doses in soil stabilization is not promoted. The purpose of the study was to evaluate the influence of the application of an artificial intelligence model on the optimization of the dosage of natural hydraulic lime, plastic and metallic fibers on the geological characteristics of a gravelly clay soil. The dosages of stabilizers and laboratory tests were used as input variables (predictors) and the values of mechanical tests as output variable. As main conclusions, an interesting application in terms of additive optimization was demonstrated in comparison with experimental results in the field. The model suggests a reduction of predominant materials, such as lime, to obtain acceptable results based on actual test results. The implications of including artificial intelligence, achieves substantial strength maintenance superior to the natural sample of 6 times, respectively, with an optimization of 4% natural lime, 2.25% plastic fiber, 10% metallic fiber and 83.75% natural soil. It is concluded that the influence of applying the artificial K-OPLS model on the real experimental dosages, implies in the reduction of lime up to 50% less, and the increase of plastic fiber in 0.75% more, the metallic fiber maintains its real dosage and the natural soil varies slightly.

Keywords: *Natural hydraulic lime; plastic fibers; metallic fibers; artificial intelligence; optimization.*

Resumen
Este estudio fue necesario debido a que en el Perú no se promueve la aplicación de recursos como la inteligencia artificial en la optimización de dosis de tratamiento en la estabilización de suelos. El propósito del estudio fue evaluar la influencia de la aplicación de un modelo de inteligencia artificial en la optimización de la dosificación de cal hidráulica natural, fibras plásticas y metálicas sobre las características geológicas de un suelo arcilloso gravoso. Como variables de entrada (predictores) se utilizaron las dosificaciones de estabilizantes y los ensayos de laboratorio, y como variable de salida los valores de los ensayos mecánicos. Como principales conclusiones, se demostró una interesante aplicación en términos de optimización de aditivos en comparación con los resultados experimentales en el campo. El modelo sugiere una reducción de los materiales predominantes, como la cal, para obtener resultados aceptables en base a los resultados reales de los ensayos. Las implicaciones de incluir inteligencia artificial, logra un mantenimiento sustancial de la resistencia superior a la muestra natural de 6 veces, respectivamente, con una optimización de 4% de cal natural, 2.25% de fibra plástica, 10% de fibra metálica y 83.75% de suelo natural. Se concluye que la influencia de aplicar el modelo artificial K-OPLS sobre las dosificaciones experimentales reales, implica en la reducción de cal hasta un 50% menos, y el aumento de fibra plástica en un 0.75% más, la fibra metálica mantiene su dosificación real y el suelo natural varía ligeramente.

Palabras clave: Cal hidráulica natural; fibras plásticas; fibras metálicas; inteligencia artificial; optimización

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DOI: 10.7764/RIC.00080.21

1. Introducción

Soil stabilization is the alteration of the physical and mechanical properties of soils to meet the specific engineering requirements of problem soils. (Taffese and Abegaz, 2021). Some issues related to the effective application of emerging trends in soil stabilization are three categories, namely geo-environmental, standardization and optimization issues, as well as proposing techniques such as predictive modeling and exploration methods such as reliability-based design optimization, response surface methodology, dimensional analysis and artificial intelligence technology to ensure efficient soil stabilization (Ikeagwuani and Nwonu, 2019). Consequently, it is difficult to determine some types of functional relationships in force enhancement that would make the accuracy of force prediction satisfactory (Alavi et al., 2008). As studies stimulate the interest within the civil engineering research community to develop interaction with applied artificial intelligence (Flood, 2008).

It is often a challenge to develop an optimum soil mix due to significant variations in soil properties from one soil to another (Mustafa et al., 2022). Several studies on AI-based two-input predictive models for predicting the physical and mechanical testing of sawdust ash (BCS)-treated black cotton for sustainable subgrade construction purposes (Onyelowe et al., 2022). They have been widely used to predict different soil properties in geotechnical applications (Kalkan et al., 2009). Therefore, it is necessary to seek a more rational approach to road construction (Ouf, 2012).

