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By
TOUALBIA YOUSOUF

Theme:

**Predictive approaches to the impact of environmental conditions on
the durability of clayey soils stabilized with mineral additives.**

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Zamila HARICHANE	Professor	University of Chlef	President
Khoudja ALI-BENYAHIA	Professor	University of Khemis Miliana	Examiner
Mohamed El-Hebib GUELLIL	Associate Professor	University of Chlef	Examiner
Ali MAKHLOUF	Professor	University of Chlef	Reporter
Billal SARI-AHMED	Associate Professor	University of Chlef	Co-Reporter

Dédicaces

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.

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المخلص

تتناول هذه الأطروحة للدكتوراه إحدى الإشكاليات الجوهرية في الهندسة الجيوتقنية، والمتمثلة في تأثير الظروف البيئية ولا سيما دورات التجمد والذوبان على فعالية ومتانة التربة الطينية المُحسَّنة بالمعادن على المدى الطويل، مثل الجير والرماد المتطاير. فقد بيّنت العديد من الدراسات التجريبية المنشورة وجود تحسّن أولي في مقاومة الضغط غير المحصور بعد التثبيت، إلا أن الأداء الميكانيكي للتربة يشهد تدهوراً تدريجياً عند تعرّضها لدورات متكررة من التجمد والذوبان. ومع ذلك، يظل التقييم التجريبي لهذه الظاهرة تحدياً قائماً بسبب صعوبة محاكاة الظروف المناخية بدقة، وضرورة التحكم المحكم في ظروف المعالجة، بالإضافة إلى التباين الملحوظ في النتائج. وتبرز هذه المحدودية الحاجة إلى اعتماد نماذج تنبؤية متقدمة.

وفي هذا السياق، تم تطوير مقاربتين نموذجين اعتماداً على قواعد بيانات تجريبية من الأدبيات لتربة مُعالجة بالجير والرماد المتطاير، وهما: نموذج إحصائي للانحدار، وشبكة عصبية اصطناعية وقد نجحت هذه النماذج في محاكاة تطور مقاومة الضغط غير المحصور للتربة المثبتة عند تعرّضها للدورات البيئية. كما أُجريت دراسات بارامترية لتحليل تأثير عدد من العوامل المؤثرة مثل عدد دورات التجمد-الذوبان، المحتوى المائي، نسبة الإضافات المعدنية، ومدة المعالجة. وأظهرت النتائج تفوق نموذج الشبكة العصبية الاصطناعية في الأداء التنبؤي وقدرته الأفضل على تمثيل العلاقات غير الخطية بين المتغيرات المدخلة واستجابة مقاومة التربة.

من خلال دمج بيانات تجريبية متنوعة والاستفادة من قدرات الذكاء الاصطناعي، تساهم هذه الأطروحة في تعزيز فهم السلوك طويل الأمد للتربة المثبتة تحت الظروف المناخية القاسية، كما توفر أدوات موثوقة لدعم التصميم الجيوتكنيكي المستدام في المناطق الحساسة بيئياً.

الكلمات المفتاحية: التربة الطينية المثبتة؛ دورات التجمد-الذوبان؛ الإضافات المعدنية؛ النمذجة الإحصائية؛ الشبكات العصبية الاصطناعية؛ مقاومة الضغط غير المحصور، المتانة.

Abstract

This doctoral thesis addresses a critical issue in geotechnical engineering: the impact of environmental conditions, particularly freeze–thaw cycles, on the effectiveness and long-term durability of stabilized clayey soils treated with mineral additives such as lime and fly ash. Numerous published experimental studies have demonstrated an initial improvement in unconfined compressive strength (UCS) following stabilization, but also a progressive deterioration of mechanical performance under repeated freeze–thaw exposure. However, experimental assessment remains challenging, due to the difficulty in realistically reproducing climatic conditions, precisely controlling curing parameters, and managing result variability. These limitations justify the adoption of predictive modeling approaches.

In this context, two modeling approaches: a statistical regression and an ANN, were developed using literature-based experimental databases for soils stabilized with lime and fly ash. These models effectively simulate the evolution of UCS in stabilized soils subjected to environmental cycles. Parametric studies were also conducted to capture the influence of several key factors, such as the number of freeze–thaw cycles, water content, additive content, and curing duration. Results show that ANN models offer superior predictive performance and better capture of nonlinear relationships between input variables and soil strength response.

By integrating diverse experimental data and leveraging the power of artificial intelligence, this work contributes to a better understanding of the long-term behavior of stabilized soils under harsh climatic conditions and provides reliable tools to support resilient geotechnical design in environmentally sensitive regions.

Keywords: stabilized clayey soils; freeze–thaw cycles; mineral additives; statistical model; artificial neural network (ANN); unconfined compressive strength (UCS)

Keywords: stabilized clayey soils; freeze–thaw cycles; mineral additives; statistical model; artificial neural network (ANN); unconfined compressive strength (UCS); durability.

Résumé

Cette thèse de doctorat aborde un enjeu crucial en géotechnique : l'influence des conditions environnementales, notamment les cycles de gel-dégel, sur l'efficacité et la durabilité des traitements des sols argileux à l'aide d'additifs minéraux tels que la chaux et les cendres volantes. De nombreuses études expérimentales publiées ont mis en évidence une amélioration initiale de la résistance à la compression non confinée (RCS) après stabilisation, mais également une dégradation progressive des performances mécaniques sous l'effet de cycles répétés de gel et de dégel. Toutefois, ces investigations expérimentales restent complexes, notamment en raison des difficultés à reproduire fidèlement les conditions climatiques réelles, à contrôler précisément les paramètres de cure et à gérer la variabilité des résultats. Ces limitations justifient le recours à des approches de modélisation prédictive.

Dans ce contexte, deux types de modèles : régression statistique et RNA, ont été élaborés à partir de données expérimentales collectés pour des sols traités à la chaux ou aux cendres volantes. Ces modèles ont permis de simuler avec précision l'évolution de l'RCS des sols stabilisés soumis à des cycles environnementaux. Des études paramétriques ont en outre été menées pour analyser l'effet de plusieurs facteurs clés, tels que le nombre de cycles gel-dégel, la teneur en eau, la teneur en additif et la durée de cure. Les résultats montrent que les modèles RNA offrent une meilleure capacité de généralisation et capturent plus efficacement les relations non linéaires entre les paramètres d'entrée et la réponse mécanique du sol.

En intégrant des données expérimentales variées et en exploitant la puissance de l'intelligence artificielle, ce travail contribue à une meilleure compréhension du comportement à long terme des sols stabilisés en conditions climatiques sévères, et propose des outils performants pour orienter la conception géotechnique dans des contextes sensibles aux variations environnementales.

Mots-clés : sol argileux stabilisés ; cycles gel-dégel ; additifs minéraux ; modèle statistique ; réseau de neurones artificiel (RNA) ; résistance à la compression non confinée (RCS) ; durabilité.

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List of Symbols

1. Abbreviations and Acronyms

	Symbol	Full Name / Description	Context / Unit
1	AASHTO	American Association of State Highway and Transportation Officials	Testing standard
2	AdaBoost	Adaptive Boosting	Machine learning
3	ANN	Artificial Neural Network	Predictive modeling
4	ASTM	American Society for Testing and Materials	Testing standard
5	BP	Backpropagation / Bayesian Programming	Neural network training
6	C	Cement	Mineral additive (%)
7	C-A-H / CAH	Calcium Aluminate Hydrate	Cementitious compound
8	C-S-H / CSH	Calcium Silicate Hydrate	Cementitious compound
9	C ₂ S	Dicalcium Silicate	Cement compound
10	C ₃ A	Tricalcium Aluminate	Cement compound
11	C ₃ S	Tricalcium Silicate	Cement compound
12	C ₄ AF	Tetracalcium Aluminoferrate	Cement compound
13	Ca(OH) ₂	Calcium Hydroxide (Hydrated Lime)	Chemical formula
14	Ca ²⁺	Calcium Ion	Chemical notation
15	CaO	Calcium Oxide (Quicklime)	Chemical formula
16	CBR	California Bearing Ratio	Soil strength (%)
17	CFA	Class C Fly Ash	Type of fly ash
18	CG	Conjugate Gradient	Optimization algorithm
19	CH	High Plasticity Clay	USCS classification
20	CI	Consistency Index	Soil property
21	CL	Low Plasticity Clay	USCS classification
22	DMT	Deep Mixing Technique	Soil treatment
23	DT	Decision Tree	Machine learning
24	ERT	Extremely Randomised Trees	Machine learning
25	F-T	Freeze-Thaw	Environmental cycle
26	FA	Fly Ash	Mineral additive (%)
27	Fe ₂ O ₃	Iron Oxide	Chemical compound
28	FFA	Class F Fly Ash	Type of fly ash
29	FN	Functional Networks	Predictive model
30	GBoost	Gradient Boosting	Machine learning
31	GGBS	Ground Granulated Blast Furnace Slag	Supplementary binder
32	GPR	Gaussian Process Regression	Machine learning
33	H ₂ O	Water	Chemical formula
34	HL	Hydrated Lime	Type of lime
35	PI	Plasticity Index	Soil property (%)
36	Lc	Lime Content	Additive percentage (%)

	Symbol	Full Name / Description	Context / Unit
37	LKD	Lime Kiln Dust	Industrial waste
38	LL	Liquid Limit	Atterberg limit (%)
39	LMBP	Levenberg-Marquardt Backpropagation	ANN training
40	MAE	Mean Absolute Error	Statistical metric (kPa)
41	MAPE	Mean Absolute Percentage Error	Statistical metric (%)
42	MARS	Multivariate Adaptive Regression Splines	Regression model
43	MC	Moisture Content	Soil water content (%)
44	MDD	Maximum Dry Density	Compaction (kg/m ³)
45	MI	Mutual Information	Feature selection
46	ML	Medium Plasticity Silt	USCS classification
47	MLR	Multiple Linear Regression	Statistical model
48	NC	Number of Cycles	Environmental count
49	OH ⁻	Hydroxide Ion	Chemical notation
50	OM	Organic Matter	Soil content (%)
51	OMC	Optimum Moisture Content	Compaction (%)
52	OPC	Ordinary Portland Cement	Type of cement
53	PL	Plastic Limit	Atterberg limit (%)
54	PSO	Particle Swarm Optimization	Optimization algorithm
55	QL	Quicklime	Type of lime
56	R ²	Coefficient of Determination	Model fit metric
57	ReLU	Rectified Linear Unit	Activation function
58	RF	Random Forest	Machine learning
59	RME	Relative Mean Error	Statistical metric (%)
60	RMSE	Root Mean Square Error	Statistical metric (kPa)
61	RVM	Relevance Vector Machine	Machine learning
62	SiO ₂	Silicon Dioxide (Silica)	Chemical compound
63	SL	Soil Clay Content	Soil composition (%)
64	SVM	Support Vector Machine	Machine learning
65	T	Curing Time	Duration (days)
66	UCS	Unconfined Compressive Strength	Soil strength (kPa)
67	UCS ₀	Initial Unconfined Compressive Strength	Baseline (kPa)
68	UCS _{FT}	UCS after Freeze-Thaw	Strength (kPa)
69	USCS	Unified Soil Classification System	Soil classification
70	W-D	Wet-Dry / Wetting-Drying	Environmental cycle
71	W/C	Water-to-Cement Ratio	Mix design (—)
72	W/L	Water-to-Lime Ratio	Mix design (—)
73	XGBoost	Extreme Gradient Boosting	Machine learning

2. Primary Variables in Equations

Number	Symbol	Description	Unit
74	UCS	Unconfined Compressive Strength	kPa or MPa
75	UCS ₀	Initial UCS of untreated soil	kPa
76	UCS _{FT}	UCS after freeze-thaw cycles	kPa
77	L _c	Lime content	%
78	FA	Fly ash content	%
79	C	Cement content	%
80	T /	Curing time	Days
81	NC	Number of freeze-thaw or wet-dry cycles	—
82	OMC	Optimum Moisture Content	%
83	MDD	Maximum Dry Density	kg/m ³
84	LL	Liquid Limit	%
85	PL	Plastic Limit	%
86	PI / IP	Plasticity Index	%
87	IC / CI	Consistency Index	—
88	W	Water content	%
89	W/C	Water-to-cement ratio	—
90	w/L	Water-to-lime ratio	—

3. Regression Model Parameters

Number	Symbol	Description	Context
91	a, b, c, d, e, f, g, h, i	Regression coefficients	General notation
92	a ₀ , a ₁ , a ₂ , ..., a _s	Specific regression constants	MLR models
93	A, B, C, D, E, F	Model parameters	Nonlinear equations
94	α	Significance level	Typically 0.05
95	β	Empirical parameter	Models
96	k / k _m	Empirical fitting parameter	—
97	m	Regression parameter	Slope

4. Statistical and Error Metrics

Number	Symbol	Description	Unit
98	R ²	Coefficient of determination	—
99	RMSE	Root Mean Square Error	kPa
100	RME	Relative Mean Error	%
101	MAE	Mean Absolute Error	kPa
102	MAPE	Mean Absolute Percentage Error	%
103	E	Percentage error	%
104	Std. Err.	Standard Error	—

Number	Symbol	Description	Unit
105	p-value / Pr	Probability value (significance)	—
106	t-value	Student's t-statistic	—
107	F-value	Fisher's F-statistic	—
108	Conf. Interval	Confidence Interval (95%)	—

5. Additional Geotechnical Properties

Number	Symbol	Description	Unit
109	γ_d	Dry unit weight	kN/m ³
110	ρ_d	Dry density	kg/m ³
111	e_i	Void index	—
112	V_v	Absolute volume of voids	—
113	V_{Li}	Absolute volume of lime	—
114	q_t	Tensile strength	kPa
115	q_c / q_u	Compressive strength	kPa
116	V_p	Primary ultrasonic wave velocity	m/s
117	pH	Potential of hydrogen	—
118	CBR	California Bearing Ratio	%
119	CA / A_c	Clay Activity	—
120	S	Sand content	%
121	G	Gravel content	%
122	Cl	Clay content	%

6. Chemical Compounds and Ions

Number	Symbol	Full Name	Type
123	CaO	Calcium Oxide (Quicklime)	Chemical compound
124	Ca(OH) ₂	Calcium Hydroxide	Hydrated Lime
125	Ca ²⁺	Calcium Ion	Ion
126	OH ⁻	Hydroxide Ion	Ion
127	SiO ₂	Silicon Dioxide (Silica)	Pozzolanic component
128	Al ₂ O ₃	Aluminum Oxide (Alumina)	Pozzolanic component
129	Fe ₂ O ₃	Iron Oxide	Mineral component
130	H ₂ O	Water	Chemical formula
131	C-S-H	Calcium Silicate Hydrate	Cementitious gel
132	C-A-H	Calcium Aluminate Hydrate	Cementitious gel
133	C ₃ S	Tricalcium Silicate	Cement compound
134	C ₂ S	Dicalcium Silicate	Cement compound
135	C ₃ A	Tricalcium Aluminate	Cement compound
136	C ₄ AF	Tetracalcium Aluminoferrate	Cement compound
137	Na ₂ O	Sodium Oxide	Fly ash component

Number	Symbol	Full Name	Type
138	K ₂ O	Potassium Oxide	Fly ash component
139	SO ₃	Sulfur Trioxide	Mineral component

7. Units of Measurement

Number	Unit	Meaning	Application
140	kPa	Kilopascals	Stress/strength
141	MPa	Megapascals	Stress/strength
142	%	Percentage	Content/properties
143	days	Time duration	Curing period
144	kg/m ³	Kilograms per cubic meter	Density
145	g/cm ³	Grams per cubic centimeter	Density
146	kN/m ³	Kilonewtons per cubic meter	Unit weight
147	m/s	Meters per second	Velocity
148	mm	Millimeters	Length
149	μm	Micrometers	Particle size
150	°C	Degrees Celsius	Temperature
151	cal/g	Calories per gram	Heat
152	psi	Pounds per square inch	Stress (Imperial)

8. Table and Figure Notation

Number	Symbol	Meaning	Usage
153	Exp	Experimental / Measured	Laboratory value
154	Pred	Predicted / Calculated	Model value
155	count	Number of data points	Statistics
156	mean	Mean value	Statistics
157	std	Standard deviation	Statistics
158	min	Minimum value	Range
159	max	Maximum value	Range
160	25%, 50%, 75%	Percentile values	Distribution
161	Param	Parameter	Model variable
162	Signif.	Significance	Statistical test
163	NT	No test conducted	Data absence
164	NA	Not available	Missing data
165	Unsp.	Unspecified	Undefined type

9. Machine Learning / ANN Notation

Number	Symbol	Description	Context
166	X / x	Input variable vector	ANN input
167	Y / y	Output variable (target)	ANN output

Number	Symbol	Description	Context
168	$f(x)$	Activation function	Neural network
169	w	Weight	Neural network
170	b	Bias	Neural network
171	η	Learning rate	Training parameter
172	epoch	Training iteration	Complete pass
173	MSE	Mean Squared Error	Loss function
174	ReLU	Rectified Linear Unit: $\max(0, x)$	Activation
175	sigmoid	Sigmoid activation	$\sigma(x) = 1/(1+e^{-x})$
176	tanh	Hyperbolic tangent	Activation
177	dropout	Regularization technique	Prevents overfitting

10. Special Subscripts / Superscripts

Number	Notation	Meaning	Example
178	UCS_0	Initial value (before treatment)	Baseline strength
179	UCS_1, UCS_4, UCS_{12}	UCS after 1, 4, or 12 cycles	Cyclic testing
180	UCS_{act}	Actual measured UCS	Laboratory result
181	UCS_{pred}	Predicted UCS	Model output
182	UCS_{un}	Unsoaked UCS	Dry condition
183	C_3S, C_2S	Cement compound subscripts	Chemical notation
184	L_2	Secondary lime coefficient	Model parameter
185	e_i	Initial void ratio	Soil mechanics

11. French–English Equivalents

Number	French	English	Meaning
186	RNA	ANN	Artificial Neural Network
187	RNC	UCS	Résistance Non Confinée / Unconfined Compressive Strength
188	Teneur en chaux	Lime content	Lc
189	Temps de cure	Curing time	T
190	Indice de plasticité	Plasticity Index	PI
191	Limite de liquidité	Liquid Limit	LL
192	Gel-dégel	Freeze-thaw	F-T
193	Humidification-séchage	Wetting-drying	W-D

12. Uncommon / Single-Use Symbols

Number	Symbol	Context	Meaning
194	HARHA	ML input	Hydrated-lime-activated rice husk ash
195	RHA	Additive	Rice Husk Ash

Number	Symbol	Context	Meaning
196	RBA	Additive	Rice Bagasse Ash
197	C_d	Equation	Cement dosage
198	w_0/a_w	Ratio	Water and cement relation
200	C_T	Composite	Total stabilizer content

General Introduction

Overview

In the field of civil and geotechnical engineering, clay soils pose a serious challenge due to their mechanical instability, moisture sensitivity, and tendency to swell or shrink under environmental variations. These soils have low load-bearing capacity and are particularly vulnerable in regions with extreme seasonal conditions. Therefore, soil stabilization has become an essential technique to improve performance and durability in infrastructure development (Bell, 1996; Edil et al., 2006).

Mineral stabilization using additives such as lime, fly ash, and cement is commonly implemented due to their pozzolanic properties, cost-effectiveness, and proven efficiency in improving soil strength and reducing plasticity (Croft, 1967; Petry and Little, 2002; Harichane et al., 2011). Lime promotes cation exchange and pozzolanic reactions, while fly ash provides silica and alumina for secondary cementation, and cement allows rapid hydration and densification of the treated soil matrix. These treatments improve several geotechnical properties, notably unconfined compressive strength (UCS), reduce moisture sensitivity, and mitigate shrink-swell phenomena, thereby enhancing the long-term stability of soils (Khatab et al., 2007; Estabragh et al., 2014).

However, despite their initial effectiveness, stabilized soils often experience strength degradation when exposed to specific environmental conditions, including freeze–thaw (F–T) cycles, wetting–drying (W–D) cycles, temperature variations, sulfate presence, or changes in water content. These often-cyclic environmental conditions can significantly impact the mechanical integrity of stabilized soils by inducing internal stresses, breaking cementitious bonds, and altering the soil's microstructure (Bin-Shafique et al., 2010; Lu et al., 2020). The effect of these cycles is particularly severe in highly plastic clays and expansive soils, resulting in significant UCS loss, increased permeability, and the formation of cracks (Yan et al., 2017).

Understanding how these environmental conditions interact with mineral stabilization mechanisms is crucial to ensure the long-term durability of geotechnical structures. In this regard, several experimental protocols have been proposed to study the effects of these climatic conditions on the properties of stabilized soils. However, these experimental investigations remain complex, mainly due to the difficulty of faithfully reproducing real climatic conditions, precisely controlling curing parameters, and managing the variability of obtained results.

Given these limitations, the use of predictive modeling approaches appears highly relevant. It is indeed necessary to establish a framework that simultaneously integrates stabilization parameters and environmental factors in order to reduce the gap between laboratory experimental results and the actual field behavior of soils.

Although significant research has been conducted in this field, few models have been developed to simulate the effects of conditions such as freeze–thaw (F–T) and wetting–drying (W–D) cycles, not only on natural soils but even less on stabilized soils. This gap severely limits the practical usefulness of existing models, particularly in regions where seasonal variations play a dominant role in soil degradation (Solanki et al., 2013; Sezer et al., 2017).

The central problem that motivated this study lies in the absence of integrated modeling approaches that account for the combined effects of mineral stabilization and environmental degradation agents on the durability of stabilized soils, particularly regarding their mechanical properties such as UCS. Moreover, the lack of reliable predictive frameworks limits the ability to anticipate real in-service performance, which may compromise the long-term reliability of geotechnical works. It is therefore essential to develop robust models capable of estimating soil performance over time under realistic environmental exposures.

Research Objectives

This doctoral research pursues a dual objective: first, to collect, classify, and present experimental databases from the scientific literature on lime- and fly ash-stabilized clayey soils; and second, to develop and validate predictive models based on two complementary approaches capable of estimating the durability of these treated soils when subjected to environmental stresses, particularly freeze–thaw cycles.

The main goal of this research is to better understand and quantify the influence of key parameters (binder content, curing time, water content, F–T cycles, etc.) by explicitly integrating environmental effects into the predictive models of stabilized soil strength.

More specifically, the study aims to:

- Evaluate the impact of environmental conditions on unconfined compressive strength (UCS);
- Examine the behavior of soils treated with lime and fly ash under such conditions;

- Compare the performance of two modeling techniques: classical statistical models and artificial neural networks (ANN).

In parallel with model development, this study seeks to identify the most effective mineral additives to ensure soil durability in demanding environments. It also aims to quantify mechanical degradation, particularly of UCS, under repeated environmental cycles, in order to provide reliable decision-making tools adapted to real field conditions.

By confronting classical statistical models with machine learning approaches (ANN), this work offers a comparative analysis of their performance and applicability in geotechnical engineering. The explicit integration of environmental variables into predictive models improves the understanding of stabilized soil behavior, refines risk assessment, and optimizes design choices.

In a context of increasing climatic instability, the ability to anticipate the long-term performance of treated soils becomes crucial for ensuring infrastructure durability. This work contributes to that goal by mobilizing computational modeling tools to enhance the resilience of structures built on lime- or fly ash-stabilized clay soils under freeze–thaw conditions.

Thesis Structure

This thesis is organized into five main chapters, framed by an introduction and a general conclusion, to cover all aspects related to the durability of stabilized clayey soils under severe environmental conditions.

- The **introduction** presents the general framework of the study, defining the scientific context, the research problem, objectives, as well as the relevance of integrating environmental effects into predictive models of stabilized soil mechanical performance.
- **Chapter 1** provides a critical analysis of previous research on clay soil stabilization using mineral additives. It highlights the improvement mechanisms brought by lime, fly ash, and cement, while emphasizing their durability limits under environmental stresses such as freeze–thaw cycles.
- **Chapter 2** offers a literature review of predictive modeling methods used to estimate UCS of treated soils. It compares traditional empirical approaches with artificial intelligence techniques, identifying commonly used variables, achieved performances, and limitations of existing models.

- **Chapter 3** describes the methodology for building the database used in this study. It presents the literature sources, selected input and output parameters, and the organization of data necessary for training and validating the models.
- **Chapter 4** develops two modeling frameworks (statistical and ANN-based) for predicting the strength of lime-stabilized clay soils under freeze–thaw cycles. It includes model performance evaluations, a parametric study, and a discussion of influential variables.
- **Chapter 5** applies the same methodology to fly ash-stabilized soils. It also compares the performance of the two modeling techniques and discusses the results in relation to the specific properties of the binders.

The **general conclusion** synthesizes the major findings, highlights the scientific and technical contributions, and provides practical recommendations for the design of treated soil-based structures. It also outlines future research perspectives, notably the integration of other types of environmental stresses and the enhancement of modeling tools.

Chapter 1

Durability of Clayey Soils Stabilized with Mineral Additives

1.1 Introduction

Soil stabilization is a vital geotechnical technique aimed at enhancing the engineering performance of problematic soils, particularly expansive clays that exhibit significant volume changes under moisture fluctuations. Among the various stabilizing agents, lime, fly ash (FA), and cement are widely adopted due to their pozzolanic properties and economic feasibility. The stabilization process improves strength, reduces plasticity, and minimizes swell-shrink behavior, which is crucial for infrastructure built on weak subgrades (Bell, 1996; Edil et al., 2006). Lime induces cation exchange and pozzolanic reactions that flocculate clay particles, while fly ash contributes silica and alumina for secondary cementitious reactions. These treatments are especially relevant in regions subjected to freeze-thaw and wet-dry cycles, where soil durability becomes paramount (Eskisar et al., 2015; Bin-Shafique et al., 2011; Roshan et al., 2022). An in-depth understanding of these additives provides a framework for optimizing soil performance under varying environmental conditions.

1.2 Environmental conditions effect on UCS of stabilized soils

Environmental conditions, particularly freeze–thaw (F–T) and wet–dry (W–D) cycles, play a critical role in the durability and long-term strength performance of stabilized clayey soils. The repeated freezing and thawing of water within soil pores leads to volumetric expansion and contraction, generating internal stresses that can disrupt cementitious bonds formed during stabilization. Lu et al. (2020) and Yan et al. (2017) demonstrated that lime-treated soils, when exposed to F–T cycles, experience reductions in UCS due to ice lens formation and microcracking. Similarly, Bin-Shafique et al. (2010) and Solanki et al. (2013) observed that fly ash-stabilized soils show UCS degradation after several F–T cycles, although these mixtures often retained higher strength than untreated soils. Cement-stabilized clays, while initially more resistant, also suffer progressive strength loss as F–T cycles increase (Eskisar et al., 2015; Zhang et al., 2021).

Wet–dry cycling further compounds these durability challenges. As reported by Harichane et al. (2010), lime and fly ash-stabilized soils exhibit noticeable UCS reduction due to moisture-induced shrinkage, leaching of stabilizers, and breakdown of cementitious gels. Chittoori et al. (2018) highlighted that lime-fly ash combinations offer improved resilience under W–D cycles compared to single-additive treatments. Cement-treated soils also show strength loss under W–D conditions, though their microstructure often remains more intact due to stronger C–S–H bond formations (Rashan et al., 2010; Estabragh et al., 2014). These studies

underscore the necessity of accounting for environmental stressors during the design and formulation of stabilization strategies, especially in climates prone to cyclic weathering.

1.3 Soil stabilization using lime

Lime stabilization has become a fundamental soil improvement technique for managing problematic expansive soils. Early researchers including [Herrin and Mitchell \(1961\)](#), [Bell \(1988\)](#), and [Greaves \(1996\)](#) demonstrated lime's remarkable ability to transform challenging soil conditions into stable foundation materials.

Plasticity modification and solidification represent the core transformations that occur during lime treatment. These changes result from cation exchange, flocculation, and pozzolanic reactions that fundamentally alter the soil's engineering properties at physical, chemical, and microstructural levels ([Croft, 1967](#); [Rajasekaran and Rao, 2002](#); [Khattab et al., 2007](#)).

The chemical stabilization process begins when calcium oxide combines with water, creating hydrated lime through an exothermic reaction that releases calcium and hydroxide ions into the soil. These ions interact with clay particles, reducing swelling tendencies and promoting particle bonding. At highly alkaline conditions ($\text{pH} \geq 12.4$), dissolved silica and alumina react with calcium to form strong cementitious compounds like calcium silicate hydrate (CSH) and calcium aluminate hydrate (CAH), which significantly enhance soil strength and bearing capacity ([Eades and Grim, 1960](#); [Al-Taie, 2005](#); [Petry and Little, 2002](#)).

1.3.1 Effect of water content on lime soil-stabilization

Water content plays a crucial role in lime-soil mixture performance. Researchers have found varying effects of water content on soil strength. [Singh and Goswami \(2012\)](#) discovered that lime-soil mixtures compacted above optimum water content can achieve higher strength after brief curing periods due to more uniform lime diffusion. The maximum strength is typically obtained when molding water content is 2-3% wet of optimum moisture content. However, [Yin et al. \(2018\)](#) and [Locate et al. \(1990\)](#) noted that excessive water content can decrease strength by reducing lime concentration and weakening inter-particle bonds.

The interaction between water content and lime stabilization is complex. High lime content requires adequate water for complete hydrolysis; otherwise, unreacted lime can negatively affect soil strength. Saturation of lime-stabilized specimens can reduce strength, with [George et al. \(1992\)](#) reporting up to 50% strength reduction. Water content significantly influences dynamic soil parameters, with shear modulus increasing up to slightly beyond optimum

moisture content before rapidly decreasing. This occurs due to thicker water films reducing soil cohesion and increased pore water pressure under dynamic loading. Notably, the impact varies between cohesive and cohesionless soils (Lu et al., 2020).

1.3.2 Effect of temperature on lime soil-stabilization

Elevated temperatures significantly accelerate pozzolanic reactions in lime-soil mixtures. Researchers found that temperature increases from 20°C to 50°C can make lime-soil reactions six times faster, leading to remarkable rises in unconfined compressive strength (UCS) and soil secant modulus. For instance, pozzolanic activity at 25°C is comparable to 7 days of curing at 11.5°C. The optimum lime content for ultimate strength varies with curing time and ambient temperature (Fig 1.1), demonstrating the critical role of temperature in chemical interactions (Al-Mukhtar et al., 2010; Zhou et al., 2019).

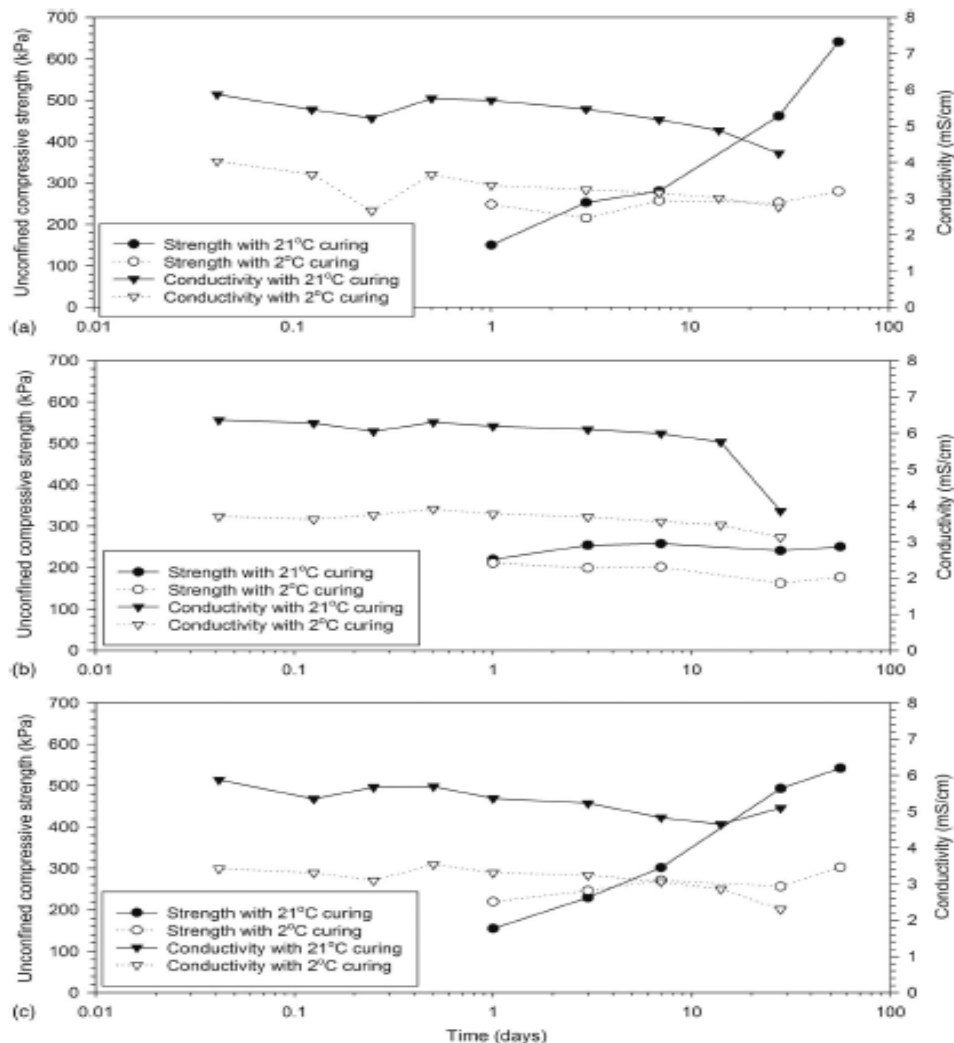


Fig 1.1. UCS and electrical conductivity as functions of curing time under varying curing temperatures for different soil types by (Zhou et al., 2019).

Low temperatures substantially impede lime stabilization processes. Pozzolanic activity can remain dormant below 4°C and may be significantly deterred below 15°C-21°C for extended periods. The North Carolina Department of Transportation recommends avoiding lime stabilization when ambient temperatures are below 7.2°C (45°F). To address these challenges, the National Lime Association suggests adopting a standard of 7-day curing at 40°C for pavement applications. Early strength gain is crucial, so construction is typically advised during warmer seasons to ensure optimal chemical reactions (Bell, 1996; Nelson et al., 2015).

1.3.3 Effect of Freeze-thaw on lime-soil stabilization

The fundamental process of freeze-thaw (F-T) cycles dramatically alters soil mechanics through water-ice volume transitions. When water freezes in saturated soil, it expands by approximately 9% (Lu et al., 2019), creating ice lenses that exert pressure on soil particles. During thawing, the enlarged voids remain, leading to plastic deformations and cracks (Lu et al., 2016). This cyclical process particularly impacts untreated soils, resulting in reduced shear strength (Thompson and Dempsey, 1977) and increased hydraulic conductivity due to crack formation (Yildiz and Soganci, 2012).

The UCS of soils during F-T cycles has been extensively studied by Yan et al. (2017) and Salih and Abdalla, (2020), who conducted tests at -23°C with 24-hour cycles, demonstrating significant strength variations between treated and untreated samples. Baldovino et al. (2021) further documented that freezing results in sharp reductions in surface deflections while thawing increases immediate deflection under traffic loading see in Fig 1.2.

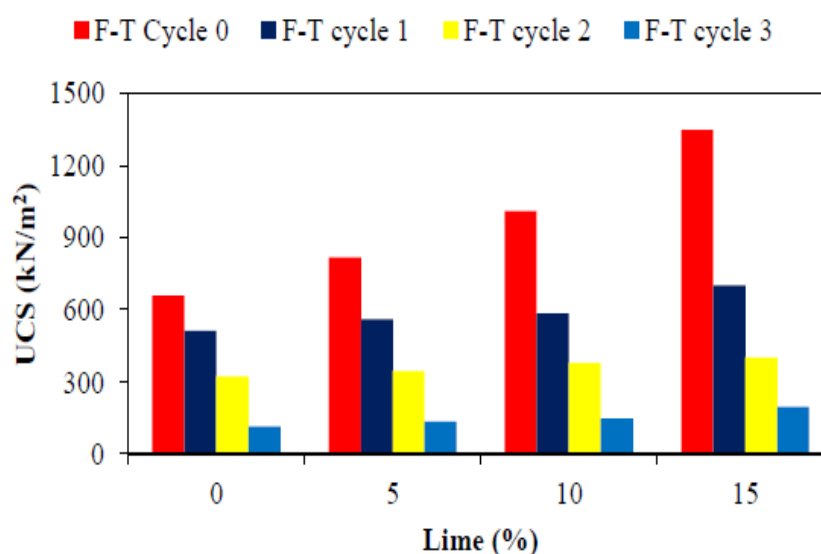


Fig. 1.2. UCS variation of lime-stabilized soil under F–T cycles (Salih and Abdalla, 2020).

The importance of proper stabilization was highlighted by [Bozbey et al. \(2018\)](#), who reported substantial increases in resilient modulus for lime-treated soils after F-T exposure. Mass loss patterns in stabilized soils were extensively studied by [Parsons and Kneebone \(2004\)](#), who found significantly better resistance in treated samples. [Nguyen \(2015\)](#) further validated these findings through detailed durability studies ([Tab 1.1](#)).

Tab. 1.1. UCS results for all soils under F-T cycles by [Nguyen \(2015\)](#).

Types of lime	Lime additives (%)	Number of F-T cycle			
		0	1	10	20
		UCS (kPa)			
A-6	0	916.37	634.56	566.35	546.98
	5	3982.42	NT	3210.74	3329.24
	7	4140.89	NT	3947.28	3646.18
A-7-6	0	778.57	593.91	534.66	527.08
	5	2990.26	NT	2611.31	2693.99
	7	2383.94	NT	2225.47	2130.38

Note : NT= No test was conducted for this F-T cycle ; UCS=Unconfined compressive strength

The effectiveness of stabilization methods, particularly lime treatment, has been well-documented. [Thompson \(1968\)](#) recorded strength decreases of approximately 120 kPa per F-T cycle for 48-hour curing periods and 50 kPa for 96-hour curing periods in lime-soil mixtures.

[McCalrthy et al. \(2014\)](#) and [solanki \(2010\)](#) emphasized the critical importance of proper lime content to prevent calcium leaching and maintain durability ([Fig 1.3](#)). [Liu et al. \(2010\)](#) provided long-term validation of lime stabilization effectiveness in field applications, while also noting the importance of proper initial treatment conditions.

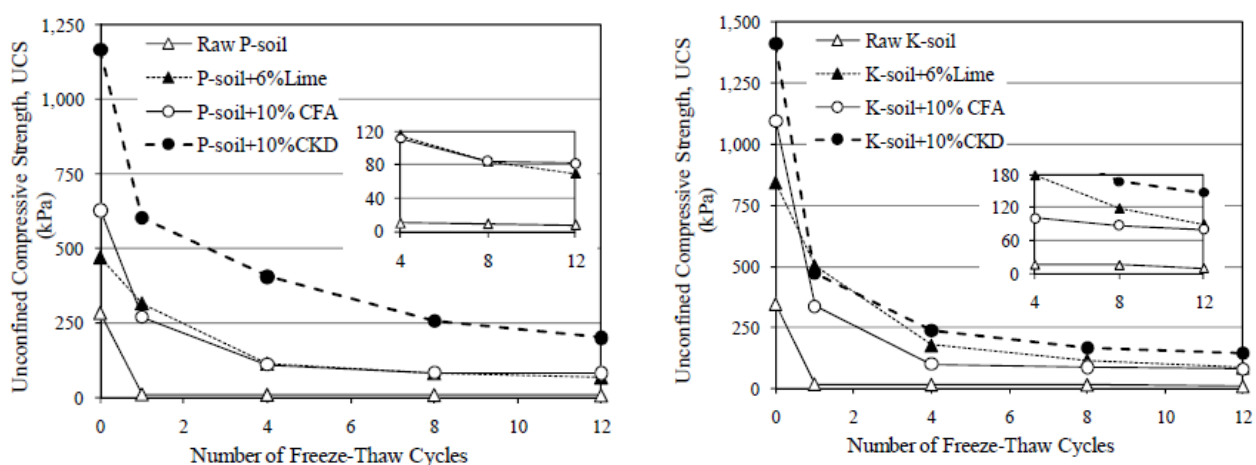


Fig. 1.3. UCS of raw and stabilized P and K soil under F-T cycles ([Solanki, 2010](#))

Lu et al. (2020) documented that lime-treated soil's dynamic resilient modulus can increase by up to 120.6% after F-T cycles, demonstrating the long-term benefits of proper stabilization. These findings continue to guide construction practices in cold regions, where maintaining structural integrity under severe environmental conditions remains crucial, with particular emphasis on the importance of proper treatment procedures and adequate curing conditions as outlined by the collected research.

1.3.4 Effect of wet-dry on lime-soil stabilization

The durability of lime-stabilized clayey soils under wet-dry (W-D) cycles has been extensively investigated for decades. Early studies to recent advancements consistently reported a reduction in the unconfined compressive strength (UCS) due to repeated moisture fluctuations. However, the extent of reduction varies depending on soil type, stabilizer content, and the number of cycles.

Jones (1958) conducted one of the earliest investigations on the durability of lime-treated soils, observing significant strength degradation due to ten cycles of wetting and drying. The UCS reduced by approximately 40%, primarily attributed to progressive breakdown of cementation bonds and soil fabric. This pioneering work highlighted the limitations of lime stabilization when exposed to fluctuating moisture conditions.

Sahoo and Pradhan (2010) studied expansive soils stabilized using a lime-treated non-expansive soil cushion subjected to wet-dry regimes. Their findings showed that lime addition substantially improved UCS after 14 days of curing, especially with 8% lime content (Tab 1.2). Although wet-dry cycles were applied, the stabilized soil retained considerable strength, suggesting that cushion techniques can enhance durability.

Tab. 1.2. Reduction in UCS of expansive soil at 1st, 4th and 12th wet dry cycles by Sahoo and Pradhan (2010).

Lime content	UCS (kPa)	UCS ₁ (kPa)	UCS ₄ (kPa)	UCS ₁₂ (kPa)	Durability Index		
					UCS ₁ /UCS	UCS ₄ /UCS	UCS ₁₂ /UCS
2	945	189	321	586	0.20	0.34	0.62
4	1062	297	446	690	0.28	0.42	0.65
6	1150	425	587	851	0.37	0.51	0.74
8	1239	496	632	904	0.40	0.51	0.73
10	1234	431	591	837	0.35	0.48	0.68

Note : UCS : Unconfined Compressive Strength of specimen moist cured for 14 days ; UCS₁, UCS₄ and UCS₁₂ : Unconfined Compressive Strength of specimen moist cured for 14 days and subjected to 1st, 4th and 12th wet-dry cycles respectively

Pedarla et al. (2011) emphasized the mineralogical influence on the durability of lime-stabilized expansive soils. The authors reported that soils with high montmorillonite content exhibited greater UCS loss after six W-D cycles compared to kaolinite-rich soils. The study recommended considering mineralogical composition when designing lime-stabilized systems for expansive soils.

Thyagaraj and Zodinsanga (2014) investigated the effect of W-D cycles on lime precipitation-treated expansive soils. Results indicated an initial UCS drop of 15–20% after the first cycle, with stabilization after four to five cycles (Fig 1.4). Notably, both treated and untreated specimens exhibited maximum swell potential during the second cycle, highlighting the early deterioration of cementation bonds.

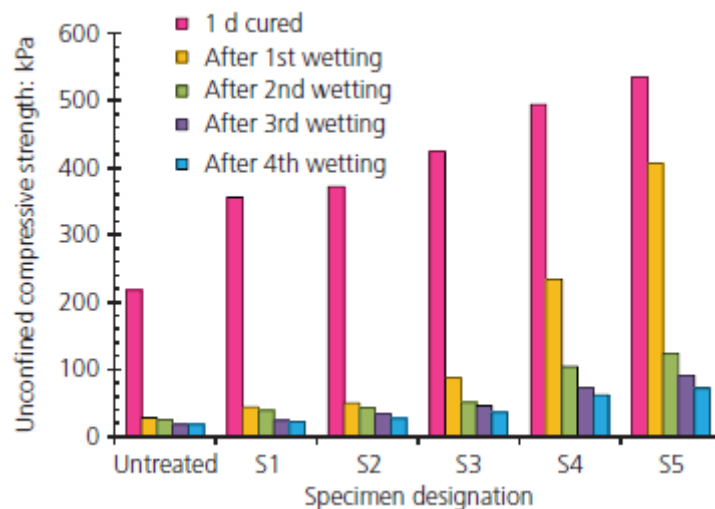


Fig. 1.4. Variation in UCS with W-D cycles for untreated and lime precipitation treated specimens (S1–S5) by Thyagaraj and Zodinsanga (2014).

ElKady et al. (2015) evaluated the intermittent wetting effects on lime-treated expansive soils. The study revealed that strength reductions occurred consistently with repeated W-D cycles. The authors stressed that cyclic moisture exposure weakens lime-treated soils, necessitating alternative approaches for improving their durability under field conditions.

Anggrainai et al. (2016) investigated the performance of lime-treated clay under cyclic moisture changes (5 W-D cycles), concluding that while stabilization improved initial UCS,

the soil exhibited gradual softening over time. Their results (Tab 1.3) showed that soils with higher clay content were more susceptible to UCS reduction, suggesting the need for supplementary stabilizers to enhance durability.

Tab. 1.3. Unconfined Compressive Strength after Wetting and Drying by [Anggrainai et al. \(2016\)](#)

Number of cycles	UCS (kPa) for specimens				
	S	L _c	L _c F	L _c FF	L _c AF
0	600	780	880	1400	1600
1	400	830	920	1400	1600
2	200	860	923	1440	1850
3	Ruin	700	1000	1510	1940
4	-	600	1030	1560	2100
5	-	500	1040	1600	2130

Note : UCS : Unconfined Compressive Strength ; S : soil ; L_c : Limed soil ; L_cF : Limed soil treated fiber ; L_cAF : Limed soil treated fiber

[Hasan et al. \(2017\)](#) assessed UCS variations in lime-stabilized soils subjected to wet-dry cycles, noting a significant reduction after the first few cycles. The findings (Tab 1.4) highlighted that soil composition influenced strength retention, with lime-treated sandy clays performing better than highly plastic clays under moisture fluctuations.

Tab. 1.4. The value of UCS after different wetting-drying cycles. ([Hassan et al., 2017](#)).

Number of cycles	UCS (kPa)	
	Soil+6.25% L _c	Soil+6.25% L _c +18.75 BA
0	976	1079
1	927	993
2	869	982
4	712	939
7	634	745
10	410	980

Note : UCS : Unconfined Compressive Strength ; L_c : Lime additive ; BA : Bagasse ash

[Chittoori et al. \(2018\)](#) evaluated the durability of lime and lime-fly ash stabilized expansive clays under twelve W-D cycles. Their results showed that lime-only treated soils experienced a UCS reduction of approximately 40–50%, whereas lime-fly ash stabilized soils maintained about 70% of their original strength. The authors attributed this improved behavior to the

additional pozzolanic reaction induced by fly ash, which helped resist the detrimental effects of cyclic moisture variations. Fig 1.5 in their study visually confirmed this trend, showing a steady decline of UCS for lime-only mixtures, while lime-fly ash samples showed superior retention.

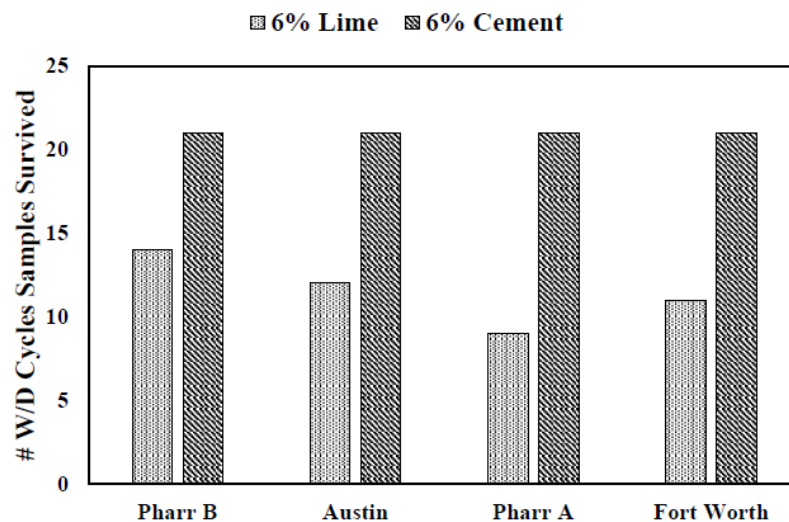


Fig. 1.5. Effect of additive type on the W-D performance of chemical stabilization (Chitoori et al., 2018).

Maafi et al. (2020) examined the performance of lime-stabilized clayey soils subjected to wet-dry cycles and reported notable strength reduction patterns. From Fig 1.6, the UCS decreased gradually with each cycle, and after 12 cycles, the reduction reached up to 50% of the initial UCS.

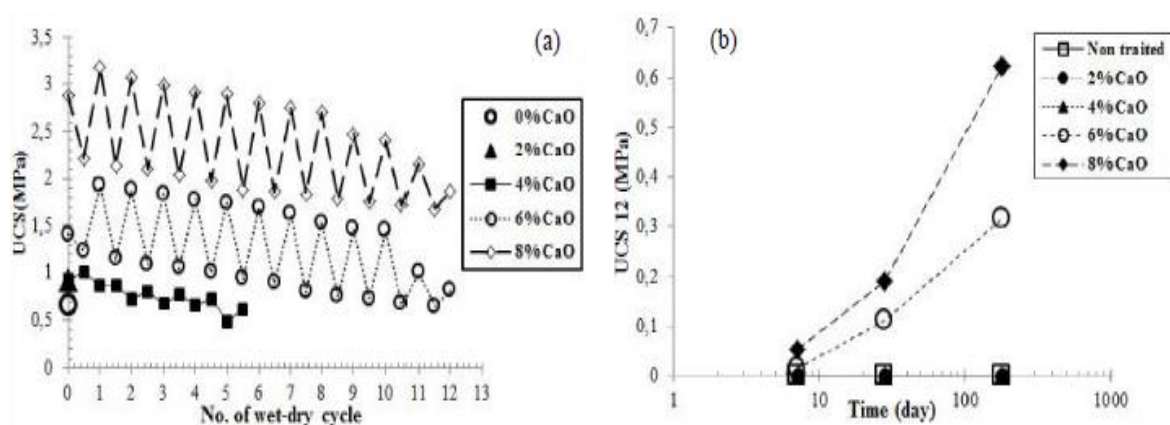


Fig. 1.6. UCS vs W-D cycles : (a) after 180 days of curing, and (b) after 7, 28 and 180 days, Maafi et al (2020).

The study pointed out that while lime effectively increases strength through pozzolanic reactions, prolonged cycling leads to degradation of cemented bonds due to leaching and

shrinkage cracking. The authors emphasized that maintaining durability under cyclic conditions remains a challenge for lime-treated soils.

Cuisinier and Masrouri (2020) compared two W-D testing protocols and found that lime-treated silty soils exhibited varying strength losses depending on the aggressiveness of the protocol (Fig 1.7). The ASTM D559 based cycles caused higher UCS degradation than controlled relative humidity cycles, indicating that test method selection plays a critical role in durability evaluation.

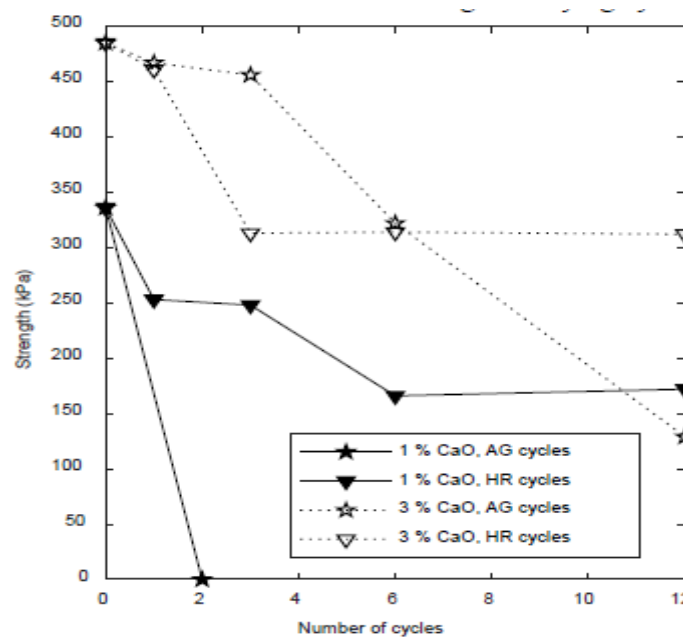


Fig. 1.7. Evolution of strength as a function of the number of W-D cycles by Cuisinier and Masrouri (2020).

Harichane et al. (2010) examined how repeated wetting and drying cycles affect clayey soils treated with lime and natural pozzolana combinations. Their research demonstrated a stark contrast in performance between treated and untreated materials. While untreated soils or those stabilized with single additives experienced severe deterioration and often completely disintegrated before reaching 12 cycles, the lime-pozzolana combination showed remarkable durability throughout the entire testing period with minimal mass loss (Fig 1.8).

The combined treatment not only preserved soil integrity but also maintained unconfined compressive strength values that exceeded initial measurements, indicating that beneficial pozzolanic reactions continued during the cycling process. The study revealed that soil type significantly influenced performance, with low-plasticity red clay responding better to

treatment than high-plasticity grey clay, emphasizing the importance of soil mineralogy in stabilization effectiveness.

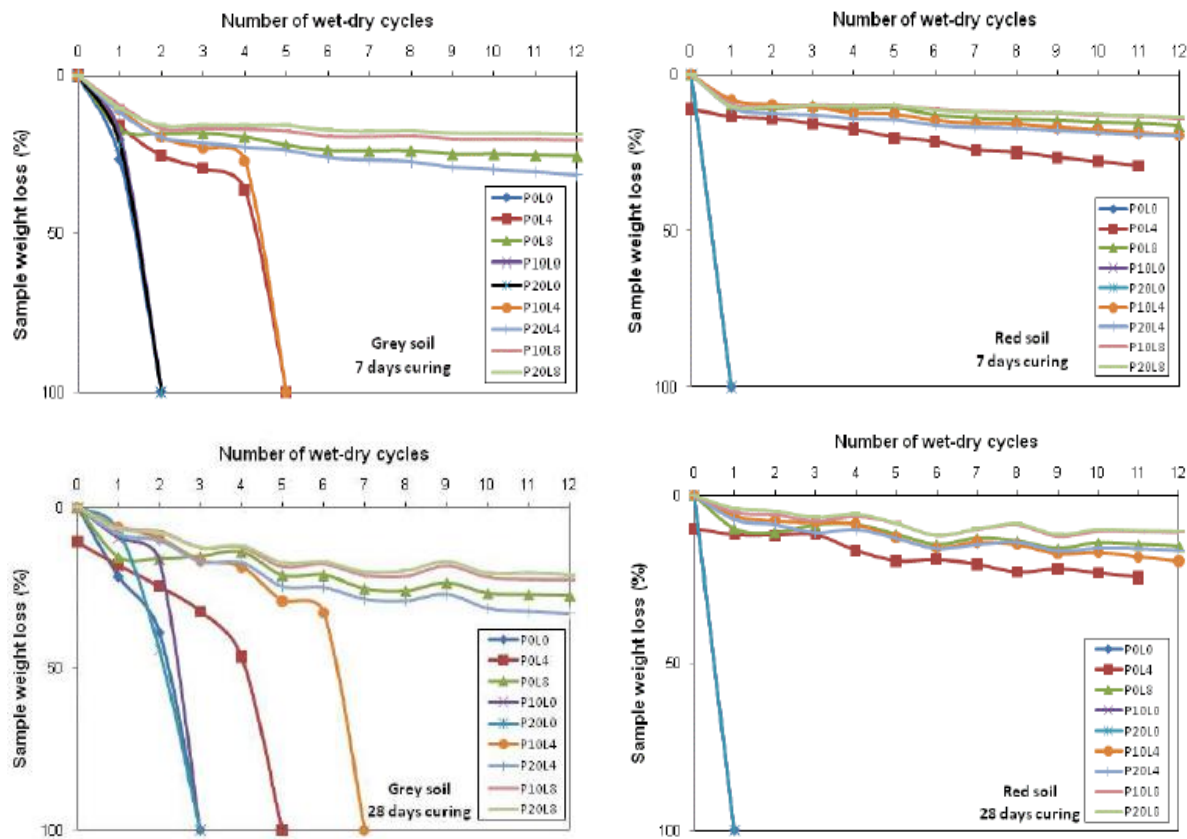


Fig. 1.8. Mass loss during W-D durability testing of soils after 7-day and 28-day curing periods (Harichane et al., 2010).

1.3.5 Effect of organic matter and sulfate content in soil stabilization

Organic matter creates significant obstacles to lime stabilization by altering soil engineering properties and consuming essential stabilizing agents. Organic clays retain excessive moisture, increasing optimum moisture content and reducing maximum dry density while consuming calcium ions critical for lime reactions (Saride et al., 2013). Research demonstrates that lime treatment becomes ineffective when organic content exceeds 1.5%, as decomposing biomass lowers soil pH and prevents proper cementitious gel formation (Thompson, 1966; Yunus et al., 2016).

Sulfate-bearing soils pose complex challenges through the formation of expansive minerals like ettringite and thaumasite that cause temperature-dependent heaving and reduced bearing capacity. When soluble sulfate content exceeds 1%, these reactions significantly compromise

structural stability, with swelling rates peaking during summer conditions (Hunter, 1988; Little et al., 2009; Rollings et al., 1999). However, extended curing periods can help mitigate expansion as cementitious compounds gradually coat ettringite crystals and prevent water infiltration (Jha and Sivapullaiah, 2016).

1.4 Soil stabilization using Fly ash

Fly Ash (FA), a byproduct of coal combustion, presents unique geotechnical properties with significant potential for soil stabilization. Characterized by spherical particles ranging from 1-50 μ m in diameter, FA is classified into two primary types: Class-F (FFA) and Class-C (CFA), differentiated by chemical composition and coal source (Cokca, 2001 ; ASTM C618-17, 2017). Predominantly composed of silica, alumina, and trace oxides, FA particles exhibit non-plastic characteristics with high specific surface area, enabling effective soil modification strategies (Yarbasi et al., 2007). CFA contains a higher proportion of lime, CaO (>20%), higher alkali and sulfate contents. The total of Al_2O_3 , SiO_2 and Fe_2O_3 presented in this type of FA is in the range of about 50% to 70%. On the other hand, FFA generally contains less lime (<10%), and the amount of $\text{Al}_2\text{O}_3 + \text{SiO}_2 + \text{Fe}_2\text{O}_3$ exceeds 70% (ASTM C618-15, 2015).

Researchers have extensively documented FA's versatile stabilization capabilities, highlighting its economic and environmental advantages over traditional chemical additives. Tastan et al. (2011) categorized CFA's benefits into three key areas: acting as a drying agent, controlling volume instability, and improving soil strength through pozzolanic reactions. High-calcium CFA, in particular, has been recognized by numerous studies (Misra, 1998; Nalbantoglu, 2004; Edil et al., 2006) as a superior stabilizing agent for expansive soils. When water is present, CFA forms cementitious compounds that enhance soil mechanical properties, whereas FFA requires additional activators like lime or cement to achieve similar results (Das and Parhi, 2006; Moghal, 2017).

1.4.1 Effect of water content on fly ash-soil stabilization

Moisture content during molding plays a pivotal role in FA-treated soil performance. Research consistently shows that regardless of FA content, strength and stability decrease with increasing molding water content (Misra et al, 2005). The optimal strength is achieved when samples are molded at 4-8% below Optimum Moisture Content (OMC). Additionally, Edil et al. (2006) found that clay-FA mixtures with 10% Class C Fly Ash (CFA) and water

content 7% above OMC showed reduced resilient modulus compared to soil compacted at OMC, though higher CFA contents (>18%) maintained improved properties even at elevated moisture levels.

1.4.2 Effect of freeze-thaw on fly ash soil stabilization

Solanki et al. (2013) examined chloride saline soil improved with fly ash and found that fly ash reduced soil porosity and enhanced strength, though the unconfined compressive strength (UCS) decreased by approximately 30% after multiple F-T cycles. Similarly, Yang et al. (2020) demonstrated that fly ash hydration products formed dense structures, mitigating F-T damage, but the stabilized soil still experienced a 20-25% strength reduction after five cycles. These studies highlight fly ash's partial effectiveness (Fig 1.9), which motivated the exploration of combined additives to achieve better F-T resistance (Li et al., 2022).

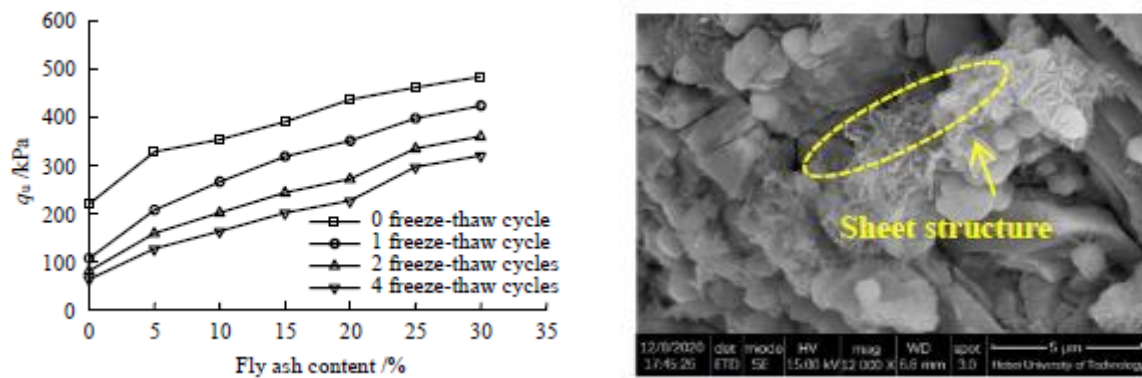


Fig. 1.9. Strength distribution and SEM of fly ash- soil with F-T cycles (Li et al., 2022).

Bin-Shafique et al. (2010) investigated the long-term performance of fly ash-stabilized soils (soft soil and expansive soil) subjected to 12 F-T cycles. Their unconfined compression tests revealed that while untreated soils exhibited low strength, the fly ash-stabilized specimens lost up to 40% of their strength after F-T exposure.

Notably, even after degradation, the stabilized soils maintained at least triple the strength of the untreated soils. Key results, including soil properties (plasticity index, UCS and vertical swell), are detailed in Tab. 1.5.

Tab. 1.5. Properties of fly ash stabilized soils before and after weathering action (Bin-Shafique et al., 2010).

		Soft soil + FA(%)				Expansive soil + FA(%)			
		0%	5%	10%	20%	0%	5%	10%	20%
Plasticity Index	After stabilization and before weathering	26	18	16	12	57	32	27	26
	After W-D cycles	26	18	15	11	58	29	26	23
	After W-D cycles (saline water)	19	15	11	8	46	24	19	17
	After F-T cycles	26	17	15	13	57	33	27	25
UCS (Kpa)	After stabilization and before weathering	212	520	713	804	180	364	456	567
	After W-D cycles	180	577	470	934	174	381	479	597
	After W-D cycles (saline water)	162	480	442	852	191	386	490	618
	After F-T cycles	136	389	456	685	94	211	304	347
Vertical swell (%)	After stabilization and before weathering	NA	NA	NA	NA	17.2	9.8	5.5	4.1
	After W-D cycles	NA	NA	NA	NA	16.9	10.2	5.6	4.3
	After W-D cycles (saline water)	NA	NA	NA	NA	14.3	8.1	4.6	3.8
	After F-T cycles	NA	NA	NA	NA	19.9	11.2	6.4	5.5

Note : UCS : Unconfined Compressive Strength ; NA : Not Available.

Sezer et al. (2017) explored the durability of sand–bentonite mixtures stabilized with class C fly ash under freeze–thaw cycles, which simulate wet–dry environmental effects. The results showed that specimens stabilized with fly ash experienced a gradual reduction in strength and visible mass loss as the number of cycles increased. Lower fly ash content (e.g., 3% and 6%) was less effective in resisting deterioration, leading to notable surface cracking and structural breakdown as shown in Fig 1.10.

However, higher fly ash dosages (9%) offered better protection due to enhanced pozzolanic bonding and matrix formation. Despite improvements, fly ash-stabilized samples were generally less durable than cement-treated ones under repeated cycles, highlighting the need for optimal dosages in durability-critical applications.

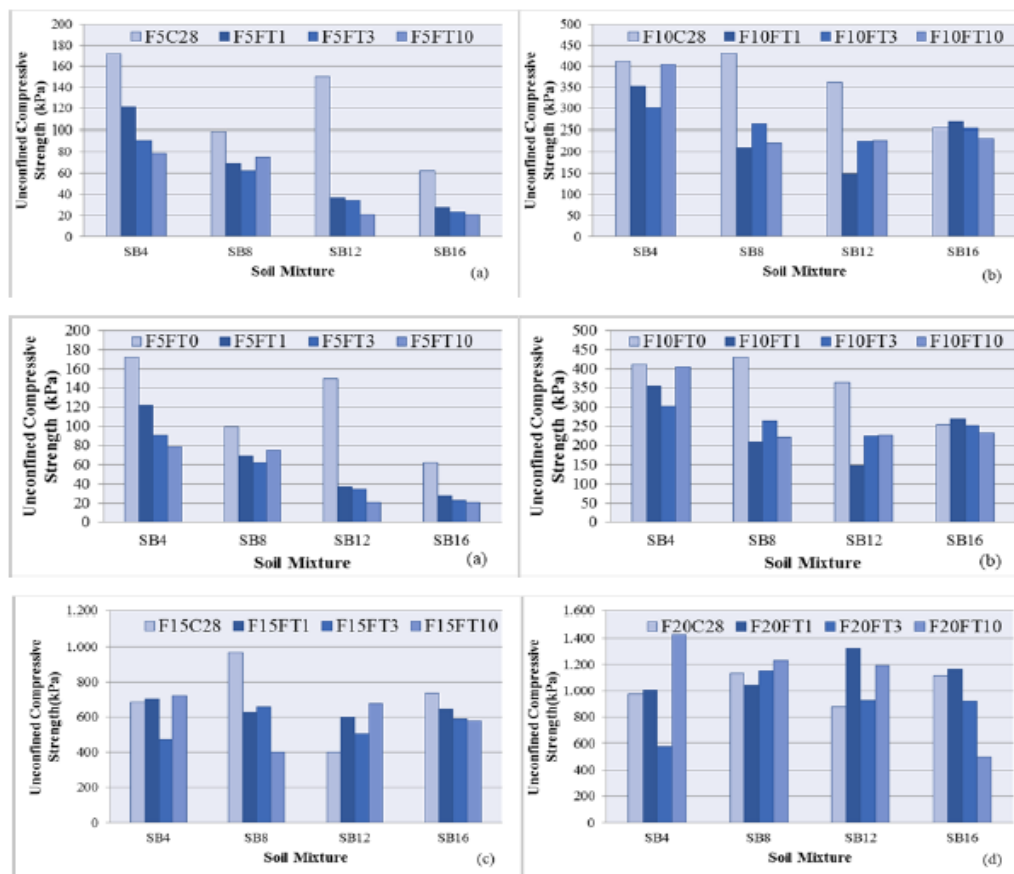


Fig. 1.10. Variation of UCS for specimens stabilized with fly ash at (a) 5%, (b) 10%, (c) 15%, and (d) 20% content (Sezer et al., 2017).

Wen et al. (2011) assessed the use of high-carbon fly ash in stabilizing recycled pavement materials, incorporating F-T durability tests in their experimental design. Their study showed that the addition of fly ash enhanced the UCS and durability of the base material even under cyclic freezing and thawing. The reported UCS values are referenced in Tab. 1.6.

Tab. 1.6. UCS of Fly Ash Mixtures Subjected to Freeze–Thaw Cycles (Wen et al., 2011).

Soil	Fly Ash content (%)	q_u (kPa) after Freeze-Thaw cycles	
		0 cycle	12 cycles
Dewey	10	71	NT
	14	NT	68
King	10	540	320
	14	520	510

Note : q_u strength after freeze-thaw cycles

Tab 1.7 presents the quantitative strength degradation of silt specimens stabilized with varying proportions of Class C fly ash (10-30%) and cement (2-8%) after seven freeze-thaw cycles. Specimens containing fly ash alone at 20-30% dosage demonstrated initial strength improvements due to pozzolanic reactions but exhibited significant vulnerability to freeze-thaw degradation, with unconfined compressive strength losses ranging from 25% to 50%. This substantial deterioration is attributed to the slow reaction kinetics of fly ash, which results in incomplete development of cementitious bonds (C-S-H and C-A-H gels) within the 28-day curing period, leaving the microstructure with elevated porosity and insufficient resistance to ice formation and hydraulic pressures during freezing phases (Altun et al., 2009).

Tab. 1.7. UCS of unprotected samples against drying after freezing-thawing cycles process (Altun et al., 2009).

Sample	Unconfined Compressive Strength (kPa)		
	1 cycle	3 cycles	7 cycles
Natural soil	154.01	510.73	1164.54
10 FA	514.70	472.97	487.87
20 FA	1236.08	1806.42	1997.20
2 C	596.18	555.44	667.72
10 FA 2 C	1426.85	1862.06	2025.02
10 FA 8 C	1212.23	1939.57	2122.40
30 FA 2 C	1864.05	2348.94	2706.65

Note : FA : Fly Ash ; C : cement

Fig 1.11 illustrates the critical influence of moisture protection during curing on the freeze-thaw durability of stabilized specimens by Altun et al. (2009). Specimens that received adequate moisture protection during the 28-day curing period through plastic wrapping or humidity-controlled storage exhibited substantially lower strength losses compared to unprotected specimens exposed to ambient atmospheric conditions. This finding emphasizes that proper moisture retention during early-age hydration is essential for developing robust pozzolanic and cementitious bonds, and that inadequate curing conditions can severely compromise the microstructural integrity and long-term durability of fly ash-stabilized soils subjected to environmental cycling.

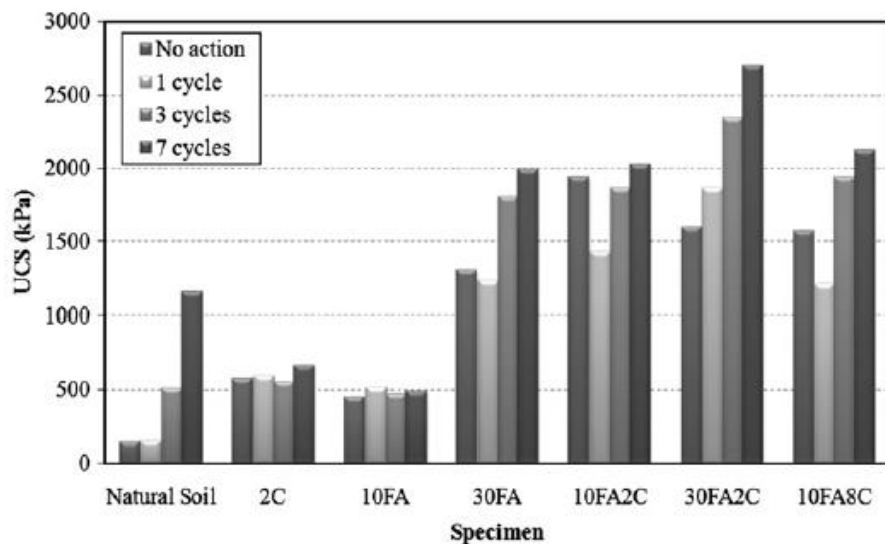


Fig. 1.11. Variation of unprotected sample strength values by number of F-T cycles(Altun et al.,2009).

Dayioglu et al. (2017) found that UCS of Belle Fourche clay stabilized with Class C fly ash increased after 2 F-T cycles (from 600 kPa to 700 kPa) but declined after 4 and 8 cycles (500 kPa), attributed to initial pozzolanic acceleration followed by bond degradation (Fig 1.12). Class F fly ash mixtures showed consistent UCS reduction (from 400 kPa to 200 kPa after 8 cycles), reflecting its lower content and weaker cementation. Lime- exhibited minimal F-T impact due to rapid cation exchange, maintaining UCS above untreated clay. The study concluded that additives with higher CaO ratios better resisted F-T-induced strength loss.

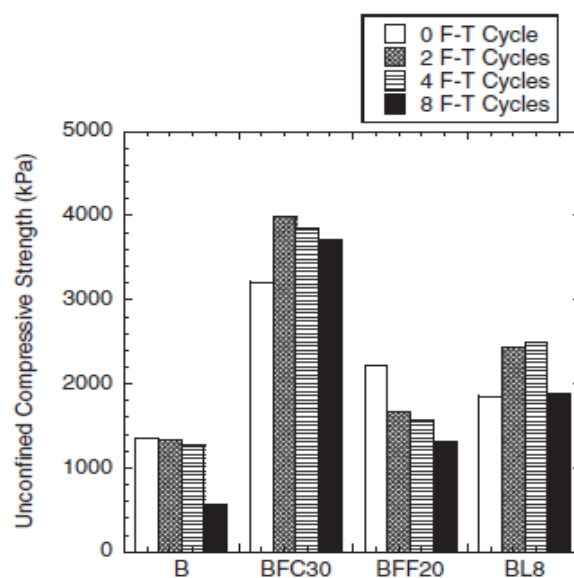


Fig. 1.12. UCS of soil and stabilized soil-additive mixtures under F-T cycles (Dayioglu et al., 2017).

[Li et al. \(2018\)](#) demonstrated that F-T cycles reduced the UCS of compacted loess by 12.4% (from 228.6 to 200.3 kPa) after 10 cycles, significantly less than the 59.9% reduction caused by wetting-drying (W-D) cycles. The elastic modulus also declined by 16%, while cohesion dropped by 21%, with negligible impact on the internal friction angle. Microstructural analysis revealed that ice-induced pore expansion and particle rearrangement drove these changes, though the closed-system F-T tests (limited water migration) mitigated damage compared to W-D cycles. The study underscored loess's greater sensitivity to moisture than temperature, aligning with prior findings on fly ash-stabilized soils ([Solanki et al., 2016](#)).

Research findings on F-T effects show interesting variations. [Yan et al. \(2017\)](#) observed that Class C fly ash-stabilized soils exhibited increased UCS after 12 F-T cycles due to ongoing pozzolanic reactions during thawing. Conversely, [Solanki et al. \(2013\)](#) reported significant UCS reductions (up to 70%) in expansive soils stabilized with high-carbon fly ash, attributing the decline to microstructural damage from ice lens formation. These contrasting outcomes highlight the influence of fly ash composition and soil type on F-T durability.

[Rosa et al. \(2016\)](#) demonstrated that fly ash stabilization generally improved the UCS of clayey soils post-F-T cycles, though reductions occurred in some mixtures. For example, Lawson clay stabilized with Columbia fly ash retained 87% of its UCS after 5 cycles, while Dewey fly ash mixtures showed a 13% reduction ([Fig 1.13](#)). The study attributed these variations to differences in fly ash cementation potential and closed-system conditions limiting moisture ingress.

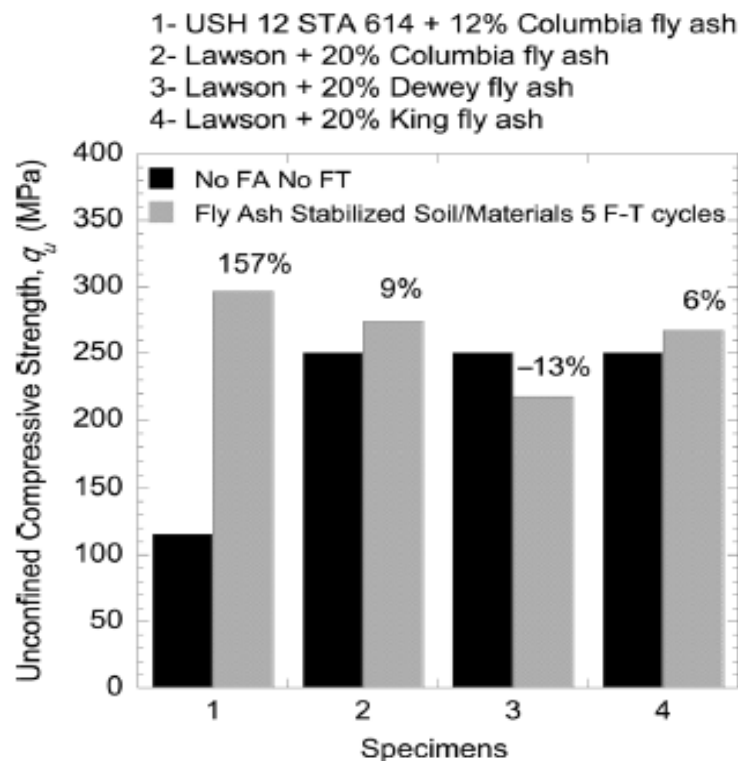


Fig. 1.13. UCS of unfrozen unstabilized soils compared with stabilized soils after F-T cycles (Rosa et al., 2016) .

1.4.3 Effect of wet-dry on fly ash soil stabilization

Multiple studies on fly ash-stabilized soils under wet-dry conditions reveal a consistent pattern: fly ash significantly improves soil strength and resilient modulus, particularly in clayey soils, but this improvement diminishes with repeated wet-dry cycling. Research by Khoury and Zaman (2003), Yan et al. (2017) and Misra (1998) demonstrates that while higher fly ash content ($\geq 12\text{-}16\%$) provides better resistance to moisture damage, wet-dry cycles eventually cause microcracking and strength reduction due to the breakdown of pozzolanic bonds. This degradation can reduce unconfined compressive strength by up to 30% (Tab. 1.8).

Tab. 1.8. Strength and pore distribution test results under wet-dry cycling conditions (Yan et al., 2017).

Time of W-D cycle	UCS (MPa)	Total pore volume (ml/g)	Large pore volume (ml/g)	Medium pore volume (ml/g)	Small pore volume (ml/g)	Micropore volumes (ml/g)
0	2.13	0.2001	0.0042	0.0231	0.0495	0.1233
1	1.61	0.2016	0.0107	0.0248	0.0477	0.1184
2	1.45	0.2095	0.0063	0.0294	0.0526	0.2095
3	1.58	0.2055	0.0141	0.0239	0.0498	0.1177
4	1.53	0.2099	0.0182	0.0204	0.0512	0.1201
5	1.61	0.2135	0.0204	0.0167	0.0511	0.1253
6	1.54	0.2071	0.0189	0.0194	0.0507	0.1181
7	1.56	0.2277	0.0248	0.0310	0.0483	0.1236
8	1.57	0.2187	0.0271	0.0228	0.0481	0.1207
9	1.54	0.2342	0.0308	0.0373	0.0492	0.1169
10	1.52	0.2383	0.0307	0.0377	0.0501	0.1198

Note : UCS : Unconfined Compressive Strength (MPa)

Comparative studies indicate that fly ash stabilization generally outperforms enzymatic treatments and liquid stabilizers (Rauch et al., 2002) in maintaining strength under wet-dry conditions, though it's less durable than cement stabilization (Prusinski and Bhattacharja, 1999). For optimal performance, emphasize the importance of proper compaction, curing, and drainage to mitigate moisture susceptibility. Despite its limitations, fly ash remains cost-effective for moderate durability requirements, especially in climates with intermittent wetting as noted by Arabi et al. (1989).

Hoover et al. (1958) studied the impact of wet-dry cycles on soil-lime-fly ash mixtures compacted above Standard Proctor density, showing that these treatments significantly improved UCS durability. After 12 W-D cycles, properly stabilized soils retained most of their strength, especially when high compaction and fly ash contents were used. The degradation in UCS was more noticeable in clayey soils compared to silts, due to their higher moisture susceptibility. UCS retention ratio across cycles, indicating that mixes with 8–12% fly ash and 3% lime maintained over 75% strength. Their early findings remain relevant today, emphasizing the need for optimal mix design to ensure long-term durability.

Medhani (1982) presented early yet detailed insights into the durability of fly ash-lime stabilized soils. They reported that Class F fly ash, when combined with lime and gypsum, initially produced a significant UCS increase due to long-term pozzolanic activity. However, after 6 W-D cycles, UCS values showed a 30–50% reduction, especially in samples with

lower lime content. UCS degradation trend across cycles and indicates that higher lime dosage improved residual strength. Their work established a foundational understanding of how additive proportions directly influence W-D durability in stabilized soils.

Li et al. (2018) investigated lime-stabilized soils under up to 10 W-D cycles and observed an initial UCS gain in the first three cycles due to ongoing pozzolanic reactions, followed by a notable decline thereafter. By the 10th cycle, UCS had dropped by more than 35%, primarily due to micro-crack formation and structural weakening (Fig 1.14). The study clearly depict this UCS trend and pore structure expansion over time. Their SEM analysis revealed larger voids and disrupted gel phases after several cycles, reinforcing that microstructural deterioration plays a key role in strength loss.

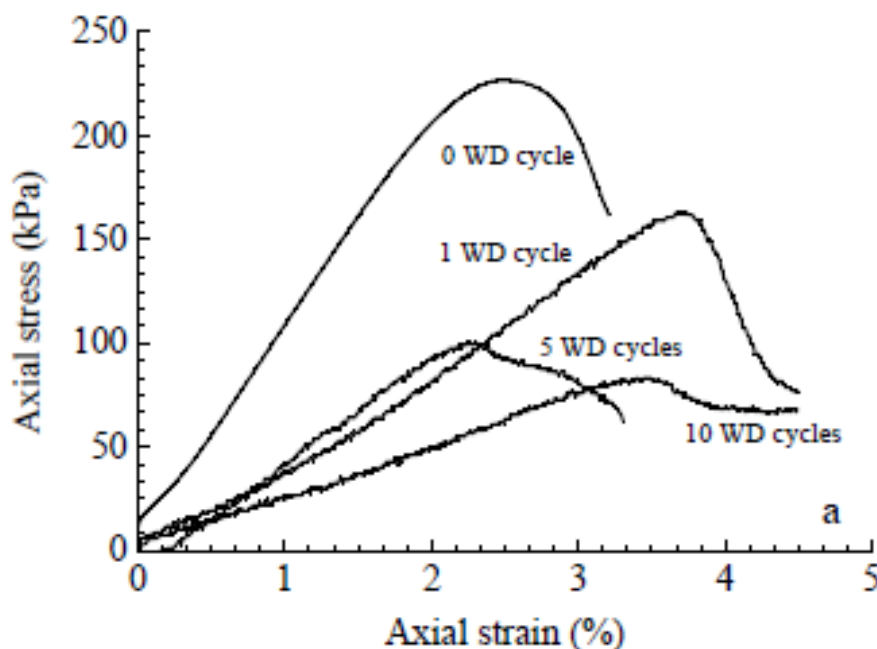


Fig. 1.14. Stress–Strain Behavior of Compacted Loess Under Varying Intensities of W-D Weathering (Li et al., 2018).

1.4.4 Effect of organic matter and sulfate content in soil stabilization

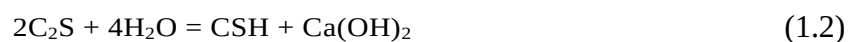
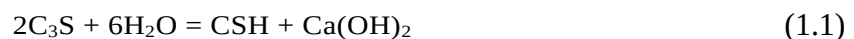
Organic matter presence significantly complicates Fly Ash soil stabilization by interfering with essential chemical processes. Research by Horpibulsuk et al. (2009) demonstrates that organic materials adsorb calcium ions, limiting their availability and reducing pozzolanic activity. This interaction leads to increased liquid and plastic limits while adversely affecting soil strength, with Tastan et al. (2011) observing an exponential decrease in strength as

organic content rises. Advises against using FA in organic-rich expansive soils due to insufficient lime content, though off-specification FA, with its higher CaO/SiO₂ ratio, may achieve modest stabilization results.

The sulfate content in Class C Fly Ash (CFA) introduces complex chemical dynamics in soil stabilization. While CFA can potentially form ettringite in alkaline conditions (Dean et al., 2009), its addition to lime-treated clay can actually reduce ettringite-induced swelling to manageable levels below 5%. This reduction occurs as FA's silica competes with ettringite formation for calcium ions. However, caution that high-sulfate FA can exacerbate ettringite formation in lime-treated expansive soils, making careful material selection crucial for controlling sulfate-induced swelling (Dermatas and Meng, 2003).

1.5 Soil stabilization using Cement

Ordinary Portland Cement (OPC) has emerged as a prominent soil stabilizer over the past century, distinguished by its widespread availability and rapid strength development capabilities (Estabragh et al., 2014). The material consists of four primary oxides: tricalcium silicate (C₃S), di-calcium silicate (C₂S), tricalcium aluminate (C₃A), and tetra calcium aluminoferrate (C₄AF). When mixed with clay and water, these compounds undergo hydration reactions (as shown in Eq 1-1 and 1-2), producing cementitious compounds like calcium silicate hydrate (CSH) and calcium aluminum hydrate, which significantly enhance soil strength (Prusinski and Bhattacharja, 1999; Chew et al., 2004).



The stabilization process involves multiple mechanisms, including hydration, cation exchange, flocculation, and pozzolanic reactions. During hydration, C₃S and C₂S react with water, releasing calcium ions and forming cementitious compounds.

This exothermic process generates approximately 120 calories of heat per gram of cement. The hydrated lime produced during these reactions further breaks down into OH⁻ and Ca²⁺ ions, contributing to soil flocculation and enabling additional pozzolanic reactions with soil silica and alumina (Estabragh et al., 2014).

1.5.1 Effect of water-cement ratio on soil-cement stabilization

Research demonstrates that cement-treated soils have optimal water-cement ratios for maximum effectiveness (Muir et al., 2005). When water content is fixed, there's a threshold beyond which additional cement cannot properly hydrate, limiting its contribution to soil strengthening. Complete hydration of Portland cement requires approximately four times more water molecules than cement molecules, making both water content and the water-cement (w/c) ratio fundamental factors in determining the engineering properties of treated clay soils (Hompton and Edil, 1998).

Lower water-cement ratios generally produce superior cementing bonds and higher unconfined compressive strength compared to higher ratios with less cement. Studies show that samples with identical w/c ratios display similar stress-strain behaviors regardless of individual water or cement amounts (Miura et al., 2001; Muir et al., 2005).

However, soil samples prepared at water contents near or above the liquid limit achieve better strength than those formed below this threshold, even with constant cement content (Lorenzo and Bergado, 2006). Additionally, lower w/c ratios enhance viscous resistance, creating more effective impermeable barriers while reducing permanent deformation (Abu-Farsakh et al., 2015).

1.5.2 Effect of temperature on soil-cement stabilization

The curing temperature plays a significant role in the development of soil-cement properties. Zhang et al. (2014) found that elevated temperatures accelerate the formation of Ca(OH)_2 and cementitious gels, enhancing both early strength gain and long-term performance.

This is particularly effective at lower pH levels where increased Ca(OH)_2 production promotes silica and alumina dissolution. According to Wang et al. (2017), specimens showcured at 60°C showed notably higher secant modulus and unconfined compressive strength compared to those cured at 40°C (Fig 1.15), while Chen et al. (2019) observed that higher temperatures led to reduced swelling pressure and pore size in the stabilized soil mass.

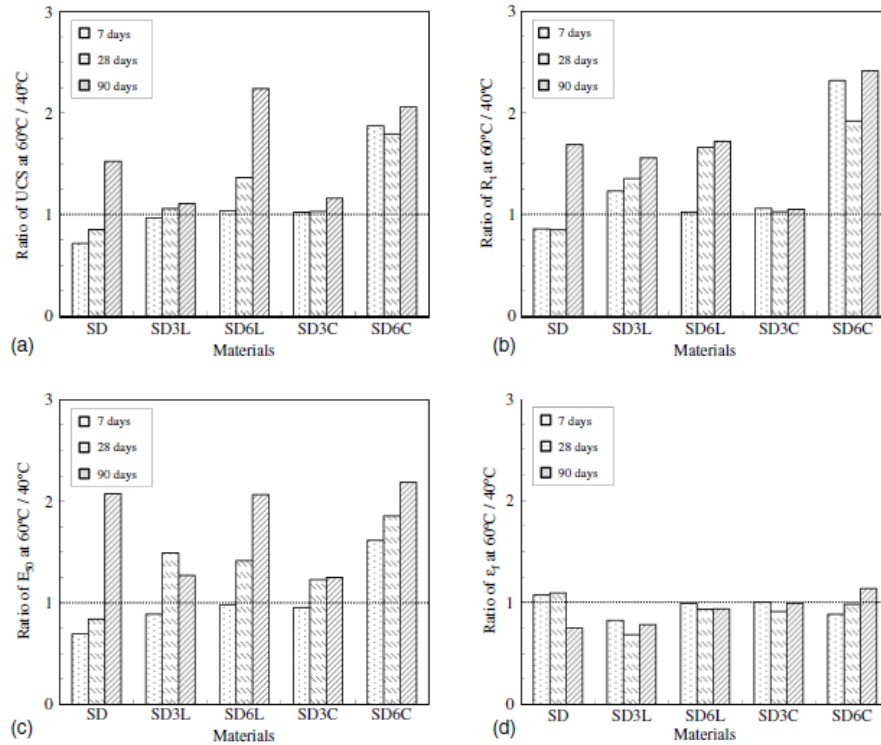


Fig. 1.15. Temperature effect on mechanical properties: ratios of strength, modulus, and strain parameters 40°C vs. 60°C, (Wang et al., 2017)

1.5.3 Effect of freeze-thaw impact on cement-soil stabilization

The resistance to freeze-thaw damage can be enhanced through proper cement content optimization. Lu et al. (2020) demonstrated that adequate cement addition helps maintain strength and resilient modulus despite repeated freeze-thaw cycles. Interestingly, Niu et al. (2024) observed an unexpected phenomenon where dynamic tensile strength showed a slight increase after the third freeze-thaw cycle, attributed to the exposure and subsequent hydration of previously unreacted cement through microcrack formation.

The durability assessment of cement-treated soils against freeze-thaw cycles follows standardized procedures outlined in ASTM D560-03 (2003). This protocol requires specimens to undergo 12 freeze-thaw cycles with prescribed brushing strokes between cycles. The total mass loss for cement-treated high plastic clays should not exceed 7% to maintain acceptable performance standards.

The cyclical process of freezing and thawing significantly impacts the structural integrity of cement-treated soils. As Zhang et al. (2021) explains, when supercooled water expands beyond available void spaces, it forces soil particles apart, leading to reduced density. This phenomenon directly affects the soil's mechanical properties, Eskisar et al. (2015)

documenting progressive strength and stiffness losses as freeze-thaw cycles increase (Fig 1.16).

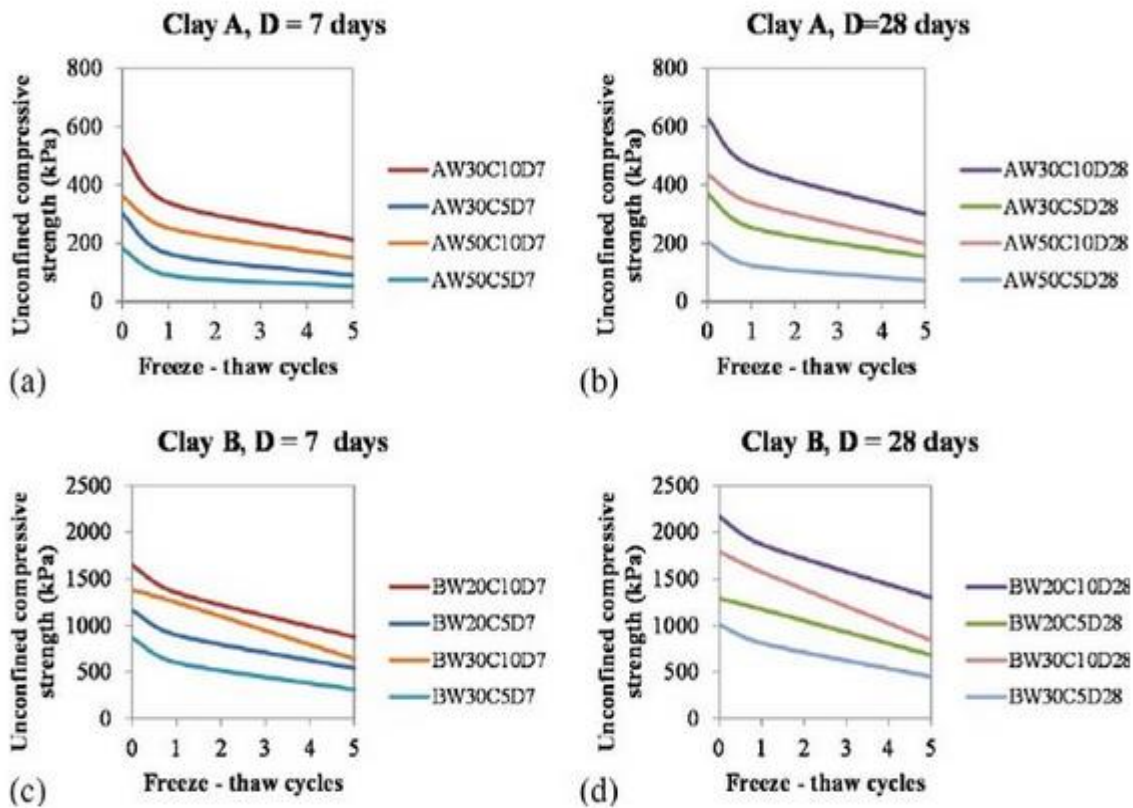


Fig. 1.16. F-T durability: relationship with different curing periods (Eskişar et al., 2015).

1.5.4 Effect of wet-dry on cement-soil stabilization

Cement stabilization remains one of the most effective techniques for improving the mechanical properties and durability of clayey soils subjected to wet-dry (W-D) cycles. Cement rapidly generates calcium silicate hydrates (C-S-H), which strongly bond soil particles and enhance UCS. Studies such as those by Horpibulsuk et al. (2010), Boardman et al. (2001), and Abdallah and Wild (2008) consistently report that while UCS can significantly increase (up to 5–10 times) after stabilization, repeated W-D cycles still induce some strength degradation due to microcracking and volume changes.

Rauchan et al. (2010) demonstrated that cement-treated silty clays maintained more than 70% of their UCS after 10 W-D cycles, especially at 12% cement content. Similarly, Boardman et al. (2001) observed that although UCS decreased by 20–30% after several cycles, samples treated with 8% cement retained structural integrity far better than untreated soils. Their

findings emphasized the importance of initial curing time longer curing improved bond development and reduced cyclic degradation.

Estabragh et al. (2014) reported less than 20% UCS reduction after 12 cycles in sandy-clay soils treated with 10% cement, supporting the argument that cement content and compaction play critical roles. They quantified the energy absorption and strength retention, reinforcing that cement stabilization outperforms lime and fly ash under repeated moisture exposure.

Osinubi and Nwaiwu (2006) also assessed tropical clays and found that UCS dropped below 50% only when cement content was $\leq 6\%$ and W-D cycles exceeded 6 repetitions. They stressed the critical role of soil mineralogy kaolinitic clays performed better than montmorillonitic ones due to lower swelling potential. Similar conclusions were drawn by Zhang and Tao (2008) and Roshan et al. (2022), who emphasized that while cement stabilization is durable, durability performance is sensitive to sulfate presence and freeze-thaw or W-D cycling. (Fig 1.17).

Overall, cement-stabilized soils offer reliable strength and durability when designed with proper cement content (8–12%), adequate curing (≥ 7 days), and attention to soil type. Despite some loss in strength with repeated cycles, cement-treated soils typically outperform other stabilizers in long-term structural integrity.

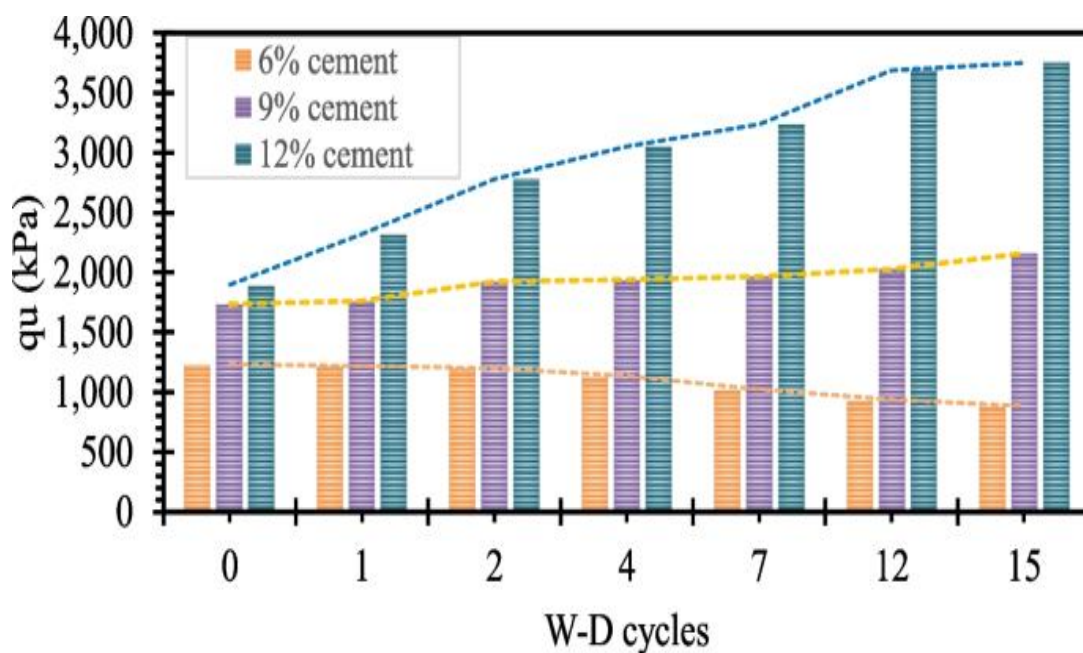


Fig. 1.17. Effect of Wet-Dry Cycling on Clay-Cement Admixture Durability After 7 Days Curing (Roshan et al., 2022).

1.5.5 Effect of organic matter on cement-soil stabilization

Organic matter significantly undermines cement stabilization by interfering with essential chemical processes. These organic compounds consume calcium ions and hydroxide that are critical for cement hydration and pozzolanic reactions, effectively blocking the formation of strong cement-soil bonds (Mitchell et al., 2025). When organic content exceeds 3-4%, strength losses can reach 15-30% for each additional 1% of organic matter, making stabilization increasingly ineffective (Hampton and Edil, 1998). Maintaining highly alkaline conditions or using supplementary materials can help counteract these detrimental effects.

Sulfate contamination causes long-term deterioration through the formation of expansive minerals like ettringite that create internal pressure and cracking in stabilized soils. Field studies document continuous heaving at rates of 0.9-0.13 mm/month, with temperature variations accelerating the damage (Rajasekaran, 2005; Rollings et al., 1999). This degradation increases both permeability and moisture retention while reducing strength, creating a cycle where more water infiltration promotes further sulfate reactions and continued deterioration over time.

While lime, fly ash, and cement are the most common soil stabilizers, researchers have investigated several other mineral-based options to improve clay soil performance under changing environmental conditions. Lime kiln dust (LKD), which comes from lime manufacturing waste, works similarly to quicklime by triggering chemical reactions that strengthen expansive clays and boost their compressive strength. Ground granulated blast furnace slag (GGBS) acts as a hydraulic binder that becomes particularly effective when mixed with alkaline materials, showing strong resistance to damage from repeated wetting and drying cycles (Estabragh et al., 2014). Silica fume and nano-silica particles are extremely fine materials with large surface areas that help pack soil particles more tightly together, creating strong gel-like compounds that protect against freeze-thaw damage by reducing pore spaces where ice can form and cause cracking (Zhang et al., 2020).