For the prediction of maximum dry density (MDD) and unconfined compressive strength (UCS) of cement-stabilized soil (Das et al., 2011), is of utmost importance for design purposes (Tinoco et al., 2020). The determination of mixture stabilization parameters has become a major concern in geotechnical applications, and artificial intelligence must be applied to predict the unconfined compressive strength (UCS) of silty soils stabilized with bottom ash (BA), jute fiber (JF) and steel fiber (SF) (Güllü and Fedakar, 2017). Based on different statistical performance criteria, functional networks (FN) and multivariate adaptive regression (MARS) techniques were found to be better at predicting MDD and UCS compared to the previously used artificial intelligence techniques, artificial neural network and support vector machine (Suman et al., 2016).

Thus, each soil type has a different optimum soil stabilizer additive content. To design the optimum soil stabilization component, reliable and efficient models are required (Ngo et al., 2022). Rigorous sensitivity-based diagnostic tests are also performed to validate and provide insight into the complexities of the decisions made by the algorithm (Eyo et al., 2022).

On the other hand, for an optimal and efficient use of cementitious additives, it is necessary to know the type of additive and its compositions; as well as the characteristics of the soil, as influential parameters in the UCS of the soil samples (Narendra et al., 2006). The interactions between initial soil properties, mix design and effective compaction in improving the UCS of stabilized soil (Tran, 2022). It appears that the maximum waste additions used in the modeling may approximate the practical limits of the waste additions used (Stegemann and Buenfeld, 2003).

In addition, the artificial neural network requires a large database to predict the unsoaked CBR with the highest performance and the lowest overfitting proportion (Khatti and Grover, 2023). A multi-objective optimization has been carried out to obtain maximum CBR values (Alam et al., 2020). Optimal and best practice quantities of stabilizers are obtained through graphical optimization of the models, applying the developed relationships to a new case further states the extent of the developed relationships and demonstrates that the proposed relationships are practical and can be used efficiently at the preliminary design stage (Ghorbani and Hasanzadehshooiili, 2018).

This study shows the influence of using AI to have a rational optimal dosage versus the experimental optimal dosage obtained in the laboratory through physical and mechanical tests of clayey gravelly soil treated with three components: natural hydraulic lime, plastic fibers and metallic fibers, respectively. It differs from other research because in Perú the application of artificial intelligence is not influential in optimal design dosages to stabilize soils of low bearing capacity, being recurrent only to use the results obtained in the laboratory for a conventional analysis.

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2. Materials and methods

2.1. Materials
2.1.1 Soil natural

For this study, soil samples were collected along the 1MF Puente Ochape, Los Hornos road, located in the district of Cascas, La Libertad, Peru. Once the location was located, the soil sample was collected from test pits that had been excavated to a depth of 1.50 m with respect to subgrade level; the road is strategically important for the movement of agricultural products and connections between surrounding communities. The samples obtained were collected in airtight bags as disturbed samples, collecting approximately 200 kilograms of soil removed from these pits, la distruicución granulométrica se observa en la (Figure 1). Their main geotechnical properties are tabulated in (Table 1)

Table 1. *Natural soil properties*

Soil testing	Characteristics	Tes Standard	Results
Sample taken	Depth (m)	---	0.5 – 1.5
Grain size distribution	Gravel larger tan 4.75 mm (%)	ASTM D422	51.5
	Sand 0.075 to 4.75 mm (%)	ASTM D422	12.4
	Silt 0.005 (%)	ASTM D422	5.1
	Clay less tan 0.005 mm (%)		31
Type of soil	Classification(USCS)	ASTM D2487	Gravel clayey with sand GC
Atterberg limits	Liquid Limit (%)	ASTM D423	32.94
	Plastic Limit (%)	ASTM D424	22.11
	Plasticity Index (%)	ASTM D4318	10.83
Additional tests	Moisture content (%)	ASTM D2216	13.6
	Specific gravity (gr/cm^3)	ASTM D854	2.62
Compaction tests	Maximum dry density (kN/m^3)	ASTM D1557	17.30
	Optimum moisture content (%)	ASTM D1557	13.98
Strength test	California Bearing Ratio without soaking (%)	ASTM D1883	7.10
	Unconfined compressive strength at 28 days (kPa)	ASTM D2166	100.03