Gypsum presents an interesting case - while it can cause problematic swelling when combined with lime in sulfate-rich soils, it can be useful in controlled applications where it forms protective crystalline structures that resist wetting-drying damage when properly contained by other cementing materials (Jha and Sivapullaiah, 2016). Non-mineral additives like polymers and enzymes create flexible frameworks that help prevent crack formation during environmental stress cycles (Petry and Little, 2002). However, these alternative

stabilizers face significant challenges when soils contain high levels of organic matter or sulfates, which interfere with the chemical bonding processes and can actually weaken the soil or cause deterioration over time ([Barman and Dash, 2022](#)). Success with these materials depends heavily on understanding the specific soil composition, ensuring additive compatibility, and following proper mixing and curing procedures. [Tab 1.9](#) provides a comprehensive summary of these and other important mineral additives and their effects on compressive strength under various environmental conditions based on published research literature.

Tab. 1.9. Summary of additional important minerals affecting compressive strength under environmental conditions from published literature

Author	Model testing	Additives used	Propoerty research	Research findings
Sumi et al. (2018)	Experimental Investigation and Model Testing of Durability Studies of Surface-Modified Coir Geotextiles	Coir Fiber ;Geotextile	UCS	Testing at different pH levels revealed that solution acidity significantly affects material strength loss, with pH being a critical factor in degradation. However, exposure to salt water, wet-dry cycling, and freeze-thaw conditions had minimal impact on geotextile tensile strength properties.
Wei et al. (2018)	Laboratory Study on Lime-Fiber Stabilization of Soils	Lime- Fiber	UCS and Shear strength	Lime and fiber addition significantly increased both friction angle and cohesion values, consequently enhancing the soil's shear strength properties.
Aryal et al. (2020)	Experimental Investigation of Clay Soil Stabilization Using Cement and Polypropylene Fiber	Cement and Polypropylene Fiber	UCS	Cement and polypropylene fiber addition enhances soil strength by improving resistance to temperature variations under wet and dry environmental conditions.
Rajae et al. (2025)	Laboratory Study of clayey soil stabilized using PPFreinforced with alkali-activated fly ash under F-T cycles	Polypropylene– Fiber ; Fly ash	UCS	Soil strength initially improved during early freeze-thaw cycles before declining in later cycles. Polypropylene fiber addition enhanced freeze-thaw resistance, with alkali-activated fly ash providing optimal durability.
Goathanan et al. (2021)	Laboratory Investigation of W-D Behavior of Lime and Alkaline Activation Stabilized Marine Clay Reinforced with Modified Coir Fiber	Coir fiber ; Lime ; Fly ash ;	UCS	Lime and alkali-activated stabilized soils experienced strength loss after extended curing due to weakened chemical bonds and moisture effects during environmental cycling freeze-thaw and wet-dry.

1.6 Conclusions

This chapter critically evaluated the performance of lime, fly ash, and cement as stabilizing agents for clayey soils subjected to varying environmental conditions. The findings emphasize that the choice and combination of these additives must be tailored to specific soil types and durability requirements. Each additive offers distinct benefits and trade-offs in terms of mechanical performance, environmental resilience, and long-term stability. Based on the reviewed data, the following conclusions are presented:

- Lime is most effective for high-plasticity clay soils, where it enhances workability and long-term strength through pozzolanic reactions, although its performance under extended freeze–thaw or wet–dry cycles may be moderate unless supplemented;
- Fly ash is a sustainable, low-cost additive that improves soil behavior through cementitious bonding but shows variability under environmental cycling; its performance depends on class type, dosage, and the presence of activators such as lime or cement;
- Cement consistently provides the highest unconfined compressive strength and durability under freeze–thaw and wet–dry conditions, due to its rapid hydration and the formation of dense, resilient matrices;
- The performance of each stabilizer under thermal cycling conditions reveals the importance of selecting additives based not only on soil classification but also on anticipated environmental stressors;
- Successful stabilization depends on optimizing multiple factors, including additive content, curing time, soil type, moisture conditions, and expected exposure to freeze–thaw or wet–dry cycles;
- Field application should be preceded by laboratory testing and supported by predictive modeling tools to ensure performance expectations are met, especially in infrastructure subjected to long-term environmental loads

The following chapter provides a comprehensive synthesis of existing research on predictive modeling approaches and artificial neural network applications documented in the literature for assessing durability performance of stabilized clayey soils. This review specifically examines published studies focusing on unconfined compressive strength prediction models for clay soils treated with various mineral additives including lime, fly ash, cement, and other stabilizing agents. The chapter analyzes the methodological approaches, model architectures,

and performance metrics reported across different research efforts, establishing the current state of knowledge in predictive modeling for soil stabilization applications and identifying gaps that warrant further investigation.

Chapter 2

*Predictive Modeling Durability of Stabilized-Soils :
Previous Studies*

2.1 introduction

Infrastructure built on clayey soils faces significant challenges when subjected to harsh environmental conditions, making soil stabilization a crucial engineering practice. Engineers commonly use mineral additives like lime, cement, and fly ash to enhance soil strength and durability, particularly in regions experiencing freeze-thaw cycles ([Dunlap et al., 1975](#); [Wen et al., 2011](#)).

Most existing research has focused on developing prediction models for stabilized soils under standard laboratory conditions. Researchers have created various empirical approaches to estimate soil strength based on factors such as additive content, curing time, and initial soil properties ([Thompson and Dempsey, 1977](#); [Solanki, 2010](#)). These conventional models have provided useful understanding of how different stabilizers affect soil behavior and have guided engineering practice for decades ([Al-Kiki et al., 2011](#); [Consoli et al., 2017](#)).

However, a significant limitation exists in current modeling approaches. The available prediction models do not account for environmental stresses, particularly freeze-thaw cycling, which can dramatically alter soil performance. This gap occurs because researchers have not developed sufficient experimental data under these challenging conditions. Parameters like moisture content, compaction effort, and additive dosage become even more critical when soils experience repeated freezing and thawing ([Sezer et al., 2017](#)).

Recent advances in computational methods have introduced new possibilities for soil behavior prediction. Machine learning (ML) techniques and artificial neural networks (ANN) now allow researchers to analyze complex relationships between multiple soil parameters more effectively ([Sihag et al., 2019](#); [Muhmed et al., 2022](#)). These modern approaches can potentially handle the intricate interactions that occur when environmental factors are considered.

This chapter examines both traditional empirical models and contemporary artificial intelligence approaches used to predict unconfined compressive strength and durability of stabilized clayey soils. The review establishes the foundation for developing more comprehensive prediction models that incorporate environmental conditioning effects, addressing a critical need in geotechnical engineering practice.

2.2. Predictive models of stabilized clayey soils

The literature review reveals that existing predictive models and artificial neural network (ANN) approaches developed by researchers focus exclusively on predicting the unconfined compressive strength (UCS) of clayey soils stabilized with mineral additives under standard laboratory conditions. However, a critical gap exists in the current body of knowledge: none of these models incorporate the effects of environmental conditions, particularly freeze-thaw and wet-dry cycles, on the UCS behavior of stabilized clayey soils. This limitation stems from the absence of comprehensive studies that address the performance of mineral-stabilized clayey soils under these harsh environmental conditions.

2.2.1. Predictive Models for Lime-Stabilized Soils

Understanding the relationship between key influencing factors and the unconfined compressive strength (UCS) of lime-stabilized clayey soils is essential for optimizing soil stabilization practices. Numerous researchers have developed empirical models to estimate UCS based on soil properties, lime content, and curing conditions. One notable contribution is the work of [Ghobadi et al. \(2014\)](#), who conducted a comprehensive experimental program on CL-class clayey soils treated with various lime contents and subjected to different curing durations. Their objective was to formulate a predictive relationship using statistical regression techniques.

Through regression analysis, the proposed model that quantifies the UCS (in kPa) as a function of lime content (L_c , in %) and curing time (T , in days). The resulting predictive [Eq 2.1](#) is:

$$UCS = 29.216 \times L_c - 0.146 \times T \quad (2.1)$$

This equation achieved a coefficient of determination $R^2=0.83$ indicating a strong correlation between the input variables and the predicted strength ([Fig 2.1](#)). The model reveals that an increase in lime content positively influences the UCS, while longer curing time slightly reduces the predicted UCS value, possibly due to the linear assumption in the regression framework which may not fully capture the non-linear strength gain typically observed in pozzolanic reactions.

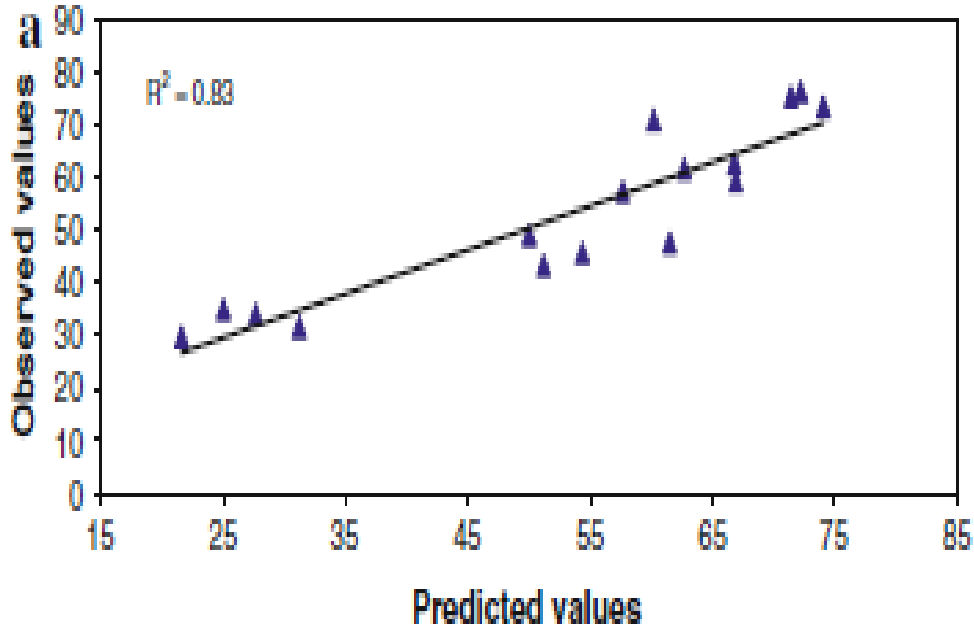


Fig. 2.1. UCS relationship between observed and predicted values by [Ghobadi et al. \(2014\)](#)

[Asgari et al. \(2015\)](#) investigated the effects of lime treatment on the mechanical behavior of clayey soils through an extensive experimental and modeling approach. Their study focused on evaluating how curing time and lime dosage affect the development of unconfined compressive strength (UCS). The proposed predictive [Eq 2.2](#) takes the following form:

$$UCS = UCS_0 + a \ln(T) \quad (2.2)$$

Where UCS in (kPa) is unconfined compressive strength, T is curing time with (days), and UCS_0 and a are coefficients obtained by least-squares regression. The model achieved a strong goodness of fit, reflecting its reliability for practical applications. The positive regression for both lime content and curing time indicate that increasing these variables contributes to higher UCS values, as expected due to the pozzolanic reaction and gradual soil-lime bond improvement. This predictive model is particularly useful for practitioners aiming to optimize lime dosage and curing schedules in stabilized clayey soils, offering a simplified yet effective estimation method for UCS without requiring intensive laboratory tests.

[Consoli et al. \(2009\)](#) developed a comprehensive empirical model that combined all experimental data for 28-day curing, achieving [Eq 2.3](#) :

$$UCS(kPa) = 5.13 \times 10^9 \times \left[\frac{V_v}{V_{Lc}} \right]^{-3.93} \quad (2.3)$$

Where, V_v is absolute volume of voids (water + air) and V_{Lc} is absolute volume of lime, with $R^2 = 0.96$. This unified model successfully predicted strength across varying moisture contents and compaction levels, proving its practical value for diverse field conditions.

Their 90-day curing model (Eq 2.4) showed the strongest correlation with $R^2 = 0.98$. The consistent 0.06 exponent across both curing periods indicated that this parameter adjustment is material-dependent rather than time-dependent, providing engineers with reliable long-term design capabilities for lime-stabilized soils.

$$UCS = 4.15 \times 10^{10} \times \left[\frac{V_v}{V_{Lc}} \right]^{-4.29} \quad (2.4)$$

Baldovino et al. (2017) established logarithmic relationships between unconfined compressive strength and curing time for lime-stabilized clayey soil, as shown in Fig 2.2. The empirical models demonstrated strong correlations with R^2 values ranging from 0.87 to 0.98, where higher lime contents produced steeper strength development curves. The Eq 2.5

$$UCS = 288.1 \times \ln(T) - 120.5 \quad (2.5)$$

Where, UCS is unconfined compressive strength and T is curing time with days, for 9% lime content exhibited the most significant strength gains, while untreated soil showed minimal improvement over time. These time-dependent models enable engineers to predict long-term soil performance and optimize construction schedules based on required strength targets.

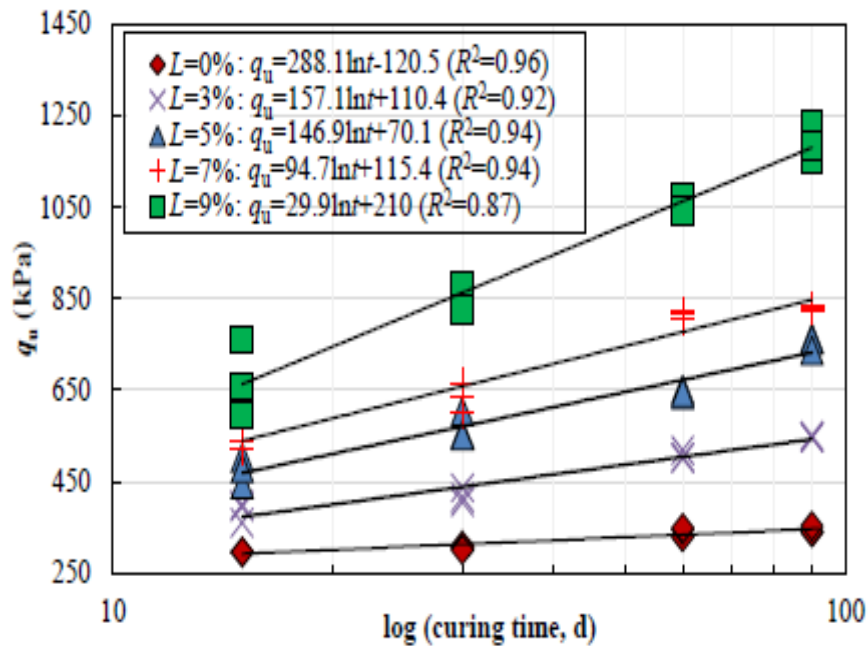


Fig. 2.2. Variation of UCS with logarithmic curing time (Baldovino et al., 2017)

Baldovino et al. (2017) also developed a linear relationship between splitting tensile and compressive strengths, presented in Fig 2.3 as presented in Eq 2.6 :

$$q_t = 0.2698 \times UCS - 59.31 \quad (2.6)$$

Where, q_t is strength tensile and UCS is unconfined compressive strength. This empirical model demonstrated that the tensile-to-compressive strength ratio (q_t/UCS) ranged from 0.17 to 0.2, increasing with extended curing periods across all lime contents tested. The strong correlation allows engineers to predict one strength parameter from the other, reducing testing requirements and costs in practical geotechnical applications. This relationship serves as an effective mix design tool for determining optimal lime content and compaction energy based on target performance criteria.

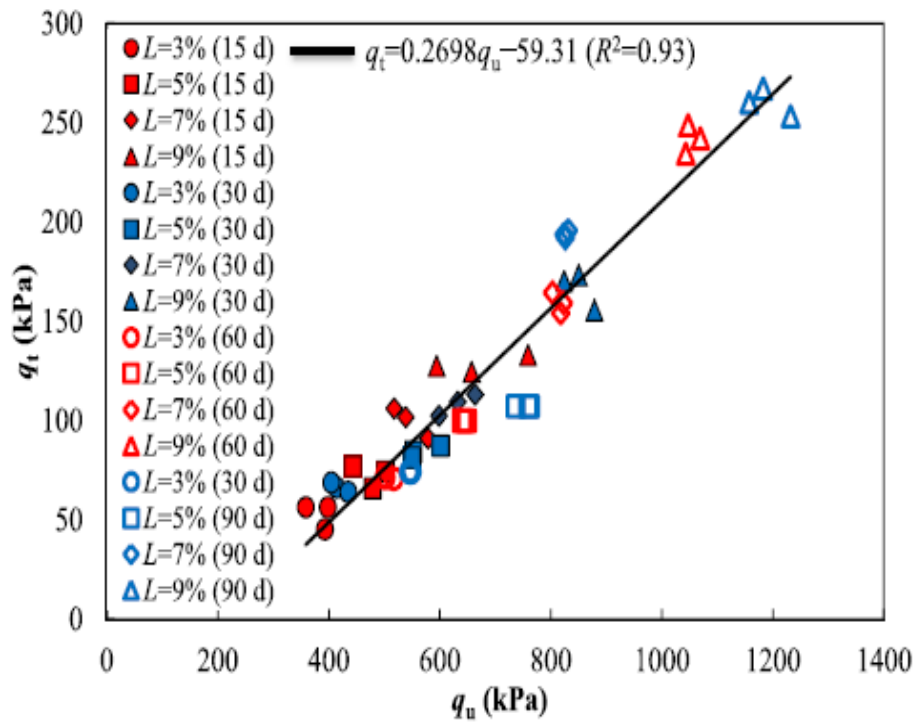


Fig. 2.3. strength tensil versus UCS by Baldovino et al. (2017)

In the study by Jahandari et al. (2017) who investigated the effects of lime content, curing time, and geogrid inclusion on the geotechnical properties of kaolinitic clay. The research focused particularly on understanding and predicting unconfined compressive strength (UCS) and other mechanical parameters through experimental data and a developed predictive model. For the lime-stabilized specimens, the predicted UCS values are moderately consistent with the measured ones, following Eq 2.7:

$$UCS_{act} = 0.7513 \times UCS_{pred} \quad (2.7)$$

For the specimens stabilized with both lime and geogrid, the model achieved a stronger correlation, expressed by the [Eq 2.8](#):

$$UCS_{act} = 1.2934 \times UCS_{pred} \quad (2.8)$$

Where, UCS_{act} present the experimental measured unconfined compressive strength and UCS_{pred} the predict measured unconfined compressive strength. These results confirm that the model provides reasonably accurate predictions, especially for samples incorporating geogrid, where the fit was closer to the 1:1 line. This indicates that the inclusion of geogrid not only enhances the mechanical behavior of stabilized clay but also improves the reliability of strength prediction models based on curing and lime content.

In a comprehensive study by [Sari-Ahmed \(2018\)](#), a predictive model was developed to estimate the UCS of clayey soils stabilized with hydrated lime. The model was designed to reduce the reliance on time-consuming and costly laboratory testing by correlating UCS with lime content and curing time. A large and diverse database of 496 data points, gathered from 52 published studies, was used to construct the model. Four mathematical formulations were tested, but the best-performing model was the following empirical [Eq 2.9](#):

$$UCS = UCS_0 + a \times L_c \times (T + 1)^b \quad (2.9)$$

Where: UCS_0 is the UCS of natural soil (in kPa), L_c is the lime content (%), T is the curing time (days), a and b are model parameters obtained from regression analysis.

This model ([Fig 2.4](#)) showed the highest accuracy among the four tested, with a coefficient of determination (R^2) of 0.800. The model was statistically validated using both t-tests and F-tests, confirming the significance of all included variables (p -values < 0.05).

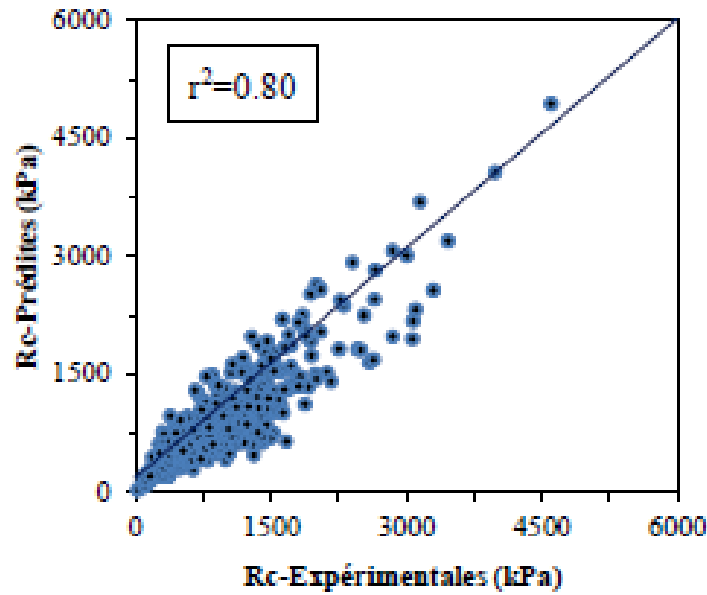


Fig. 2.4. Experimental VS predicted UCS of claye soil stabilized with lime by [Sari-Ahmed \(2018\)](#)

Furthermore, the model was recommended for lime contents below 10% and curing periods ranging from 0 to 90 days, covering typical conditions encountered in civil engineering applications such as road subgrades, embankments, and landfills.

[Sakr et al. \(2008\)](#) conducted a detailed investigation on the stabilization of soft clay soils with high organic content using varying lime percentages and different curing periods. To better understand and quantify the improvement in mechanical behavior, they developed a set of empirical models using multiple linear regression analysis. These models aimed to predict key geotechnical parameters, including UCS, based on lime content (L_c , in %) and curing time (T , in days). Among the results, a notable predictive model for UCS was formulated in [Eq 2.10](#):

$$UCS = 6.28 + 8.68 \times L_c + 0.47 \times T \quad (2.10)$$

This equation demonstrated a strong correlation with experimental values, having a correlation coefficient $R=0.91$, which reflects its reliability for estimating UCS in similar soil-lime systems. The positive coefficients of both lime content and curing time confirm that increasing either parameter leads to a notable gain in strength, consistent with the cementation effects produced by pozzolanic reactions. This statistical model provides engineers with a practical tool for quickly estimating the strength of lime-treated soft clays without the need for extensive lab testing, especially useful during preliminary design stages.

Al-Amoudi et al. (1995) examined water: lime ratio effects on lime-stabilized sabkha soils, focusing on the pozzolanic reactions that differ from cement mechanisms. Their research considered how high salt content in sabkha soils affects lime-soil interactions and long-term strength development. Eq 2.11 represents their regression model with $R^2 = 0.875$, demonstrating reliable prediction of the relationship between water: lime ratios and compressive strength in these saline conditions. Where (W/L_c) represent the the ratios (water/lime).

$$UCS = 1555.4 - 624.2 \times \left(\frac{W}{L_c}\right) + 62.9\left(\frac{W}{L_c}\right)^2 \quad (2.11)$$

Where (W/L_c) represent the the ratios (water/lime).

Sharma and Singh (2018) developed empirical models to predict the unconfined compressive strength (UCS) of lime-stabilized expansive clay based on experimental data. Presented in Fig 2.5, they proposed both linear and nonlinear regression models to relate UCS with lime content. The best-fitting model was exponential, defined by the Eq 2.12:

$$UCS = 6.74 \times L_c - 0.33 \times T + 35.67 \times LL - 33.94 \times PI - 30.40 \times pH + 0.92 \times Vp + 24.42 \times OMC - 21.90 \times MDD - 1394.73 \quad (2.12)$$

where L_c is the lime content (%), T is curing time (days), LL and PI are limit liquid and plasticity index, pH lime percentage, Vp is potential of hydrogen, primary ultrasonic wavevelocity (m/s), OMC is optimum moisture content (%), MDD is maximumdry density (g/cm³) and UCS is unconfined compressive strength.

Yielding a high coefficient of determination $R^2 = 0.96$, and low error values (RMSE = 25.89, MAPE = 16.59%). These results confirm that UCS increases exponentially with lime addition, reflecting the progressive enhancement of soil strength due to pozzolanic reactions.

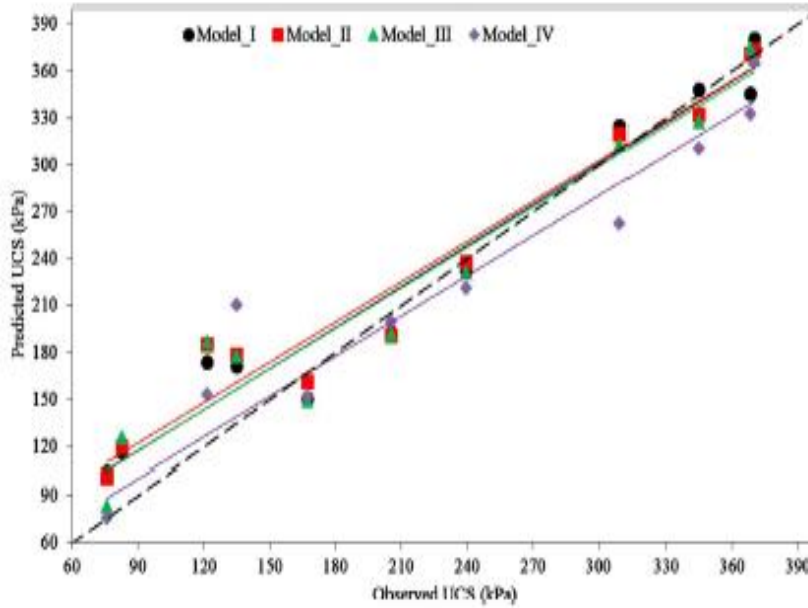


Fig. 2.5. Predicted vs. Observed UCS Values with 1:1 Reference Line by [Sharma and Singh \(2018\)](#)

[Naveed et al. \(2024\)](#) developed empirical models to predict the unconfined compressive strength of lime-stabilized expansive soil for pavement subgrade applications. Their mathematical expression for unsoaked UCS present in [Eq 2.13](#):

$$UCS = a_1 + a_2 \times T + a_3 \times L_c + a_4 \times T \times L_c + a_5 \times L_c^2 \quad (2.13)$$

Where a_1 , a_2 , a_3 , a_4 and a_5 are statistical paramaters, with T representing curing period and L_c representing lime percentage. The model achieved a coefficient of determination R^2 of 0.95 and a root-mean-square error (RMSE) of 66.49 kPa, demonstrating good accuracy in predicting the strength behavior of lime-treated expansive soil. The study concluded that 4% lime content by weight provides optimal improvement for highway subgrade construction, with UCS values increasing by up to 523% compared to untreated soil after 28 days of curing.

2.2.2. Predictive Models for Fly Ash-Stabilized Soils

[Sari-Ahmed et al. \(2018\)](#) developed an empirical model to predict the unconfined compressive strength (UCS) of high-plasticity clayey soils stabilized with fly ash, based on a comprehensive database of 218 experimental data points. Their model, presented as [Eq 2.14](#) expressed as:

$$UCS = \frac{UCS_0}{[(1 + \ln(a \times FA + 1))^{-[log_{10}(b \times T + 1) + 1]}]} \quad (2.14)$$

Where, UCS_0 is the initial UCS of untreated soil, FA is the fly ash content (%), T is the curing time (days), a and b are the regression parameters. The model demonstrated strong statistical performance with an R^2 value of 0.84, indicating that 84% of the variance in unconfined compressive strength is explained by the proposed equation. Statistical validation through t-test and F-test analyses confirmed high significance levels ($p < 0.05$), while the relative mean error of approximately 6.5% demonstrates acceptable predictive accuracy for practical engineering applications.

[Fig 2.6](#) in the paper visually confirms the accuracy of this UCS model, showing that most predicted UCS values align closely with the experimental data, especially for clayey soils with a high plasticity index stabilized using various fly ash dosages and curing durations. The model effectively captures the strength gain with both increasing fly ash content and curing time, making it a valuable tool for preliminary design in geotechnical engineering. The authors conclude that such statistical models are useful alternatives to time-consuming lab tests and suitable for practical applications in subgrade improvement and earthwork design

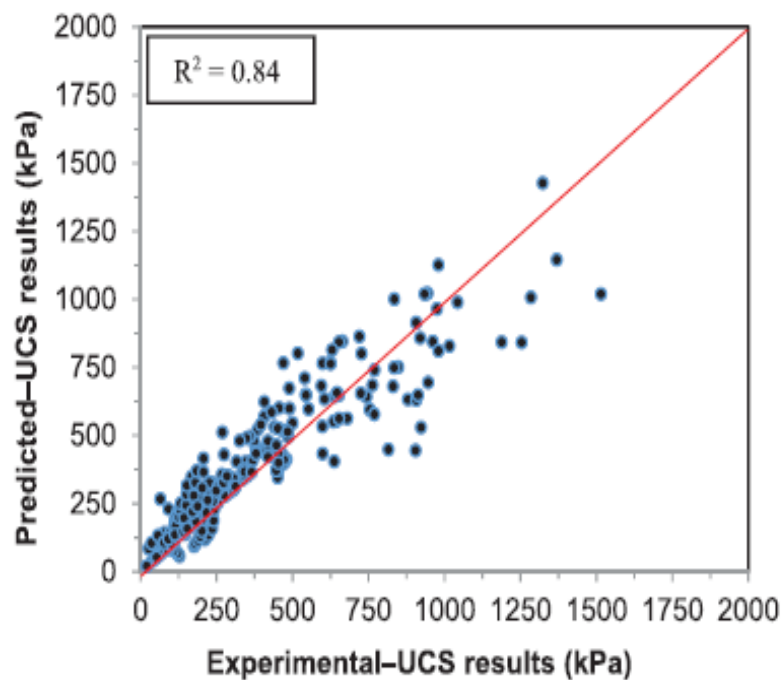


Fig. 2.6. Regression analysis of UCS in FA-stabilized high-plasticity clay soils ([Sari-Ahmed et al., 2018](#)).

[Sezer et al. \(2006\)](#) developed an empirical model to predict the unconfined compressive strength (UCS) of high-plasticity clay stabilized with a very high-lime fly ash, without using

any additional activator. Based on a multiple regression analysis, they proposed the following Eq 2.15:

$$UCS = 247,10 + 22.29 \times FA + 7.50 \times T \quad (2.15)$$

Where, FA is the fly ash content and T is the curing time. The model demonstrated a moderate correlation with experimental data, showing an R^2 of 0.6921, indicating a fair prediction accuracy over a 90-day curing period.

Fig 2.7 by Sezer et al. (2006) in their study compares the measured and predicted UCS values, revealing that while the trend is captured reasonably well, some data points deviate beyond the 95% confidence interval. The clay used had a plasticity index (PI) of 41.3%, classifying it as CH soil, and the strength improvement was especially noticeable at 15% FA content. The model's relative performance supports its usefulness as a preliminary design tool, although its lower R^2 compared to more recent models suggests potential for refinement with broader datasets.

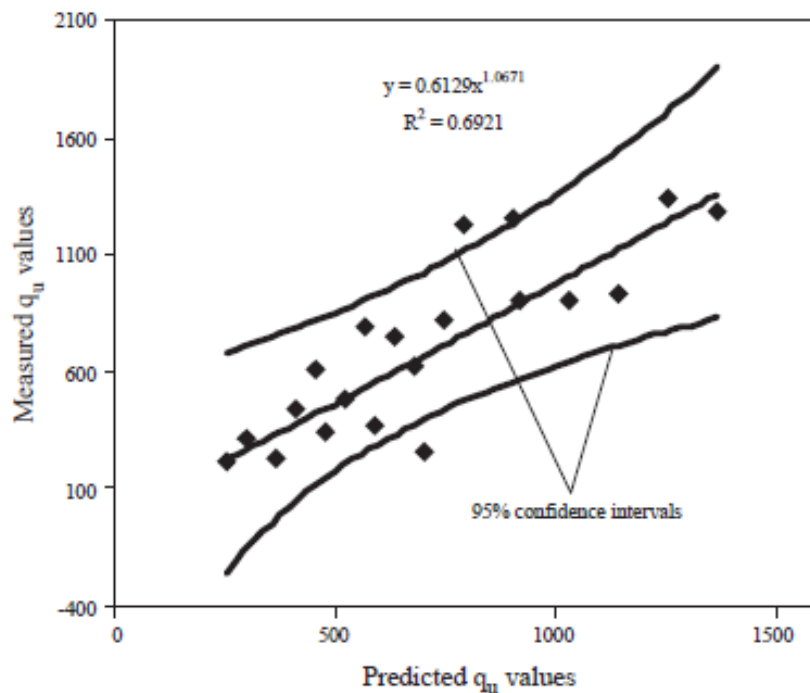


Fig. 2.7. Measured VS predicted UCS values by Sezer et al. (2006).

Yu et al. (2007) developed an empirical model to predict the unconfined compressive strength (q_c) of clay soils stabilized with fly ash, as presented in Eq 2.16:

$$UCS = 8 \times T^{0.4} \times FA + 430 \quad (2.16)$$

Where FA represents fly ash content (%) and T signifies curing time (days). This model exhibited a high determination coefficient with $R^2 = 0.92$ (Fig 2.8), indicating strong predictive capability, with minimal errors in comparison to experimental results.

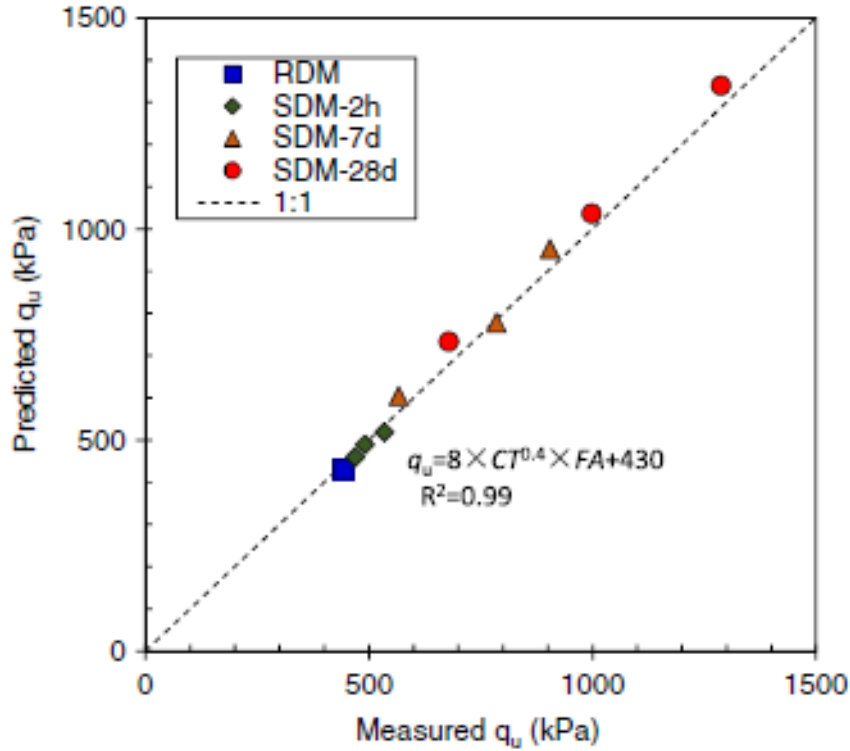


Fig. 2.8. Measured UCS versus predicted UCS by Yu et al. (2007)

The model effectively captures the influence of fly ash percentage and curing duration on strength, validated across different clay types including CH and ML, with the strength increasing proportionally with fly ash content and curing time. The empirical relationship thus provides a reliable estimation tool for assessing stabilization performance in various clay soils, demonstrating the importance of both parameters in strength development.

2.2.3. Predictive Models for Cement-Stabilized Soils

Asgari et al. (2015) also examined the performance of cement as a stabilizing agent for clayey soils and proposed an independent regression model to predict the UCS based on cement content and curing time. This part of the study involved laboratory testing of clay samples treated with varying percentages of cement and exposed to multiple curing durations. The resulting empirical model was expressed as follows in Eq 2.2. This model aids in estimating the strength behavior of cement-treated soils under different conditions, supporting efficient stabilization design with reduced experimental workload.

Zhang et al. (2024) proposed an empirical model to predict the unconfined compressive strength (UCS) of cement-stabilized Qiantang River silty clay, the studied soil is a low-plasticity silty clay (CL) with a plasticity index of 17%, and the results demonstrate that UCS consistently decreases with higher w/c ratios.

This reinforces the model's practical value in optimizing sustainable mix designs for soft clay stabilization. Incorporating the effects of curing time and water-to-cement ratio (W/C). Their model, presented as Eq 2.17, is expressed :

$$UCS = (A_4 \times \ln(T) + B_4) \left(\frac{W}{C}\right)^{C_4} = (2.13 \times \ln(T) + 4.66) \left(\frac{W}{C}\right)^{-2.20} \quad (2.17)$$

where T is the curing time in days, and W/C is the mixing water-to-cement ratio.

The model demonstrated excellent predictive accuracy with $R^2 = 0.998$ at 28 days and strong agreement between predicted and measured UCS values across different mix designs (Fig 2.9). However, the standard Chinese technical code tends to overestimate strength for extended curing periods like 90 days, suggesting code revisions are needed.

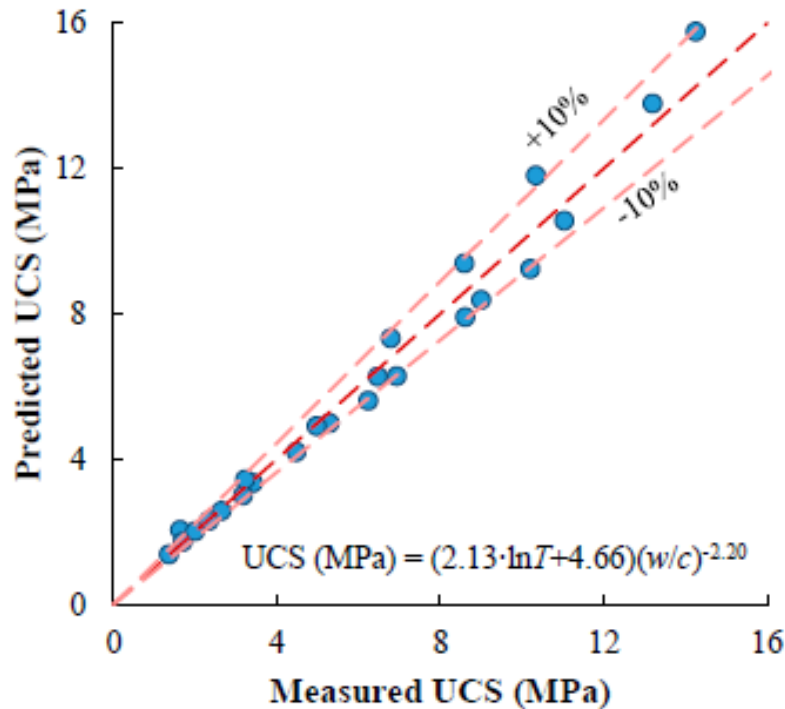


Fig. 2.9. Comparing of measured and predicted UCS by Zhang et al. (2024)

Al-Amoudi et al. (1995) investigated how water: cement ratio affects the compressive strength of cement-stabilized sandy sabkha soils. They developed regression models to predict strength behavior in these saline soil conditions, accounting for the unique interaction between cement hydration products and the existing soil matrix. Eq 2.18 represents their best-fit model with a coefficient of determination $R^2 = 0.875$, indicating strong correlation between experimental observations and theoretical predictions for cement-stabilized sabkha soil.

$$UCS = 1555.4 - 624.2 \times \left(\frac{W}{C}\right) + 62.9 \times \left(\frac{W}{C}\right)^2 \quad (2.18)$$

Where (W/L) represent the ratios (water/Cement).

Sunitsakul et al. (2012) examined the empirical model that correlates the UCS of cement-stabilized bases with the cement/water additive, specifically through the simplified Eq 2.19 :

$$UCS = a \times \left(\frac{CBR}{\frac{W}{C}}\right)^b \quad (2.19)$$

Where, UCS unconfined compressive strength at 7 days of curing time, CBR soaked CBR at 95 percent of maximum dry density based on modified Proctor compaction, W/C water to cement ratio and a, b fitting parameters determined from statistical analyses.

Using this form, achieved a coefficient of determination R^2 of 0.751 after excluding outliers, indicating a good predictive fit. The model, visualized in Fig 2.10, showed close agreement between measured and predicted UCS values. This supports conclusion that the soaked CBR and water-to-cement ratio are dominant predictors of UCS in cement-treated soils.

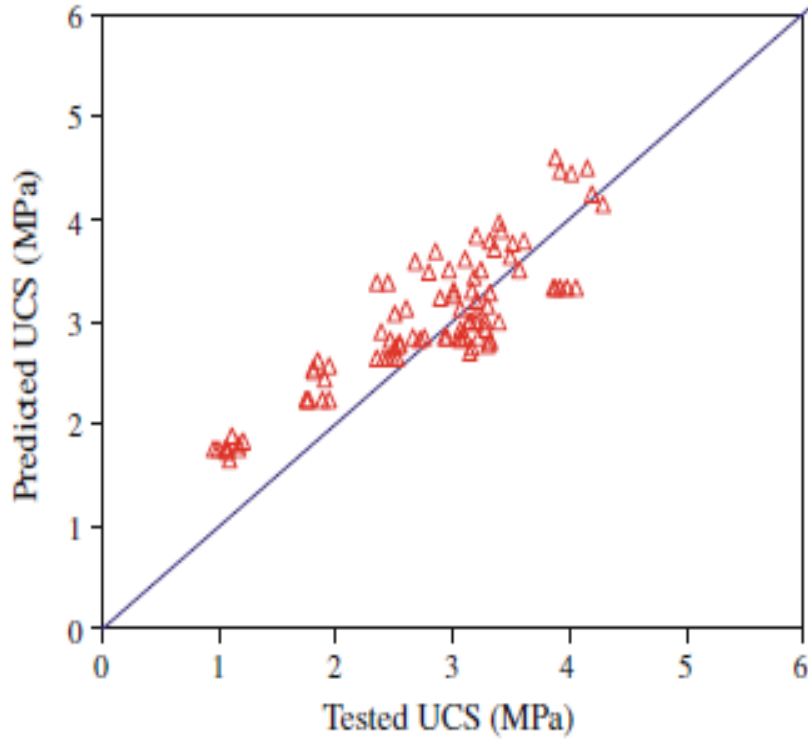


Fig 2.10. Comparison between predicted and tested UCS by [Sunitsakul et al. \(2012\)](#).

[Jafer et al. \(2016\)](#) proposed an empirical model to estimate the unconfined compressive strength (UCS) of cement-stabilized soft clay from Hightown. The model is expressed in [Eq 2.20](#) as:

$$UCS = -140.32 + 14.52 \times C + 3.76 \times T \quad (2.20)$$

Where C is the cement content (%) and T is the curing duration (days). This regression model achieved a coefficient of determination $R^2 = 0.92$, indicating a strong correlation between predicted and measured values. [Fig 2.11](#) in their study visually confirms this good fit, showing a close alignment of experimental and predicted UCS values, with minimal error.

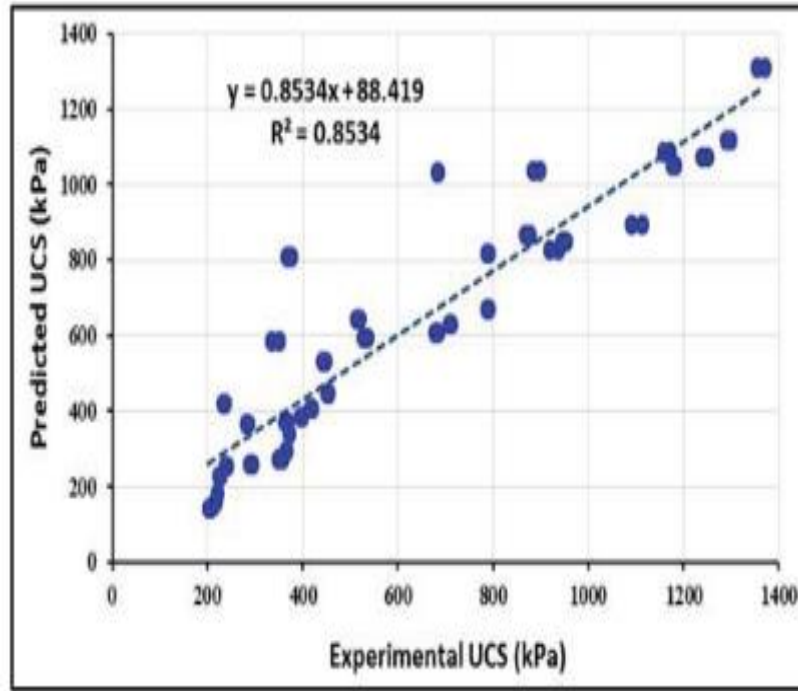


Fig. 2.11. Experimental versus predicted UCS values by [Jafer et al. \(2016\)](#)

[Jaritngam et al. \(2013\)](#) developed empirical models to estimate the UCS of lateritic soil stabilized with ordinary Portland cement, based on cement content (C), curing time (T), and dry density (DD). Two regression equations were proposed in [Eq 2.21](#) and [Eq 2.22](#):

$$UCS = -6.045 + 7.685 \times C + 0.713 \times T \quad (2.21)$$

$$UCS = -108.468 + 7.607 \times C + 0.674 \times T + 476.656 \times DD \quad (2.22)$$

achieving a correlation coefficient of $R^2 = 0.971$. The second, more comprehensive model ([Eq 2.22](#)) incorporates an additional density parameter and resulting in an improved correlation of $R^2 = 0.976$. These models showed high accuracy, with maximum absolute errors under 11%.

[Fig 2.12](#) compares predicted UCS values from [Eq 2.22](#) with experimental results and shows excellent alignment, especially at higher cement contents and curing times. The soil used is classified as SC (clayey sand) with a plasticity index of 15.8%, and strength improvement was clear at 7% and 9% cement. The models offer reliable tools for predicting UCS in pavement base design using locally available lateritic soil.

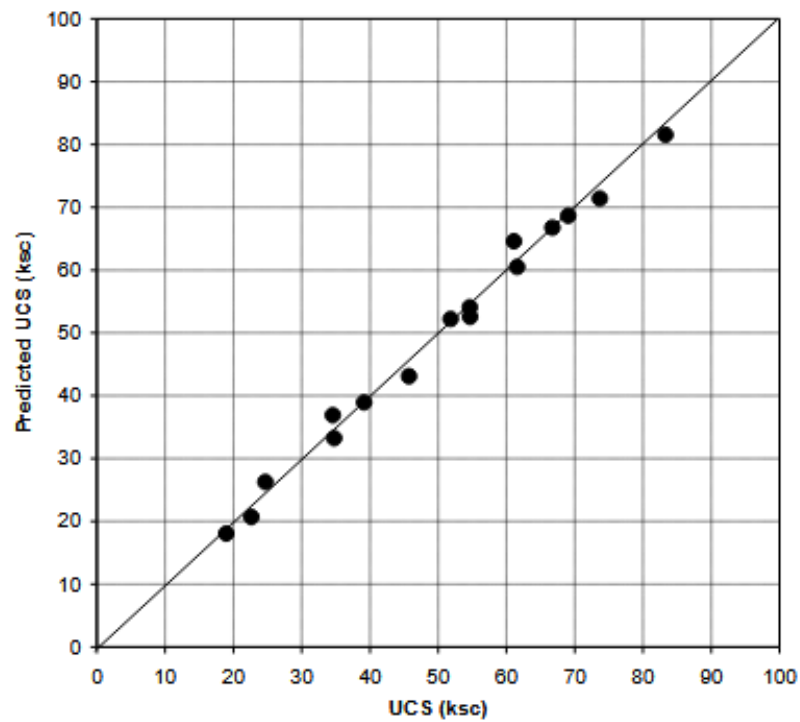


Fig. 2.12. Comparison of Experimental data and predicted values by [Jaritngam et al. \(2013\)](#)

Numerous models exist in the literature, reflecting the significance of this technique and parameter. [Tab 2.1](#) consolidates the discussed models and other equations from various researchers.

Tab. 2.1. Summary of additional important models for estimating compressive strength published in the literature

Authors	Model formula	Variables	Additives used
Kaniraj and Havanagi (1999)	$UCS = UCS_0 + \frac{T}{m \times T + c}$	UCS_0 : initial strength in (kPa) ; T : curing time in (days) ; m and c are paramater regression	Ciment
Anagnostopoulos and Chatziangelou (2008)	$UCS = -326.8 - 1170.09 \times Ln(W) + 1292.06 \times Ln(LL) + 0.523 \times (C) \times (S)^{1.417} (Ln(T))^{0.608}$	W : water content in (%) ; LL : limit liquid in (%) ; C and S : ciment and sand content in (%)	Ciment
Rachan et al. (2010)	$UCS = \frac{a}{(\frac{W}{C \times (1+k.FA)})^b}$	w : water content in (%) ; C and FA : ciment and fly ash content in (%) ; a, b and k are empirical paramaters	Ciment+Fly ash
Khoury et al. (2012)	$\log \left(\frac{UCS}{UCS_{w_{opt}}} \right) = a + \frac{b - a}{1 + e^{\ln \left(\frac{-b}{a} \right) + K_m X (w - w_{opt})}}$	$\frac{UCS}{UCS_{w_{opt}}}$: strength and strength in optimal water content ; a, b and k_m are statistical paramaters ; W is water content; W_{opt} is optimal moisture content	Fly ash
Ma et al. (2016)	$UCS_T = \frac{a}{[\frac{W}{C + (\alpha \times C + \beta) \times FA}]^b}$	A, b, α and β are paramaters model ; C and FA are ciment and fly ash content in (%) ; W : water content in (%) and T : curing time in (days)	Ciment+ Fly ash
Ma et al. (2018)	$UCS = \frac{T}{1.47 \times 10^{-4} \times T + 0.002e^{-0.17(\frac{e_i}{C_T})}}$ $C = C + \left([1.69 \times 10^{-6}(T - 67.4)^2 + 0.00216] \times C_i + \frac{T}{2.77 \times T + 21.79} \right) FA$	e_t : vaccum index ; C : stabilizer obtained by combining a CSCN (cement-based composite) ; C and FA are ciment and fly ash content in (%) and T : curing time in (days)	Ciment+ Fly ash
Islam et al. (2015)	$UCS = 1100.275 - 28.410 \times W + 6.314 \times LL + 5.10 \times C - 57.427 \times S$ $UCS = 446.657 - 6.208 \times W + 2.322 \times LL + 3.619 \times L - 59.742 \times S$	W : water content in (%) ; LL : limit liquid ; C, L_C and S : ciment, lime and sand content respectivley	Lime and Ciment

2.3. Artificial intelligence-models of stabilized clayey soils

Current research shows that while artificial neural networks have been used in geotechnical engineering, their application to predict durability of stabilized clayey soils under environmental stress remains limited. Most studies focus on experimental testing of how lime, cement, and fly ash affect soil properties like strength and volume change during freeze-thaw cycles, but researchers have not effectively converted these experimental findings into comprehensive machine learning models. The available data from laboratory testing has not been fully utilized to create predictive tools that can forecast long-term soil performance under varying environmental conditions.

Existing ANN models in soil stabilization typically address strength prediction without considering environmental effects like freeze-thaw cycling. These models use basic soil properties and additive information as inputs but ignore the significant impact of repeated environmental stresses that affect real pavement performance. Most current approaches focus on predicting static strength values rather than dynamic durability characteristics that change over time, which limits their usefulness for practical engineering applications where environmental durability is crucial for infrastructure design.

This research gap creates an opportunity to develop a comprehensive ANN model that combines material properties with environmental conditioning effects. Our approach integrates multiple environmental factors, including freeze-thaw and wet-dry cycles, with various mineral additive types and dosages into a single predictive framework. This integrated method offers significant advantages by providing engineers with an effective tool for optimizing soil stabilization strategies based on specific environmental conditions, leading to more accurate long-term performance predictions and improved infrastructure design practices.

2.3.1 Overview of the application of Artificial Neural Networks (ANNs) in soil stabilization

Artificial Neural Networks (ANNs) are increasingly recognized in geotechnical engineering for their powerful ability to predict the behavior of stabilized soils, especially when traditional empirical or physically-based models fall short ([Sari-Ahmed et al., 2024](#)). Soils, particularly clayey and expansive types, often display nonlinear responses when treated with stabilizers. ANN's flexibility in learning from complex, multivariate data makes it an ideal tool to forecast key engineering properties without explicitly programming the physical relationships.

For instance, ANN models have been applied successfully to forecast properties like permeability, compaction, and unconfined compressive strength (UCS), making them useful in pavement design, embankment analysis, and subgrade evaluation ([Tizpa et al., 2015](#)).

A central focus of ANN application is the prediction of UCS a vital parameter in assessing the load-bearing capacity and strength improvement of stabilized soils. Traditional UCS testing is time-consuming and sensitive to multiple factors ([Sari-Ahmed et al., 2024](#)), but ANN models have shown high accuracy in simulating UCS values when trained on relevant inputs such as soil plasticity, compaction parameters, and mineral additive content ([Suman et al., 2016](#)). [Sathyapriya et al. \(2017\)](#) utilized ANN to predict UCS of expansive clay stabilized with bottom ash and eco-sand, outperforming regression models. Similarly, [Shahiri and Ghasemi \(2017\)](#) showed how ANN could predict UCS of soils stabilized with cement and copper slag, identifying water content as the most influential variable through sensitivity analysis.

The integration of mineral additives such as lime, fly ash, and cement in soil stabilization has further enhanced the utility of ANN models. These additives chemically alter the soil structure, improving strength and durability. However, their interaction with soil properties varies depending on dosage, curing time, and environmental conditions making predictive modeling a challenge for conventional techniques. ANN models, trained with these input variables, have been successful in simulating the nonlinear relationships governing the strength gain of stabilized soils. Studies by [Alavi et al. \(2010\)](#) and [Das et al. \(2011\)](#) demonstrated that ANN can effectively model how lime and cement dosages impact maximum dry density (MDD) and UCS. The ability to include a wide range of variables such as liquid limit, plasticity index, and curing time makes ANN indispensable in evaluating the mechanical performance of treated soils.

Understanding ANN's architecture helps explain its predictive power. Typically, ANN models used in soil stabilization are feedforward multilayer perceptrons with input, hidden, and output layers. The input layer takes in soil and treatment parameters such as plasticity indices, additive content, and curing duration. These inputs are passed through hidden layers where weighted computations and activation functions help detect complex patterns, and finally, the output layer generates predictions like UCS or MDD. This architecture enables the model to learn from empirical data without relying on fixed equations, adapting to different soil types and stabilizing agents ([Wang and Al-Tabbaa, 2013](#)). The model's learning capacity makes it suitable for both lab-scale experiments and field-scale applications.

In summary, the application of ANNs in soil stabilization offers a fast, reliable, and adaptable solution for predicting geotechnical properties especially when dealing with stabilized clays using lime, cement, and fly ash. These models not only reduce the reliance on exhaustive experimental testing but also allow for the optimization of stabilizer proportions for better performance. As construction practices evolve, incorporating ANN-based tools into soil design workflows can significantly enhance the decision-making process, ensuring safety, cost-effectiveness, and sustainability. The growing body of literature strongly supports this integration, highlighting ANN's relevance in modern geotechnical and infrastructure engineering (Nadakumar and Ganesan, 2024; Merouane and Mamoune, 2018).

2.3.2 ANN Models for Lime-Stabilized Soils

Muhmed et al. (2022) illustrate the performance of their ANN model in Fig 2.13 and 2.14 by comparing predicted and experimentally measured UCS values for training, testing, and validation datasets, as well as for the combined data ensemble. In the training phase (Fig 2.13), the network achieved an R^2 of 0.97, indicating that 97 % of the variability in measured UCS could be captured by the model's predictions. For the testing subset (Fig 2.13), the relationship between predicted and actual UCS yielded an R^2 of 0.93, demonstrating that the ANN maintained excellent predictive capability on data unseen during training. During validation (Fig 2.13), the model obtained an R^2 of 0.92, confirming its generalization performance and robustness across differing sample conditions. When all data points were plotted together (Fig 2.14), the overall R^2 remained at 0.92, underscoring the model's high accuracy across the full range of soil and curing parameters.

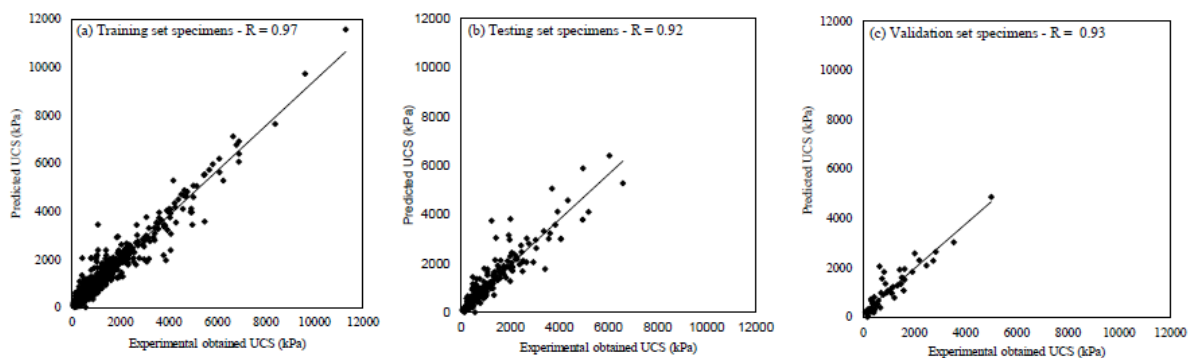


Fig. 2.13. Measured vs. predicted UCS values by ANN for (a) training, (b) testing, and (c) validation phases (Muhmed et al., 2022)

Visually, data points cluster tightly around the 1:1 bisector line, especially at lower UCS values, highlighting the network's precision in estimating strength gains of lime-treated soils.

Only a handful of outliers deviate slightly from the bisector, suggesting that extreme or less common combinations of input variables may introduce marginal prediction errors.

The coherent clustering of points around the bisector in both individual and combined plots confirms that the chosen architecture (8–19–1) effectively captured the complex, nonlinear interactions among inputs liquid limit, plastic limit, dry unit weight, water content, fine content, temperature, lime content, and curing time. Moreover, the low mean squared error (0.0039) and mean absolute error (0.037) reported for the final model reinforce its high fidelity (Muhmed et al., 2022).

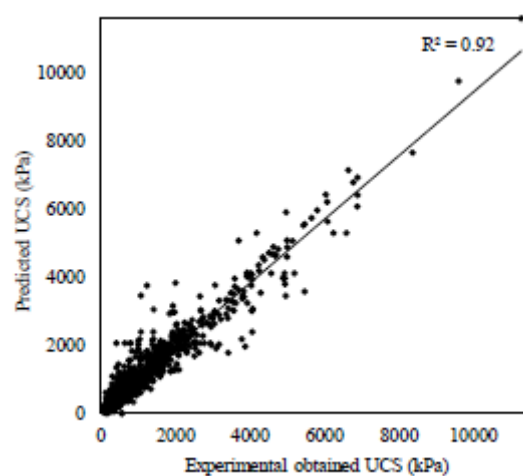


Fig. 2.14. Measured vs. predicted UCS values using ANN 8-19-1 model (Muhmed et al., 2022)

In the other hand, Muhmed et al. (2024) developed another robust ANN and linear regression models to predict the UCS of lime-treated soils. An extensive experimental database comprising 1,120 specimens was utilized. Eight input parameters were considered: liquid limit, plastic limit, dry unit weight, water content, fine content, lime content, curing temperature, and curing time. The optimal ANN architecture featured three layers with 19 hidden neurons. The ANN model demonstrated superior predictive accuracy compared to the regression model, with curing time identified as the most influential factor affecting strength gain.

Taleb-Bahmed (2018) developed an artificial neural network (ANN-UCS) model, to predict the unconfined compressive strength (UCS) of lime-treated clay soils. The model used three input parameters: the initial UCS of the untreated soil, the curing time, and the lime content. With a network architecture of one hidden layer containing 11 neurons and trained using the

Levenberg-Marquardt algorithm, the ANN showed good predictive capability. A total of 355 data points were compiled, with 249 for training, 53 for testing, and 53 for validation.

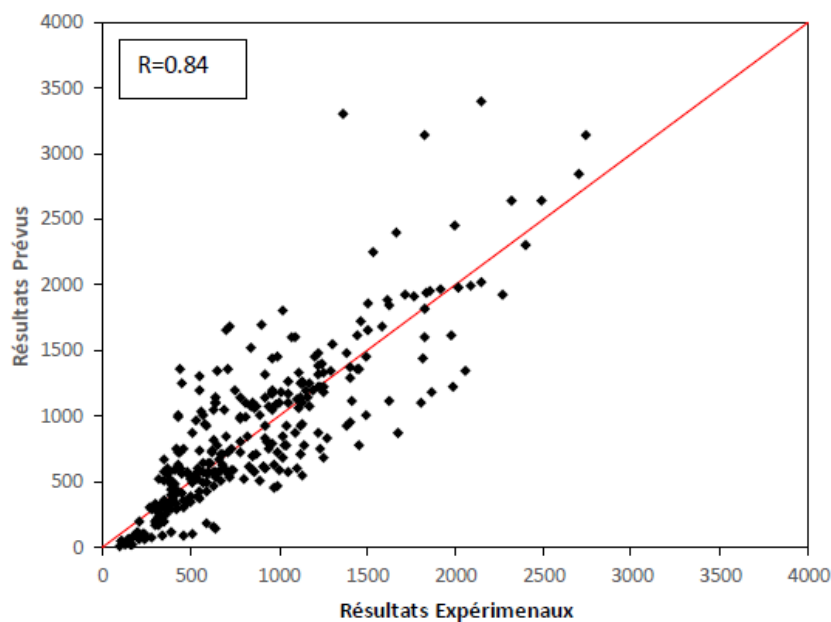


Fig. 2.15. Correlation between experimental and predict UCS value by [Taleb-Bahmed \(2018\)](#)

The performance of the ANN-UCS model was validated using external data from [Mohsen et al. \(2015\)](#), [Jahandari et al. \(2017\)](#), and [Portelinha et al. \(2012\)](#), achieving a coefficient of determination $R^2 = 0.96$. The model also demonstrated a mean prediction error of 8.32% across different data sources. In addition, during training and testing stages, the regression plot ([Fig.2.15](#)) indicated a high correlation with $R = 0.84$ between predicted and experimental UCS values. This confirms the model's strong generalization ability within the range of data used.

[Keneddy et al. \(2021\)](#) applied three ANN algorithms-Levenberg-Marquardt Backpropagation (LMBP), Bayesian Programming (BP), and Conjugate Gradient (CG) to model the UCS of expansive clay treated with hydrated-lime activated rice husk ash. The study utilized 121 datasets with seven input variables-hydrate lime content, liquid limit, plastic limit, plasticity index, optimum moisture content, clay activity, and maximum dry density. The ANN architecture was 7-10-3, and training was performed using MATLAB's neural network toolbox.

For UCS prediction, the Bayesian algorithm performed best, achieving an R^2 of 0.989 for the testing dataset. The model also exhibited a low root mean square error (RMSE) of 14.12 and

mean absolute error (MAE) of 0.92 in testing. The soil was classified as A-7-6 expansive clay, with a high plasticity index decreasing from 45% to 14% after stabilization. These results confirm the ANN model's robustness in capturing strength gains from hydrate lime treatment and its suitability for geotechnical design in sustainable infrastructure.

Taleb-Bahmed et al. (2024) developed and assessed multiple machine learning models including ANN-derived hybrid frameworks to predict the unconfined compressive strength (UCS) of lime-stabilized cohesive soil. A total of 371 data points were compiled from the literature, considering inputs such as initial UCS of the untreated soil, lime content, and curing period.

Among all models tested (GPR ; SVM and DT), the PSO-optimized Laplacian kernel-based Relevance Vector Machine (RVM or UCS16) model emerged as the best performer. It achieved a R^2 of 0.9896 in training and 0.9158 in testing, as illustrated in Fig 2.16, which presents scatter plots comparing predicted and actual UCS values.

Additionally, the model attained a very low RMSE of 0.0164 (training) and 0.0496 (testing), confirming high predictive accuracy. The performance metrics indicated minimal error and strong agreement with measured UCS, validating the ANN-inspired model's capability to capture complex nonlinear relationships in lime-stabilized soils.

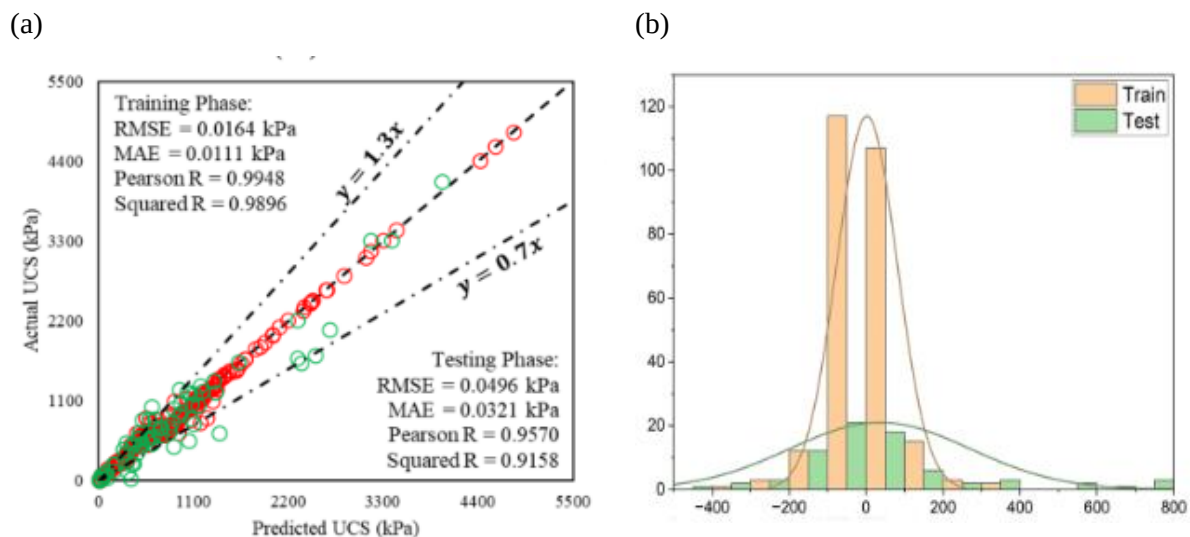


Fig. 2.16. Statistical plot : (a) Actual versus predicted UCS, (b) : Error histogram in training and testing by Taleb-Bahmed et al. (2024)

2.3.3. ANN Models for Fly Ash-Stabilized Soils

Gnananandarao et al. (2022) present the ANN performance in Fig. 2.17, comparing predicted versus experimental UCS values for fly ash–stabilized organic clay. The ANN model achieved an R^2 of 0.91, markedly exceeding the semi-empirical benchmark ($R^2 = 0.74$). Visually, data points cluster tightly around the 1:1 bisector across the full UCS range, indicating accurate estimation for both low and high-strength specimens; only rare outliers deviate slightly, suggesting marginal errors for extreme input combinations.

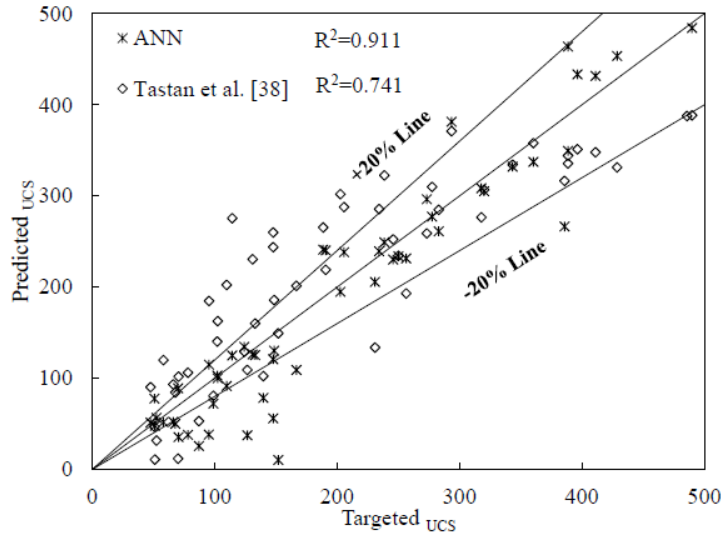


Fig. 2.17. Comparison of ANN-predicted UCS with target values and literature results (Gnananandarao et al., 2022).

The network was built with an 8-19-1 architecture using eight inputs (CaO/SiO₃ ratio, organic content, fly ash content, UCS₀, pH, etc.) and trained through 500 epochs to minimize MSE, yielding robust learning. During training, the ANN obtained an R^2 of 0.96, underscoring its strong fitting capability. On unseen testing data, R^2 remained high at approximately 0.95, confirming effective generalization (Gnananandarao et al., 2022).

The low M.S.E. and M.A.E. values reported further validate minimal dispersion between predicted and experimental UCS. Collectively, these graphical results demonstrate that the ANN effectively captures the complex, nonlinear interactions among soil and stabilization parameters, offering reliable UCS predictions for fly ash–stabilized organic clays. This performance supports deploying the ANN model to reduce reliance on extensive laboratory testing in geotechnical design (Gnananandarao et al., 2022).

Binal et al. (2020) developed an artificial neural network (ANN) model to predict the unconfined compressive strength (UCS) of clayey soils stabilized with various types of fly

ash. The study used a dataset compiled from their own tests and 17 case studies, involving parameters such as fly ash content (FA), liquid limit (LL), plastic limit (PL), clay activity (Ac), optimum moisture content (OMC), and maximum dry density (MDD). For the 28-day cured samples, the ANN model trained with these six input parameters achieved a testing phase correlation coefficient of $R^2 = 0.638$ and a root mean square error (RMSE) of 49.52. As shown in Fig. 2.18.a, the predicted UCS values followed the actual measurements with moderate accuracy.

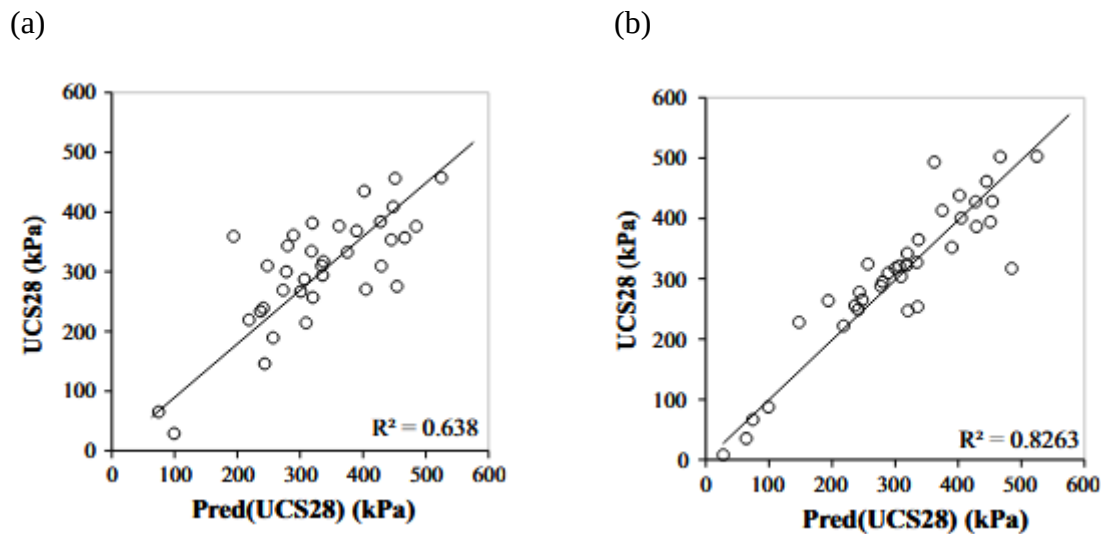


Fig. 2.18. The relationship between real and predicted data of the 28-day cured samples mixed FA, (a) : without UCS₁, (b) : within UCS₁ by Binal et al. (2020).

A second ANN model was constructed by including the one-day cured UCS (UCS₁) as an additional input, which significantly improved performance. This model yielded a higher R^2 of 0.826 and a lower RMSE of 29.55 for predicting 28-day UCS, as depicted in Fig 2.18.b. The improvement highlights the strong predictive role of early-age strength in long-term behavior. The study soil was classified as CH (high plasticity clay) with a plasticity index of 57%, and the ANN architecture used five neurons in the hidden layer with backpropagation (Rprop) training. The results suggest that ANN is a powerful tool for estimating UCS in fly ash-stabilized clayey soils, especially when early strength data are available.

2.3.4. ANN Models for Cement-Stabilized Soils

Ngo et al. (2021) developed and evaluated an artificial neural network (ANN) model to predict the UCS of cement-stabilized soils based on a dataset of 216 laboratory samples. The model was trained using a multilayer perceptron architecture, optimized via random search,

and validated with 5-fold cross-validation to ensure robustness. The optimized ANN architecture used 50 neurons and the Adam optimizer, resulting in excellent performance. The model achieved an average correlation coefficient (R) of 0.925, a root mean square error (RMSE) of 419.82 kPa, and a mean absolute error (MAE) of 292.2 kPa on the testing dataset, as shown in the performance figures (Fig 2.19). These results reflect a high degree of alignment between predicted and measured UCS values, with points closely distributed around the ideal 1:1 line in both training and testing scenarios.

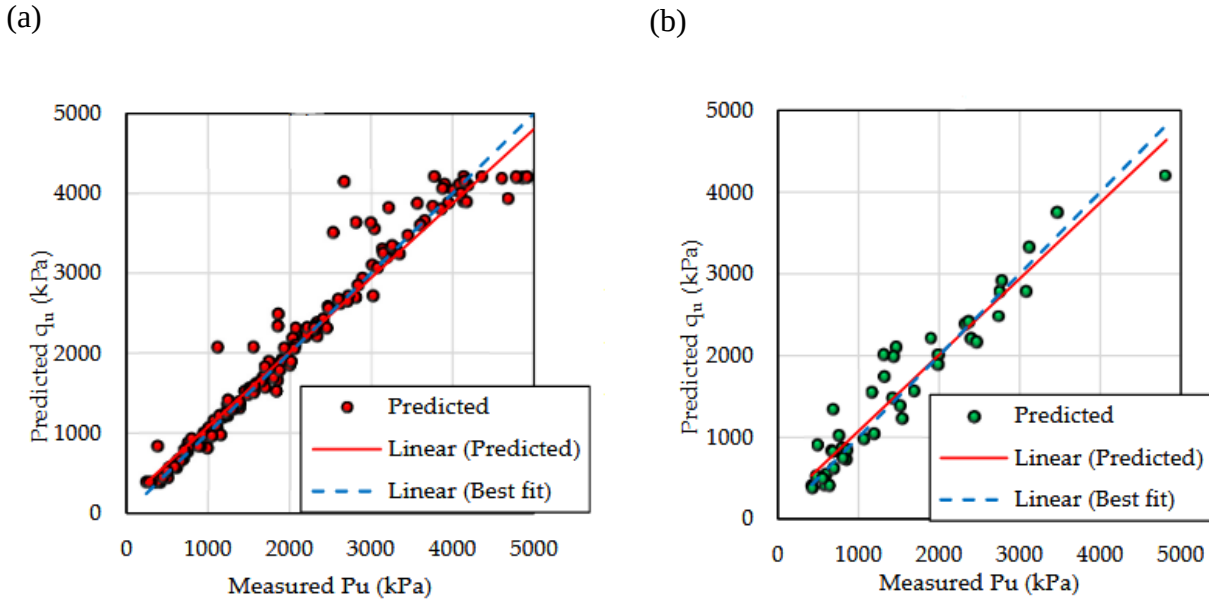


Fig. 2.19. Measured and predicted UCS values of cement-stabilized soil using ANN for (a) training and (b) testing datasets (Ngo et al., 2021).

The ANN consistently demonstrated stability across 300 random sampling simulations, maintaining low standard deviations in performance indicators. Furthermore, the visual plots of predicted versus measured UCS confirmed minimal dispersion, highlighting the model's strong generalization capability. The study concludes that ANN can reliably capture the complex relationships between multiple input variables such as moisture content, wet density, curing time, and cement dosage and the resulting UCS. Overall, this work underscores the ANN's potential as a powerful, time-saving alternative to conventional testing in geotechnical applications.

Suman et al. (2016) developed artificial intelligence models to predict the unconfined compressive strength (UCS) of cement-stabilized soils using Functional Networks (FN) and Multivariate Adaptive Regression Splines (MARS). The study utilized a dataset of 51 samples, with 37 used for training and 14 for testing, considering seven input parameters

including liquid limit, plasticity index, clay, moisture content, and cement content. The ANN-inspired FN model demonstrated strong predictive capability, as shown in Fig 2.20.

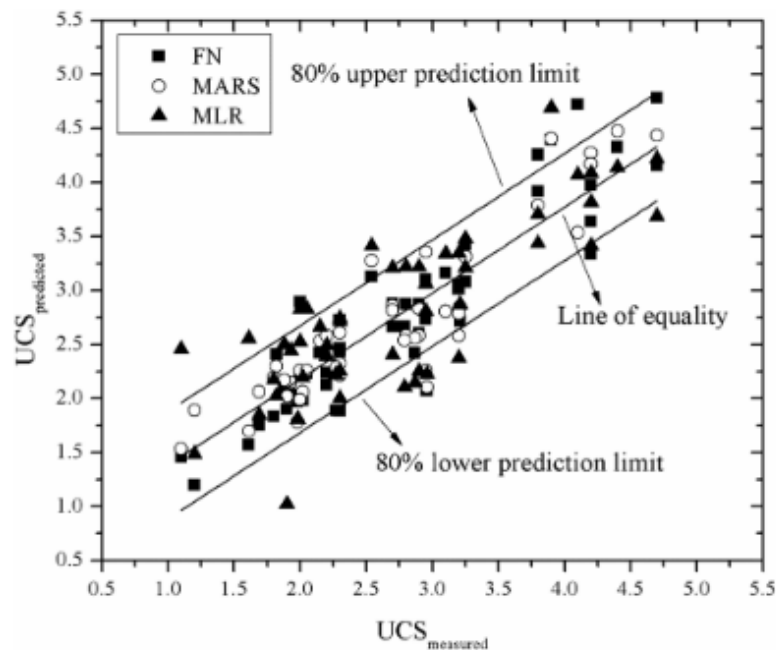
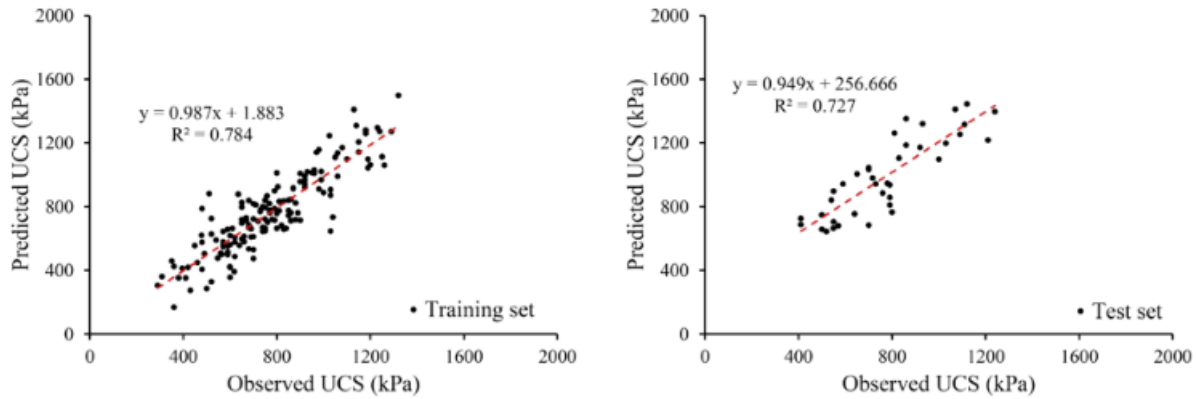


Fig. 2.20. Measured vs. predicted UCS values using FN, MARS, and MLR models (Suman et al., 2016)

where most data points fell within the 80% prediction confidence interval. For the UCS prediction, the FN model achieved a correlation coefficient (R) of 0.927 for training data and 0.951 for testing data, with corresponding Nash-Sutcliffe efficiency coefficients of 0.86 and 0.70. The MARS model, also assessed in Fig 2.20, achieved a similar level of accuracy, with R values of 0.927 and 0.954 for training and testing, respectively, and efficiency scores of 0.85 and 0.81. The scatter plots in the figures showed that predicted values closely followed the line of equality, indicating minimal deviation between measured and predicted UCS.

Fazel-Mojtahedi et al. (2023) proposed a data-driven approach using ANNs to predict the UCS of cement-stabilized soils treated via the Deep Mixing Technique (DMT). The model development was based on a dataset of 192 laboratory samples with eight input parameters, including cement content, water-cement ratio, curing time, plasticity index, and untreated UCS.

(a)



(b)

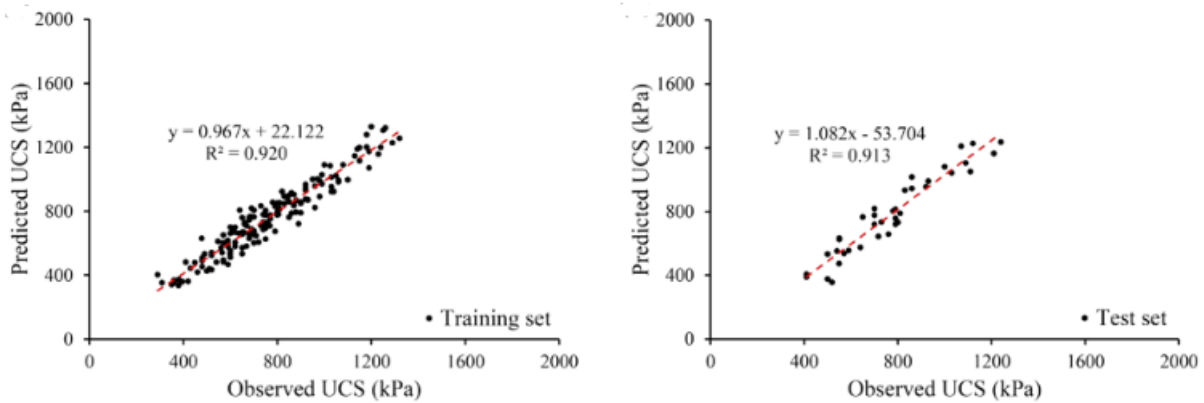


Fig. 2.21. ANN model performance for UCS prediction soil-cement using (a) hold-out and (b) k-fold cross-validation on training and test sets (Fazel-Mojtahedi et al., 2023).

A mutual information (MI) method was first applied to rank the input variables by relevance, helping reduce model complexity. The ANN structure was optimized using a grid search method, leading to a three-layer feed-forward network with an architecture of [5, 3, 1] and activation functions. The model performance was validated using both Hold-out and K-fold cross-validation techniques, with the latter showing superior predictive accuracy. As reported, the best model under K-fold with early stopping achieved an R^2 of 0.913 for the test set and a root mean square error (RMSE) of 47.8 kPa (Fig 2.21), demonstrating high generalization capacity.

The performance plots showed predicted values closely tracking the experimental results, with minimal dispersion and strong alignment along the ideal 1:1 line. Sensitivity analysis confirmed the water-cement ratio and cement content as the most influential factors. Finally,

the model's predictions were validated against a real field case, yielding an R^2 of 0.83 (Fig 2.22), reinforcing the ANN's applicability for practical DMT strength forecasting in geotechnical engineering.

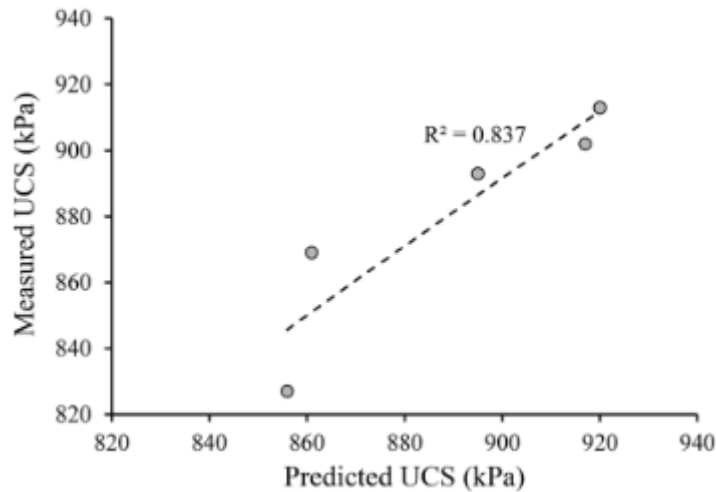


Fig. 2.22. Measured vs. ANN-predicted UCS of in-situ improved soil samples (Fazel-Mojtahedi et al., 2023).

Salahudeen et al. (2020) developed artificial neural network models to predict the strength of cement kiln dust-treated expansive clay using back-propagation algorithms. Their study used multilayer perceptrons with eight input parameters including soil properties like specific gravity, shrinkage characteristics, and compaction parameters to predict unconfined compressive strength at different curing periods. The research utilized 72 datasets that were systematically divided into training, testing, and validation groups to ensure model reliability.

The optimized neural network architecture (8-11-1) showed excellent performance in predicting soil strength across all curing periods. The models achieved strong correlation coefficients ranging from 0.9783 to 0.9942 for specimens cured at 7, 14, and 28 days, all well above the 0.8 threshold considered indicative of strong predictive capability. This high accuracy demonstrates the model's ability to capture the complex relationships between various soil properties and strength development over time.

The study demonstrated that artificial neural networks could effectively capture the complex nonlinear relationships between soil properties and strength characteristics. Statistical performance indicators including mean absolute error, root mean square error, and correlation coefficients confirmed the reliability and accuracy of the predictive models.

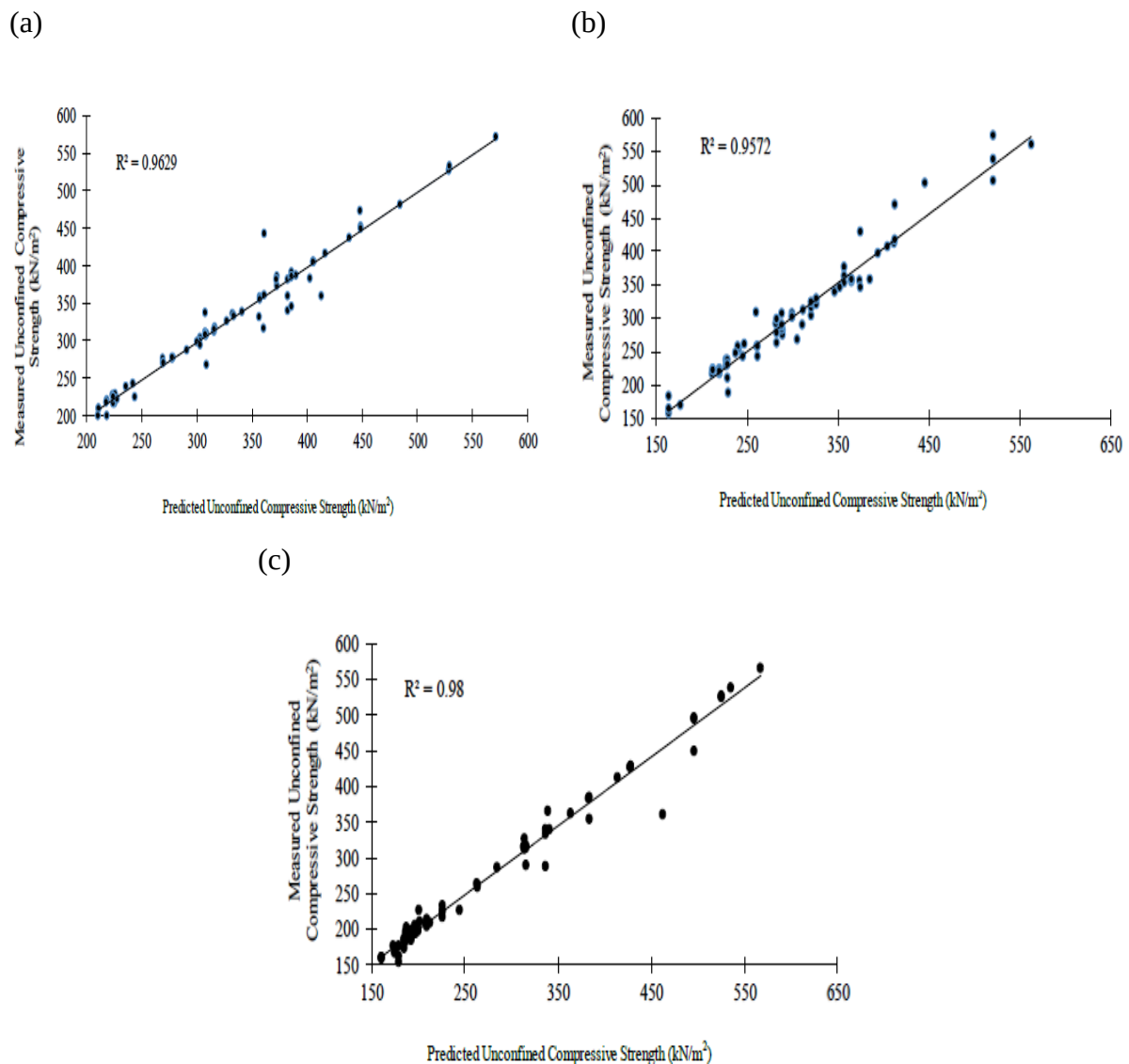


Fig. 2.23. Measured vs. ANN-predicted UCS values for (a) 7-day, (b) 14-day, and (c) 28-day curing periods (Salahudeen et al., 2020)

Numerous models exist in the literature, reflecting the significance of this technique and parameter. Machine learning approaches have been increasingly applied to predict the unconfined compressive strength (UCS) of clayey soils stabilized with mineral additives, demonstrating superior accuracy and capability in handling complex, non-linear relationships between soil properties and stabilization parameters. Tab 2.2 consolidates the discussed models from various researchers, including the advanced machine learning techniques developed for UCS prediction of stabilized clayey soils.

Tab. 2.2. Summary of additional important models (AI) for predicting ther unconfined compressive strength, published in the literature

Authors	ML techniques	Soil type	Data number	Miniral additives	Input variables	Output variable	R ² Performance
Ahmed et al. (2024)	GPR ; SVM	Clay soil	121	HARHA	HARHA ;LL ; PL ; PI ; OMC ; CA ; MDD ;UCS	UCS	R ² =0.9998 (SVM)
Sari-Ahmed et al. (2024)	XGBoost	Various soils	341	Lime	F ; L _c ; T ;UCS ₀	UCS	R ² =0.9100
Eyo et al. (2022)	DT ;RF ;ERT ; AdaBoost ;GBoost	Various soils	392	Lime ; cement ; rice husk ash ; bagasse ash	L _c ; C ; LL ; PL ;IP ;RHA ; RBA	UCS	R ² =0.9000 (GBoost)
Suman et al. (2016)	ANN ;SVM ; FN ;MARS ; MLR	Clay soils	51	Lime ; cement	LL ; PI ; S ; G ; L _c ; W ; C	UCS	R ² =0.9500 (MARS)
Tinico et al. (2016)	MR ; ANN ; SVM	Clay soils	269	Cement	SL ;OM ; w ₀ /a _w ;C _d ; S ;T ; C ;L ₂	UCS	R ² =0.9300 (SVM)

Where, **HARHA** : hydrated-lime-activated rice husk ash ; **L_c**: lime content; **LL** : liquid limit ; **PL** : plastic limit ; **PI** : plasticity index ; **CA** : clay activity ; **MDD** : maximum density dry ; **UCS** : unconfinned compressive strength ; **GPR** : Gaussian process regression ; **SVM** : Support vector machine ; **F** : fiber ; **UCS₀**:initial inconfinned compresevie strength ; **XGBoost** : extreme gradient boost tree ;**DT** : descision tree ; **RF** : random forest ; **ERT** : extrmely randomised trees ; **GBoost** : gradient boosting ; **C** : ciment ; **RHA** : rice husk ash ; **RBA** : rice bagasse ash ; **FN** : functional networks ; **MARS** : multivariate adaptive regression splines ; **MLR** : Multilinear regression ; **SL** : soil clay content ; **OM** : Soil organic matter content ; **w₀/a_w** : Relation between water and cement content ; **C** : cement dosage ; **T** : curing time ; **S** : Coefficient related with the cement type ; **L₂** : Coefficient related with the secondary binder

2.4. Conclusions

This chapter reviewed the evolution of predictive methods for estimating the unconfined compressive strength (UCS) of stabilized clayey soils. The discussion focused on both traditional empirical models and modern machine learning approaches applied to soils treated with additives such as lime, fly ash, and cement. Based on the reviewed literature, the main conclusions drawn are as follows:

- Empirical regression models have effectively quantified the relationship between UCS and influencing factors such as curing time, additive content, and soil plasticity, providing a practical foundation for strength prediction;
- Cement-stabilized soils consistently exhibited higher UCS values than lime- or fly ash-stabilized soils, due to the rapid hydration and cementation reactions, making them favorable for short-term strength gains;
- Lime and fly ash-treated soils showed gradual strength development over time, with pozzolanic reactions significantly improving long-term UCS depending on dosage and curing conditions;
- Artificial neural network (ANN) models have demonstrated superior prediction capabilities compared to conventional regression models, particularly in capturing nonlinear and multivariate interactions among soil and treatment parameters;
- ANN architectures trained on datasets of soil and additive properties achieved high R^2 values and low error metrics, showing strong alignment with experimental UCS measurements;
- Sensitivity analysis across various ANN studies identified curing time, stabilizer percentage, and dry density as the most influential variables for UCS prediction;
- AI-based prediction models offer a reliable alternative to time-intensive laboratory testing, supporting rapid assessment and efficient design processes in geotechnical engineering;
- While ANN models enhance prediction accuracy and efficiency, they are best used in conjunction with standard laboratory testing to account for site-specific variability and ensure robust engineering decisions

The subsequent chapter builds upon these theoretical foundations by presenting a systematic approach to input parameter selection and database compilation for soil stabilization analysis. This following section details the comprehensive methodology for collecting and organizing

experimental data from various sources, focusing specifically on clayey soils treated with lime and fly ash additives. The chapter establishes the framework for creating a robust database that serves as the foundation for developing both empirical and machine learning models, ensuring that the selected input variables accurately represent the key factors influencing soil stabilization performance under different treatment conditions.

Chapter3

Database Compilation for Soil Stabilization Analysis

3.1 Introduction

In geotechnical engineering, stabilizing clayey soils is essential due to their inherent issues with plasticity, low strength, and susceptibility to environmental degradation. Lime and fly ash are among the most widely used stabilizing agents, valued for their chemical reactivity, cost-effectiveness, and ability to significantly enhance the strength and durability of problematic soils. This chapter compiles and standardizes experimental data from decades of global research, focusing on how these additives influence the unconfined compressive strength (UCS) of clayey soils subjected to freeze–thaw (F–T) cycles. The dataset includes soils treated with either lime or fly ash and captures variations in curing time, additive dosage, initial UCS, and soil plasticity. All records are aligned with ASTM and AASHTO testing protocols to ensure consistency. By unifying these parameters into a single structured database, the chapter provides a solid foundation for both empirical comparison and predictive modeling, helping guide the development of more resilient and sustainable soil stabilization strategies.

3.2. Environmental input factors influencing stabilized soil properties

The selection of geotechnical properties for analyzing unconfined compressive strength (UCS) in lime-stabilized clayey soils represents a critical scientific approach to addressing the complex challenges encountered in construction projects worldwide. Earth structure projects frequently confront problematic soils characterized by multifaceted engineering challenges, including excessive settlement, swelling, shrinkage, erosion and reduced bearing capacity ([Harichane et al., 2010](#)). Unconfined compressive strength emerges as a pivotal parameter in civil engineering applications, serving as a fundamental indicator of soil strength and structural integrity across critical infrastructures such as roadway subgrades, road embankments, earth dams, and pavement design ([Laguros, 1962](#); [Jigheh and Azarnia, 2017](#); [Kang et al., 2014](#)). The comprehensive analysis of geotechnical properties demands a nuanced approach that transcends surface-level assessments, requiring a profound understanding of the intricate interactions between soil composition, stabilization techniques, and environmental conditions.

The scientific selection of geotechnical properties is meticulously grounded in an evaluation of parameters that significantly influence the unconfined compressive strength of lime-stabilized clayey soils. Eight critical properties have been identified as paramount to

understanding soil behavior: Lime Content (L_c), which demonstrates direct impact on clayey soil resistance to environmental degradation; Initial UCS (UCS_0), serving as a crucial baseline for stabilization effectiveness; Number of Freeze-Thaw cycles (NC), revealing progressive soil strength deterioration; Curing Time (T), demonstrating significant influence on strength development through pozzolanic reactions; Optimum Moisture Content (OMC), playing a critical role in compaction and frost heave susceptibility; Maximum Dry Density (MDD), impacting freeze-thaw resistance and strength development; Plasticity Parameters (LL and PI), influencing soil workability and interaction with stabilizing agents; and Consistency Index (IC), providing insights into soil behavior under varying environmental conditions (Aldaoood et al., 2014; Zhang et al., 2019; Ghazavi and Roustaei, 2010; Yildiz et al., 2012; Al-Mukhtar et al., 2010; Aldaoood et al., 2016; Liu et al., 2019). This comprehensive approach allows researchers to develop sophisticated models that capture the complex interactions between these properties, providing unprecedented insights into soil stabilization mechanisms.

Environmental conditions, particularly freeze-thaw, emerge as critical determinants of soil behavior and structural integrity. Expansive clays in cold regions represent a particularly challenging scenario, characterized by complex degradation mechanisms that dramatically compromise soil strength and bearing capacity (Ghazavi et al., 2010; Hotineanu et al., 2015; Salih et al., 2020). These environmental cycles induce sophisticated degradation processes, including ice lens formation, pore pressure variations, chemical bond disruption, and moisture content fluctuations. The interaction between moisture content and lime stabilization represents a particularly intricate phenomenon, where excessive moisture can impede chemical reactions between lime and soil particles, while inadequate moisture may hinder proper lime hydration and its strength-enhancing capabilities (Esmer et al., 1969; Yildiz and Soğanci, 2012). This delicate balance underscores the complexity of soil stabilization in dynamic environmental contexts, highlighting the critical need for comprehensive research and advanced predictive modeling.

The approach to geotechnical property selection transcends technical considerations, encompassing broader environmental and economic implications. By optimizing stabilizing material usage, engineers can achieve multifaceted benefits including reduced resource consumption, decreased greenhouse gas emissions, minimized construction project carbon footprint, enhanced infrastructure durability, and optimized long-term economic investments

(Garg and Tai, 2013; Ransom et al., 2019). Statistical models offer distinct advantages in this comprehensive analysis, providing transparency and interpretability that AI-based approaches often lack. They facilitate hypothesis testing, confidence interval construction, and detailed analysis of individual parameter significance, offering clear understanding of variable interactions (Kolias et al., 2005; Sari-Ahmed et al., 2018). The methodology represents a holistic approach to geotechnical engineering, bridging scientific rigor with practical application. By developing sophisticated predictive models for UCS in lime-stabilized clay soils subjected to freeze-thaw, researchers can provide engineers with powerful tools for addressing complex environmental challenges, ultimately contributing to more sustainable, resilient, and efficient engineering solutions in challenging environmental conditions (Al-Mukhtar et al., 2010; Liu et al., 2019).

3.3 Lime additive dataset collection and processing under freeze-thaw

3.3.1 Data sources

The comprehensive database was meticulously assembled through an exhaustive literature review spanning nearly six decades of geotechnical research, incorporating 18 scientific studies published between 1963 and 2022. The research sources encompass a diverse range of experimental investigations on lime-stabilized clay soils, representing a global perspective on soil stabilization techniques. Key contributing studies include pioneering work by Walker et al. (1967) and Dunlap (1967), through to more recent investigations by Yang et al. (2020) and Jafari and Lajevardi (2022).

The database's robustness was further enhanced by validation using independent research from Shandaala (1964), Dayioglu et al. (2017), Aldaood et al. (2018), and Li et al. (2022). This comprehensive approach ensured a representative and diverse dataset that captures the evolution of lime stabilization techniques and understanding over nearly six decades of geotechnical research. Were included as explanatory variables (Tab 3.1).