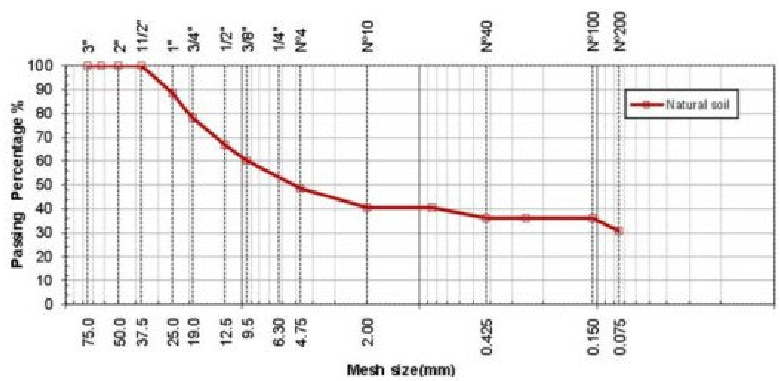

Figure 1. *Grain size distribution of natural soil*

2.1.3 Natural hydraulic lime

The lime used for the study was in the form of natural hydraulic lime Ca $(OH)_2$ manufactured by a Peruvian company. It comes in fine powder form and was commercially selected in bags of 20 kilograms. Some of its physical properties are its white or almost white (beige) color, its specific gravity is 1.30, it is not very soluble in water and its pH is 12.18. Also shown are some chemical compositions of the lime used, as shown in (Table 2).

DOI: 10.7764/RIC.00080.21

Table 2. *Chemical characteristics of natural hydraulic lime*

Chemical name	Proportion
Calcium hydroxide (Ca $(OH)_2$)	80.00 - 90.00% Approx.
Calcium oxide (CaO)	60.00 - 70.00% Approx.
Calcium oxide (CaO)	0.30% Approximate
Magnesium oxide (MgO)	0.44% Approximate
Aluminum oxide (Al_2O_3)	0.12% Approximate
Aluminum oxide (Al_2O_3)	0.053% Approximate

2.1.3 Plastic Fibers (PF)

The fiber used in this study was acquired from recycled plastic bottles (PET) and, being the collection center nearby recyclers in the district of Chepén, Peru. It was not treated before being included in the treated soil, it was only washed with detergents to get rid of dirt and it was manually cut in established dimensions.

2.1.4 Metallic Fibers (MF)

The fiber was collected from manufactures in the process of turning metal parts in the surrounding area of the department of La Libertad, Peru, and was then washed with detergent to remove grease and dirt. The metallic fiber did not undergo any treatment before being included in the soil mixture; it was used only with a simple anticorrosive bath after having been washed and sanded, as shown in (Figure 2). The physical properties of the metallic and plastic fibers used in the study are tabulated in (Table 3).

Table 3. *Physical characteristics of plastic fiber and metallic fiber*

Proof	Plastic fiber	Metallic fiber
Color	Transparent	Silver
Qualification	Recycled	Recycled
Size width (mm)	5	5
Size length (mm)	40	100
Thickness (mm)	0.65	1
Surface texture	Lisa	Lisa
Specific gravity	0.92	-
Unit weight (gr/cm^3)	0.91	-
Water absorption (%)	0	0

Figure 2. *Additives, (a) Natural hydraulic lime, (b) plastic fibers and metallic fibers*

2.2 Methods
2.2.1 Atterberg limits

This test is based on the (ASTM D4318, 2010), belongs to the development of the Atterberg limits. These are key parameters that help to define the plastic nature of soil samples passing the N° 40 mesh, from which the liquid limit (LL), plastic limit (PL) and plasticity index (PI) can be obtained, PI being the subtraction of LL-PL, respectively as shown in

(Figure 3

Figure 3. *Treated soil (a) Liquid limit, (b) Plastic limit, (c) Moisture content*

2.2.2 Compaction

The test is the process using the standard (ASTM D1557, 2012) where it implies the decrease of voids within the soil sample without damaging its structure. As the optimum moisture content (OMC) and maximum dry density (MDD), respectively as shown in (Figure 4).