Tab. 3.1. Data set from the literature used to build the UCS_{FT} model.

Data source	L _c (%)	UCS (kPa)	T (day)	CI	OMC (%)	NC	Data number
Walker et al, 1967	0-10	172.37-2227.01	0-45	1.10	27.0	0-20	07
Walker and Krebs, 1963	0-8	82.74-1434.11	0-4	1.81-2.39	25.29.9	0-10	13
Dunlap et al, 1975	2-7	433.47-2465.57	7-28	0.86-0.89	19.7-23.6	0-3	12
Sweeny et al,1989	2-4	187.00-1156.20	7-195	0.94	30.6	0-2	12
Abdi, 2011	1-5	414.16-3061.00	1-90	1.26	21.0	0-4	40
Kayak and Baykal, 2012	4-8	264.54-654.29	28	0.75-1.01	24.0-42.0	0-20	04
Yildiz and Soğanci, 2012	6	375.00-995.00	1-28	1.30	17.5	0-3	10
Olgun, 2013	0-2	104.18-210.00	0-28	1.59	26.3	0-7	04
Rahman, 2014	0-7	527.54-4143.80	0-7	1.07-1.29	14.7-15.1	0-20	17
Hotineanu et al, 2015	3-5	313.88-2356.97	3-300	1.06-1.26	25.1-39.2	1-10	24
Nguyen, 2015	1-5	150.00-5190.00	7-365	1.06-2.19	18.8-15.6	0-10	34
Tebaldi et al, 2016	0-2	450.00-1522.58	0-28	1.49	17.5	0-10	05
Boz and Sezer, 2018	0-3	26.00-357.00	0-28	1.00	30.0	0-10	09
Gupta and Prasad, 2018	0-7.5	98.00-1498.50	0-28	0.55	42.0	0-05	34
Ismeik and Shaqour, 2018	0-8	109.50-1631.00	0-28	1.82	14.7	0-20	17
Liu et al, 2019	3-15	89.00-1888.00	7-28	1.13	15.6	0-60	31
Yang et al, 2020	0-5	698.00-1382.50	0-1	1.26	13.6	0-14	11
Jafari and Lajevardi, 2022	7-10	305.00-756.00	0-28	1.21	16.5	0-09	06
Total number of data							290

Were, L_c : lime content (%) ; UCS : Unconfined compressive strength (kPa) ; T : curing time (Days) ; CI : consistency index ; OMC : optimum moisture content (%) ; NC : cycles number for freeze-thaw

3.3.2. Database structure and preprocessing

The database is structured around 290 experimental data points, carefully curated to represent the complexity of lime-stabilized clay soils. The soil samples were rigorously classified using the Unified Soil Classification System (USCS), revealing a nuanced composition: 52% high plasticity clays (CH) and 48% low plasticity clays (CL), which together represent the majority of clayey soils. As shown in Fig 3.1. The data integration process considered multiple critical factors to ensure database integrity, including soil classification, lime additive types, and the presence of organic matter. Preprocessing techniques involved standardizing experimental conditions and data representation across different studies.

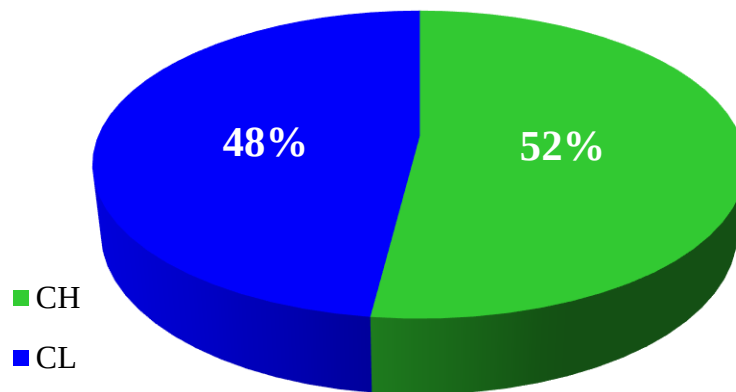


Fig. 3.1. Percentage distribution of soil classes in the dataset used for UCS modeling of lime-stabilized clays under F-T conditions

The experimental protocols adhered to established testing standards to ensure the reliability and comparability of results. A significant 65% of the tests were conducted following ASTM standards, which are widely recognized for their rigorous and systematic guidelines. An additional 15% of the tests utilized AASHTO standards, reflecting their relevance to transportation and geotechnical engineering applications. The remaining 20% employed other methodological approaches, showcasing the diversity in experimental design and the effort to explore alternative or supplementary testing frameworks in Fig 3.2.

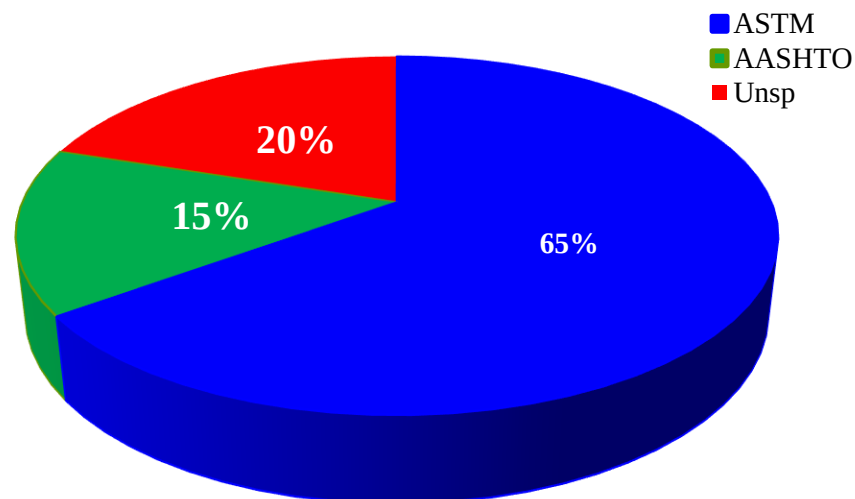


Fig. 3.2. Standards and testing protocols used for F-T evaluation of lime-stabilized soils.

This distribution of standards emphasizes the robust nature of the dataset, ensuring that the data collection process was consistent, precise, and adaptable to various research objectives. Freeze-thaw testing, a critical aspect of the study, predominantly adhered to the [ASTM D560](#)

standard, ensuring uniformity in evaluating the impact of cyclic environmental stress on lime-stabilized clay soils.

In terms of lime stabilization techniques, the composition of lime used in the experiments further highlights the diversity in methodological approaches. Quicklime was the predominant type, employed in 47% of the samples, while 43% utilized hydrated lime. The remaining 10% of tests used unspecified lime types, reflecting a degree of variability in material selection as presented in Fig 3.3.

This range of lime types allowed the study to capture a broad spectrum of soil-lime interactions, providing insights into how different lime compositions affect soil stabilization. By combining standardized testing protocols with varied lime compositions, the experimental framework ensured a comprehensive evaluation of lime-stabilized clay soils under diverse environmental conditions, particularly freeze-thaw cycles. This thorough approach underscores the dataset's robustness, enabling nuanced analyses and reliable conclusions.

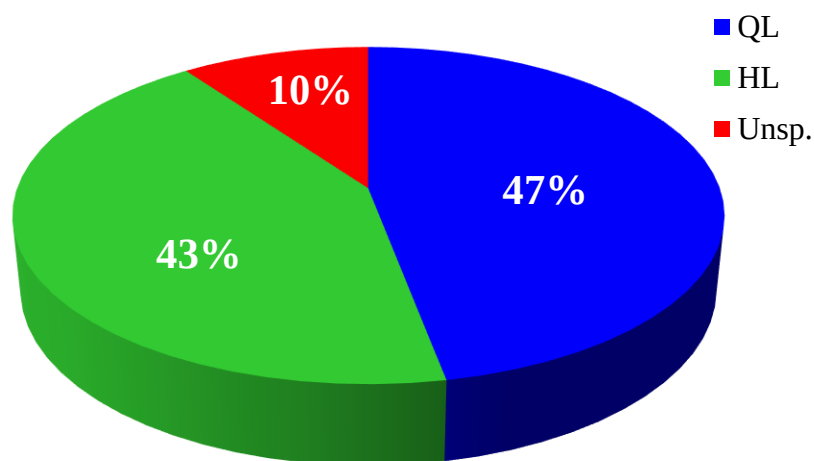


Fig. 3.3. Distribution of lime types used in the dataset.

4.3.3. Statistical overview of data

Tab. 3.2 illustrate the statistical characterization of the database unveils a multifaceted and intricate dataset that encapsulates the complex interactions between lime stabilization, soil properties, and mechanical performance. The lime stabilization characteristics demonstrate a nuanced approach to soil modification, with lime percentages ranging from 0% to 15%, reflecting a mean of 4.57% that highlights the subtle yet significant impact of lime content on

soil behavior. Mechanical properties reveal dramatic variability in unconfined compressive strength (UCS), with initial UCS showing a mean of 331.61 kPa across a range of 74-917 kPa, and experimental UCS exhibiting an even more pronounced variability, averaging 964.22 kPa with an extensive range from 26 to 5190 kPa. This substantial variation underscores the profound influence of lime stabilization on soil strength and the complexity of geotechnical interactions.

The soil characteristics present an equally complex narrative, with plasticity index demonstrating remarkable diversity, ranging from 7% to 254% and averaging 30.38%. This wide range reflects the heterogeneous nature of clay soils and their differential response to lime stabilization. The liquid limit, averaging 58.06% and spanning from 28.6% to 298%, further illustrates the significant variability in soil composition and behavior. The consistency index, with a mean of 1.22 and a range of 0.55-2.39, provides additional insight into the soil's structural and mechanical properties, indicating substantial variations in soil consistency and potential stabilization effectiveness.

Tab. 3.2. Comprehensive summary of collected geotechnical data for model development

	Param	count	mean	Std	min	25%	50%	75%	Max
L_c (%)	Input	290	4.57	2.90	0.00	3.00	5.00	6.00	15.00
UCS₀ (kPa)	Input	290	331.61	211.80	74.00	187.00	275.00	412.00	917.00
T (days)	Input	290	38.94	76.11	0.00	7.00	28.00	28.00	365.00
LL (%)	Input	290	58.06	37.77	28.60	42.00	45.75	59.00	298.00
IP (%)	Input	290	30.38	32.14	07.00	19.00	22.00	26.94	254.00
OMC (%)	Input	290	23,16	9,38	13,65	15,60	21,00	29,50	42,00
MDD (Kg/m³)	Input	290	17.80	18.11	1.81	11.90	16.00	17.74	102.70
CI	Input	290	1,22	0,43	0,55	1,06	1,13	1,29	2,39
NC	Input	290	4.23	7.02	0.00	0.00	2.00	5.00	60.00
Exp UCS (kPa)	Output	290	964.22	822.60	26.00	450.00	732.50	1248.14	5190.00

Where, L_c : lime content (%) ; UCS : Unconfined compressive strength (kPa) ; T : curing time (Days) ; LL : liquid limit (%) ; IP : plasticity index (%) : OMC : optimum moisture content (%) ; MDD : maximum density dry (Kg/m³) ; CI : consistency index ; NC : cycles number for freeze-thaw.

Experimental conditions reveal critical contextual information that frames the database's comprehensive nature. The curing time, ranging from 0 to 365 days with an average of 38.94 days, demonstrates the extensive temporal spectrum considered in the research, capturing both short-term and long-term stabilization effects. Freeze-thaw cycles, averaging 4.23 but ranging from 0 to 60 cycles, highlight the database's robust exploration of environmental stress impacts on lime-stabilized soils. The optimum moisture content, averaging 23.16% and ranging from 13.65% to 42%, further emphasizes the dynamic interplay between soil hydration, lime stabilization, and mechanical performance.

This statistical characterization transcends mere numerical representation, offering a comprehensive window into the complex, nonlinear relationships governing lime-stabilized clay soils. The extensive variability across parameters suggests that no single factor exclusively determines soil behavior, but rather, a sophisticated interplay of multiple variables creates the ultimate geotechnical response.

The database's breadth and depth provide researchers and engineers with an unprecedented analytical resource for understanding, predicting, and optimizing soil stabilization techniques across diverse environmental and geological contexts.

The frequency distribution analysis, illustrated in the [Fig 3.4](#), provides a visual representation of the data's distribution across various parameters. This comprehensive approach offers unprecedented insight into the behavior of lime-stabilized clay soils, capturing the intricate relationships between stabilization techniques, soil properties, and environmental conditions.

The database's multi-dimensional nature allows for robust statistical modeling and artificial neural network (ANN) approaches, providing researchers with a powerful tool for understanding and predicting the performance of lime-stabilized clay soils under diverse environmental challenges.

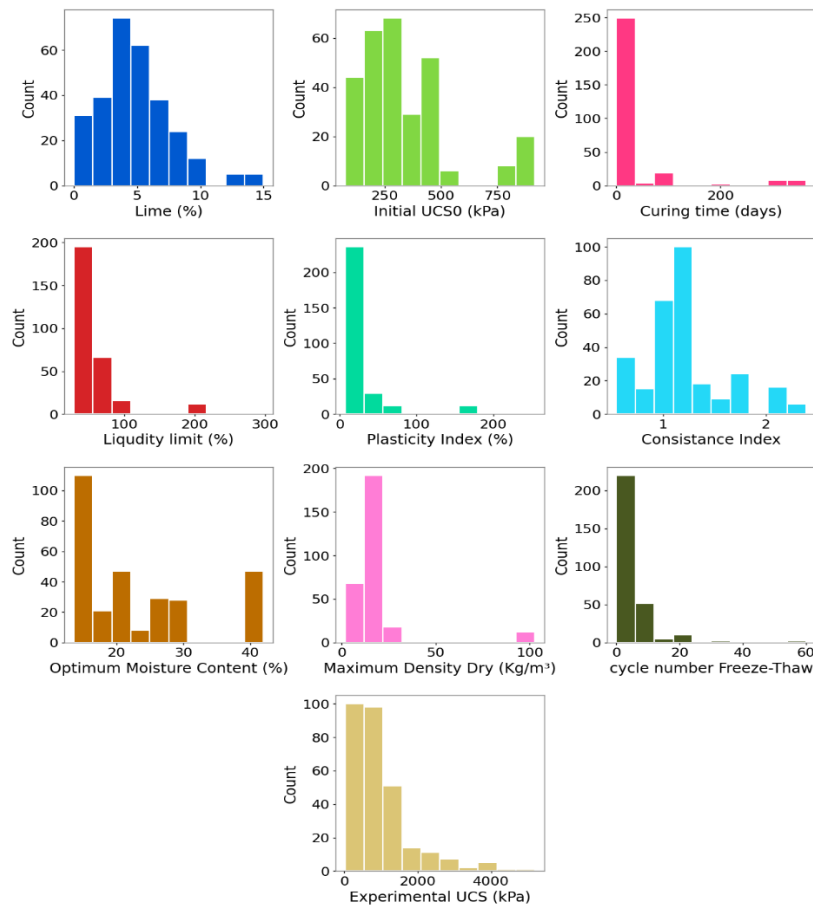


Fig. 3.4. Frequency distribution of data for each parameter in the collected database.

The density plots reveal distinct distribution patterns across ten geotechnical parameters, each showing unique statistical characteristics. Most parameters exhibit unimodal distributions with varying degrees of skewness and spread. The L_c parameter shows a classic bell-shaped distribution centered around 5 units, while parameters like T , IP , LL , and NC display right-skewed distributions with peak densities concentrated near lower values (Fig 3.5).

The MDD parameter demonstrates a particularly sharp, narrow distribution around 20 units, indicating consistent measurements with minimal variation. In contrast, OMC exhibits a bimodal distribution with two distinct peaks, suggesting the presence of two different soil categories or testing conditions within the dataset.

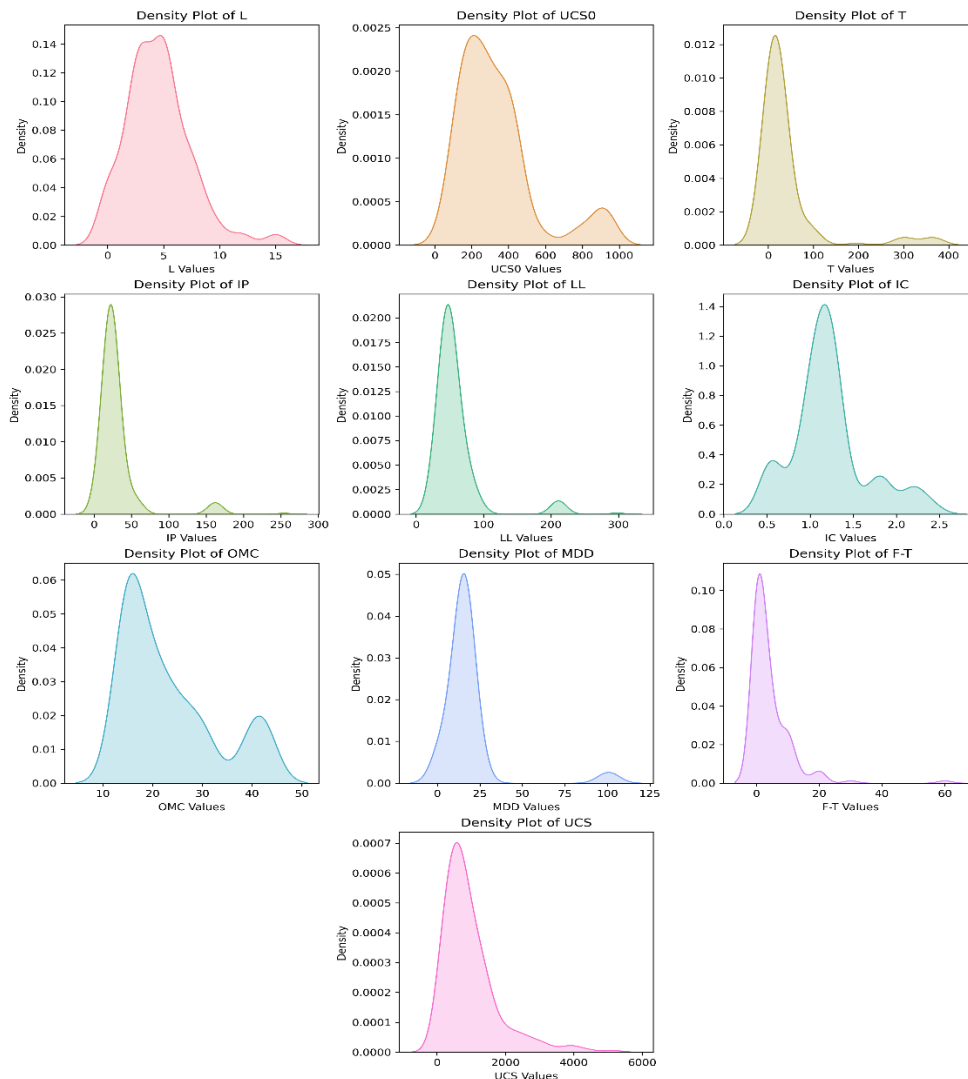


Fig. 3.5. Probability density distributions of geotechnical parameters in soil testing dataset.

The strength-related parameters UCS_0 and UCS show markedly different distribution characteristics compared to the physical property parameters. UCS_0 displays a right-skewed distribution with most values concentrated below 400 units but extending to approximately 1000 units, indicating moderate variability in soil strength measurements. The UCS parameter demonstrates the most extreme distribution, with values ranging from near zero to 6000 units, creating a highly elongated right tail.

This extensive range suggests significant diversity in soil strength properties, possibly reflecting different soil types, treatment methods, or curing conditions. The IC parameter presents an interesting multimodal pattern with the primary peak around 1.0 and smaller secondary peaks, indicating multiple distinct soil classification categories within the dataset.

[Fig 3.6](#) illustrates a correlation heatmap that visualizes the relationships among several key parameters influencing the UCS of lime-stabilized clayey soil subjected to freeze-thaw cycles.

The color gradient represents the correlation coefficients, ranging from -1 (strong negative correlation) to +1 (strong positive correlation). Darker shades signify stronger relationships, while lighter shades indicate weaker or negligible correlations. From the heatmap, it is evident that UCS exhibits a moderate positive correlation with lime content (L, 0.28), initial UCS (UCS0, 0.36), and curing time (T, 0.38), underscoring the significant role these parameters play in enhancing soil strength. On the other hand, UCS shows a weak negative correlation with optimum moisture content (OMC, -0.26), implying that higher moisture levels slightly diminish compressive strength. Interestingly, parameters like the liquid limit (LL), plasticity index (IP), consistency index (IC), and freeze-thaw cycles (F-T) exhibit negligible correlations with UCS, suggesting their limited direct impact under the tested conditions.



Fig. 3.6. Correlation heatmap of parameters influencing ucs of lime-stabilized clayey soil under F-T cycles

This heatmap serves as a critical tool for understanding the relative significance of stabilization factors, offering insights that can guide the optimization of soil stabilization techniques for improved performance under challenging environmental conditions.

3.4. Fly ash additive dataset collection and processing under freeze-thaw

3.4.1 Data sources

The dataset used for this analysis was compiled from 11 scientific studies published between 2009 and 2022, representing a substantial and comprehensive body of research focused on the behavior of clayey soils stabilized with Fly ash under various environmental conditions. This time span highlights over a decade of focused research and development in the field of geotechnical engineering.

The studies encompass experimental investigations carried out under diverse conditions, reflecting the global effort to understand and optimize Fly ash stabilization techniques for enhancing soil strength and durability. Contributions come from prominent researchers, including [Altun et al. \(2009\)](#), [Binshafique et al. \(2010\)](#), [Solanki \(2010\)](#), [Wen et al. \(2011\)](#), [Yu et al. \(2017\)](#), [Sezer et al. \(2017\)](#), [Mehedi et al. \(2018\)](#), [Li et al. \(2018\)](#), [Yang et al. \(2020\)](#), [Zhuo et al. \(2021\)](#), and [Li et al. \(2022\)](#), underscoring the multidisciplinary and international collaboration within this field of study.

Together, these studies provide a robust dataset comprising 188 data points. Each data point encapsulates a wide range of experimental variables, such fly ash content, curing time, liquid limit, plasticity index, consistency index, optimum moisture content, maximum dry density, and the number of freeze-thaw cycles.

The inclusion of such diverse parameters ensures a comprehensive understanding of the underlying mechanisms influencing soil behavior. This dataset ([Tab 3.5](#)) serves as a crucial foundation for identifying correlations, developing predictive models, and enhancing the performance of Fly ash-stabilized soils under challenging environmental conditions. The meticulous documentation and broad scope of these studies highlight the commitment of researchers to advancing the science of soil stabilization and its applications in real-world geotechnical challenges.

Tab. 3.3. Data compilation for predicting F-T impact on UCS in fly ash stabilized clay soils.

Data source	FA (%)	UCS (kPa)	T (day)	LL (%)	IP (%)	CI (%)	OMC (%)	MDD (kg/m ³)	NC	Data number
Altun et al 2009	0-30	136.03-973.22	28	30.0	24.0	0.73	12.4	15.6	0-7	12
Binshafique et al 2010	0-20	120.00-212.00	7	36.0-81.0	17.0-57.0	0.96-1.74	64.0-26.0	15.1-21.2	0-12	22
Solanki 2010	0-10	296.44-361.66	7	26.0-58.0	7.0-27.0	1.07-1.74	12.4-23.3	16.3-17.8	0-12	45
Wen et al 2011	0-18	232.15-636.88	7	51.0	32.0	0.99	19.1	10.7	0-2	6
Yu et al 2016	0-30	179.84-405.50	1-24	61.50	19.3	1.63	30.0	12.9	0-12	8
Sezer et al 2017	0-20	58.20-1180.0	28	90.0	44.0	1.58	20.2	15.1	0-10	20
Mehedi et al 2018	0-10	122.64-354.48	7	24.1	3.2	2.20	16.5	16.7	0-3	12
Li et al 2018	0-15	212.15-229.35	7	26.3	5.05	1.65	13.0	19.2	0-10	6
Yang et al 2020	2.5	358.86-449.64	0-14	28.6	11.9	1.25	13.65	18.4	0-14	4
Zhuo et al 2021	0-20	213.37-834.56	28	21.0	7.5	1.14	12.4	19.6	0-11	29
Li et al 2022	0-25	63.95-468.38	0-35	30.6	11.8	1.06	18.0	17.1	0-4	24
Total number of data										188

Where, FA : fly ash content (%) ; UCS : Unconfined compressive strength (kPa) ; T : curing time (Days) ; LL : liquid limit (%) ; IP : plasticity index (%) ; CI : consistency index ; OMC : optimum moisture content (%) ; MDD : maximum density dry (Kg/m³) ; NC : cycles number for freeze-thaw.

3.4.2 Database structure and preprocessing

Clayey soils categorize based on the UCS. This classification provides a systematic framework for understanding soil behavior under various conditions. The UCS categorization ensures that distinct soil types are represented accurately in the analysis, enabling an effective evaluation of their engineering properties. The clayey soils were classified into multiple UCS ranges, each corresponding to a specific category that reflects their mechanical performance. For instance, soils with lower UCS values signify weaker materials, while higher UCS values indicate stronger soils suitable for specific engineering applications. This classification highlights the variability inherent in clayey soils and the importance of capturing this range to establish accurate relationships between soil properties and the performance of fly ash additives. The soil classification analysis revealed a nuanced composition of the studied

materials. High plasticity clayey soils (CH) dominated the dataset, comprising 54% of the samples, indicating their prevalence in geotechnical investigations. Low plasticity clayey soils (CL) represented 32% of the samples, while medium plasticity silty soils (ML) accounted for 14%. such illustrate in Fig 3.7, demonstrating the complex and varied nature of soil compositions encountered in engineering applications.

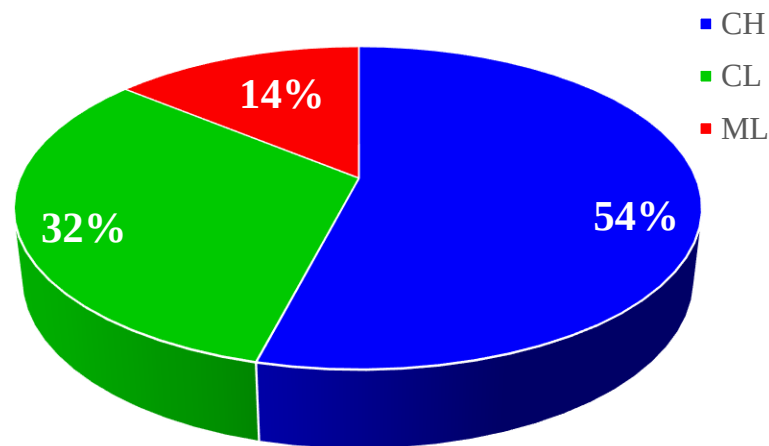


Fig. 3.7. Soil class distribution in the dataset for UCS modeling of fly ash-stabilized clays under F-T conditions.

Fig 3.8 illustrates the classification of standards according to UCS. This categorization emphasizes adherence to regulatory or engineering standards to ensure the database aligns with established guidelines for geotechnical applications. The standards were grouped into performance ranges, ensuring consistency and reliability in comparing experimental results with industry benchmarks. The standardization of research methods played a crucial role in maintaining data quality and comparability across geotechnical studies. The ASTM standards were predominant, with 69% of studies following these well-established protocols. These standards provided researchers with detailed procedures for sample collection, testing parameters, and analysis methods, ensuring consistency and reliability in the results. The remaining 31% of studies employed alternative methodological approaches, as illustrated in Fig 3.8. This diversity in methodology reflects the dynamic nature of geotechnical research, where researchers often need to adapt or develop new testing methods to address specific research questions or unique soil conditions. These alternative approaches ranged from modified standard procedures to innovative testing techniques, contributing to the advancement of geotechnical testing methodologies.

This distribution of methodological approaches demonstrates both the field's reliance on established standards and its capacity for methodological innovation when required by specific research demands. This structured approach enables a clearer understanding of how the data compares to both theoretical expectations and real-world requirements, reinforcing the importance of compliance with recognized norms in soil stabilization practices.

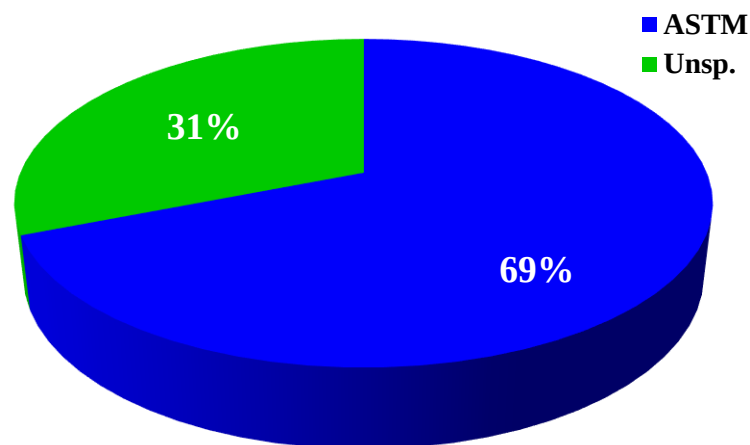


Fig. 3.8. Overview of f-T test standards applied to fly ash-stabilized soils in the dataset.

[Fig3.9](#) presents the classification of fly ash additives, also according to Fly ash-UCS, a byproduct of industrial processes, has diverse chemical and physical properties that significantly impact its suitability for soil stabilization. This figure highlights how different types of fly ash additives contribute uniquely to improving UCS. The classification scheme categorizes the additives into ranges based on their performance, showing a distribution that aligns with the observed effects of fly ash on the soils tested. Present the fly ash additives in the geotechnical engineering database demonstrated a diverse range of compositions, with fly ash class C representing the largest proportion at 81% of the samples. Fly ash class F constituted 19% of the additives, highlighting the varied approaches to soil stabilization techniques. This variability underscores the importance of selecting the appropriate type of fly ash to achieve desired stabilization outcomes. By classifying additives into categories, the study establishes a foundation for understanding their relative efficacy and compatibility with specific soil types.

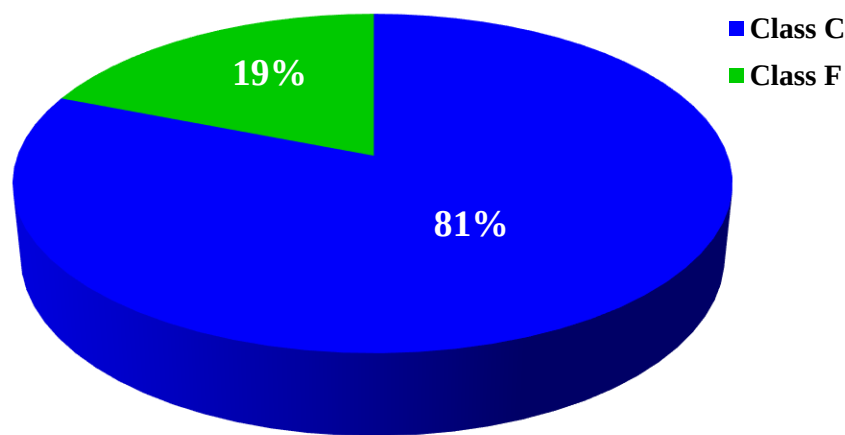


Fig. 3.9. Fly ash class distribution in the dataset used for UCS modeling.

3.4.3. Statistical overview of data

[Tab 3.6](#) illustrates the statistical characterization of the dataset, unveiling its multifaceted and intricate nature, which encapsulates the complex interactions between fly ash stabilization, soil properties, and mechanical performance. Fly ash percentages range from 0% to 12%, with a mean of 9.18%, reflecting a subtle yet significant influence on soil behavior. Mechanical properties exhibit dramatic variability, with initial UCS showing a mean of 263.36 kPa across a range of 11-670 kPa. Experimental UCS demonstrates even greater variability, averaging 315.16 kPa and spanning an extensive range from 10 to 3177 kPa. These variations underscore the profound effects of fly ash stabilization on soil strength and highlight the complexity of geotechnical interactions.

The soil characteristics further reveal a complex narrative. The plasticity index, ranging from 8% to 85% and averaging 20.40%, reflects the heterogeneous nature of clay soils and their differential responses to stabilization. The liquid limit, with a mean of 42.26% and a range from 25% to 130%, underscores the significant variability in soil composition and behavior. The consistency index, averaging 1.31 with a range of 0.80-3.60, offers additional insights into the structural and mechanical properties of soils, indicating substantial variations in consistency and stabilization effectiveness.

Tab. 3.4. Comprehensive summary of collected geotechnical data for model development

	Param	count	mean	std	min	25%	50%	75%	Max
FA (%)	Input	187.00	9.18	3.03	0.00	0.50	4.00	6.00	12.00
UCS ₀ (kPa)	Input	187.00	263.36	183.69	111.48	244.00	298.13	600.00	670.21
T (days)	Input	187.00	14.87	69.13	0.00	7.00	7.00	90.00	180.00
LL (%)	Input	187.00	42.26	21.53	25.00	56.00	60.90	67.00	130.00
IP (%)	Input	187.00	20.14	17.00	8.00	31.40	34.00	45.00	85.00
OMC (%)	Input	187.00	17.13	6.02	10.20	23.00	25.00	30.00	36.40
MDD (Kg/m ³)	Input	187.00	12,30	6,58	0,00	9,40	13,80	15,18	17,20
CI	Input	187.00	1.31	0.56	0.80	0.91	1.06	1.10	3.60
NC	Input	187.00	4.10	3.86	0.00	1.00	3.00	7.00	21.00
Exp UCS (%)	Output	187.00	315.16	586.56	10.11	105.90	297.00	599.33	3177.30

Where, FA : fly ash content (%) ; UCS : Unconfined compressive strength (kPa) ; T : curing time (Days) ; LL : liquid limit (%) ; IP : plasticity index (%) ; CI : consistency index ; OMC : optimum moisture content (%) ; MDD : maximum density dry (Kg/m³) ; NC : cycles number for freeze-thaw.

Experimental conditions provide critical contextual information, framing the comprehensive nature of the database. The curing time spans from 0 to 180 days, with an average of 14.87 days, capturing both short-term and long-term stabilization effects. Freeze-thaw cycles, averaging 4.10 and ranging from 0 to 21 cycles, highlight the database's robust exploration of environmental stress impacts. Optimum moisture content averages 17.13%, ranging from 10.20% to 36%, while maximum dry density, with a mean of 12.30 and a range of 6.58-17.20, emphasizes the dynamic interplay between soil hydration, fly ash stabilization, and mechanical performance.

This statistical characterization transcends mere numerical representation, offering a comprehensive window into the nonlinear relationships governing fly ash-stabilized clay soils. The extensive variability across parameters suggests that no single factor exclusively determines soil behavior. Instead, a sophisticated interplay of multiple variables shapes the geotechnical response. The dataset's breadth and depth provide an invaluable resource for researchers and engineers seeking to understand, predict, and optimize soil stabilization techniques across diverse environmental and geological contexts.

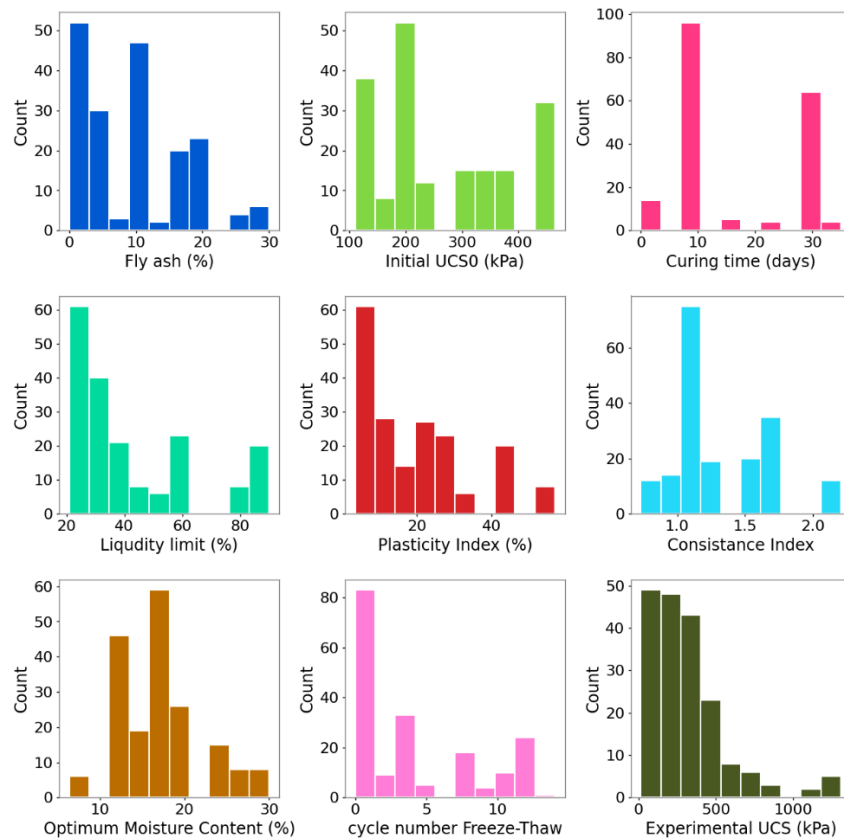


Fig. 3.10. Frequency distribution of counts for each parameter in the collected database.

The visualization of the frequency distribution for each parameter provides in Fig 3.10, who illustrate the occurrence rates of specific values across the dataset. This analysis plays a crucial role in identifying patterns and trends, which are essential for understanding the overall structure of the data. For instance, it highlights how certain ranges of parameters, such as moderate UCS values or typical fly ash percentages, occur more frequently than others. These frequency distributions also help in pinpointing anomalies, such as rare parameter values that deviate significantly from the norm, which may indicate experimental errors or unique cases warranting further investigation.

Fig 3.11 present the density plots reveal that several soil parameters exhibit multimodal distributions, indicating diverse soil categories within the dataset. FA, T, and OMC parameters show clear bimodal patterns with two distinct peaks, suggesting different treatment approaches or environmental conditions. The IC parameter displays a complex three-peak pattern, reflecting multiple soil consistency classifications.

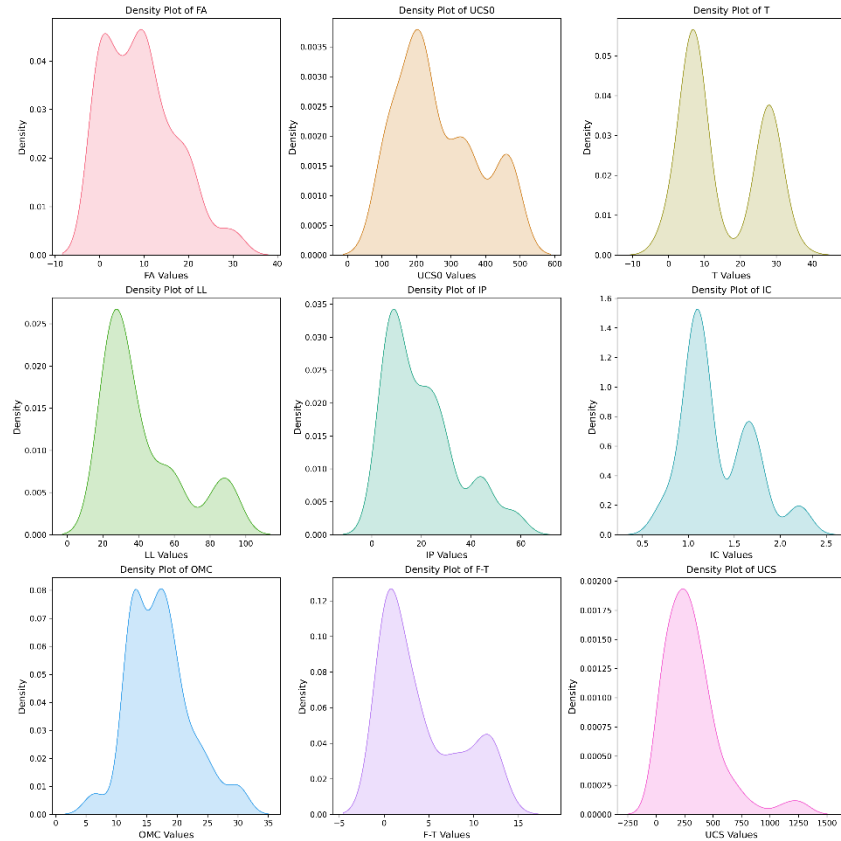


Fig. 3.11. Probability density distributions of geotechnical parameters in soil testing dataset

Most parameters demonstrate concentrated distributions with narrow peaks, indicating consistent measurement ranges. The F-T parameter shows minimal freeze-thaw exposure for most samples, while LL and IP exhibit typical right-skewed patterns for clay properties. UCS maintains the most extreme range extending to 1500 units, confirming its role as the primary variable driving dataset variability, while UCS0 shows a more moderate spread up to 600 units.

Fig 3.12 presents a correlation heatmap that highlights the relationships among key parameters influencing the unconfined compressive strength (UCS) of fly ash-stabilized clayey soils subjected to freeze-thaw cycles. The color gradient reflects correlation coefficients, with values ranging from -1 (indicating strong negative correlations) to +1 (indicating strong positive correlations). Darker shades represent stronger correlations, while lighter shades denote weaker or negligible associations. This visual tool provides a clear and intuitive understanding of how various stabilization factors interact. UCS demonstrates a moderate positive correlation with fly ash content (FA, 0.62) and curing time (T, 0.35), underscoring their pivotal role in enhancing soil strength. Conversely, initial UCS shows a weak negative correlation with optimum moisture content (OMC, -0.14) and maximum dry

density (MDD, -0.12), suggesting that higher moisture and density values slightly diminish compressive strength.



Fig. 3.12. Hit Map for the distribution of counts for each parameter in the collected database.

Interestingly, parameters such as the liquid limit, plasticity index, consistency index, and freeze-thaw cycles exhibit negligible correlations with UCS under the tested conditions, suggesting their limited direct influence on the mechanical behavior of stabilized soils. However, their indirect roles cannot be overlooked, as they may interact with other factors in complex ways. This heatmap serves as an essential analytical tool, revealing the relative significance of various parameters and guiding the optimization of stabilization techniques. It provides critical insights for improving soil performance in challenging environments, particularly where freeze-thaw cycles and other environmental stressors are significant concerns.

3.5 Conclusions

This chapter presented a comprehensive statistical exploration of two experimentally curated databases focused on the behavior of clayey soils stabilized with lime and fly ash under freeze–thaw (F–T) conditions. By compiling and harmonizing data from over sixty years of published research, the chapter established a robust and unified foundation for understanding the influence of various geotechnical, environmental, and treatment parameters on unconfined compressive strength (UCS).

For both lime- and fly ash-stabilized soils, the analysis revealed significant variability in soil composition, curing durations, additive content, and F–T cycle exposure. Lime-treated soils exhibited notable improvements in long-term UCS, particularly when high-plasticity clays were treated with extended curing durations. Conversely, Class C fly ash not only enhanced mechanical strength but also offered environmental benefits by valorizing industrial by-products.

The statistical evaluations encompassing frequency distributions, probability density functions, and correlation heatmaps demonstrated that UCS performance is governed by a complex interplay of factors, with additive dosage, curing time, and initial soil properties being among the most influential. The high degree of consistency in testing standards (especially ASTM and AASHTO) across the datasets reinforces the reliability of the compiled information and supports its use in predictive modeling.

Building upon these comprehensive findings and established database, the following chapter presents the development and validation of predictive modeling approaches for lime-stabilized clayey soils. This subsequent analysis focuses on creating both empirical regression models and artificial neural network (ANN) frameworks to predict soil performance parameters. The chapter provides detailed comparative evaluation between traditional statistical modeling techniques and advanced machine learning approaches, examining their respective capabilities in capturing the complex nonlinear relationships inherent in chemically stabilized soil systems under environmental loading conditions.

Chapter 4

*Predicting Soil Strength in Freeze-Thaw Environments
for Lime-Stabilized Clay*

4.1. Introduction

Predicting the unconfined compressive strength (UCS) of lime-stabilized clayey soils subjected to freeze-thaw (F-T) cycles is crucial for designing resilient geotechnical structures, particularly in regions with seasonal climatic variations. Traditional empirical approaches such as statistical regression have been widely applied in geotechnical engineering due to their interpretability and relatively low computational demands (Solanki, 2010; Wen et al., 2011). However, these models often struggle with multicollinearity and nonlinear interactions among soil parameters (Farrar and Glauber, 1967; Shrestha, 2020), limiting their effectiveness under complex environmental stressors like F-T cycles.

In recent years, the advent of Artificial Neural Networks (ANNs) has offered a data-driven alternative capable of capturing intricate, nonlinear dependencies among input variables (Ferentinou and Sakellariou, 2007). ANN models can learn from large datasets to provide high-accuracy predictions, outperforming traditional statistical models in several geotechnical applications (Sathyapriya et al., 2017). However, they require more substantial computational resources and often sacrifice transparency for performance. This chapter presents the development, comparison, and validation of both statistical and ANN-based models for predicting UCS under F-T conditions, offering engineers a dual-path methodology with distinct advantages and constraints.

4.2. Development of UCS_{FT} statistical model

The development of the UCS_{FT} statistical model aimed to establish a predictive relationship between the unconfined compressive strength (UCS) of lime-stabilized clayey soils and key influencing factors under freeze-thaw (F-T) conditions. Initially, a multiple linear regression (MLR) model was constructed; however, it was limited by assumptions of linearity and multicollinearity among input variables such as liquid limit, plasticity index, and optimal moisture content. To overcome these challenges, a nonlinear regression approach was adopted, enabling a more accurate representation of the complex interactions affecting UCS. The final model incorporated parameters such as lime content, curing time, number of F-T cycles, and initial UCS, and was validated through statistical significance tests and external data comparisons. This development provided a reliable, interpretable framework for estimating UCS under environmental stress, offering practical value for soil stabilization projects.

4.2.1. Formulation and analysis of the UCS_{FT} model

The predictive model's structure plays a crucial role in understanding the interactions between input parameters and their impact on the unconfined compressive strength under freeze-thaw conditions (UCS_{FT}). Initially, a multiple linear regression model was considered, expressed as Eq 4.1:

$$UCS_{FT} = a_0 + a_1 \times Lc + a_2 \times T + a_3 \times NC + a_4 \times OMC + a_5 \times LL + a_6 \times IP + a_7 \times IC + a_8 \times UCS_0 \quad (4.1)$$

The UCS_{FT} represents the unconfined compressive strength of freeze-thaw cycled, lime-stabilized clay soils, which is influenced by several key factors. These include the lime content (Lc), curing duration (T), number of freeze-thaw cycles (NC), optimal moisture content (OMC), liquid limit (LL), plasticity index (IP), consistency index (IC), and the initial unconfined compressive strength of natural soil (UCS₀). The relationship between these parameters is defined through regression analysis, with empirical constants ($a_0, a_1, a_2, \dots, a_8$) used to quantify their contributions within the model.

However, for this linear model to be reliable, certain assumptions, such as linearity, independence, and multicollinearity, must be validated (Farrar and Glauber, 1967; Shrestha, 2020). While the independence assumption was met, the linearity assumption was not consistently satisfied, especially regarding curing duration (T), as reported in various studies. Furthermore, multicollinearity posed significant challenges due to strong correlations among variables such as LL, IP, OMC, and UCS₀, making it difficult to interpret the individual contributions of these factors.

To address these limitations, a nonlinear regression model was developed to better capture the complex relationships between the input parameters and UCS_{FT}. This approach proved to be more effective in representing the interactions influencing the strength of lime-stabilized soils subjected to freeze-thaw cycles.

The nonlinear empirical equation was designed using multivariate analysis, incorporating relationships identified in previous studies (Solanki, 2010; Wen et al., 2014).

Tab. 4.1. A statistical analysis of the UCS_{FT} model of lime-stabilized clayey soils

Equation	Model parameters	t-test results	Signif. Param
$UCS_{FT} = A \times \left(\frac{UCS_0}{IC} \right) \times \left[\frac{(L_c^C + B)}{D \times NC + E \times OMC + 1} \right]^{Log_{10}((F \times T + 1) + 1)}$	A=0.619	Std. Err. =0.436	Yes
		t- value =14.20	
		$P > t = 0.000$	
		[95% Conf. Interval] 0.533 0.705	
	B= 0.642	Std. Err. = 0.0562	Yes
		t- value =11.41	
		$P > t = 0.000$	
		[95% Conf. Interval] 0.531 0.752	
	C=3.863	Std. Err. =0.506	Yes
		t- value =7.64	
		$P > t = 0.000$	
		[95% Conf. Interval] 2.867 4.857	
	D=0.034	Std. Err. = .0058	Yes
		t- value =5.71	
		$P > t = 0.000$	
		[95% Conf. Interval] 0.022 0.045	
	E=0.068	Std. Err. = 0.0101	Yes
		t- value =6.72	
		$P > t = 0.000$	
		[95% Conf. Interval] 0.048 0.087	
	F=0.442	Std. Err. =.0011	Yes
		t- value =3.99	
		$P > t = 0.000$	
		[95% Conf. Interval] 0.224 0.661	
R^2	F value	P_r	Signif. Model
0.802	204.75	0.000	Yes

Among the models tested, the proposed Eq 4.2 demonstrated the best fit with the experimental data, as detailed in Tab 3.1. The model's predictive accuracy was further validated through statistical tests and performance metrics, as summarized in Tab 4.2. This approach provides a robust framework for analyzing the behavior of lime-stabilized clay soils under freeze-thaw conditions :

$$UCS_{FT} = A \times \left(\frac{UCS_0}{IC} \right) \times \left[\frac{(L_c^C + B)}{D \times NC + E \times OMC + 1} \right]^{Log_{10}((F \times T + 1) + 1)} \quad (4.2)$$

With :

- UCS_{FT} : represents the unconfined compressive strength of freeze-thaw cycle, lime-stabilized clay soils.
- L_c : is the lime content.
- T : denotes curing duration.
- NC : indicates the number of freeze-thaw cycles.
- OMC : refers to the optimal moisture content.
- LL : is the liquid limit.
- IP : represents the plasticity index.
- IC : corresponds to the consistency index.
- UCS_0 : is the initial unconfined compressive strength of natural soil.
- $a_0, a_1, a_2, \dots, a_8$ are empirical constants determined through regression analysis.