Figure 4. *Compaction test with treated soil*

2.2.3 California Bearing Capacity (CBR)

The CBR method is used to evaluate the resistance of the subgrade, subbase and base of the soil. The whole process is repeated for each sample, but with different types of compaction at 25 and 56 blows, respectively, the reading of the day is made every 24 hours for each mold that is in the water, and at 96 hours once the last reading is obtained (ASTM D1883, 2021), as shown in (Figure 5).

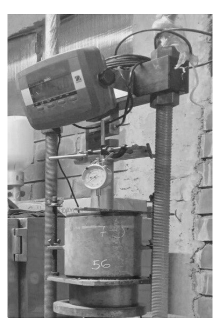

Figure 5. *California bearing capacity in treated soil sample*

2.2.4 *Unconfined Compressive Strength (UCS)*

The unconfined compression test, simple or uniaxial, is a test that allows to obtain an ultimate soil load data, and allows to relate to the shear strength of the soil and delivers a load result can be used in projects that require conservative values based on the standards (ASTM D2166, 2016), as shown in (Figure 6).

Figure 6. *Unconfined compressive strength in treated soil*

2.2.5 *Dosage in experimental laboratories*

The experiment is divided into three groups. First group, with respect to the natural soil sample called S0, it was analyzed to obtain its natural geotechnical characteristics. Second group, with respect to the mixture of natural hydraulic lime as a cementitious material called S1, a fixed dose of 8% was used to replace the dry soil, after having analyzed its optimum lime percentage. The third group, considering the optimum lime in conjunction with the combinations of PF and MF as stabilizers to replace the gravelly clayey soil, were named S2, S3, S4, S5, respectively. Evaluating the effects that bring the combination of these three additives working together, on the geotechnical properties of the soil, for a better detail of the designations and the proportions of each additive are shown in (Table 4). Combined soil stabilization techniques were established to improve the engineering properties of problematic soils (i.e., clayey gravels, clayey or silty sands, very plastic clays of low strength and high deformability), chemical and physical stabilization techniques exist, which in this study were combined to perform joint stabilization.

Table 4. *Description of experimental samples*

Group	Notation	Sample mixture (%)			
		Natural soil	Natural hydraulic lime	Plastic fibers	Metallic fibers
1	S0	100	0	0	0
2	S1	92	8	0	0
3	S2	86.5	8	0.5	5
	S3	80.5	8	1.5	10
	S4	74	8	3	15
	S5	67.5	8	4.5	20

2.2.6 *Application of artificial intelligence for optimal dosing*

Regarding the optimal programmed dosage, it was applied by artificial intelligence with an international web software called Ellistat, using real results of the experimental dosage obtained in the laboratory, the proportions are shown in (Table 5), (Figure 7).

Revista Ingeniería de Construcción RIC
Vol 38 Nº3 2023
www.ricuc.cl
DOI: 10.7764/RIC.00080.21