Statistical significance is critical in evaluating the predictive power of the UCS-FT model and the contribution of each predictor to soil strength variability. The model incorporates six empirical constants (A, B, C, D, E, and F) corresponding to key explanatory variables: L_c (lime content), T (curing time), NC (number of cycles), OMC (optimum moisture content), LL (liquid limit), IP (plasticity index), and UCS_0 (initial unconfined compressive strength).

To rigorously validate the model's statistical integrity, we employed a comprehensive statistical analysis approach. Student's t -tests were conducted to assess the significance of individual predictors, with a predefined significance level of $\alpha = 0.05$. The statistical hypothesis for each constant followed a standard format: H_0 (null hypothesis) positing that the constant equals zero, indicating no significant impact, and H_1 (alternative hypothesis) suggesting the constant is non-zero and therefore a significant predictor. Rejection of the null hypothesis was determined by p-values falling below the 0.05 significance threshold, which would indicate statistically significant predictors.

To complement these individual predictor analyses, we additionally applied a Fisher F -test to evaluate the overall model significance. This multi-layered statistical validation approach ensures a robust and comprehensive assessment of the model's predictive capabilities and statistical reliability.

The comprehensive significance tests, meticulously detailed in Tab 4.1, provide compelling evidence of the model's statistical robustness and predictive power. By integrating the R^2 value with rigorous statistical significance assessments of individual predictors, we have developed a highly reliable mathematical framework for quantifying unconfined compressive strength under freeze-thaw conditions.

Fig 4.1 visually confirms the model's predictive accuracy by showing a strong correlation between predicted and experimental values, further validating its reliability as a predictive tool for geotechnical engineering applications. This reformulation maintains the technical depth while reducing redundancy and improving the clarity of the statistical validation process.

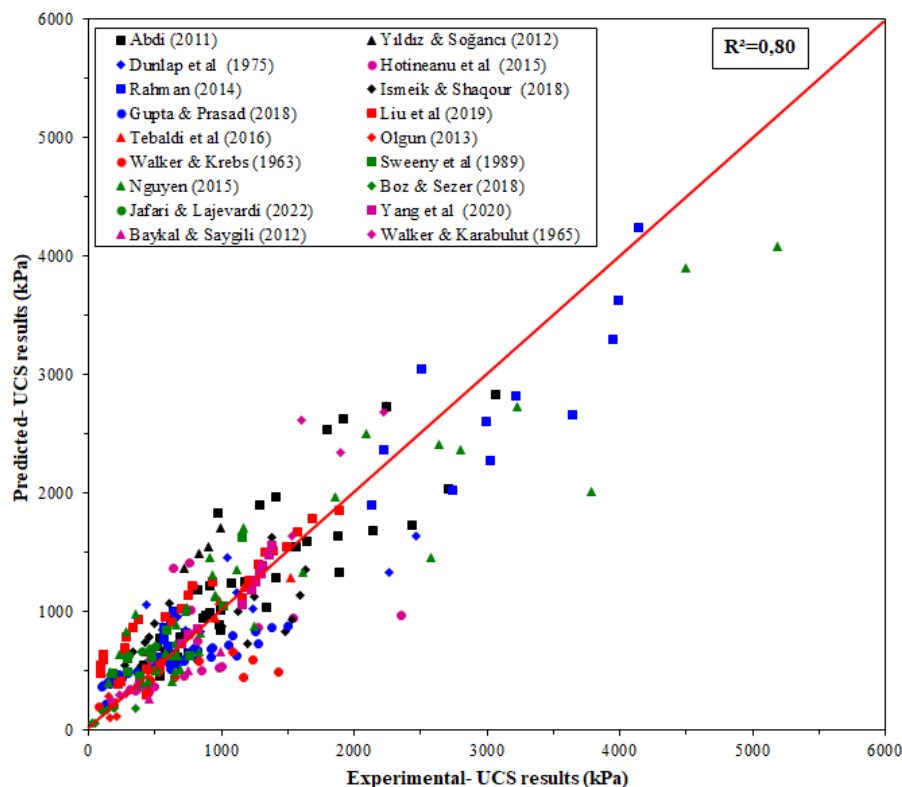


Fig. 4.1. Regression analysis of UCS in lime-stabilized clayey soils under F-T conditions

The model's exceptional accuracy and statistical validation not only confirm its theoretical soundness but also demonstrate its practical utility as an advanced analytical tool in geotechnical engineering. Specifically, the research offers unprecedented insights into soil stabilization mechanisms, enabling engineers and researchers to more precisely predict and understand material behavior under complex environmental stress conditions, thereby advancing our fundamental understanding of soil mechanics and structural resilience.

4.2.2. Validation of the UCS_{FT} model

A validation study was carried out to assess the accuracy of the proposed model by comparing its predictions to experimental values obtained from additional published geotechnical research. The comparison involved calculating the relative error using Eq 4.3, where “*O_{exp}*” represents the experimental output (derived from collected research data used in model adjustment) and “*O_{pred}*” is the model-predicted output. The relative error was determined as:

$$E(\%) = \left| \frac{O_{pred} - O_{exp}}{O_{pred}} \right| * 100 \quad (4.3)$$

The statistical model was validated using 30 data pairs sourced from the literature (Shandaala, 1964; Dayioglu et al., 2017; Aldaood et al., 2018; Li et al., 2022). The validation process involved extracting predictor values such as lime content, curing duration, the number of freeze-thaw cycles, and optimal moisture content from these studies. These values were then used as inputs in the proposed model to predict the unconfined compressive strength under freeze-thaw conditions (UCS_{FT}). The predicted values were compared with the experimental data from the same sources to evaluate the model's performance.

The differences between the predicted and experimental values were analyzed, with the results summarized in Fig 4.2 and Tab 4.2. To quantify the performance of the model, the Relative Mean Error (RME) was employed as a key metric. RME reflects the average discrepancy between the predicted values and the experimental results, calculated based on Equation 1. This approach provides a comprehensive evaluation of the model's predictive capability.

Tab. 4.2. Error between experimental and predicted UCS values validation – database.

	Lc(%)	UCS0 (kPa)	T (days)	I _c	OMC (%)	F-T Cycles	UCS- Exp (kPa)	UCS- Pred (kPa)	E (%)	RME (%)
Shandaala, 1964	05.00	477.81	10.00	1.44	33.80	0.00	756.36	695.20	08.79	12.62
	05.00	477.81	10.00	1.44	33.80	5.00	680.11	637.18	06.73	
	05.00	477.81	10.00	1.44	33.80	10.00	466.09	586.45	20.53	
	10.00	477.81	10.00	1.44	33.80	0.00	1237.61	1003.90	23.28	
	10.00	477.81	10.00	1.44	33.80	5.00	1074.20	920.12	16.75	
	10.00	477.81	10.00	1.44	33.80	10.00	977.68	846.85	15.45	
	15.00	477.81	10.00	1.44	33.80	0.00	1356.89	1294.83	04.79	
	15.00	477.81	10.00	1.44	33.80	5.00	1252.78	1186.77	05.56	
	15.00	477.81	10.00	1.44	33.80	10.00	1222.44	1092.27	11.92	
	20.00	477.81	10.00	1.44	33.80	0.00	1338.96	1577.98	15.15	
	20.00	477.81	10.00	1.44	33.80	5.00	1235.54	1446.29	14.75	
	20.00	477.81	10.00	1.44	33.80	10.00	1225.20	1331.13	07.96	
Dayioglu et al, 2017	00.00	1358.13	07.00	1.36	17.60	0.00	1453.25	1537.19	05.46	05.52
	08.00	1358.13	07.00	1.36	17.60	0.00	4301.25	4637.66	07.25	
	00.00	1358.13	07.00	1.36	17.60	2.00	1341.65	1463.47	08.32	
	08.00	1358.13	07.00	1.36	17.60	2.00	4200.28	4415.25	04.87	
	0.00	1358.13	07.00	1.36	17.60	4.00	1311.25	1395.31	06.02	
	8.00	1358.13	07.00	1.36	17.60	4.00	4152.87	4209.62	01.35	
	0.00	1358.13	07.00	1.36	17.60	8.00	1157.96	1273.50	09.07	
	8.00	1358.13	07.00	1.36	17.60	8.00	3912.66	3842.11	01.84	
Aldaoood et al, 2018	3.00	190.0	28	2.25	11.00	0.00	765.5	691.29	10.73	01.37
	3.00	190.0	28	2.25	11.00	1.00	640.2	663.54	03.52	
	3.00	190.0	28	2.25	11.00	3.00	576.3	612.76	05.96	
	3.00	190.0	28	2.25	11.00	5.00	539.5	567.48	04.93	
	3.00	190.0	28	2.25	11.00	7.00	635.0	526.96	20.50	
	3.00	190.0	28	2.25	11.00	10.00	490.9	473.73	03.63	
Li et al., 2022	0.00	223.60	00.00	1.07	18.00	0.00	223.60	225.15	00.69	05.51
	6.00	223.60	01.00	1.07	18.00	0.00	461.93	491.35	05.99	
	0.00	223.60	00.00	1.07	18.00	1.00	211.21	221.76	04.76	
	6.00	223.60	01.00	1.07	18.00	1.00	431.57	482.78	10.61	
Total RME										06.25

Fig 4.2 presents the findings of the validation study, showcasing the RME value. The total RME was approximately 6.25%, indicating that the proposed model achieves high accuracy in predicting the UCS of lime-stabilized clay soils subjected to freeze-thaw cycles. This low error value confirms the reliability and robustness of the model in capturing the complex interactions influencing soil strength under such conditions.

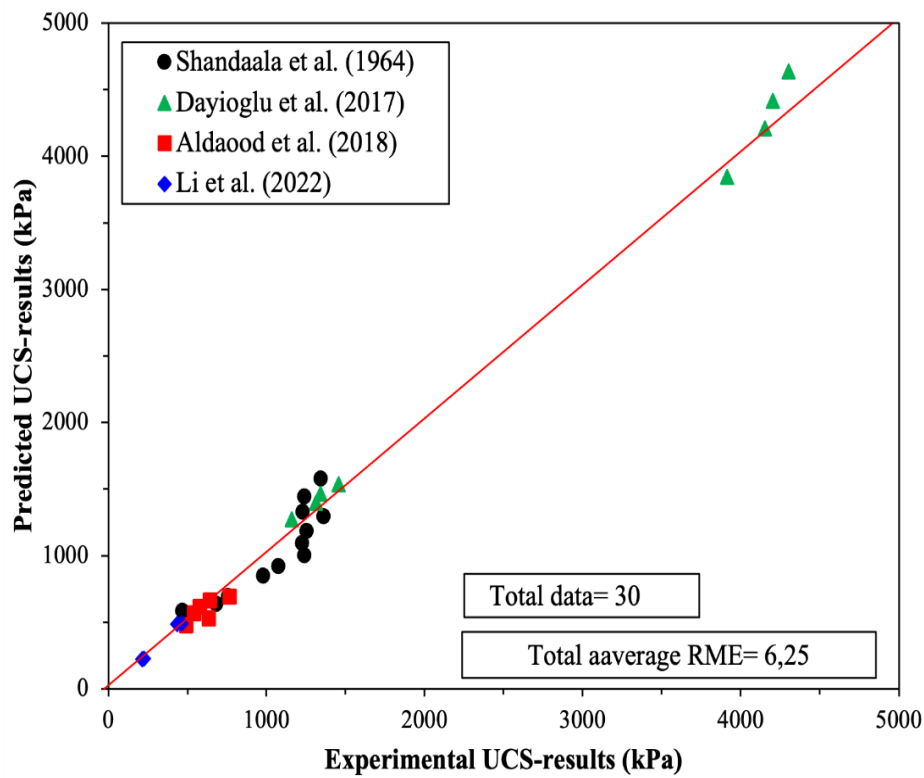


Fig. 4.2. RME measured VS predicted UCS for lime-stabilized clayey soils during F-T cycles

4.2.3. Parametric analysis

A comprehensive parametric analysis was performed to rigorously assess the statistical model's predictive capabilities across diverse soil stabilization scenarios. By systematically varying key parameters such as lime content, number of freeze-thaw cycles, optimum moisture content (OMC), plasticity index (PI), and initial curing time, we subjected the model to a thorough validation process.

The analysis revealed the model's exceptional robustness, demonstrating its ability to accurately predict unconfined compressive strength (UCS) values within the specified parameter ranges. This methodical investigation not only validates the model's theoretical framework but also provides critical insights into the complex mechanical behavior of lime-stabilized clayey soils under freeze-thaw conditions, thereby expanding our understanding of geotechnical material performance and predictive modeling techniques.

4.2.3.1 Effect of lime content on UCS

[Fig 4.3](#) presents a comprehensive visualization of the unconfined compressive strength (UCS) evolution across different freeze-thaw cycles, based on our proposed predictive model. Maintaining a constant initial UCS of 200 kPa, the analysis systematically explores the impact of lime content variation from 1% to 9% and the progression of freeze-thaw cycles ranging from 0 to 12. This nuanced graphical representation reveals the complex interplay between lime stabilization and cyclic temperature fluctuations, demonstrating how incremental changes in lime content and increasing freeze-thaw exposure progressively influence the mechanical properties of clayey soils. The model's predictive capabilities are particularly evident in the detailed trajectory of strength modifications, offering critical insights into the material's resilience and degradation mechanisms under challenging environmental conditions.

For a curing time of 7 days, the UCS values show significant improvement with increasing lime content but diminish as the number of freeze-thaw cycles increases. With an initial UCS of 200 kPa, soils treated with 5% and 7% lime exhibited UCS values of 530 kPa and 670 kPa after 3 cycles of freeze-thaw, respectively, after three freeze-thaw cycles, representing increases of 265% and 335%. However, after seven freeze-thaw cycles, the UCS values for the same lime contents were 480 kPa and 565 kPa, corresponding to increases of 240% and 282%. These results highlight that while lime stabilization is effective, the degradation caused by freeze-thaw cycles is evident even in the early curing phase.

At 14 days of curing, the UCS values continue to increase with lime content but show enhanced resistance to freeze-thaw cycles compared to the 7-day curing period. For example, soils with 7% lime content maintain a higher residual strength even after multiple freeze-thaw cycles. According to [Yildiz and Soğancı \(2012\)](#). This suggests that the extended curing time allows for further development of pozzolanic reactions, which enhance the soil structure and durability, providing better resistance against the disruptive effects of freeze-thaw conditions.

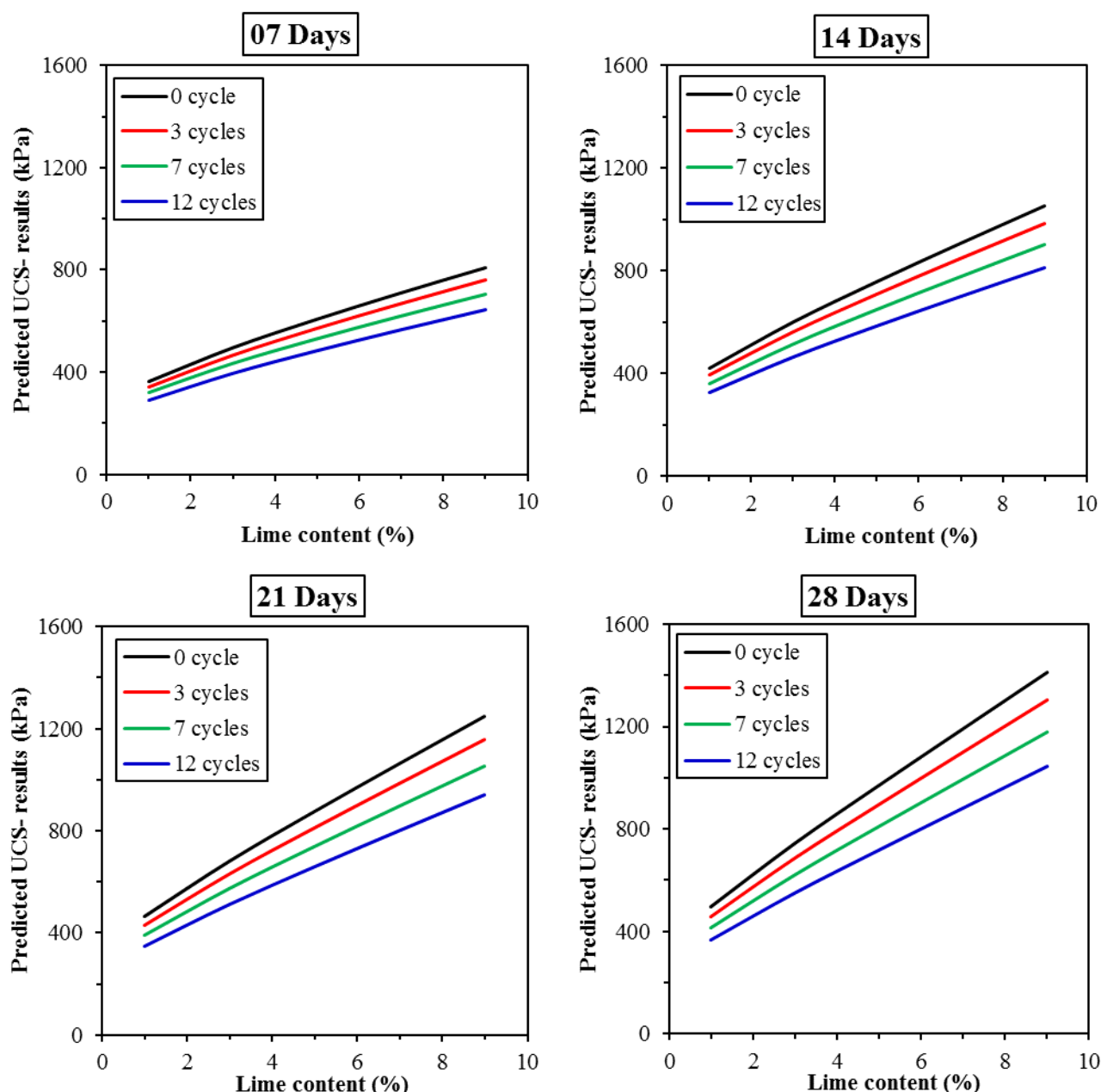


Fig. 4.3. Impact of lime content on UCS of stabilized clayey soils across various F-T cycles

With 21 days of curing, the UCS values exhibit further improvements, indicating the continued progression of lime-induced pozzolanic reactions. For instance, soils treated with 5% and 7% lime sustain higher UCS values after freeze-thaw cycles compared to shorter curing periods. This extended curing time promotes the formation of calcium silicate hydrate (C-S-H) and calcium aluminate hydrate (C-A-H) gels, which significantly strengthen the soil matrix, mitigating the structural damage caused by freeze-thaw cycles (Al-Mukhtar et al., 2012).

At 28 days of curing, the UCS values reach their peak levels across all lime contents. The residual strength of soils after 12 freeze-thaw cycles is significantly higher compared to shorter curing times, showcasing the full potential of lime stabilization. For example, the UCS reduction is limited to approximately 10–15%, as reported by [Yildiz and Soğancı \(2012\)](#), highlighting the effectiveness of prolonged curing in minimizing the adverse effects of freeze-thaw cycles on stabilized soils.

The comparative analysis reveals that longer curing times consistently improve the UCS of lime-stabilized clay soils, with higher lime contents providing additional resistance to freeze-thaw damage. For example, at 7 days of curing and after 7 freeze-thaw cycles, UCS values increased by approximately 240% with 5% lime, whereas at 28 days, the UCS reductions due to freeze-thaw cycles were minimal. This trend underscores the importance of curing time in enhancing the stability and durability of lime-stabilized soils.

The observed trends can be attributed to the pozzolanic reactions between lime and soil, which progress more effectively with extended curing times. The formation of C-S-H and C-A-H gels strengthens the soil structure and enhances its ability to resist freeze-thaw damage. Even though freeze-thaw cycles slow down these reactions, the residual strength remains significantly higher for soils with longer curing times, demonstrating the robustness of lime stabilization in cold climates.

These findings align with previous studies, such as those by [Al-Mukhtar et al. \(2012\)](#), [Wen et al. \(2014\)](#), and [Solanki \(2010\)](#), which demonstrated that lime stabilization reduces UCS loss under freeze-thaw conditions. For instance, [Wen et al. \(2014\)](#) observed that the UCS of soils treated with 6% lime decreased from 996 kPa to 381 kPa within 7 days of curing under freeze-thaw cycles, while [Solanki \(2010\)](#) reported reductions of 82% and 89% for 28-day cured samples. These comparisons validate the model's ability to predict UCS trends and the importance of curing time in achieving optimal soil stabilization.

4.2.3.2 Effect of Moisture content on UCS

This study ([Fig 4.4](#)) examines the effect of varying moisture content (MC) on the UCS of soils stabilized with 5% lime over curing periods of 7, 14, 21, and 28 days. The results reveal a complex interplay between curing time, moisture levels, and environmental stresses, highlighting the dual roles of curing duration in enhancing strength and the detrimental impact

of excessive moisture. The analysis provides valuable insights into the optimization of soil stabilization techniques for improved durability in freeze-thaw-prone environments.

After 7 days of curing, the UCS of clayey soil stabilized with 5% lime increased significantly from a baseline of 200 kPa to 700 kPa for soil with MC of 15%, achieving a 350% improvement. For higher moisture contents of 20%, 25%, and 30%, the UCS values were observed at 620 kPa, 575 kPa, and 520 kPa, corresponding to increases of 310%, 287%, and 260%, respectively. This highlights a decreasing trend in strength as MC rises. The observed reduction in UCS with higher MC is due to surplus water hindering compaction and lime-soil chemical reactions. Additionally, the presence of high moisture during freeze-thaw cycles induces pore pressure changes that exacerbate structural degradation, as noted by [Liu et al. \(2019\)](#).

At 14 days, the UCS of the soil continued to improve due to extended lime-soil reaction time. For 3 cycles freeze-thaw, an MC of 15%, the UCS reached approximately 925 kPa, showing a further improvement over 7 days. Similarly, soils with MCs of 20%, 25%, and 30% recorded UCS values of 790 kPa, 710 kPa, and 670 kPa, indicating increases of 460%, 395%, 355%, and 335%, respectively, over the initial strength. Compared to the 7-day period, the additional curing improved the UCS by about 10-12% across all MC levels. However, the adverse effects of higher MC remained prominent, reiterating that excess water limits the stabilization efficiency by affecting the curing and compaction processes.

The 21-day curing period showed continued UCS improvement, albeit at a slower rate. At 15% MC, the UCS reached approximately 1005 kPa, an increase of 500% from the baseline. For MCs of 20%, 25%, and 30%, the UCS values were 920 kPa, 810 kPa, and 750 kPa, respectively, corresponding to strength improvements of 460%, 405%, and 375%. The percentage improvement compared to the 14-day period was moderate, at 5-7%. This plateau in UCS gain indicates that lime-stabilized reactions approach equilibrium, especially at higher MCs where the negative effects of water content dominate.

At the culmination of 28 days, UCS results showed the most significant improvements but also highlighted diminishing returns at higher MCs. Soils with 15% MC achieved a UCS of 1260 kPa, a 630% improvement. Soils at 20%, 25%, and 30% MC achieved UCS values of 1030 kPa, 895 kPa, and 820 kPa, marking increases of 515%, 447%, and 410%, respectively. Despite the long curing time, the UCS at higher MC levels still trailed behind due to limited

lime reactivity in wetter conditions. The data affirm that prolonged curing benefits lime stabilization, but excessive moisture content remains a critical limiting factor.

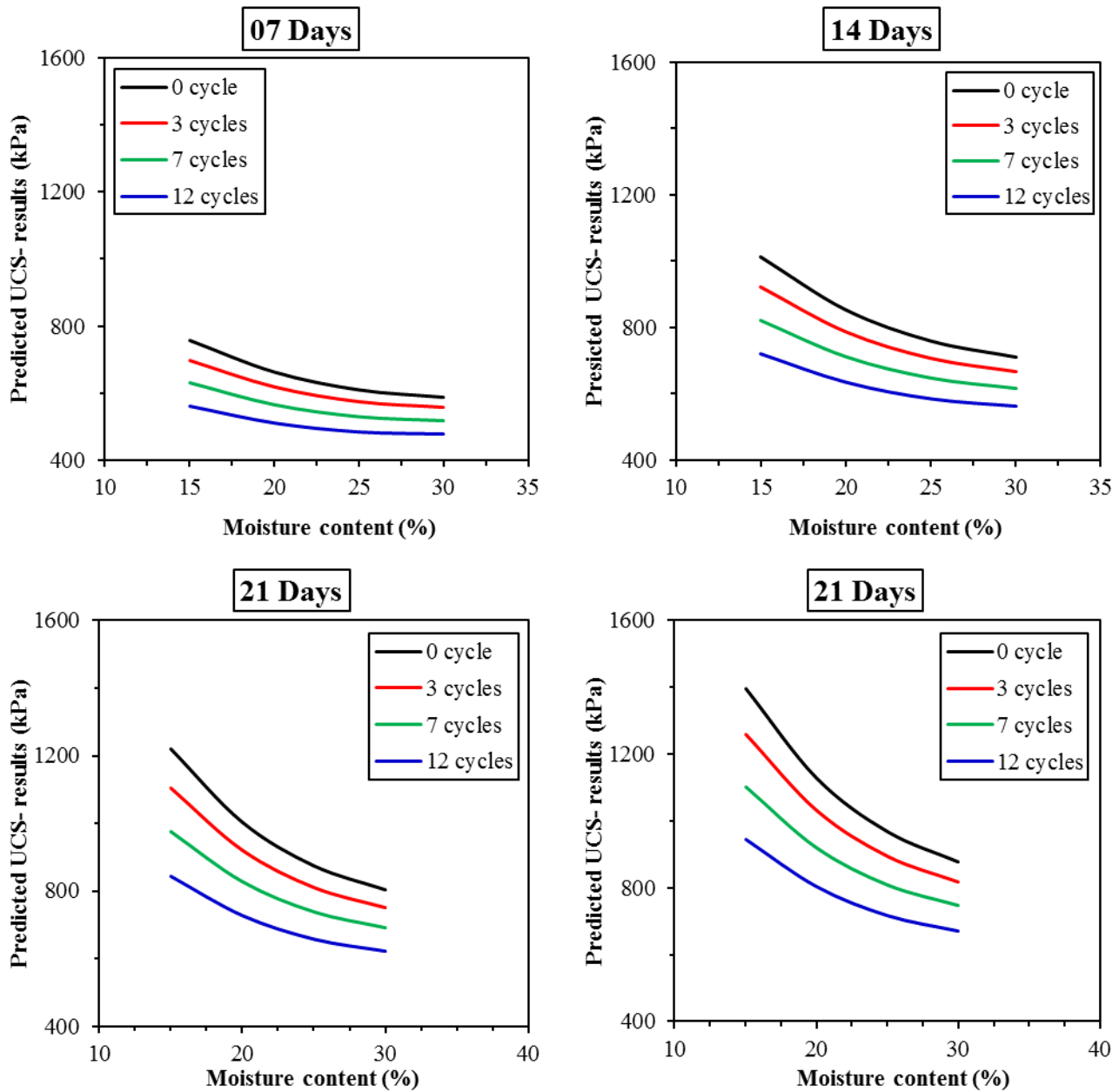


Fig. 4.4. Impact of moisture content on UCS of stabilized clayey soils across various F-T cycles at 5% of lime content.

Soils stabilized with 5% lime exhibit excellent resistance to freeze-thaw cycles, with relatively low reductions in strength even at higher moisture content levels. For example, a UCS reduction of approximately 10-15% was observed after 12 freeze-thaw cycles, as corroborated by studies like [Yildiz and Soğanci \(2012\)](#). This confirms the critical role of

extended curing periods in achieving optimal stabilization and durability for lime-treated clay soils.

The study demonstrates that curing time significantly enhances the UCS of lime-stabilized clayey soils, with strength gains diminishing as MC increases. The 7-day period shows rapid initial gains, while subsequent periods (14, 21, and 28 days) exhibit progressively smaller increases. Higher MC reduces UCS gains due to its interference with compaction and lime-soil reactions, as supported by [Gadouri et al. \(2017b\)](#). Additionally, freeze-thaw cycles exacerbate strength reduction, particularly in wetter soils, by inducing pore pressure and structural degradation, echoing findings by [Liu et al. \(2019\)](#). This underscores the importance of optimizing moisture content during soil stabilization and considering environmental conditions for long-term performance.

4.2.3.3 Effect of curing time on UCS

The curing time and lime content significantly affect the UCS of clayey soils stabilized under freeze-thaw conditions ([Fig 4.5](#)). Prolonged curing allows for enhanced soil-lime reactions, forming cementing agents that improve soil strength, as noted by [Bandara et al. \(2016\)](#). This analysis investigates the UCS variations for lime contents of 3%, 5%, 7%, and 9% over curing durations, providing insights into the combined effects of curing time and lime dosage on stabilization performance.

For soils stabilized with 3% lime, the UCS shows notable improvements with curing time but remains the lowest among all lime contents. After 7 days of curing, the UCS was approximately 497 kPa, representing a 43% increase compared to the initial UCS of 200 kPa under 0 freeze-thaw cycles. Prolonging curing to 28 days raised the UCS to 742 kPa, a 60% improvement. Despite the positive trends, the lower lime content limited the formation of cementing agents, reducing its effectiveness in stabilizing the soil under freeze-thaw conditions. This result emphasizes the need for higher lime content for more robust stabilization, especially for soils exposed to repeated freeze-thaw cycles.

At 5% lime content, the UCS gains were significantly higher than at 3%. For 7 days of curing, the UCS reached 585 kPa, representing a 52% increase from the initial UCS of 200 kPa under 0 freeze-thaw cycles. At 28 days, the UCS rose to 895 kPa, an improvement of 75%. Prolonged curing demonstrated a strong positive impact, as the lime-soil reactions continued to produce more cementing agents over time. However, freeze-thaw cycles caused noticeable

strength reductions, with UCS values decreasing progressively at 3, 7, and 12 cycles, indicating the vulnerability of even moderately stabilized soils to environmental stresses.

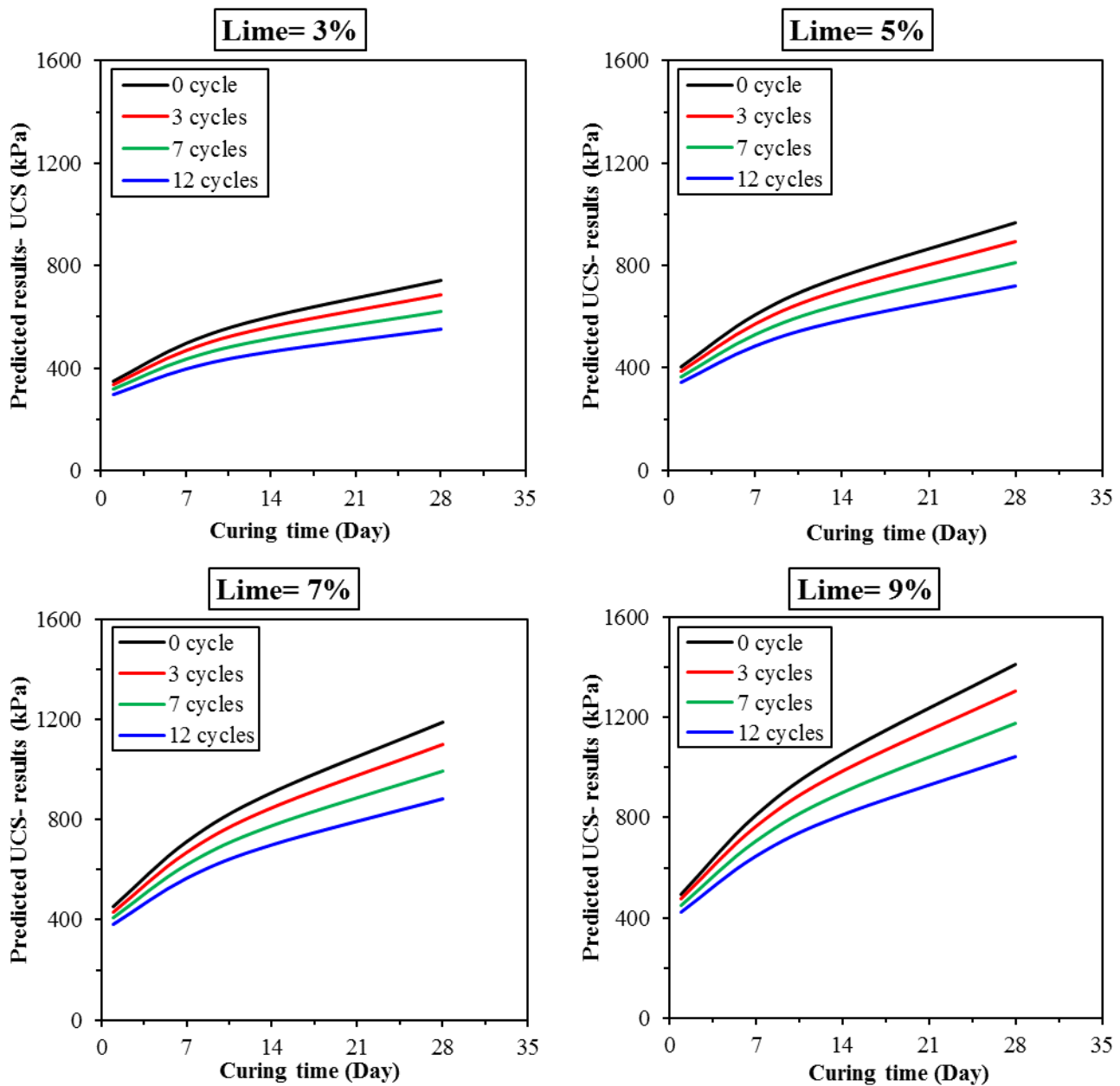


Fig. 4.5. Impact of curing timet on UCS of stabilized clayey soils across various F-T cycles at 200 kPa of UCS_0

Soils stabilized with 7% lime exhibited marked improvements in UCS. After 7 days of curing, the UCS was approximately 711 kPa, showing a 61% improvement over the initial UCS. Extending curing to 28 days resulted in a UCS of 1190 kPa, representing an improvement of 86%. These results demonstrate the greater efficacy of higher lime content in improving soil strength through more extensive formation of cementitious compounds. Despite this, the

impact of freeze-thaw cycles remained significant, reducing UCS by approximately 30% when exposed to 12 cycles. This highlights the importance of balancing lime content and curing time to optimize soil performance.

With 9% lime content, the highest UCS values were achieved, underscoring the role of increased lime in stabilization. After 7 days of curing, the UCS reached approximately 850 kPa, reflecting a 70% increase. At 28 days, UCS peaked at 1350 kPa, an improvement of 95%. This substantial strength gain demonstrates the effectiveness of higher lime dosages in creating a durable soil structure resistant to environmental degradation. However, prolonged freeze-thaw exposure still reduced UCS by up to 35%, suggesting that even highly stabilized soils are not immune to such stresses, although they retain higher overall strength compared to lower lime contents.

The results indicate that UCS improves with both curing time and lime content, but prolonged curing has a more pronounced effect than lime dosage, particularly at lower percentages. The highest strength levels were achieved at 9% lime content, with curing extending up to 28 days. Freeze-thaw cycles negatively impacted UCS across all lime percentages, although higher lime contents mitigated these effects more effectively. These findings align with [Bandara et al. \(2016\)](#), who attributed strength improvements to the cohesive bonding between soil particles facilitated by lime reactions in the presence of water. This study underscores the need for optimized lime content and curing durations to achieve durable stabilization under challenging environmental conditions.

4.3 Development of ANNs model UCS_{FT}

4.3.1 ANN Structure and Function

Artificial Neural Networks (ANNs) are computational systems that mimic human brain data processing, enabling autonomous prediction of input-output relationships through training patterns. These models offer significant advantages over traditional approaches in functionality and adaptability ([Murlidhar et al.,2020](#)).

Artificial neurons serve as fundamental units within ANN models, processing data in parallel, mirroring the functionality of a biological brain. ([Khandelwal., 2009](#)). [Ferentinou and Sakellariou \(2007\)](#) pioneered the modeling of neural networks. Modeling by constructing a binary decision unit that achieved higher accuracy through cumulative weight assignment and activation function application. [Sudheer and Mathur \(2012\)](#) further established that ANN

systems comprise interconnected nodes organized in parallel layers, with neuron connection patterns significantly influencing network classification and behavior.

ANNs can be categorized into two functional classifications: feedback and feedforward. The multilayer perceptron (MLP) stands as the most prevalent type within feedforward multi-layer networks, processing input data using activation functions across consecutive layers (Simpson., 1990). The backpropagation (BP) learning algorithm enhances network learning through a gradient-based procedure consisting of forward and backward stages. According to Bishop (2012). During each phase, input signals progress forward while transmitting error signals for output layer nodes.

These error rates then propagate backward, leading to weight and bias adjustments. Various activation functions generate neuron outputs based on problem complexity, with sigmoid transfer functions commonly used for non-linear scenarios. Fig 4.6 illustrates the systematic diagram of an artificial node j .

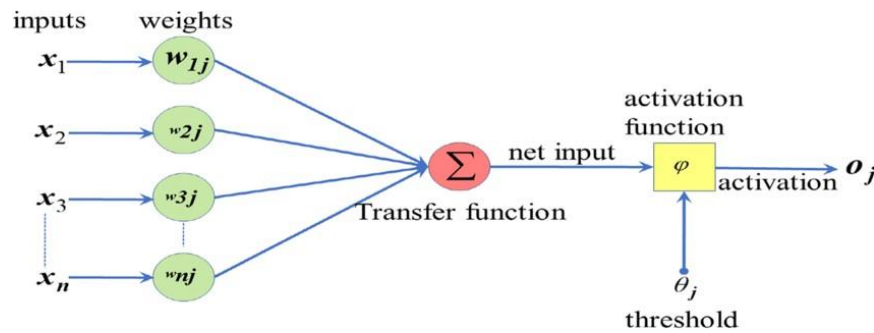


Fig. 4.6. Mathematical shema model for the artificial neuron (Bishop, 1995).

4.3.2 Neural Network-Model Architecture Development

The performance of neural network models in geotechnical applications depends on various parameters related to network topology and learning processes (Majdi et al., 2013; Ceryan et al., 2013 and Sathyapriya et al., 2017).

In the specific research described, a neural network model was developed using TensorFlow's Keras API to predict the UCS of clayey soil. This model utilizes nine input features, likely representing various clayey soil properties and conditions relevant to UCS prediction. The model's architecture follows a sequential design, which means the layers are stacked in a straightforward sequence, each layer feeding into the next as presented in Fig 4.7.

The input layer of this model consists of 64 neurons, each using the Rectified Linear Unit (ReLU) activation function. The ReLU function, defined as $f(x) = \max(0, x)$, allows positive values to pass through unchanged while setting negative values to zero. This choice of activation function ensures robust feature extraction capability by introducing non-linearity into the model without suffering from the vanishing gradient problem often encountered with other activation functions.

To enhance the model's efficiency and stability, a Batch Normalization layer is incorporated after each dense layer. Batch Normalization normalizes the inputs to each layer, which can speed up training by reducing internal covariate shift, allow for higher learning rates, and reduce the dependence on careful initialization of the network weights. Following the Batch Normalization layer, a Dropout layer with a rate of 0.1 is added. This means that during training, 10% of the neurons are randomly deactivated, which helps prevent overfitting by reducing interdependent learning among neurons.

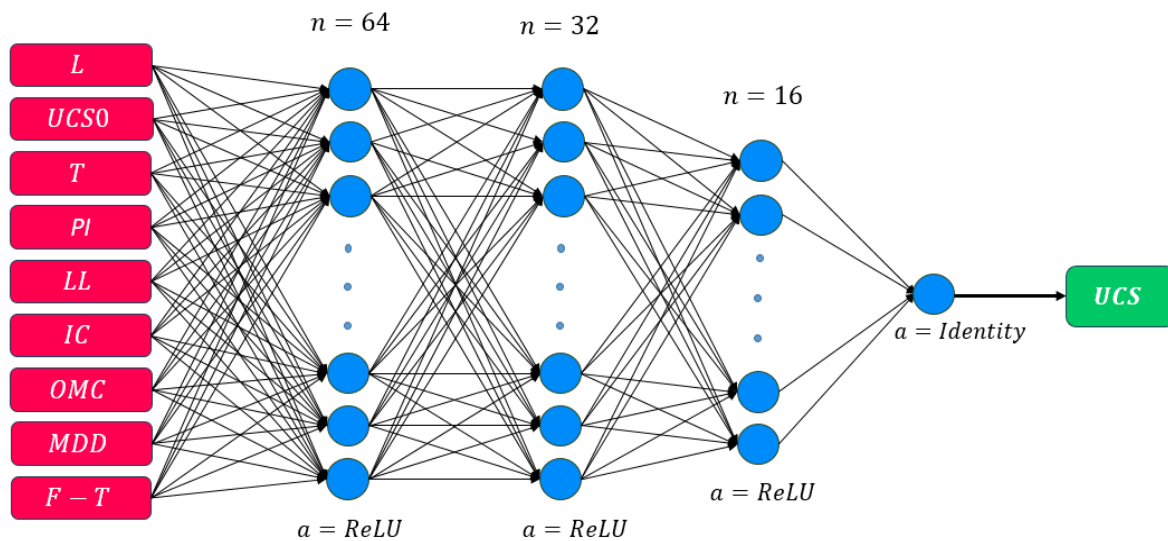


Fig. 4.7. Architecture used in ANNs model for UCS prediction

The sequence of Dense, Batch Normalization, and Dropout layers is repeated in subsequent layers, but with progressively fewer neurons (32 and 16). This reduction in the number of neurons helps to reduce feature dimensions and focus on the most significant interactions between features. It's a form of dimensionality reduction that allows the model to distill the most important information as data flows through the network.

The final layer of the model consists of a single neuron with a linear activation function. This configuration is appropriate for regression tasks like UCS prediction, as it allows for

continuous output values. The overall architecture can be described as deep and regularized, incorporating mechanisms like Batch Normalization and Dropout to maintain robustness and prevent overfitting.

It's worth noting that determining the optimal number of hidden layers and neurons often requires a process of trial and error. While complex problems may benefit from deeper architectures, simpler architectures with one hidden layer and a limited number of neurons are often preferred for faster learning and potentially better generalization. The choice of architecture depends on the specific problem at hand and the characteristics of the available data.

The development of these neural network models leverages the most effective available techniques in machine learning and artificial intelligence. These models serve as powerful tools for engineers and researchers in understanding and predicting soil behavior in geotechnical applications. They can provide valuable insights in scenarios where traditional analytical methods might be limited, offering a data-driven approach to complex geotechnical problems. As research in this field continues, these models are likely to become increasingly sophisticated and accurate, further enhancing their utility in geotechnical engineering practice.

4.3.3 ANNs UCS-model prediction performance

Fig 4.8 presents the UCS_{FT} model's training, valid, test phase results with the globally performance model. Subfigure (a) showing the correlation between predicted and actual UCS values for lime-stabilized clayey soils under freeze-thaw conditions in the training phase. This analysis involves the development of a predictive model using a training dataset to establish the relationship between various input parameters and the UCS values. The correlation coefficient (R^2) is a statistical measure that indicates how well the model fits the training data. In this context, with 75% of the dataset used for training phase, the correlation coefficient value of $R^2 = 0.98$ in the training phase signifies a strong correlation between the predicted UCS values generated by the model and the actual experimental UCS values from the training dataset.

A high R^2 value close to 1 indicates that the model can explain a large proportion of the variance in the UCS values based on the input parameters considered during training. Therefore, this coefficient demonstrates that the UCS_{FT} model developed during the training phase shows a high level of accuracy and reliability in predicting the UCS values of lime-stabilized clayey soils subject freeze-thaw conditions based on the selected input parameters.

The UCS_{FT} model's validation phase performance using 20% of the training dataset (Fig 4.8-b), demonstrating the model's predictive accuracy through correlation analysis ($R^2 = 0.87$). The Valid Analysis of UCS in lime-stabilized clayey soils under freeze-thaw conditions focuses on assessing the UCS_{FT} model's predictive performance through a validation dataset. This approach evaluates the model's ability to accurately predict UCS values in conditions where lime-stabilized clayey soils undergo freeze-thaw cycles.

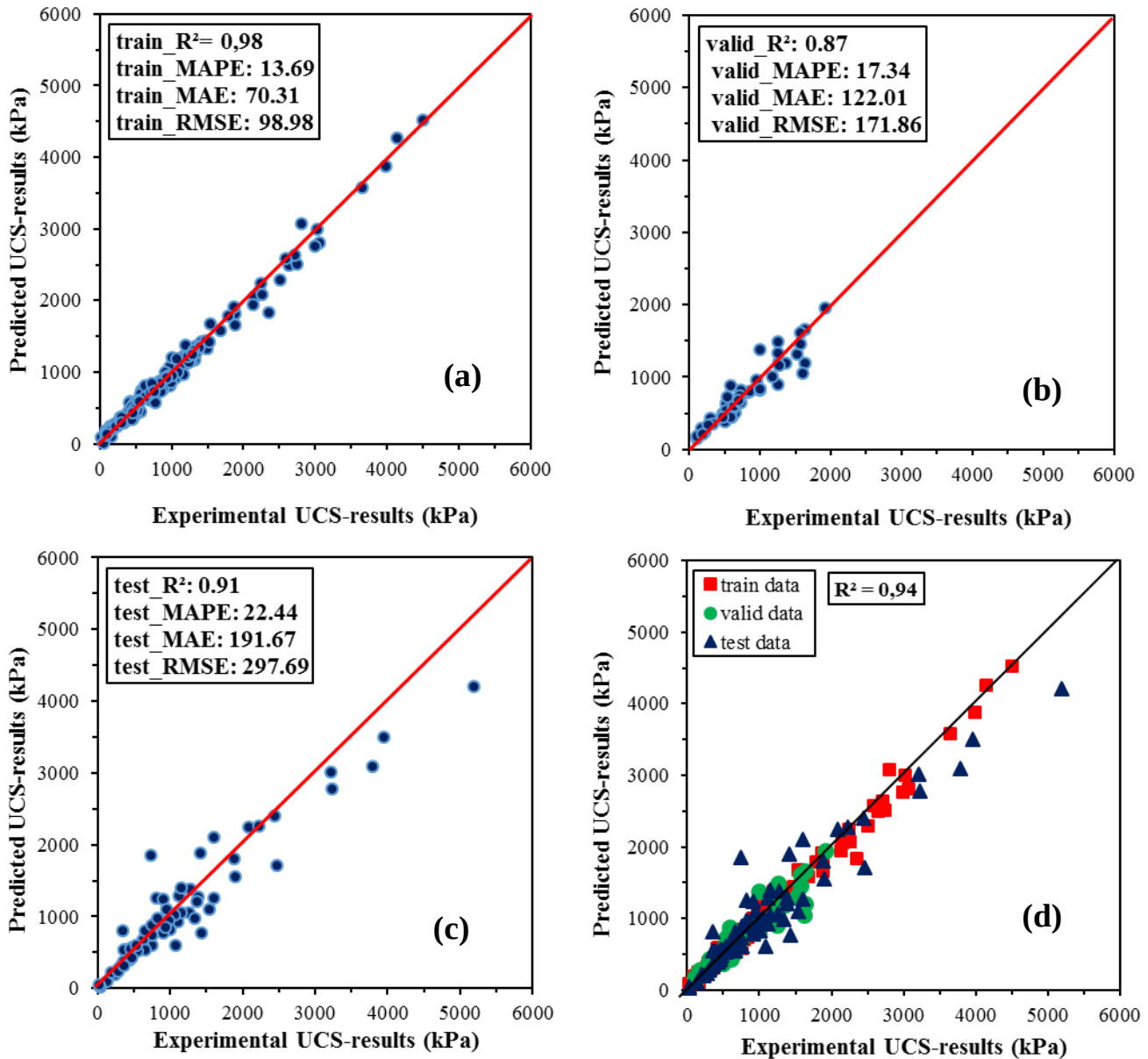


Fig. 4.8. Regression analysis for the development of the UCS_{FT} model for clayey soils stabilized with lime.

In the validation phase, a correlation coefficient 87% indicates a moderately strong relationship between the predicted UCS values and the experimental UCS values, suggesting the model's reasonably high predictive accuracy for UCS in these specific soil conditions.

Overall, this result provides a comprehensive view of the UCS_{FT} model's performance in the validation phase, offering insights into the model's ability to predict UCS values for lime-stabilized clayey soils under freeze-thaw conditions and highlighting the accuracy and reliability of the model's predictions.

The test analysis of UCS in lime-stabilized clayey soils under freeze-thaw conditions, using a 25% unseen data subset from the global database (Fig 4.8-c). With an R^2 value of 0.91, this plot demonstrates a strong linear correlation between predicted and experimental UCS values, underscoring the model's predictive capability.

An R^2 value of 0.91 indicates that the model explains 91% of the variability in UCS, highlighting its accuracy in forecasting UCS under freeze-thaw conditions on new data. This high level of correlation reinforces confidence in the model's ability to generalize well to unseen data, supporting its application in assessing soil behavior and guiding engineering decisions.

The development and performance of the UCS_{FT} model for lime-stabilized clayey soils under freeze-thaw conditions. It features predicted UCS values plotted against experimental UCS results for the train, valid, and test data subsets, providing a comprehensive analysis of the model's efficacy.

Also, Fig 4.8-d showcases a strong linear correlation between predicted and experimental UCS values across all data subsets, as indicated by the high R^2 value of 0.94. Notably, the distribution of data points around the regression line is well-centered, indicating precise predictions with minimal discrepancies. However, outliers or deviations from the regression line may highlight areas where the model struggles to accurately predict UCS values.

Overall, the demonstrates of the model's effectiveness in predicting UCS values for lime-stabilized clayey soils under freeze-thaw conditions, offering valuable insights for engineering decisions and soil behavior analysis. This visual representation aids in evaluating the model's performance and guiding refinements based on observed discrepancies or outliers, thereby enhancing confidence in its accuracy and utility for similar conditions.