Table 5. *Ratios and results for intelligent artificial model base*

Natural hydraulic lime (%)	Plastic fibers (%)	Metallic fibers (%)	Natural soil (%)	Plasticity index (%)	OMC (%)	MDD (kN/m^3)	CBR soaked (%)	UCS (28-day breakage)
0	0	0	100	10.74	13.9	17.76	7.4	110.23
0	0	0	100	10.89	14.29	17.4	7.1	97.31
0	0	0	100	10.86	13.75	16.75	6.8	92.55
8	0	0	92	7.34	15.02	18.13	14.78	352.71
8	0	0	92	6.67	15.3	17.51	13.97	343.12
8	0	0	92	7.1	14.2	17.07	13.89	345.64
8	0.5	5	86.5	N.P	14.42	13.73	15.9	497.44
8	0.5	5	86.5	N.P	13.4	14.1	15.21	487.23
8	0.5	5	86.5	N.P	13.89	13.9	15.3	495.15
8	1.5	10	80.5	N.P	12.6	18.21	18.33	865.17
8	1.5	10	80.5	N.P	13.35	17.73	17.84	856.08
8	1.5	10	80.5	N.P	12.75	18.18	17.53	858.87
8	3	15	74	N.P	13.56	17.99	16.33	506.74
8	3	15	74	N.P	12.84	17.67	15.47	498.46
8	3	15	74	N.P	12.91	17.88	15.6	501.1
8	4.5	20	67.5	N.P	14.21	17.81	14.3	212.19
8	4.5	20	67.5	N.P	13.86	17.31	15.33	209.23
8	4.5	20	67.5	N.P	13.62	17.54	15.05	205.49

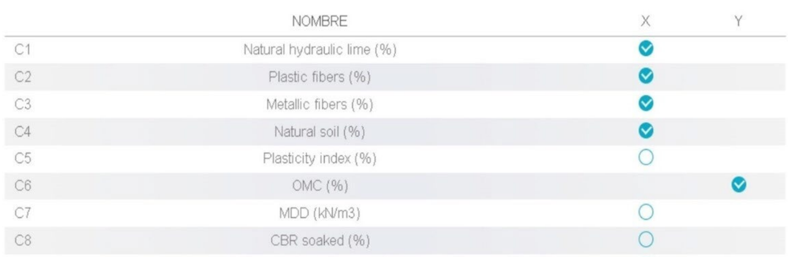

Figure 7. *Configuration of the intelligent model using the X (independent factor), Y (dependent factor)*

3. Results and discussions

3.1 Properties of the treated soil

As shown in (Figure 8(a)), the Atterberg limit test based on ASTM D4318, shows that the clayey gravelly natural soil (S0) has a plastic index of 10.83%, which unlike sample S1 its plastic index reduced by 35% compared to sample S0, showing to be effective against soil plasticity. However, samples S2, S3, S4 and S5 did not show any plasticity. However, other studies, as indicated by Aishwarya and Priya (Aishwarya and Priya Rachel, 2023) show that there is an increase in liquid limit and plastic limit by adding basalt fiber to sandy clay. And a decrease in the plasticity index, it was found that the optimum amount is that the recycled PET fiber at 1.2%, Mishra and Kumar (Mishra and Kumar Gupta, 2018).

The MDD and OMC, show inversely proportional values, considering ASTM D1557, with respect to this compaction test shows an OMC of 12.90% for an MDD of 18.04 kN/m^3, being values of sample S3, which optimized better the water for an adequate compaction, as shown in (Figure 8(b)). According to (Ratna Prasad R. et al., 2018) the most extreme dry density of unadulterated soil increased from 17.59 kN/m^3 to 18.53 kN/m^3 per lime increase from 0% to 5% and OMC decreased from 21.5% to 14.14%.

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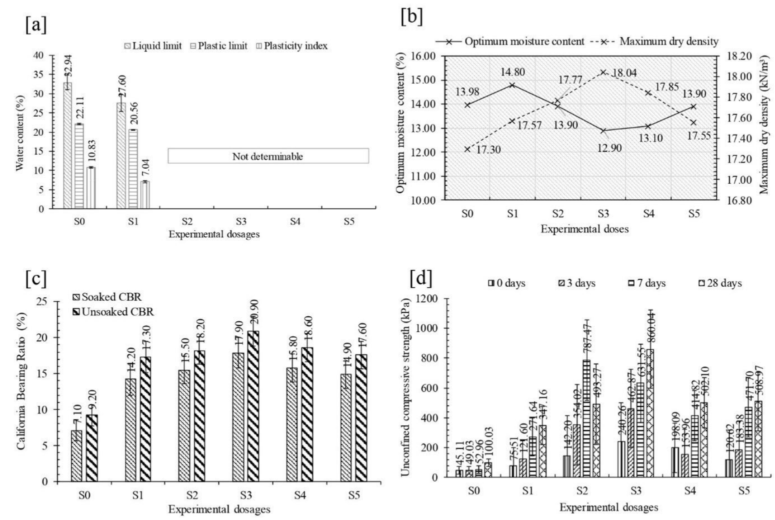

Figure 8. *Effect of additives on (a) plasticity index, (b) compaction, (c) California bearing capacity, (d) Unconfined compressive strength*

As shown in (Figure 8(c)), the bearing capacity of California in the soaked condition showed progressive increases of 100%, 118.31%, 152.11%, 122.54% and 109.86% for samples S1, S2, S3, S4, S5, respectively. Likewise, in its unsoaked state it showed increases of 88.04%, 97.83%, 127.17%, 102.17% and 91.30% for samples S1, S2, S3, S4 and S5, respectively. Regarding metallic fibers, they show that their best performance is at 15% fiber (8.5% of CBR), improving notably their support performance compared to the results of the standard sample (6.3% of CBR), because at higher doses the addition of fiber is ineffective (Cabalar et al., 2020).

The UCS results show great findings as observed in (Figure 8(d)), with samples S0 showing a UCS of 100.03 kPa at 28 days of breakage, however, experimental samples S1, S2, S3, S4, S5 showed increases with respect to sample S0 of 247.06%, 393.14%, 759.80%, 401.96% and 408.82%, respectively. The presence of a low amount of steel fibers shows a detrimental effect in terms of UCS Correia et al. (Correia et al., 2017).

3.2 Optimal dosages using artificial intelligence

The regression models show different R^2 fitting values, considering the laboratory tests elaborated for OMC, MDD, CBR and UCS, respectively. The values represented are the result of the different dosages according to the results described above, shown in (Figure 9).

The model in (Figure 9(a)) shows an R^2: 0.989 according to the K-OPLS model, being a representation of an overfit for this test. Regarding (Figure 9(b)) shows an R^2: 0.768 according to the K-OPLS model, being a representation of an overfit for this test. The model in (Figure 9(c)) shows an R^2: 0.599 according to the K-OPLS model, being a representation of an overfit for this test. Regarding (Figure 9(d)) shows an R^2: 0.967 according to the K-OPLS model, being a representation of an overfit for this test. Regarding (Figure 9(e)) shows an R^2: 0.906 according to the K-OPLS model, being a representation of an overfit for this test. The fit values show close proximity to excellent coordination and laboratory test performance.

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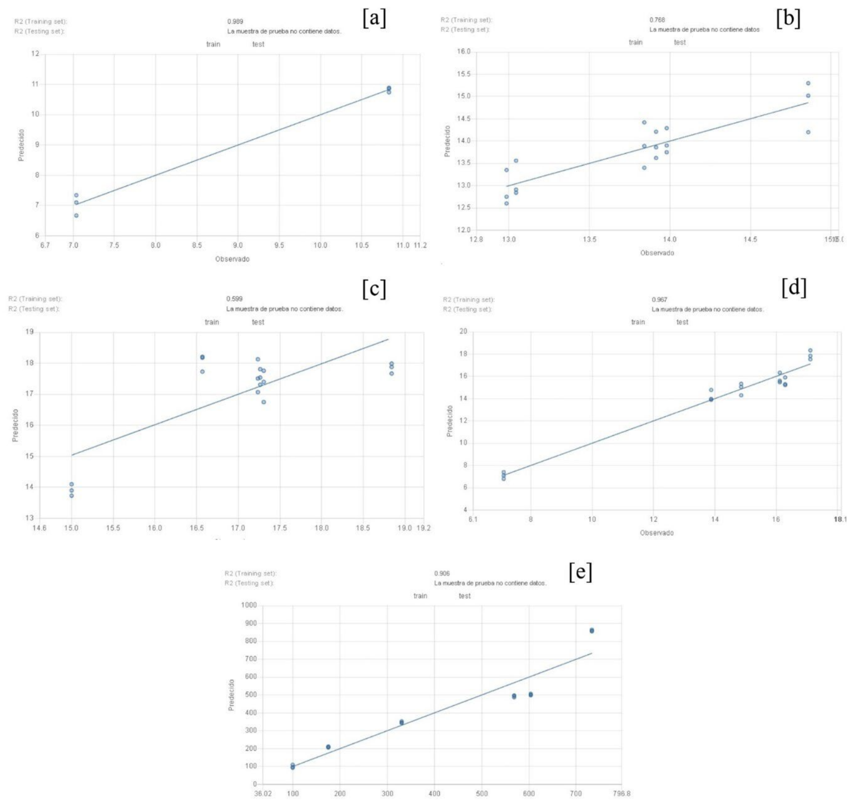