4.3.4 Parametric analysis based on ANNs model results

The ANN-model was evaluated through comprehensive parametric analysis, focusing on UCS predictions across varying lime contents, freeze-thaw cycles, and curing times. The analysis incorporated characteristic compaction parameters (OMC, MDD), plasticity measures (LL, PI), consistency index (IC) and initial UCS, demonstrating the model's robustness in predicting lime-stabilized clayey soil behavior under freeze-thaw conditions.

4.3.4.1 Effect of lime content on UCS

[Fig 4.9](#) depicts the evolution of UCS gain in stabilized soils over varying numbers of freeze-thaw cycles. The study maintains a consistent initial UCS value of 500 kPa while manipulating lime content from 0% to 13% and adjusting the number of cycles from 1 to 7. Additionally, the parameters for Optimum Moisture Content (OMC), Maximum Dry Density (MDD), Liquid Limit (LL), Plasticity Index (PI), and consistency index (IC) were set at 30%, 10 kg/m³, 60%, 40%, and 0.88 respectively, with curing durations of 07, 14, 21, and 28 days.

It is well-established that increasing lime content in clayey soils enhances their UCS under normal conditions. This relationship has been consistently documented across multiple studies ([Arabi et al., 1989](#); [George et al., 1992](#); [Bell et al., 1996](#); [Kassim et al., 2004](#); [Harichane et al., 2011](#); [Yeldiz et al., 2012](#); [Ghodabi et al., 2014](#) and [Sari Ahmed et al., 2022](#))

[Fig 4.9](#) shows that, the percentage of lime content increases, the UCS values also increase for all freeze-thaw cycle numbers. However, the rate of increase in UCS values decreases as the number of freeze-thaw cycles increases. The same behavior was observed by several researchers ([William et al., 1974](#); [Solanki et al., 2010](#); [Abdi et al., 2011](#); [Al kiki et al., 2011](#); [Firouzi et al., 2015](#)).

The impact of lime content on UCS varies across different curing periods and freeze-thaw cycles. During the early curing period of 7 days with one freeze-thaw cycle, UCS values show significant improvement with increasing lime content. The progression demonstrates clear strength enhancement, with values ranging from 380 kPa at 0% lime content, increasing to 1220 kPa at 5% lime, further rising to 1895 kPa at 9% lime, and reaching 2310 kPa at 13% lime content. This trend indicates that an increase in lime content correlates with a substantial enhancement in UCS, suggesting improved soil stabilization performance with higher lime concentrations. Similar observations were ([Sayguli et al., 2019](#)).

Similarly, for curing time periods (14-28 days) show that increased lime content consistently improves UCS values. Though effectiveness decreases with more freeze-thaw cycles. With 3 freeze-thaw cycles, UCS values increase proportionally with lime content, the predicted UCS values for 0% to 13% lime content are 275 kPa to 2130 kPa, respectively. This demonstrates lime stabilization's effectiveness in maintaining soil strength under freeze-thaw conditions (Shafiei et al., 2023).

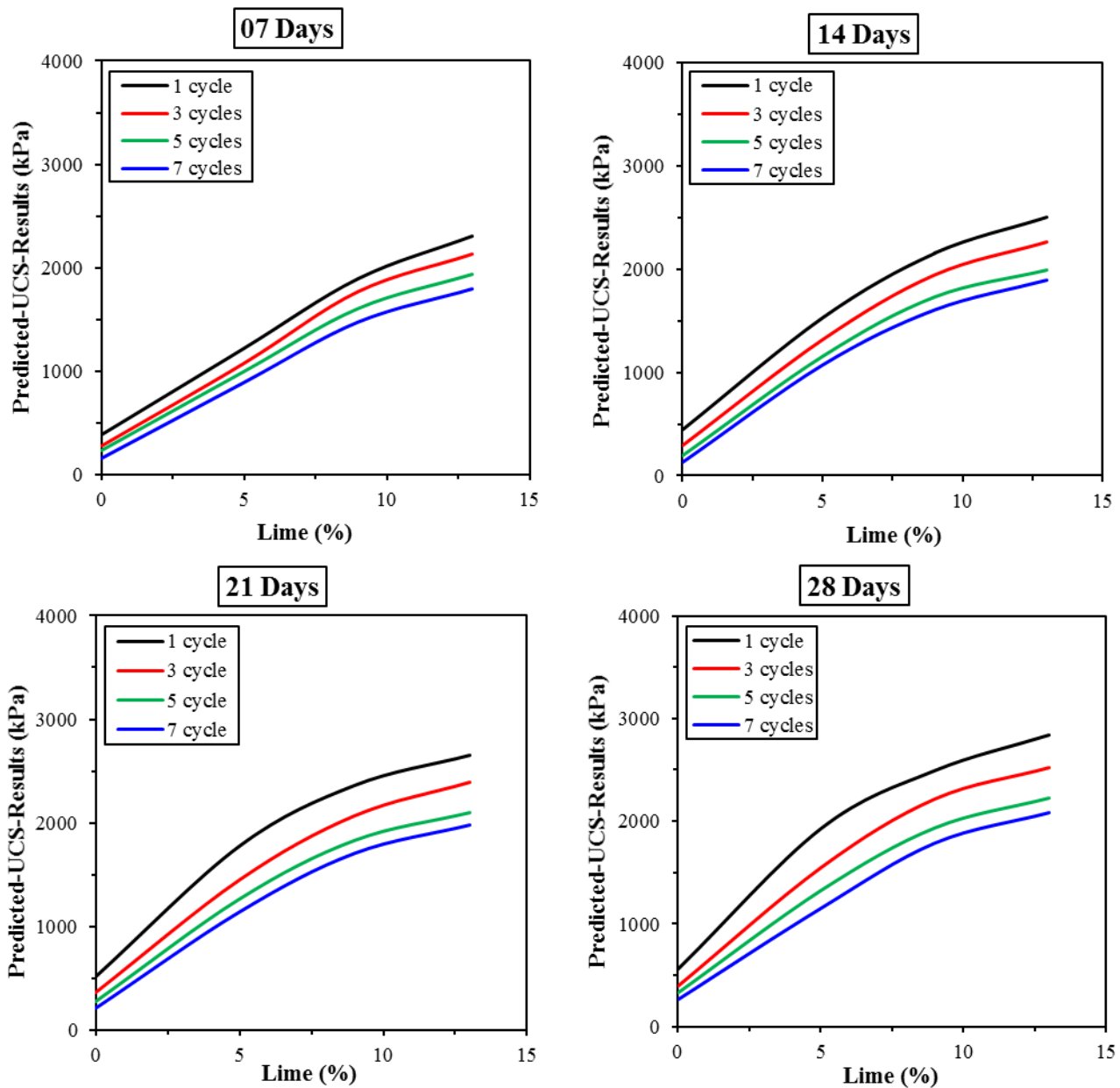


Fig. 4.9. Impact of lime content on UCS of stabilized clayey soils across various F-T cycles

For extended curing periods of 28 days, the impact of freeze-thaw cycles becomes more evident. With three freeze-thaw cycles, the addition of 5% lime results in UCS values of 1550 kPa, representing a 310% increase from the initial value. This improvement is even more pronounced with 9% lime content, reaching 2220 kPa, marking a 445% increase from the initial strength. When subjected to 7 freeze-thaw cycles, the soil maintains significant strength improvement, though at reduced levels. At this stage, 5% lime content yields 1150 kPa (230% increase from initial), while 9% lime content achieves 1785 kPa (350% increase from initial), [Yilmaz et al. \(2018\)](#). This is expected as freeze-thaw cycles can cause damage to the soil structure and reduce its strength. However, the results also indicate that the UCS of stabilized clay soils with higher lime contents is less affected by the freeze/thaw cycles, suggesting that lime can enhance the resistance of clay soils to freeze/thaw damage. ([Firouzi et al., 2015](#)) reported similar findings.

According to [Yildiz et al. \(2012\)](#), while freeze-thaw cycles typically reduce UCS by 10-15%, higher lime contents demonstrate improved resistance to freeze-thaw damage. The pozzolanic reaction continues during freeze-thaw cycles, albeit at a slower rate, producing calcium silicate hydrate (C-S-H) and calcium aluminate hydrate (C-A-H) gels that enhance material strength and durability ([Harichane et al., 2011](#)). Notably, freezing and thawing do not halt the pozzolanic reaction but rather slow it down in clay soils stabilized with lime, suggesting that lime stabilization remains a viable option for clay soils even in colder seasons.

Recent studies have provided additional validation of these findings. Notably, [Wen et al. \(2014\)](#) documented significant changes in strength characteristics, with initial UCS values of 990 kPa declining to 380 kPa after two freeze-thaw cycles with 6% lime content and a 7-day curing period, resulting in a strength retention of 39%.

The model developed by [Solanki et al. \(2010\)](#), observed substantial UCS reductions under more severe conditions of 12 freeze-thaw cycles with 6% lime content after 28 days of curing. Their results showed reductions from 490 to 90 kPa in one soil type and 860 to 95 kPa in another, representing decreases of 82% and 89% respectively. These findings continue to align with earlier research by [Dempsey et al. \(1968\)](#), demonstrating the consistent nature of lime stabilization effects across different study periods.

4.3.4.2 Effect of Moisture content content on UCS

[Fig 4.10](#) illustrates the relationship between MC and UCS of lime-stabilized clayey soils under different freeze-thaw cycle conditions, with a 5% lime content. The study examines

various curing times (7, 14, 21, and 28 days) and moisture contents (15, 20, 25, and 30%). The findings reveal a decrease in UCS as MC increases, demonstrating the significant influence of MC on soil strength across freeze-thaw cycles (Lui et al., 2019).

The results show that in Fig 4.10 with a 7-day curing period, the UCS values progressively increase with freeze-thaw cycles, reaching a peak of 2080 kPa after 7 cycles. Similar strength improvements were observed for longer curing periods of 14, 21, and 28 days, indicating that extended curing times enhance soil stability and strength development.

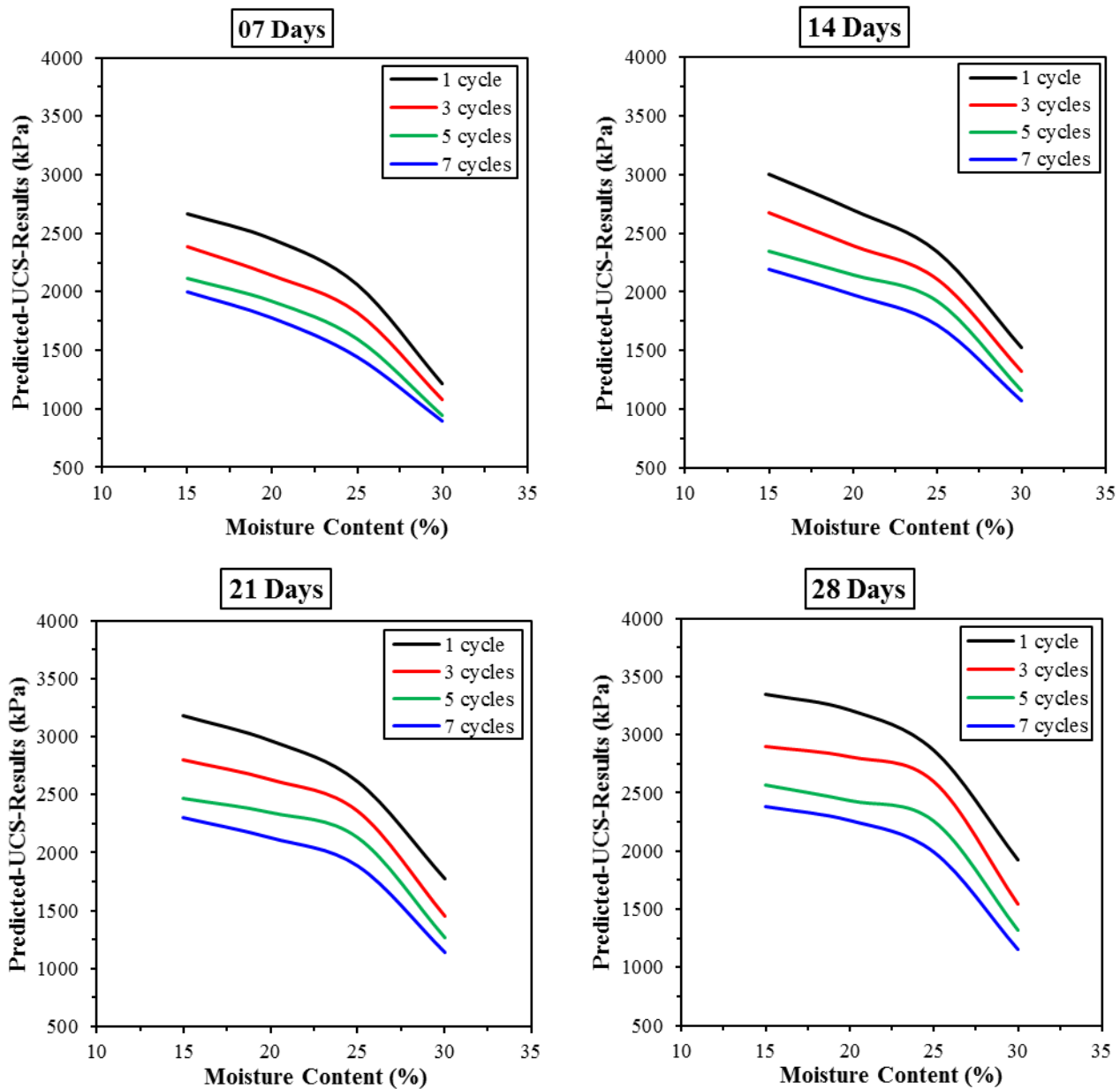


Fig. 4.10. Impact of MC on UCS of stabilized clayey soils across various F-Tcycles in 5% lime content.

The curves consistently show higher UCS values with longer curing times, reinforcing the importance of curing periods in improving soil durability through lime stabilization. Adequate curing duration is crucial in achieving optimal stabilization outcomes, especially under freeze-thaw cycles that challenge soil stability. Each curing period and MC level are analyzed through trends in the results, providing insights into the cumulative effects of these variables.

Research by [Khoury et al. \(2013\)](#) confirms that excess MC in clayey soils can impede compaction, weakening the foundation. Additionally, high MC levels disrupt the chemical reactions necessary for stabilization, leading to reduced strength. Freeze-thaw cycles worsen this by generating high pore pressure during freezing, causing soil expansion and reduced strength after thawing, as described by [Lui et al. \(2019\)](#). Excess MC, combined with insufficient stabilization, results in degradation due to soil particle expansion and contraction, gradually reducing UCS. In contrast, [Aldaood et al. \(2014\)](#) emphasize maintaining MC within optimal ranges for effective stabilization, as adequate compaction and lime-soil reaction improve UCS, even under freeze-thaw conditions.

4.3.4.3 Effect of Curing time on UCS

[Fig 4.11](#) illustrates the impact of curing duration on the UCS of clayey soils stabilized under varying freeze-thaw cycle counts. The study examined UCS values in kPa for curing periods of 7, 14, 21 and 28 days, along with 1, 3, 5, and 7 freeze-thaw cycles with 500 kPa initial UCS. Results showed that UCS increases with extended curing duration and decreases with higher frequency of freeze-thaw cycles.

Based on the [Fig 4.11](#), there is a clear trend showing how lime content and curing time affect UCS in stabilized clayey soils. At 0% lime, the maximum UCS reaches only about 500 kPa after 28 days, while at 13% lime, it achieves approximately 3000 kPa under the same conditions. A significant finding is that increasing freeze-thaw cycles consistently reduces strength across all lime contents, with 1 cycle freeze-thaw always showing the highest strength and 7 cycles showing the lowest.

The most impressive strength improvement occurs between 0% and 5% lime, where maximum UCS jumps from 500 kPa to about 2500 kPa. However, the incremental benefit diminishes between 9% and 13% lime content, suggesting an optimal lime content around 9%. The curing time effect is most pronounced in the first 14 days, after which the strength gain rate slows down, particularly evident in the higher lime content samples. The highest

strength levels across all lime percentages occurred with extended curing durations. [Bandara et al. \(2013\)](#) attributed this improved strength to cohesive bonding among soil particles through cementing agents formed by lime and water interaction. The strength improvement over time was influenced by lime's reactivity and pozzolanic activity, determined by reactive silica and free lime content ([Harichane et al., 2010](#)).

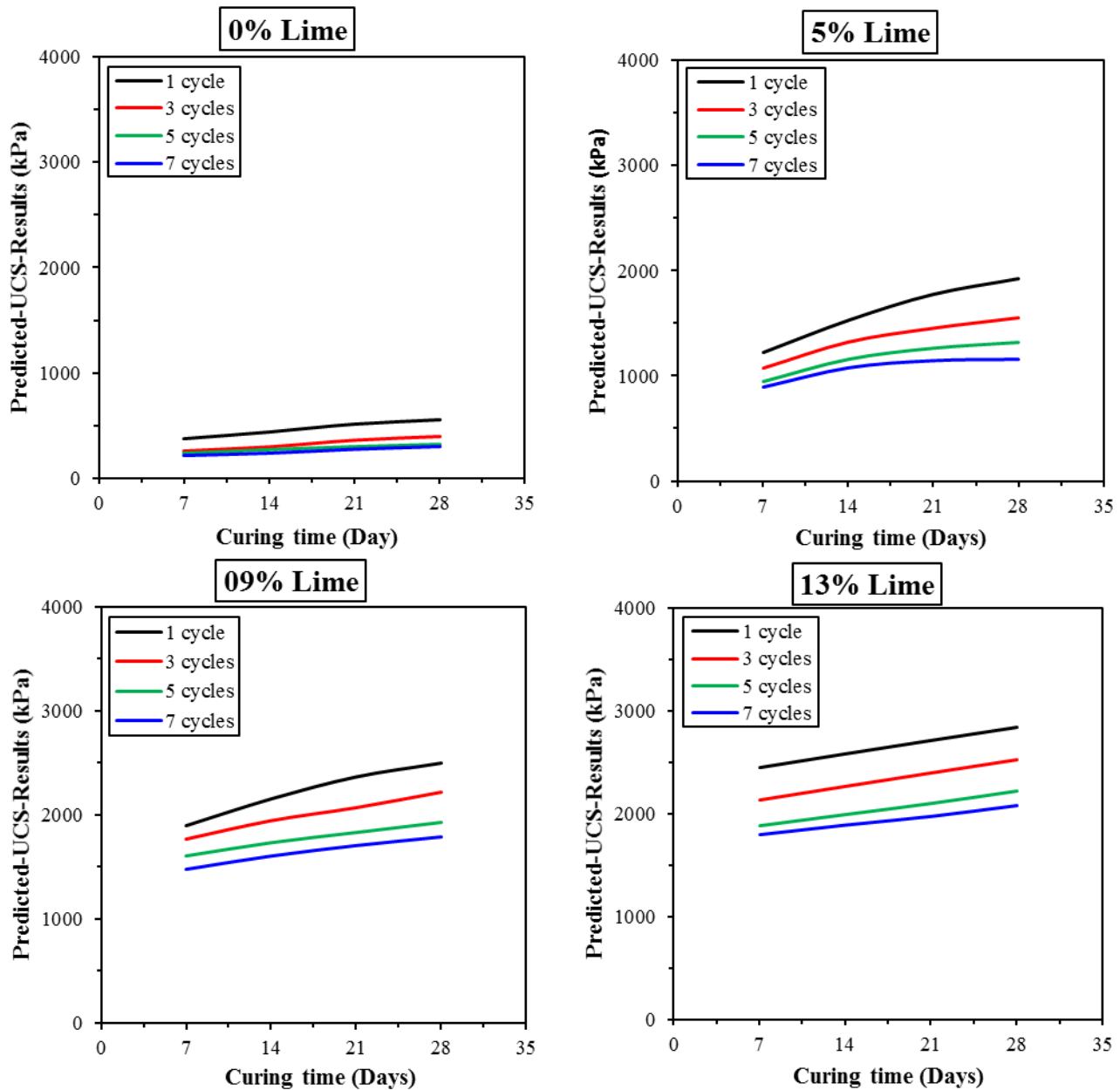


Fig. 4.11. Impact of curing timet on UCS of stabilized clayey soils across various F-T cycles at 500 kPa of UCS_0 .

The process involves two key mechanisms, lime ionization in water generating hydroxide ions (OH^-) that raise pH (Gadouri et al., 2017d), and silica dissolution in the alkaline environment reducing OH^- ions and pH levels. Freeze-thaw cycles physically disrupt these bonds, as shown by Dunlap et al. (1975) and Bandara et al. (2016). The speed of lime dissolution, initially rapid and gradually slowing, is affected by both chemical reactions and mechanical stress from freeze-thaw cycles (Al Daood et al., 2018).

4.4 Comparative Analysis of Statistical and ANNs Models for Predicting UCS in Freeze-Thaw Conditions

This section provides a critical evaluation of two modeling approaches traditional statistical regression and artificial neural networks (ANNs) for predicting the unconfined compressive strength (UCS) of lime-stabilized clayey soils under freeze-thaw (F-T) conditions. The statistical model, developed using regression techniques, offered good interpretability and moderate accuracy ($R^2 = 0.80$) with a validation error of around 6.25%. Its key strength lies in the clarity of parameter influence, making it useful for engineering decisions. However, it faced challenges due to multicollinearity and assumed linear relationships, which are often unrealistic for complex geotechnical interactions.

In contrast, the ANN model showed superior predictive performance across all phases training ($R^2 = 0.98$), validation ($R^2 = 0.87$), and testing ($R^2 = 0.91$). It successfully captured nonlinear interactions among variables such as lime content, moisture, curing time, and freeze-thaw cycles, even when statistical assumptions were violated. Though more complex and computationally demanding, the ANN model demonstrated better generalization and adaptability to varied input conditions, making it especially valuable when large datasets are available.

The optimized comparison table clearly reflects these findings, highlighting the trade-offs between the two approaches. While statistical models are faster, simpler, and more interpretable, ANNs offer unmatched accuracy and flexibility in modeling complex soil behaviors. Tab 4.3 aids in model selection based on project needs favoring statistical models for quick, transparent analysis and ANNs for high-precision, data-rich environments. This complementary use of both models provides a robust strategy for predicting UCS under environmental stress.

Tab. 4.3. Comparative summary between statistical model and ann model for UCS prediction

Criteria	Statistical model	ANN model
R² (train ;valid ;test)	0.80	0.98 ;0.78 ;0.91
Root mean error (RME)	6.25%	5% (test)
Root mean squart error(RMSE)	366.06 kPa	297.69 kPa (test)
Assumption required	Linearity, independence	None
Interpretability	High (coefficient, t-test, confidence intervals)	Low (black-box model)
Data requirement	Moderate	Hight
Computitional demand	Low	Hight (especially during training)
Generalization ability	Limited to calibration range	Hight (within training domain)
Sensitivity to input errors	Hight	Moderate
Usability for Field Design	High (fast, interpretable)	Medium (requires software, pre-trained model)

4.5 conclusions

This chapter has developed and evaluated two predictive frameworks for estimating UCS in lime-stabilized clayey soils exposed to freeze-thaw cycles: a traditional statistical regression model and a deep learning-based ANN model. The key findings can be summarized as follows:

- Statistical regression models offer good predictive capability ($R^2 = 0.80$) and excellent interpretability but are sensitive to variable correlation and assume linear behavior.
- ANN models achieved high prediction performance with $R^2 = 0.98$ (training), 0.87 (validation), and 0.91 (testing), indicating superior accuracy over traditional methods.
- Statistical models are better suited for rapid assessments and design transparency, especially with smaller datasets.

- ANN models, though computationally intensive and less interpretable, are more robust in capturing complex nonlinear relationships among soil parameters.
- Parametric analysis confirmed the critical influence of lime content, curing time, and moisture content on UCS behavior under F-T conditions. Both models captured these trends, though ANNs provided more detailed behavioral transitions.

Ultimately, this comparative study supports a hybrid modeling philosophy: using statistical models for interpretive insight and ANN models for high-precision prediction. This dual approach enhances the reliability of UCS estimation in geotechnical engineering, especially under variable and challenging environmental conditions.

Building upon the successful development of predictive models for lime-stabilized clayey soils, the subsequent chapter extends this modeling framework to investigate clay soil stabilization using fly ash as the primary mineral additive. This following analysis applies the same dual modeling approach combining statistical regression and artificial neural network techniques to evaluate the effectiveness of fly ash treatment under freeze-thaw cycling conditions. The chapter maintains consistent methodological approaches while exploring the unique characteristics and performance patterns associated with fly ash stabilization.

Chapter 5

*Predicting Soil Strength in Freeze-Thaw Environments
for Fly Ash-Stabilized Clay*

5.1 introduction

Predicting the unconfined compressive strength (UCS) of clayey soils treated with fly ash (FA) is a critical step in ensuring the durability and load-bearing capacity of stabilized ground in cold regions. Fly ash, an industrial by-product rich in amorphous silica and alumina, reacts pozzolanically with soil calcium to form cementitious compounds that enhance soil cohesion and stiffness (Harichane et al., 2011). Numerous studies have developed empirical and mechanistic models to estimate UCS based on FA dosage, moisture conditions, curing time, and intrinsic soil properties (Altun et al., 2009; Binshafique et al., 2010). Yet under cyclic freeze–thaw (F–T) exposure, strength predictions become more complex as ice lens formation and thaw consolidation interact with cementation processes.

To address these challenges, researchers have proposed both statistical regression models which offer transparent relationships between key variables and strength output and data-driven machine learning approaches, particularly artificial neural networks (ANNs), which can capture nonlinear dependencies without prior assumption of functional form (Yang et al., 2020; Li et al., 2018). In this chapter, building upon the FA–clay database presented in Chapter 3, we first develop a statistical regression model to quantify the primary factors influencing UCS under freeze–thaw cycling, then construct and train an ANN on the same dataset to learn the intricate coupling among variables directly from data. By comparing model performance and conducting parametric analyses, we identify the most significant drivers of freeze–thaw strength and offer practical guidance for FA stabilization design.

5.2. Development of UCS_{FT} statistical model

The UCS_{FT} statistical model was developed to predict the strength of FA-stabilized clayey soils under freeze–thaw conditions. Initially, we applied a multiple linear regression approach, but we encountered challenges due to intercorrelated variables and nonlinear relationships between soil properties such as liquid limit and plasticity index. To overcome these limitations, we adopted a nonlinear regression method that more effectively captured the complex interactions among factors like fly ash content, curing time, freeze–thaw cycles, and the initial strength of the untreated soil. The final model was validated through statistical testing and comparison with experimental data, providing engineers with a practical tool for estimating soil performance in harsh environmental conditions.

5.2.1. Formulation and analysis of the UCS_{FT} model

Understanding how various soil parameters influence unconfined compressive strength under freeze–thaw (UCS_{FT}) conditions is essential in evaluating the performance of fly ash–stabilized clayey soils. Initially, a multiple linear regression model was proposed to quantify the effect of factors such as FA content, curing time, number of freeze–thaw cycles, and geotechnical properties including liquid limit, plasticity index, consistency index, and optimum moisture content. The model was expressed in the following linear form in Eq 5.1:

$$UCS_{FT} = a_0 + a_1 \times Lc + a_2 \times T + a_3 \times NC + a_4 \times OMC + a_5 \times LL + a_6 \times IP + a_7 \times IC + a_8 \times UCS_0 \quad (4.1)$$

In this equation, UCS_{FT} represents the compressive strength after freeze–thaw cycles; FA denotes the fly ash content; T is curing time; NC is the number of freeze–thaw cycles; OMC represent optimum moisture content, MDD is maximum dry density, LL, PI, and IC, liquid limit, plasticity index, and consistency index, respectively; and UCS₀ refers to the initial unconfined compressive strength of untreated soil. Each coefficient (a₀ to a₈) was calculated through regression analysis to reflect the empirical influence of each parameter.

Despite its clear formulation, the linear regression model faced several statistical limitations. While residual independence was validated, the assumption of linearity was not always appropriate, especially regarding curing duration and FA dosage. More significantly, multicollinearity was evident among the geotechnical variables particularly LL, PI, and OMC which impaired the model’s ability to distinguish the individual contributions of each predictor. These findings are consistent with earlier observations in soil modeling literature (Sari-Ahmed et al., 2018).

To address these shortcomings, a nonlinear regression approach was adopted. The updated model included transformations such as logarithmic scaling of curing time and a power term for moisture content, capturing the intricate behavior of FA-treated soils subjected to F–T cycles. This approach aligns with the methods previously explored by Ibdah et al. (2025), who demonstrated improved performance of nonlinear models for soil behavior. The new formulation presented in the Tab.5.1 significantly enhanced the prediction quality and model interpretability.

Tab. 5.1. A statistical analysis of the UCS-FT model of Fly ash-stabilized clayey soils

Equation	Model parameters	t-test results	Signif. Param
$UCS = a \times UCS_0 \times \left[\left(\frac{A}{B} \right) \times C \right]$	A=0.317	Std. Err. =0.333	Yes
		t- value =0.000	
		P > t =0.000	
		[95% Conf. Interval] 0.656 0.657	
	B= -3.211	Std. Err. = 1.00	Yes
		t- value =-2.449	
		P > t =0.000	
		[95% Conf. Interval] -6.00 -1.00	
	C=7.302	Std. Err. =3.00	Yes
		t- value =2.467	
		P > t =0.000	
		[95% Conf. Interval] 1.00 13.00	
	D=23.201	Std. Err. = 12.00	Yes
		t- value =1.987	
		P > t =0.000	
		[95% Conf. Interval] 0.00 46.00	
	E=0.127	Std. Err. = 0.0101	Yes
		t- value =0.135	
		P > t =0.000	
		[95% Conf. Interval] 0.266 0.267	
	F=7.682	Std. Err. =0.812	Yes
		t- value =0.00	
		P > t =0.000	
		[95% Conf. Interval] 0.255 0.668	
	g = 8.575	Std. Err. =0.903	Yes
		t- value =0.00	
		P > t =0.000	
		[95% Conf. Interval] 0.178 0.425	
	H= 0.027	Std. Err. =0.00	Yes
		t- value =0.777	
		P > t =0.000	
		[95% Conf. Interval] 0.00 0.00	
	I= 0.577	Std. Err. =1.00	Yes
		t- value =1.089	
		P > t =0.000	

		[95% Conf. Interval]	0.00 2.00
R^2	F value	P_r	Signif. Model
0.836	175.922	0.000	Yes

Among all the equations tested, Eq 5.2 showed the strongest agreement with actual laboratory results, as shown in Tab 3.5. The model's reliability was confirmed through additional statistical checks and the calculation of performance metrics, as presented in Tab 5.2.

This method creates a solid foundation for understanding how fly ash-treated clay soils behave when exposed to freezing and thawing cycles.

Original formula :

$$UCS = a \times UCS_0 \times \left[\frac{(FA + 1) + b \times LL + c \times IP + d \times IC^2}{e \times FT + f \times \left(\frac{OMC}{100}\right) + g \times \left(\frac{MDD}{100}\right)} \times LOG10(h \times (T + 1)) + i \times \frac{(FA + 1)}{100} \right] \quad (5.2a)$$

Simplified version :

$$UCS = a \times UCS_0 \times \left[\left(\frac{A}{B}\right) \times C \right] \quad (5.2b)$$

Where :

$$A = (FA + 1) + b \times LL + c \times IP + d \times IC^2 \quad (5.3)$$

$$B = e \times FT + f \times \left(\frac{OMC}{100}\right) + g \times \left(\frac{MDD}{100}\right) \quad (5.4)$$

$$C = LOG10(h \times (T + 1)) + i \times \frac{(FA + 1)}{100} \quad (5.5)$$

Where :

- FA (%): Fly Ash content, which refers to the percentage of lime added to the clayey soil.
- UCS_0 (kPa): Initial unconfined compressive strength of the soil before stabilization.
- T (days): Curing time, indicating the duration for which the soil-lime mixture is allowed to cure.
- LL (%): Limit of liquidity
- IP (%): Plastisity index.
- IC: Consistency index, representing the relative firmness or stiffness of the natural clayey soil.

- OMC (%): Optimum moisture content, the moisture level at which the soil achieves its maximum dry density.
- MDD (Kg/m^3): Maximum density dry.
- F-T cycles: Freeze-thaw cycles, indicating the number of freeze-thaw cycles the soil undergoes. NC: Number of freeze-thaw cycles to which the soil is subjected.
- a, b, c, d, e, f, g, h, i: Constants in the model representing specific coefficients that quantify the influence of the respective parameters on the UCS.

The reliability of this model was further assessed using statistical indicators. Student's *t*-tests were applied to test the significance of each coefficient, with the null hypothesis assuming that the predictor has no impact on UCS_{FT} . In all cases, the *P-values* were below the 0.05 significance level, supporting the alternative hypothesis that each variable meaningfully contributes to strength prediction (Jafer et al., 2016; Sari-Ahmed et al., 2020, 2022). For example, the coefficient associated with fly ash (FA) content was statistically significant, confirming its critical role in enhancing strength through pozzolanic reaction. In parallel, a Fisher *F-test* was used to evaluate the global significance of the model, and the result reinforced its overall reliability and relevance (Davis, 2002). Confidence intervals constructed around each coefficient further confirmed the robustness of the parameter estimates.

The statistical findings are summarized in Tab 5.1, which details the coefficient values, *t*-scores, *p*-values, and associated confidence intervals. The combination of a high coefficient of determination (R^2), low error rates, and statistically significant predictors demonstrates the model's strong performance. This comprehensive analysis validates the nonlinear regression model as a robust tool for estimating UCS_{FT} in lime-stabilized clays, providing valuable insights for pavement design and geotechnical stabilization projects exposed to seasonal freezing.

Fig 5.1 illustrates the regression performance by plotting predicted UCS_{FT} values against experimental measurements. The resulting fit shows a strong correlation, reflecting the model's accuracy and confirming its practical applicability. Such visual validation, alongside rigorous statistical testing, highlights the model's effectiveness as a predictive framework for UCS behavior under environmental stress, positioning it as a valuable asset in the field of soil stabilization.

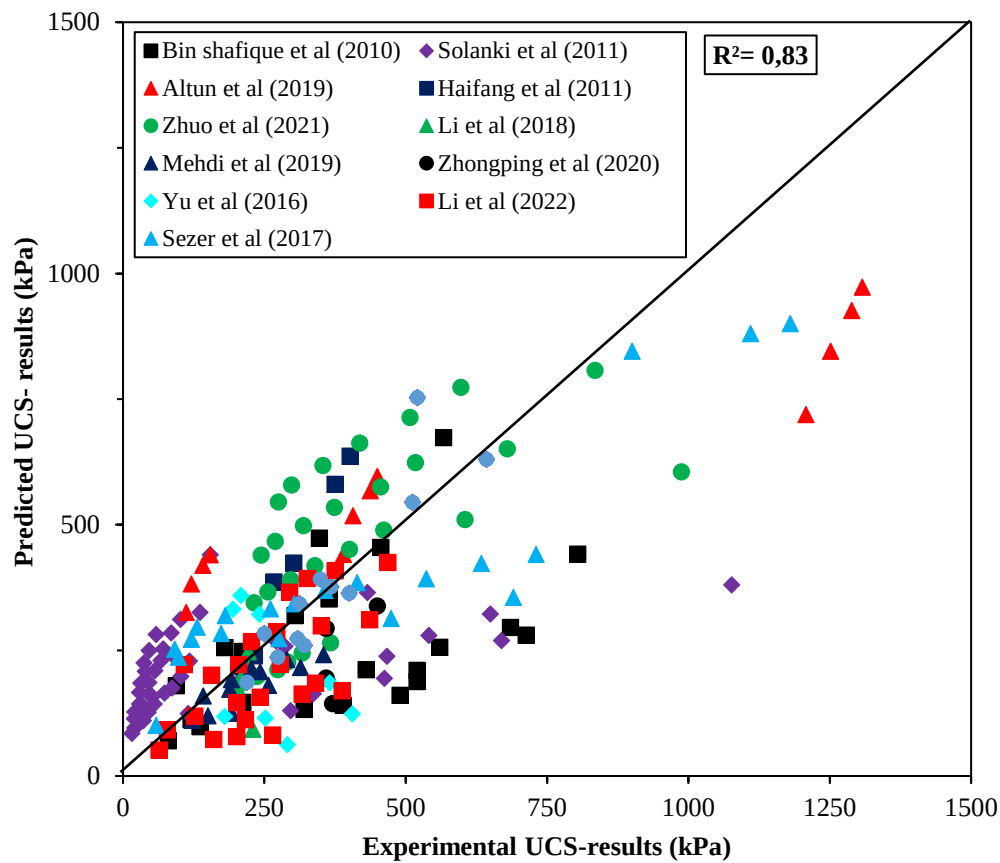


Fig. 5.1. Regression analysis of UCS in Fly Ash-stabilized clayey soils under F-T conditions

5.2.2. Validation of the UCS-FT model

To verify the predictive reliability of the proposed UCS-FT model, a comprehensive validation exercise was undertaken using an independent dataset collected from recent published studies. This dataset consisted of 39 experimental data pairs sourced from the works of [Bandara et al. \(2024\)](#), and [Binshafique et al. \(2011\)](#), specifically selected to represent a variety of soil conditions and stabilization scenarios involving fly ash. Each validation entry included key predictor values such as fly ash dosage, curing duration, liquid limit, plasticity index, optimum moisture content, maximum dry density, and the number of freeze-thaw cycles. These parameters were input into the calibrated model to generate predicted UCS-FT values. The predicted results were then compared directly against their corresponding experimental values reported in the literature. The performance of the model was assessed through relative mean error (RME), calculated using [Eq 4.3](#). This metric offers a normalized measure of prediction error by evaluating the average relative difference between

predicted and observed UCS values across the dataset. The validation results are illustrated in Fig 5.2 and summarized in Tab 5.2.

Tab. 5.2. Error between experimental and predicted UCS values validation– database.

	FA (%)	UCS0 (kPa)	T (day)	LL (%)	IP (%)	I _c	OMC (%)	MDD (kg/m ³)	NC	UCS Exp (kPa)	UCS Pred (kPa)	E (%)	RME (%)
Bandara et al 2024	15	315.3	1	48.1	21.5	1.3	20.0	9.5	0	305.31	254.51	19.96	9.27
	15	315.3	1	48.1	21.5	1.3	20.0	9.5	1	235.83	242.54	2.77	
	15	315.3	1	48.1	21.5	1.3	20.0	9.5	3	195.84	221.70	11.67	
	15	315.3	1	48.1	21.5	1.3	20.0	9.5	7	180.77	189.19	4.45	
	15	315.3	1	48.1	21.5	1.3	20.0	9.5	12	147.82	159.88	7.54	
Shamshad and Nimer 2024	0	180.0	7	79.0	53.0	1.0	26.0	15.1	0	180.00	225.01	20.00	6.05
	5	180.0	7	79.0	53.0	1.0	26.0	15.1	0	319.00	311.67	2.35	
	10	180.0	7	79.0	53.0	1.0	26.0	15.1	0	410.00	403.23	1.68	
	15	180.0	7	79.0	53.0	1.0	26.0	15.1	0	470.00	499.70	5.94	
	0	180.0	7	79.0	53.0	1.0	26.0	15.1	12	149.00	158.16	5.79	
	5	180.0	7	79.0	53.0	1.0	26.0	15.1	12	215.00	219.07	1.86	
	10	180.0	7	79.0	53.0	1.0	26.0	15.1	12	270.00	283.43	4.74	
Binshafiqu et al 2011	0	179.0	7	64.0	41.0	1.0	23.0	15.9	0	179.00	176.27	1.55	19.69
	10	179.0	7	64.0	41.0	1.0	23.0	15.9	0	433.00	322.19	34.39	
	20	179.0	7	64.0	41.0	1.0	23.0	15.9	0	540.00	488.60	10.52	
	0	179.0	7	64.0	41.0	1.0	23.0	15.9	24	174.00	93.64	86.38	
	10	179.0	7	64.0	41.0	1.0	23.0	15.9	24	184.00	170.64	7.83	
	20	179.0	7	64.0	41.0	1.0	23.0	15.9	24	268.00	258.78	3.56	
	0	179.0	7	64.0	41.0	1.0	23.0	15.9	0	179.00	176.27	1.55	
	10	179.0	7	64.0	41.0	1.0	23.0	15.9	0	433.00	322.19	34.39	
	20	179.0	7	64.0	41.0	1.0	23.0	15.9	0	540.00	488.60	10.52	
	0	179.0	7	64.0	41.0	1.0	23.0	15.9	24	112.00	93.36	19.97	
	10	179.0	7	64.0	41.0	1.0	23.0	15.9	24	202.00	170.64	18.38	
	20	179.0	7	64.0	41.0	1.0	23.0	15.9	24	240.00	258.78	7.26	
	0	179.0	7	64.0	41.0	1.0	23.0	15.9	0	179.00	176.27	1.55	
	10	179.0	7	64.0	41.0	1.0	23.0	15.9	0	433.00	322.19	34.39	
	20	179.0	7	64.0	41.0	1.0	23.0	15.9	0	540.00	488.60	10.52	
	0	348.6	7	81.0	57.0	0.9	26.0	15.1	0	191.00	271.18	29.57	
	10	348.6	7	81.0	57.0	0.9	26.0	15.1	0	456.00	482.49	5.49	
	20	348.6	7	81.0	57.0	0.9	26.0	15.1	0	667.00	714.62	6.66	
	0	348.6	7	81.0	57.0	0.9	26.0	15.1	24	149.00	146.95	1.40	
	10	348.6	7	81.0	57.0	0.9	26.0	15.1	24	294.00	261.45	12.45	
	20	348.6	7	81.0	57.0	0.9	26.0	15.1	24	360.00	387.24	7.03	
	0	348.6	7	81.0	57.0	0.9	26.0	15.1	0	191.00	271.18	29.57	
	10	348.6	7	81.0	57.0	0.9	26.0	15.1	0	456.00	482.49	5.49	
	20	348.6	7	81.0	57.0	0.9	26.0	15.1	0	667.00	714.62	6.66	
	0	348.6	7	81.0	57.0	0.9	26.0	15.1	24	164.00	146.95	11.60	
	10	348.6	7	81.0	57.0	0.9	26.0	15.1	24	258.00	261.45	1.32	
	20	348.6	7	81.0	57.0	0.9	26.0	15.1	24	344.00	387.24	11.17	
Total RME													11,34

The comparison demonstrated that the model is capable of closely replicating experimental behavior across a diverse range of soil and stabilization conditions. The calculated RME was approximately 11.34%, indicating that the model maintains strong accuracy even when tested on data outside the calibration set.

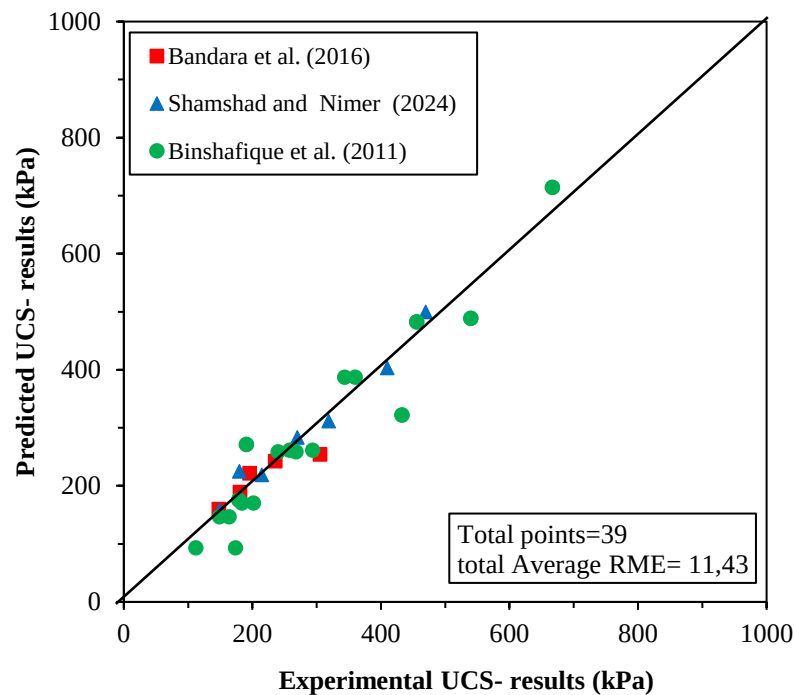


Fig. 5.2. RME Error analysis: laboratory vs. predicted ucs values for fly ash-treated clay soils subjected to F-T cycling.

This low error percentage suggests that the predictive framework is robust and generalizable, making it a reliable tool for estimating the unconfined compressive strength of fly ash–stabilized clayey soils subjected to freeze–thaw cycles. The graphical and tabular outputs from this validation study reinforce the model’s practical applicability in geotechnical engineering. The comparison demonstrated that the model is capable of closely replicating experimental behavior across a diverse range of soil and stabilization conditions. The calculated RME was approximately 11.34%, indicating that the model maintains strong accuracy even when tested on data outside the calibration set. This low error percentage suggests that the predictive framework is robust and generalizable, making it a reliable tool for estimating the unconfined compressive strength of fly ash–stabilized clayey soils subjected to freeze–thaw cycles. The graphical and tabular outputs from this validation study reinforce the model’s practical applicability in geotechnical engineering.

5.2.3. Parametric analysis

The performance of fly ash–stabilized clayey soils under freeze–thaw conditions is governed by multiple factors whose individual and combined effects can significantly influence strength development and durability. To explore these influences in depth, a parametric analysis was carried out based on experimental trends extracted from the database. This study focuses on three critical parameters fly ash content, moisture content, and curing duration and examines how variations in these factors impact unconfined compressive strength (UCS) through successive F–T cycles. The findings, presented in [Fig 5.3](#) to [5.5](#), provide insights into optimal stabilization conditions and help guide practical applications in geotechnical engineering.

5.2.3.1. Effect of fly ash content on UCS

[Fig 3.5](#) illustrates the predicted behavior of unconfined compressive strength (UCS) in clayey soils stabilized with varying fly ash contents (0% to 30%) and subjected to up to 12 freeze–thaw cycles. The model simulations were based on an initial UCS of 200 kPa, providing insight into how different fly ash dosages influence strength development and deterioration during cyclic freezing and thawing. This parametric study helps clarify the interaction between pozzolanic reactivity, binder content, and resistance to thermal stress.

At 7 days of curing, UCS increases significantly with higher fly ash content. However, the strength gain is tempered by the number of freeze–thaw cycles. For instance, soils treated with 15% and 20% fly ash reached UCS values of 410 kPa and 497 kPa respectively after just 3 cycles representing increases of 205% and 248%. Yet, after 9 cycles, these values dropped to 341 kPa and 413 kPa, marking reduced gains of 170% and 206%. These results suggest that while fly ash improves early strength, freeze–thaw damage still affects performance during initial curing.

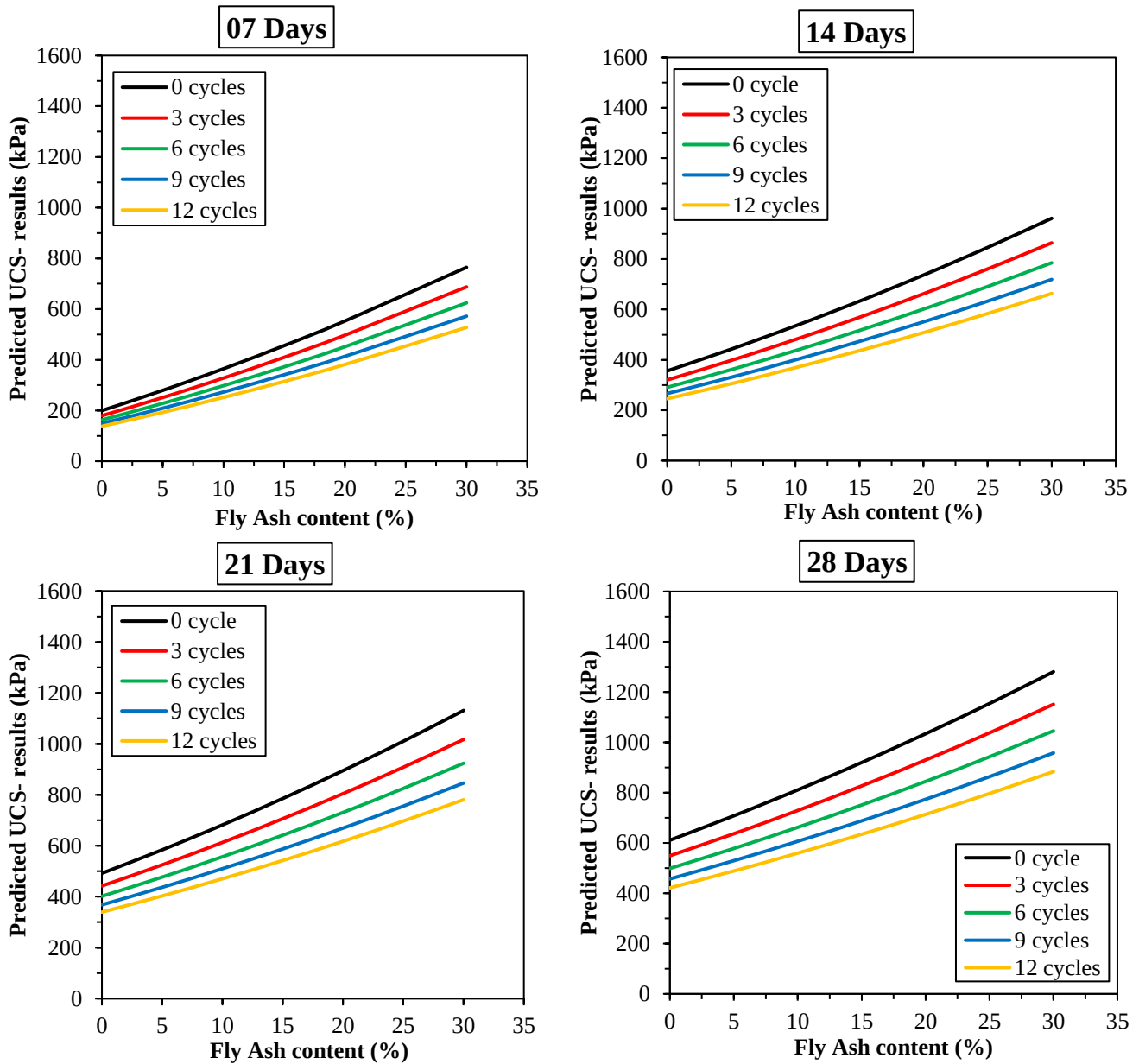


Fig. 5.3. Impact of Fly Ash and Curing Time on UCS of stabilized clayey soils across various F-T cycles

With 14 days of curing, soils exhibited better resistance to F-T effects. The UCS continued to improve with increased fly ash content, and samples stabilized with 15% fly ash retained higher residual strength after multiple cycles. This improvement is likely due to the ongoing pozzolanic reactions that continue to strengthen the soil matrix, enhancing its ability to resist freezing-related damage (Li et al., 2018).