Figure 9. *Statistical regressions of (a) plasticity index, (b) OMC test, (c) MDD test, (d) CBR test, (e) UCS test.*

The K-OPLS model used shows the predictive capacity of the algorithm, that is the fundamental and the most important thing, which is nothing more than the graphical modeling of all the variables, the dependent variables were considered: plasticity index, OMC, MDD, CBR and UCS, on the other hand, the independent variables were: natural soil, natural hydraulic lime, plastic fiber and metallic fiber, respectively. This is why the interactions between initial soil characteristics, mix design and effective compaction in improving the UCS of treated soils are so important (Tran, 2022).

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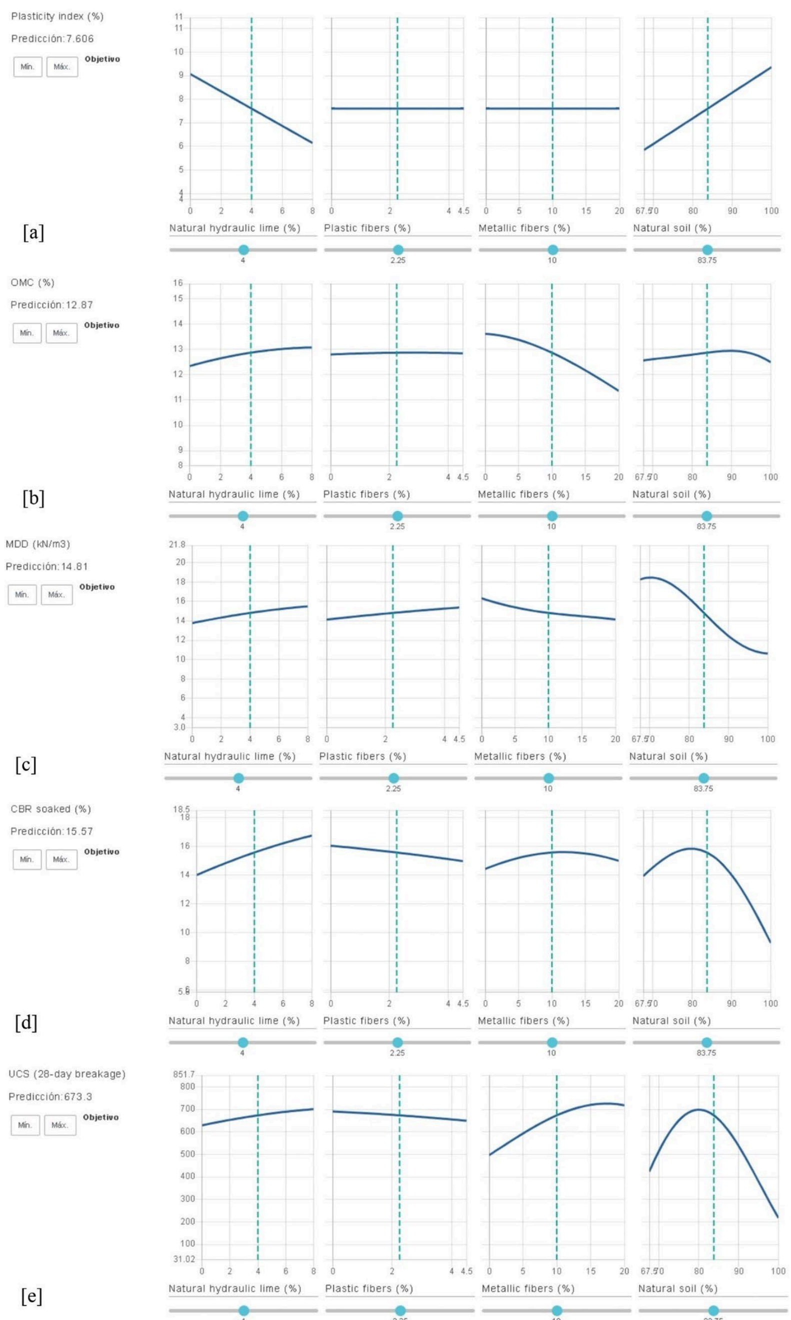

Figure 10. *Optimization of additive dosage for optimum geological properties (a) plasticity index, (b) OMC test, (c) MDD test, (d) CBR test, (e) UCS test.*

As shown in (Figure 10), the optimization using artificial intelligence algorithms reveals optimal results considering all the tests performed using an artificial K-OPLS model, where it shows that the tests analyzed as plasticity index, OMC, MDD, CBR and UCS, with the experimental results used. It was necessary to determine effective doses of natural hydraulic lime, plastic fiber and metallic fiber at (4%, 2.25%, 10%) and with respect to the natural soil a constant value of 83.75%. These optimal percentages compared to the values of the S3 sample carried out in the field (it shows to be better compared to the other samples); a great difference is observed in the use of plastic fiber due to the fact that its content increases by 0.75%. However, it is observed the reduction of natural hydraulic lime being 50% less than its real dosage, in addition it maintains the percentage of metallic fiber of 10%, and as a consequence it varies in the replacement of natural soil.

The findings show the practicality of including AI for optimal ideal dosage versus experimental dosages that are imposed due to laboratory tests, objecting only to dosages based on individual mechanical behavior (Ghorbani and Hasanzadehshooiili, 2018).

4. Conclusions

The experimental study on the influence of artificial intelligence in the optimization of the dosage of optimal natural hydraulic lime, plastic and metallic fibers on the geological characteristics of a treated soil. It was determined dosages where it was combined with four contents of PF and four contents of MF to study the effect of the modification in the stabilization of the soil with a fixed dose of natural lime. The use of an artificial model in the optimization of the additives suggests non-radical changes of some of its components influencing the reduction of lime and increase of plastic fibers. The results of the study show important revelations:

The tests showed a significant behavior in the dosage (80.5%), natural hydraulic lime (8%), plastic fiber (1.5%) and metallic fiber (10%) dosages belonging to sample S3 compared to its other samples S0, S1, S2, S4 and S5, respectively, which showed a reduction in their mechanical and physical capacities.

Experimental sample S3 showed better performance in treated soil properties with OMC of 12.90%, MDD of 18.04 kN/m3, CBR soaked of 17.90% and UCS of 860 kPa, respectively.

The R2 values for the tests submitted with artificial intelligence show an overfit at 0.989 and the lowest R2 at 0.599, these values compete for an artificial K-OPLS model.

The application of artificial intelligence with the K-OPLS model shows as findings that the optimization dosage of additives suggests using natural soil (83.75%), natural hydraulic lime (4%), plastic fiber (2.25%) and metallic fiber (10%), where the reduction of lime is observed up to 50% less and increases the dosage of plastic fiber by 0.75%, respectively.

In general, it is concluded that the application of artificial intelligence with the K-OPLS model significantly influences the resource optimization of the additives used in laboratory tests, using as independent factors the natural hydraulic lime, plastic fibers, metallic fibers and the natural soil, on the other hand, as dependent factors the physical and mechanical properties of the clayey gravelly soil.

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