By 21 days, the strength development became more pronounced. Soils with 15% and 20% fly ash showed greater UCS retention after freeze-thaw cycles compared to earlier curing

periods. This improvement is linked to the formation of cementitious products such as calcium silicate hydrate (C–S–H) and calcium aluminate hydrate (C–A–H), which bind the particles and reduce susceptibility to thermal cracking (Bandara et al., 2016).

At 28 days, the UCS reached its peak for all fly ash dosages. For example, the 15% fly ash mix achieved 825 kPa after three F-T cycles, and even after 12 cycles, strength losses remained below 43%. This performance demonstrates the near-complete development of pozzolanic bonding and the formation of a dense, resilient matrix. Such long-term durability is consistent with findings from Yi et al. (2014), who highlighted the importance of prolonged curing for improved freeze–thaw resistance.

Interestingly, the best durability was observed in mixes containing between 10% and 20% fly ash, where strength losses occurred more gradually. In contrast, both low (5%) and high (20%) dosages showed faster deterioration under repeated cycles. This pattern is consistent with results from Yu et al. (2017), who emphasized the need to optimize fly ash content to balance early strength and long-term durability. Overall, the model identifies 10–12% fly ash as the optimal range for enhancing both UCS and freeze-thaw performance.

The study further confirms that longer curing periods significantly improve UCS and durability. For example, a 7-day cured sample with 15% fly ash showed a 170% UCS increase after 9 F–T cycles. However, samples cured for 28 days retained much higher strength levels with only minor losses, underscoring the importance of extended curing for long-term stability. These findings are well supported by existing literature. Previous studies by Dayioglu et al. (2017), and Solanki et al. (2016) showed that fly ash stabilization effectively mitigate strength loss due to freeze-thaw effects. Sezer et al. (2017) also observed that soils treated with 15% fly ash saw UCS decline from 730 kPa to 474 kPa under 28-day curing with cyclic freezing. Similarly, Cheng (2021) reported strength reductions of up to 88% under similar conditions. These results validate the predictive model and emphasize the crucial role of both curing time and fly ash content in improving the freeze-thaw performance of treated soils.

5.2.3.2. Effect of moisture content on UCS

Fig 5.4 presents the effect of varying moisture content (MC) on the unconfined compressive strength (UCS) of clayey soil stabilized with 10% fly ash and cured over 7, 14, 21, and 28

days. The results reveal a delicate balance between curing time and moisture conditions, both of which significantly influence strength development under freeze-thaw exposure. While longer curing enhances UCS through continued pozzolanic activity, higher moisture content tends to reduce strength by interfering with compaction and chemical reactions.

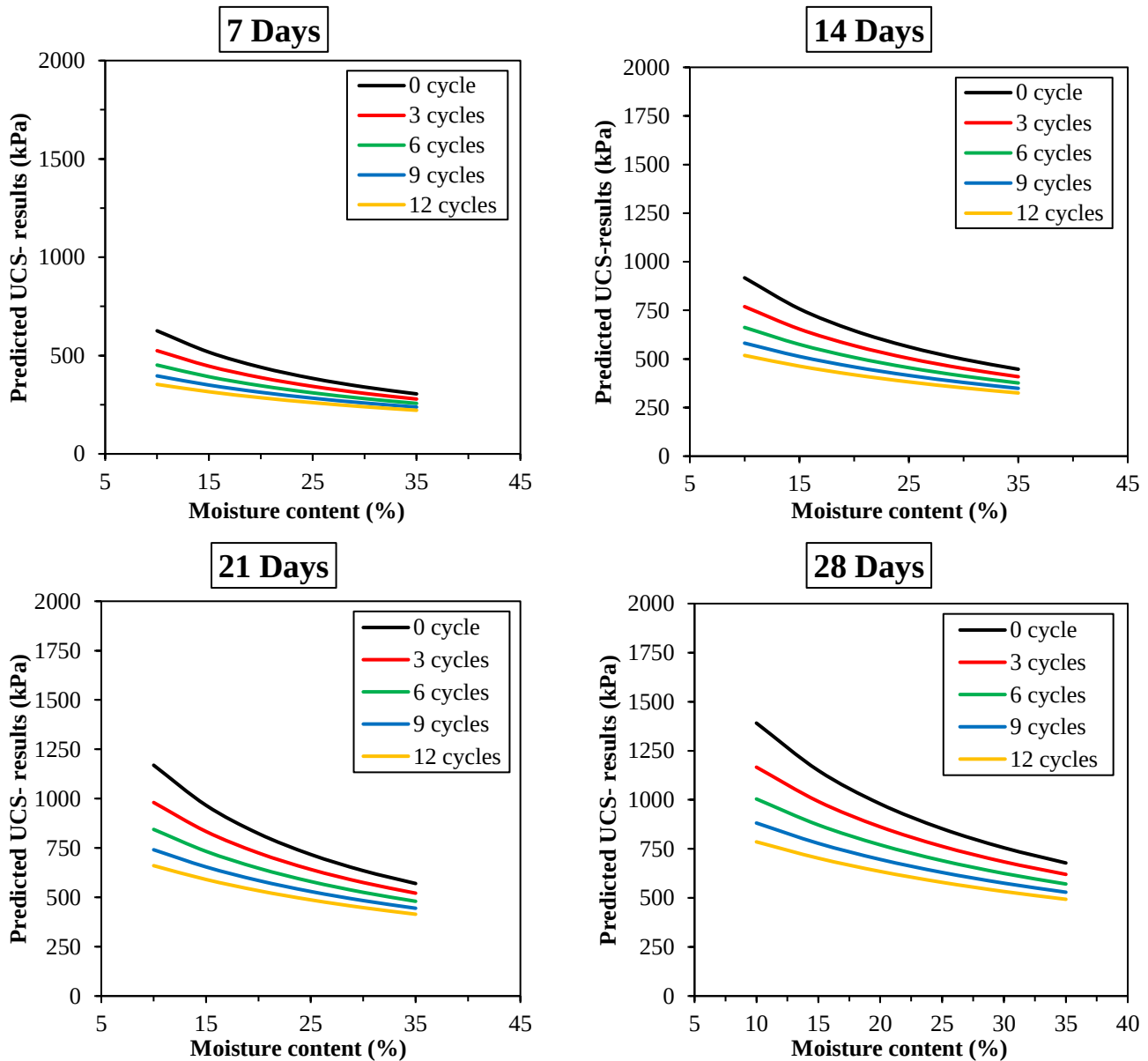


Fig. 5.4. Effect of MC on the UCS of Clayey Soils Stabilized with 10% Fly Ash under Various F-T Cycles

After 7 days of curing, the UCS improved markedly, reaching 625 kPa at 10% moisture content an increase of 312% from the initial 200 kPa. However, higher moisture contents led to reduced gains: 520 kPa (at 15% MC), 385 kPa (at 25% MC), and 305 kPa (at 35% MC).

The decline in strength with increasing moisture is attributed to excess water disrupting compaction and hindering the stabilization reactions, while also promoting pore pressure fluctuations during F-T cycles, as noted by [Su \(2012\)](#).

At 14 days, UCS values continued to rise, with soils at 10% MC reaching 665 kPa under 6 F-T cycles. The corresponding strengths for 15%, 25%, and 35% MC were 557 kPa, 455 kPa, and 376 kPa, respectively reflecting improvements of 10–15% over the 7-day period. Nonetheless, the adverse effects of high moisture persisted, reaffirming its negative role in stabilization efficiency.

After 21 days, the strength increase began to plateau. The UCS at 10% MC peaked at 844 kPa marking a 422% increase from the initial value. For 15%, 25%, and 35% moisture contents, the respective strengths were 732 kPa, 580 kPa, and 480 kPa, respectively. These results indicate that while pozzolanic reactions continued, their rate slowed, particularly in wetter conditions where water content limited further gains.

By 28 days, UCS values reached their highest levels. Soils at 10% MC achieved 1004 kPa (a 502% increase from the initial value), with corresponding values of 871 kPa, 680 kPa, and 570 kPa for 15%, 25%, and 35% MC. Despite extended curing, higher MC still constrained the full potential of fly ash stabilization. These results confirm that while prolonged curing enhances durability, excessive moisture remains a key limiting factor due to its impact on strength development and freeze-thaw performance.

The study reveals that curing time plays a crucial role in improving unconfined compressive strength, with the most significant gains occurring within the first 14 days. However, higher moisture content works against these improvements by creating poor compaction conditions and hindering the chemical reactions necessary for stabilization. The situation becomes even more challenging when soils are exposed to freeze-thaw cycles, which cause substantial strength loss that's particularly pronounced in wetter conditions. The research indicates that the best results are achieved when moisture content is controlled around 10% and curing is extended to 21-28 days. These conclusions align well with recent work by [Alem and Eselami \(2024\)](#) and [Liu et al. \(2019\)](#), reinforcing the importance of carefully balancing moisture conditions and curing time to achieve long-lasting soil stabilization.

5.2.3.3 Effect of curing time on UCS

The curing time and fly ash content significantly affect the UCS of clayey soils stabilized under freeze-thaw conditions (Fig 5.5). Prolonged curing allows for enhanced soil-lime reactions, forming cementing agents that improve soil strength, as noted by Bandara et al. (2016). This analysis investigates the UCS variations for initial strengths (UCS_0) of 200, 300, 400 and 500 kPa over curing durations and for soils stabilized with 10% fly ash, providing insights into the combined effects of curing time and initial UCS dosage on stabilization performance.

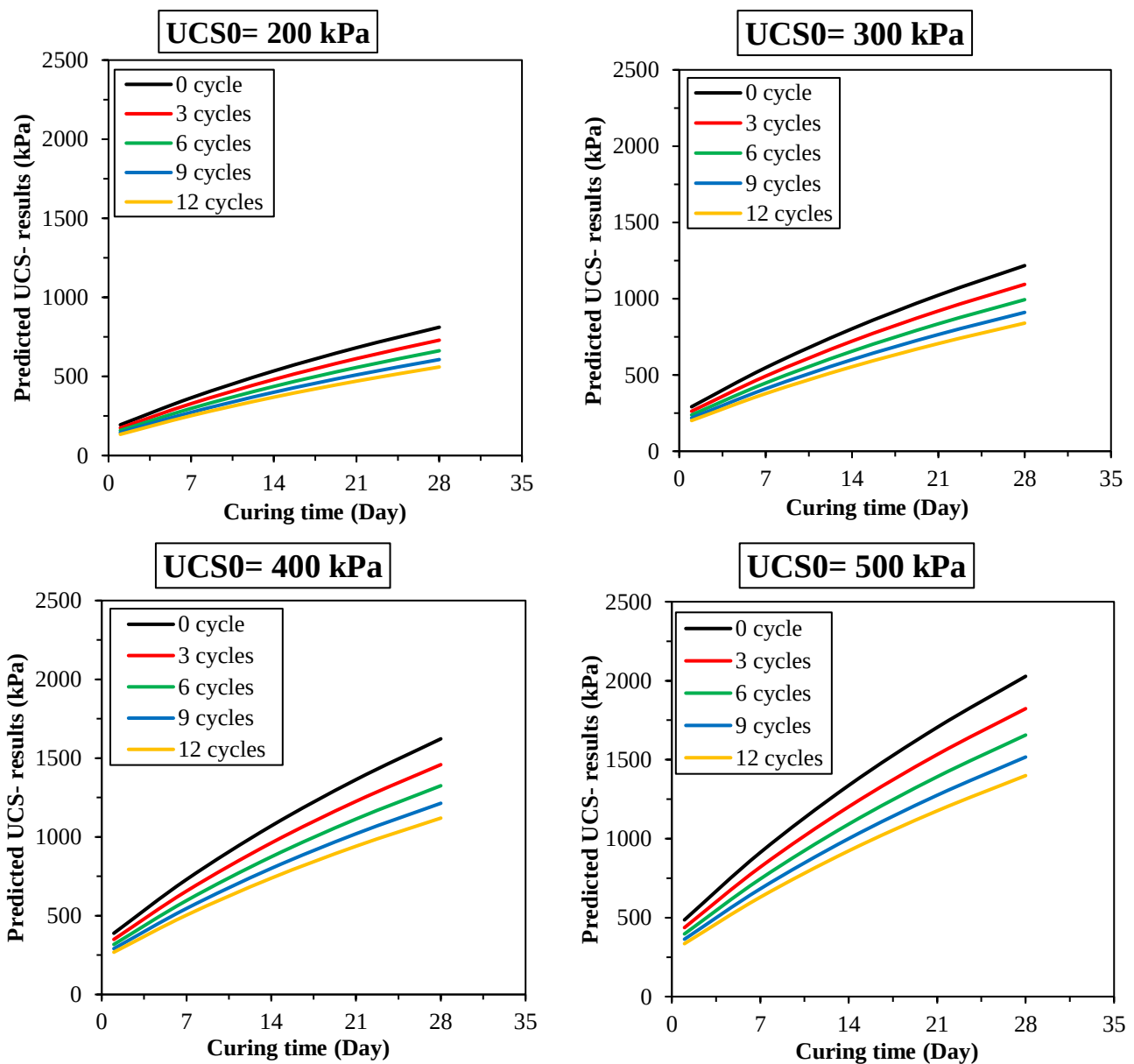


Fig. 5.5. Impact of curing time on UCS of stabilized clayey soils across various F-Tcycles with 10% of fly ash content.

From the first initial UCS, the curve shows a steady increase in UCS from 200 kPa at 1 day to 811 kPa at 28 days under no freeze-thaw exposure. Despite this strength gain, F-T cycles significantly lower UCS at each curing point. After 12 cycles, UCS only reaches 559 kPa, indicating a 30% reduction relative to the unexposed sample. Strength increases rapidly up to 14-21 days, then plateaus, a typical behavior for pozzolanic reactions in fly ash-stabilized soils (Boardman et al., 2001). This demonstrates the positive impact of curing time but also the vulnerability of stabilized soils to repeated thermal cycles (Dash and Hussain, 2012).

Here, in the second initial UCS of 300 kPa, the UCS grows from 292 kPa at 1 day to 1217 kPa at 28 days in the control case. F-T exposure (12 cycles) leads to 839 kPa at 28 days again about a 31% drop from the control sample. The trend parallels the 200 kPa case, showing that curing time provides consistent strength improvements across base UCS levels (Solanki et al., 2010). However, the relative loss due to freeze-thaw remains nearly constant, indicating that higher initial strength doesn't offer immunity to cyclic damage.

UCS without freeze-thaw exposure (case of initial UCS of 400 kPa) increases from 389 kPa (1 day) to 1622 kPa (28 days), while 12 freeze-thaw cycles samples reach 1119 kPa a 35% reduction. The shape of the curves and strength evolution mirror the previous figures. Cementitious products from pozzolanic reactions continue to develop over time but are impaired by cyclic expansion and contraction during F-T exposure (Yilmaz, 2018). This confirms that even at higher stabilization levels, F-T damage remains a limiting factor in long-term performance.

The highest UCS₀ (500 kPa) shows the strongest values: 2028 kPa after 28 days without cycles, and 1399 kPa after 12 cycles. Strength increases rapidly up to 14–21 days, after which it flattens. The reduction due to freeze-thaw cycles is once again around 33%. This confirms that higher UCS₀ values amplify final strength outcomes, but durability trends remain unchanged. The behavior aligns with known limitations of pozzolanic soil stabilization under environmental loading (Orakoglu et al., 2017).

The predictive model demonstrates that UCS improves significantly with longer curing times, reaching up to 2028 kPa at 28 days for higher UCS₀ values. However, freeze–thaw cycles consistently reduce strength by around 30%, regardless of the initial UCS. These findings underscore the importance of curing duration in fly ash-stabilized soils, while also

highlighting the persistent vulnerability to cyclic thermal stress reinforcing the need for additional measures to improve freeze–thaw resistance (Solanki et al., 2010; Dash and Hussain, 2012 ; Mahedi et al., 2019).

5.3 Development of ANNs model UCS-FT

5.3.1 Artificial Neural Network-Model Architecture Development (ANN-model)

Fig 5.6 illustrates the architecture of the artificial neural network (ANN) developed for predicting the unconfined compressive strength (UCS) of clayey soils stabilized with fly ash under freeze-thaw conditions. The network is structured with an input layer containing eight neurons, each corresponding to a key input parameter such as fly ash content, curing time, number of freeze-thaw cycles, moisture content, liquid limit, plasticity index, consistency index, and initial UCS. This input layer feeds into a single hidden layer composed of nine neurons, optimized through trial and error to balance learning capacity and generalization (Jeremiah et al., 2021). The hidden layer uses a sigmoid activation function, which introduces nonlinearity and allows the model to capture complex patterns in the data. The network concludes with a single output neuron, using a linear activation function to generate continuous UCS predictions (Ferentinou and Fakir, 2017).

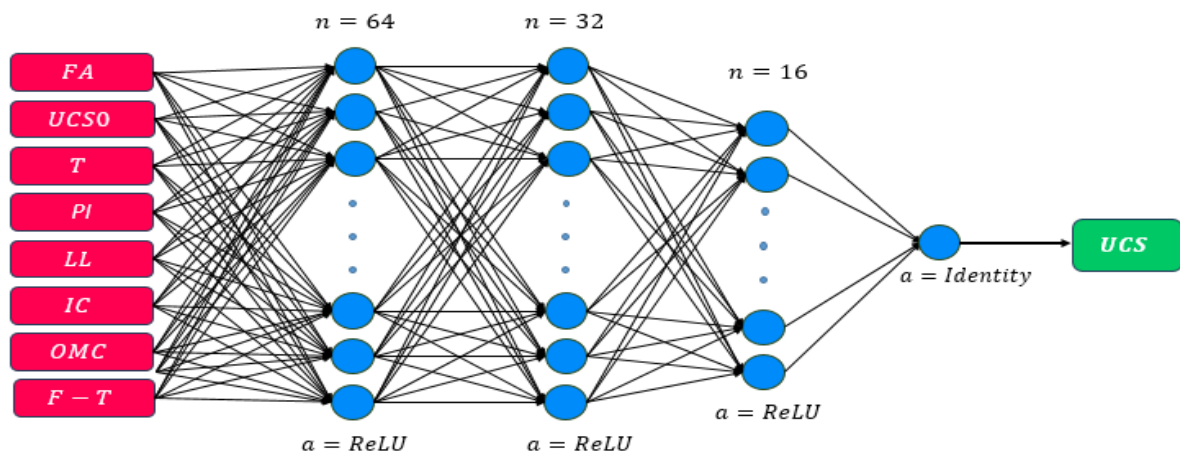


Fig. 5.6. Architecture used in ANNs model for UCS prediction

This ANN is trained using the Levenberg–Marquardt backpropagation algorithm, a robust and fast-converging method particularly suited for regression problems in small- to medium-sized datasets (Gouthan and Krishnaiah, 2023). Additional techniques such as input normalization, randomized weight initialization, and dropout regularization were employed to ensure stable convergence and avoid overfitting during training (Jalal et al., 2024). Compared to

conventional models like multiple linear regression, this ANN architecture offers significant advantages in flexibility and accuracy. Unlike MLR, which assumes a linear correlation, the ANN can learn nonlinear relationships between multiple soil parameters and UCS without requiring an explicit functional form (Alavi et al., 2019; Sezer et al., 2017). Such architectures have become widely adopted in geotechnical modeling due to their adaptability and predictive power. ANNs are now commonly applied to problems involving soil strength, slope stability, compaction behavior, and permeability. Studies by Ghanizadeh et al., (2022) have further confirmed their reliability in modeling soil performance under complex environmental loading, particularly freeze-thaw cycles. In this context, Fig 5.6 presents a clear example of a carefully constructed neural network capable of delivering accurate and generalizable UCS predictions for fly ash-stabilized soils.

5.3.2 UCS_{FT} Model Performance Analysis

The UCS-FT model demonstrates exceptional performance during its training phase, where it learned to predict the strength of clayey soils treated with fly ash and exposed to freeze-thaw cycles. Using 70% of the available data for training, the model achieved an impressive correlation coefficient of $R^2 = 0.95$, meaning it can accurately predict 95% of the variation in soil strength values. This high accuracy indicates that the model successfully captured the complex relationships between various soil properties and environmental factors that influence how these treated soils behave under harsh freezing and thawing conditions (Fig 5.7-a).

When tested with fresh validation data representing 20% of the dataset, the model maintained strong predictive capabilities with an R^2 value of 0.89 (Fig 5.7-b). This validation phase is crucial because it shows how well the model performs on data not used during training, which is essential for real-world applications. The slight decrease from the training accuracy is normal and expected, demonstrating that the model can generalize its learning to new situations without being overly fitted to the training data. This performance level gives engineers confidence that the model can reliably predict soil behavior in practical engineering scenarios.

The final testing phase used the remaining 30% of data to provide an independent assessment of the model's overall effectiveness, achieving an R^2 value of 0.85. This comprehensive evaluation across training, validation, and testing phases reveals that the UCS-FT model consistently delivers reliable predictions for soil strength under freeze-thaw conditions (Fig

5.7-c). The strong linear relationships observed in all phases, combined with data points clustering closely around the prediction line, confirm the model's practical value for engineering applications. While some outliers exist, they highlight specific conditions where additional refinement might be beneficial, ultimately supporting informed decision-making in soil stabilization projects. Fig 5.7-d offers an integrated view of the entire dataset, combining training, validation, and testing results. The overall R^2 of 0.92 achieved in this aggregated plot further reinforces the robustness and generalization capability of the model.

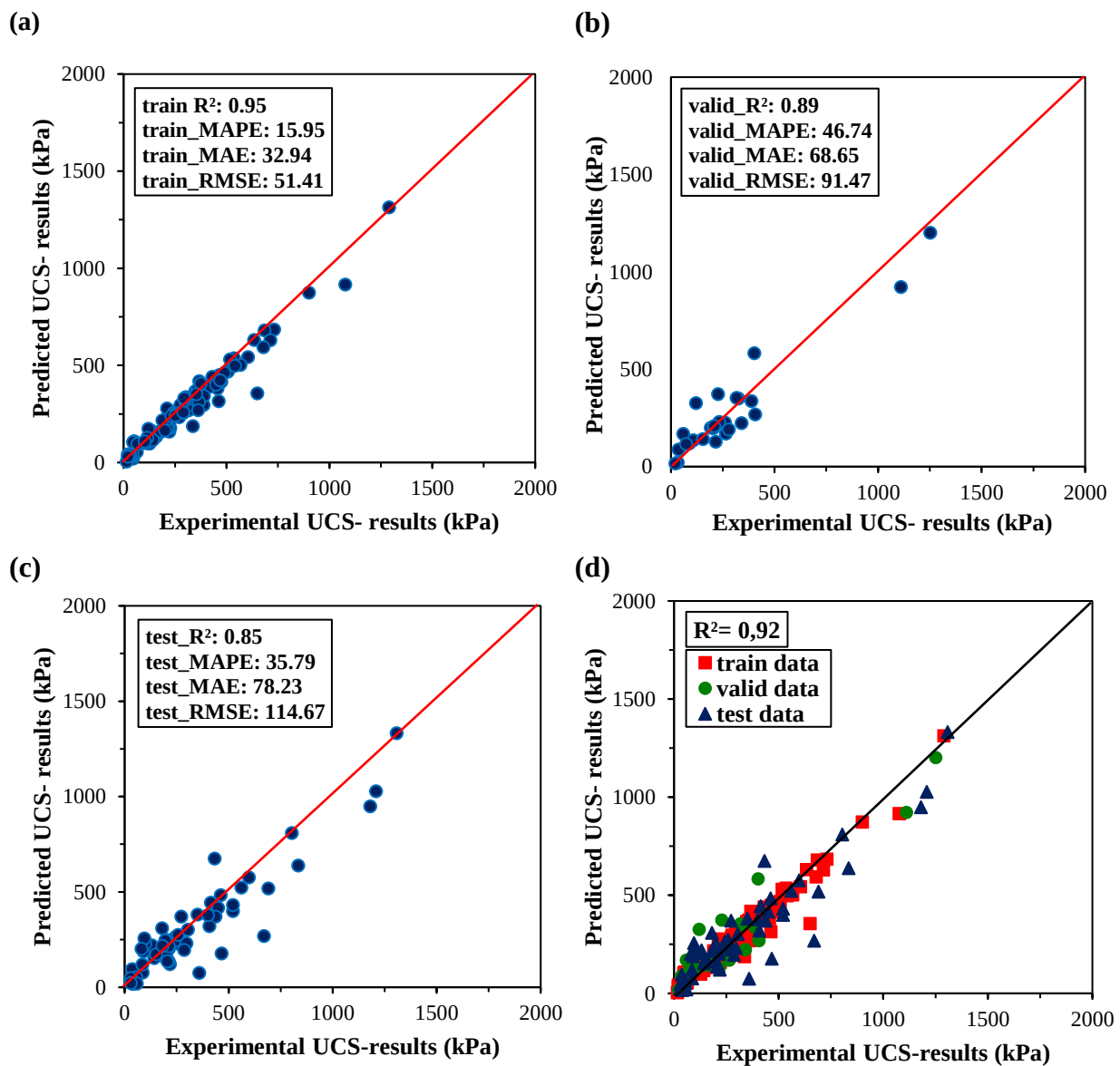


Fig. 5.7. The regression analysis for the development of the UCS-FT model for clayey soils stabilized with Fly Ash : (a) Train phase, (b) valid phase, (c) test phase, (d) globally model.

5.3.3 Parametric analysis based on ANNs model results

The ANN model was assessed through a detailed parametric study, evaluating its performance in predicting UCS across different fly ash contents, freeze–thaw cycles, and curing durations. Key input variables including optimum moisture content (OMC), liquid limit (LL), plasticity index (PI), consistency index (IC), and initial UCS were integrated into the analysis, highlighting the model’s effectiveness in simulating the behavior of fly ash-stabilized clayey soils under freeze–thaw conditions.

5.3.3.1 Effect of Fly Ash content on UCS

[Fig 5.8](#) presents the effect of fly ash content (0–30%) on the UCS of clayey soil with an initial strength of 250 kPa, subjected to 0–9 freeze–thaw cycles. Tests were conducted over curing periods of 7, 14, 21, and 28 days. The assumed soil properties include an optimum moisture content of 15%, a liquid limit of 80%, a plasticity index of 40%, and a consistency index of 1.44, corresponding to a highly plastic clay profile. The figure highlights the interaction between pozzolanic strength gain and freeze–thaw deterioration under varying stabilization and curing conditions.

At 7 days, UCS remains relatively low due to limited pozzolanic reaction. With 30% fly ash, UCS reaches 950 kPa without freeze–thaw, compared to just 250 kPa for untreated soil. However, after 9 freeze–thaw cycles, UCS drops to 650 kPa a reduction of 30–35%. This decline is linked to incomplete cementation and pore expansion from ice formation. [Jiang et al. \(2024\)](#) reported porosity increases of up to 20% from freeze–thaw, while [Bragar et al. \(2022\)](#) highlighted early-age vulnerability to structural damage due to immature binder formation.

At 14 days, UCS improves significantly, reaching ~1250 kPa for 30% fly ash without F–T exposure, and retaining 950 kPa after 9 cycles. The strength gain is attributed to the formation of C–A–S–H gels that densify the soil ([Kennedy et al., 2021](#); [Aslan Topçuoglu, 2025](#)). Though microcracking and pore widening still occur under F–T, the better-developed matrix offers enhanced resistance. [Jiang et al. \(2024\)](#) and [Bragar et al. \(2022\)](#) observed structural weakening and UCS losses of up to 40% in similarly treated soils, matching the trends shown here.

At 21 days, pozzolanic reactions are more mature, with UCS peaking at 1500 kPa (0 cycles) and 1150 kPa after 9 cycles a 23% drop. The formation of well-established C–S–H and C–A–

S–H gels increases soil cohesion and reduces pore volume (Turan et al., 2022). Jiang et al. (2024) noted that longer curing reduces F–T-induced pore expansion, explaining the slower rate of strength loss. Despite improvements, repeated cycles still cause microstructural damage and highlight the need for continued durability optimization.

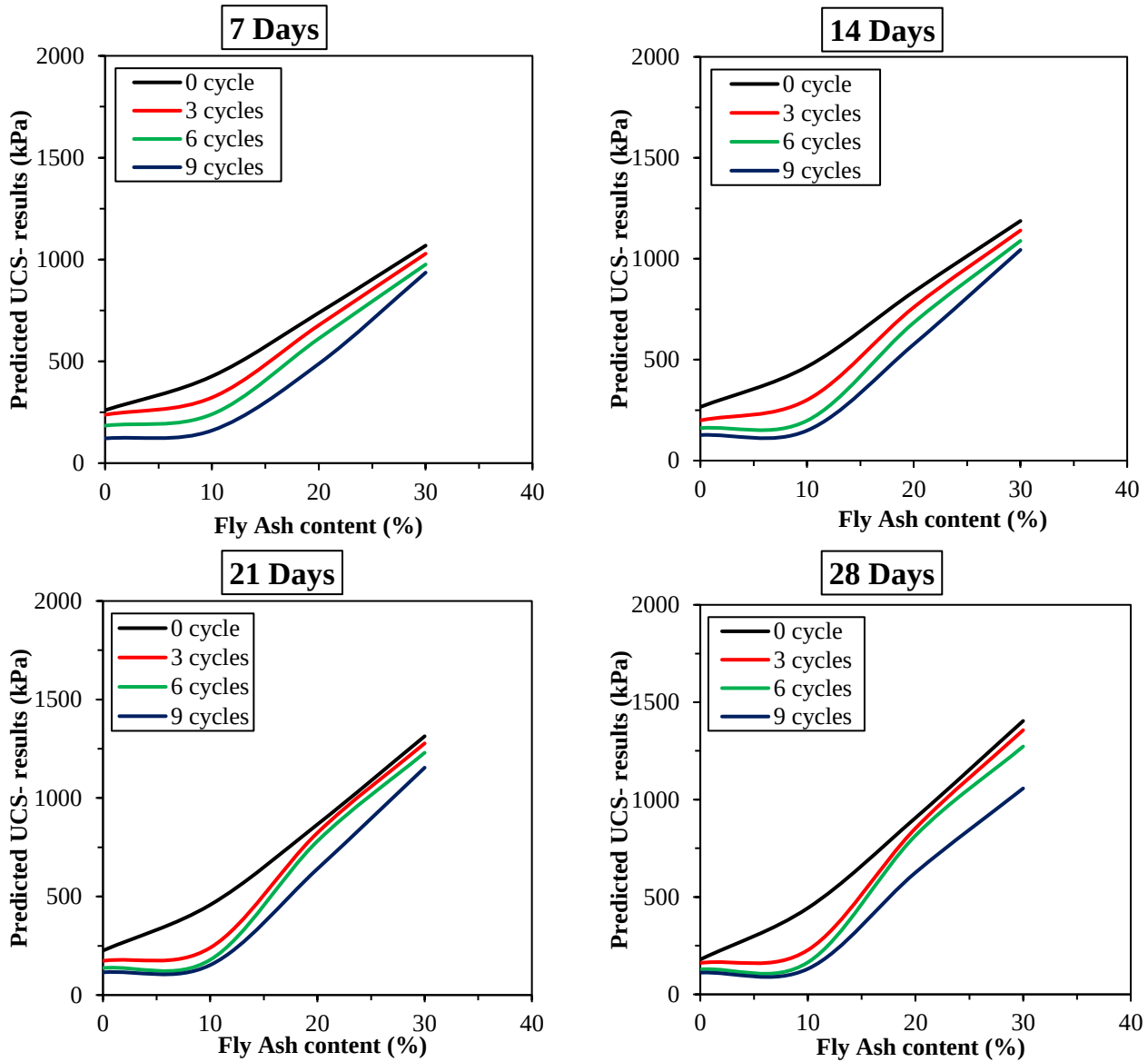


Fig. 5.8. Impact of Fly Ash on UCS of stabilized clayey soils across various F-T cycles

After 28 days, UCS reaches its highest value of 1700 kPa at 30% fly ash and 1350 kPa after 9 cycles only a 20% reduction. This strength reflects full pozzolanic reaction and dense cementation (Turan et al., 2022). The strong matrix resists pore expansion, though some damage persists due to ice pressure. Bragar et al. (2022) recorded up to 44% loss in less-cured soils, emphasizing the advantage of extended curing. These findings are also supported by

[Orakoglu et al. \(2017\)](#), who stress the importance of both fly ash dosage and cure time for long-term performance.

[Fig 5.8](#) confirms that UCS increases significantly with fly ash content and curing time, rising from 250 kPa (0% FA) to 1700 kPa (30% FA, 28 days). However, freeze–thaw cycles reduce UCS across all cases by 30–35% at 7 days and 20% at 28 days. This degradation results from ice-induced microcracking and pore expansion ([Jiang et al., 2024](#); [Bragar et al., 2022](#)). While longer curing and higher fly ash content improve durability, freeze–thaw resilience remains a challenge that requires careful material and curing optimization ([Orakoglu et al., 2017](#)).

5.3.3.2 Effect of moisture content on UCS

[Fig 5.8](#) illustrates the relationship between moisture content (MC) and UCS of fly ash-stabilized clayey soils under different freeze-thaw cycle conditions, with a 20% fly ash content and initial strength UCS_0 of 250 kPa. This investigation considers a range of curing periods (7 to 28 days) and moisture levels (5% to 20%). The findings reveal a decrease in UCS as MC increases, demonstrating the significant influence of MC on soil strength across freeze-thaw cycles. Similar trends were also reported by [Lui et al. \(2019\)](#).

At early curing (7 days), the moisture content plays a major role in UCS performance. Samples compacted near the optimum moisture content ($OMC = 15\%$) exhibit the highest initial strength (650–800 kPa), while those with very low or high moisture show reduced UCS (often more 500 kPa). Excess water weakens soil fabric by forming thick water films that lower cohesion between clay particles ([Rajaei et al., 2025](#)). During freeze–thaw cycles, wetter samples are more vulnerable due to the formation of ice lenses that expand and fracture. This leads to rapid UCS loss up to 40–45% after several cycles. In comparison, well-compacted samples retain more strength, though they too degrade under cyclic loading ([Xiong et al., 2025](#)).

After two weeks, curing contributes to partial structural improvement, but moisture content remains a controlling factor. The optimum-moisture mix still shows the highest UCS (970 kPa), while highly saturated samples remain weaker (400 kPa). [Han et al. \(2025\)](#) reported ~25% lower cohesion in soils with 22.6% moisture compared to those with 16.5%. Under freeze–thaw, the wetter samples suffer progressive damage, though their percentage strength loss may appear lower due to already poor initial strength. For instance, they observed only 18% cohesion loss in highly wet samples, compared to 45% in moderately moist ones,

underscoring that high moisture lowers strength in absolute terms even if relative loss is smaller.

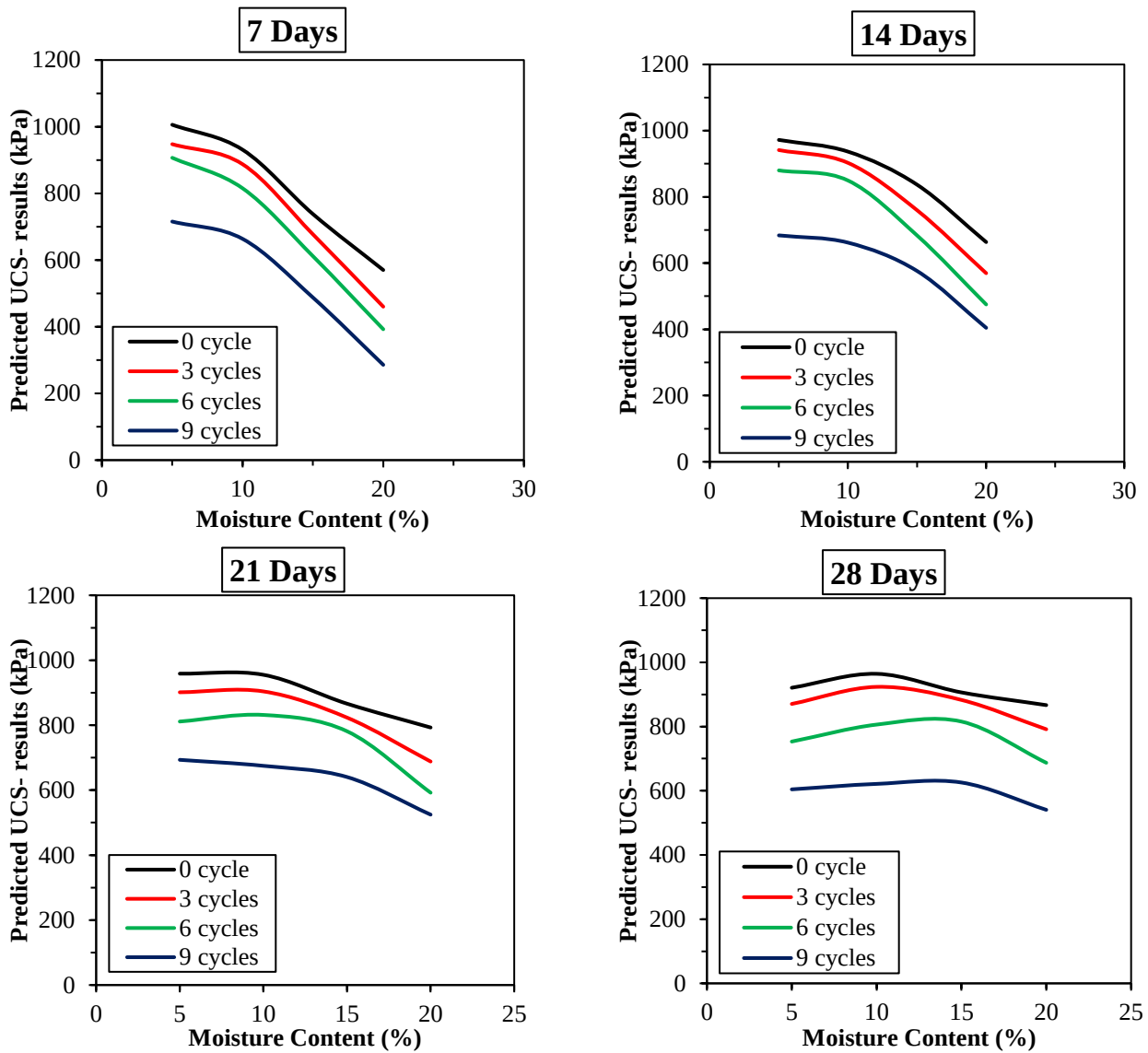


Fig. 5.9. Impact of MC on UCS of stabilized clayey soils across various F-Tcycles

The 21-day results represent a critical maturation phase where peak UCS values reach of 960 to 790kPa across an expanded optimal moisture range (8-15%), with heavily cycled specimens (9 cycles) retaining 60-70% of unfrozen strength, demonstrating substantial freeze-thaw durability improvement. Strength values show more gradual decline at higher moisture contents, maintaining 500-600 kPa at 20% moisture compared to 300-400 kPa at earlier curing periods. highlighting the importance of extended curing. The improved performance stems from completion of primary pozzolanic reactions and establishment of secondary

reaction products that create a more robust pore structure capable of accommodating moderate moisture variations while maintaining structural integrity through enhanced clay-fly ash chemical bonding (Yadav and bag, 2024).

At 28 days, UCS reaches its maximum values across all moisture conditions. For the moisture sample, UCS peaks around 920 kPa, while high-moisture mixes remain limited (540 kPa) under 9 cycles freeze-thaw. Despite the matured pozzolanic structure, excessive water still weakens initial strength and allows ice expansion to form new macrovoids under freeze-thaw exposure (Zhou et al., 2023). Even after 9 cycles, well-compacted samples retain most of their strength (600 kPa), whereas saturated ones may drop below 540 kPa. This final stage demonstrates how excessive water content continues to undermine durability even with full curing (Cheng et al., 2021).

5.3.3.3 Combined Effect of Initial Soil Strength and Curing Duration on UCS

The ANN model's performance at $UCS_0 = 200$ kPa show sustained strength gain, albeit less aggressively. The no-cycle curve rises from about 525 kPa at 1 day to 938 kPa at 28 days (80% increase). The highest-cycle curve similarly grows from 307 to 546 kPa (Fig 5.10). The trend is monotonic with time, reflecting that longer curing (hydration of fly ash) increases UCS, in agreement with established behavior (Cheng et al., 2021). Freeze-thaw cycles again yield a notable gap: at 28 days the 9 F-T cycle strength (546 kPa) is roughly 42% lower than the no-cycle strength (938 kPa). This percentage drop is larger than in the predictive model, suggesting the ANN may capture more conservative durability. Nevertheless, both models agree that cycles degrade strength in stabilized soil (Chen et al., 2019).

For $UCS_0 = 250$ kPa, the predicted curves (4 series) also rise with curing. The 0 cycle F-T series goes from 503 kPa at 1 day to 995 kPa at 28 days (approximately doubling in the strength), and the 9 cycles F-T series from 307 kPa to 541 kPa. Notably, one curve shows a slight drop at 7 days (307 to 286 kPa) before recovering, likely reflecting modeling scatter, nonetheless it resumes increasing thereafter. Overall, the ANN outputs are smoother than those of the statistical model, but still show larger gains as curing proceeds. Freeze-thaw again lowers UCS of 995 to 541 kPa at 28 days is approximately 46% drop), mirroring expected frost damage. These results reaffirm that curing time remains vital for strength buildup (Xiong et al., 2025).

From the $UCS_0 = 300$ kPa, in this case the ANN shows a clear increase in UCS: the no-cycle curve climbs from 532 kPa at 1 day to about 1088 kPa at 28 days (roughly double). The 9 cycles F-T curve rises from 196 kPa to 485 kPa. One series exhibits a pronounced 14 to 21 days jump (281 to 419 kPa) before leveling, suggesting a possible reaction threshold in the model. Regardless, all series trend upward overall. As expected, longer curing yields higher UCS (Bin-Shafique et al., 2011), while additional freeze-thaw cycles keep the curves significantly below the control. At 28 days the frozen curve is less than half the unfrozen UCS, consistent with frost-induced weakening. These patterns (UCS roughly inversely correlated with cycles and growing with curing) align with findings that stabilized clays lose strength after repeated freeze-thaw (Jeremiah et al., 2021).

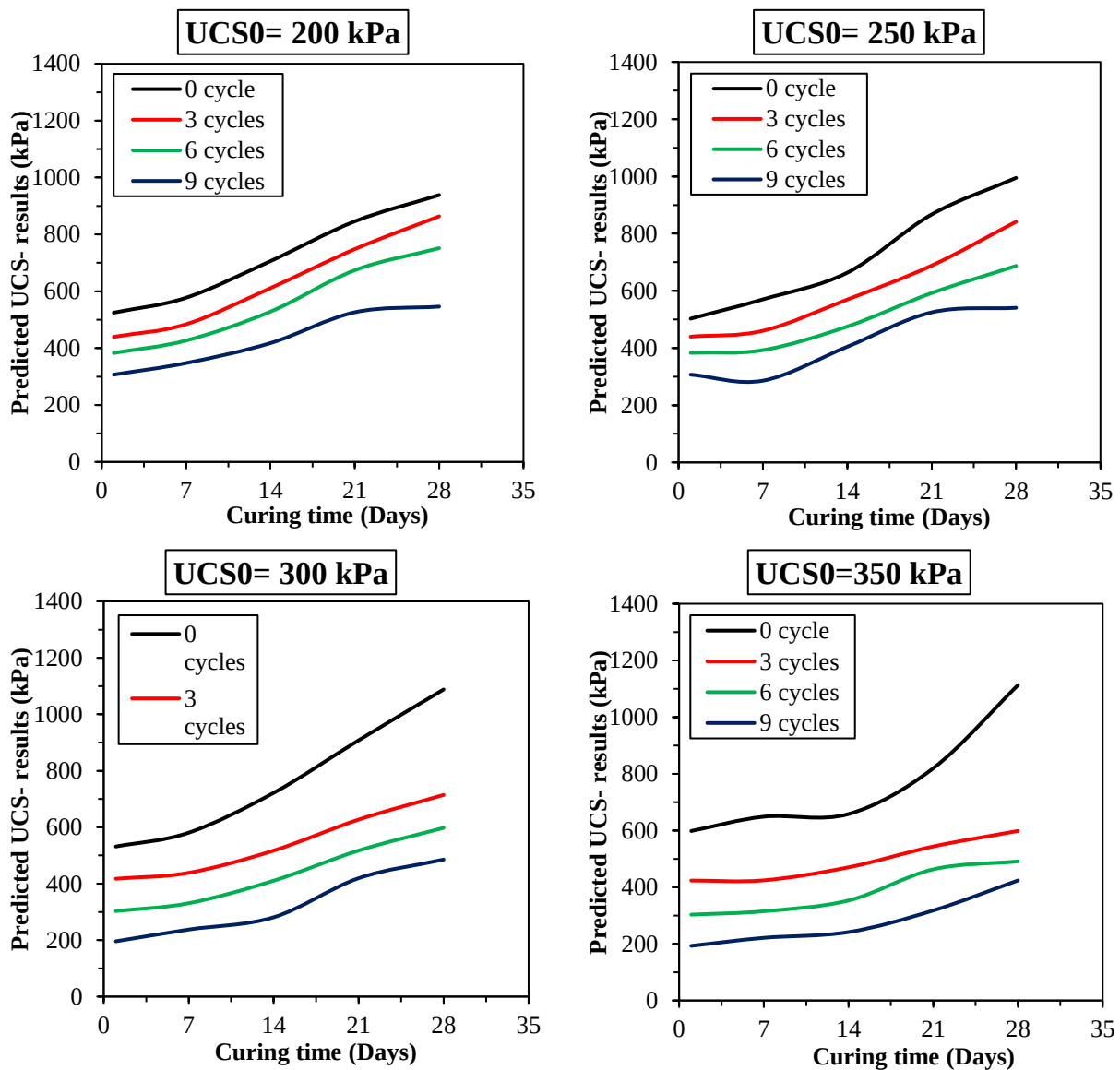


Fig. 5.10. Impact of Curing time and Initial Soil Strength on UCS of stabilized clayey soils across various F-T cycles

Here, from $UCS_0 = 350$ kPa, the highest UCS_0 case shows unique curvature. The control curve goes from 598 kPa from 1 day to 1113 kPa from 28 days. Interestingly, it plateaus around 14 days (648 to 658 kPa) and then jumps late. This may indicate a delayed curing effect or model artifact. Nonetheless, by 28 days the unfrozen sample has reaching nearly double the initial strength for 1 day. Freeze–thaw series similarly climb (e.g. from 193 to 423 kPa) but remain well below. The overall gain (showing a 2.6- fold strength gain for unfrozen) confirms that curing helps bind the soil even in the ANN model. The persistent strength differences between no-cycle and cycled samples (1113 vs 423 kPa at 28d) underscore that freeze–thaw greatly reduces UCS here as well, consistent with frost damage causing cohesion loss. Similar observations were also reported by other researchers ([Ma et al., 2023](#)).

The ANN model confirms that curing time improves UCS, but predicts greater strength loss due to freeze-thaw cycles ranging from 42% to 62%. While peak UCS values are slightly lower than those from the predictive model, the trends are consistent, validating ANN’s utility in forecasting soil behavior under environmental loading. These outcomes highlight ANN’s effectiveness in modeling complex curing–durability interactions and stress the need to mitigate freeze–thaw damage for sustainable stabilization.

5.4 Comparative Analysis of Statistical and ANNs Models

Both the statistical regression model and the ANN model have been calibrated and validated against the same database of fly ash–stabilized clayey soils subjected to freeze–thaw (F–T) cycles. While the statistical model offers explicit equations and parameter significance measures, the ANN provides a data-driven mapping that inherently captures nonlinear interactions. The table below summarizes their relative performance, interpretability, and practical strengths and limitations.

The comparative evaluation between statistical and artificial neural network approaches reveals distinct advantages tailored to different engineering applications in freeze-thaw performance assessment ([Tab 5.3](#)). Statistical models provide superior interpretability through transparent coefficient analysis, enabling engineers to identify critical variables and quantify their individual contributions to soil behavior under thermal cycling conditions.

Tab. 5.3.Comparative summary between statistical model and ann model for
UCS prediction

Criteria	Statistical model	ANN model
R² (train, valid. and test)	0.84 (train)	0.95 (train), 0.89 (validation), 0.85 (test)
Root mean error (RME)	11.43%	9.04%
Root mean squart error(RMSE)	152.88 kPa	114.67 kPa
Assumption required	Linearity, independence	None
Interpretability	High (evaluated through hypothesis testing)	Low (black-box model)
Data requirement	Moderate-fewer paramater	Higher- more data for stable
Computitional demand	Low- closed- form solution	Hight (especially during training)
Generalization ability	Limited to calibration range	Hight (within training domain)
Sensitivity to input errors	Hight	Moderate
Usability for Field Design	High (fast, interpretable)	Medium (requires software, pre-trained model)

This clarity supports informed decision-making in design parameter selection and quality control protocols. Conversely, the ANN demonstrates superior pattern recognition capabilities, achieving higher training accuracy through its ability to automatically detect and model complex nonlinear interactions between multiple variables without requiring predetermined mathematical relationships or data transformations.

While statistical methods offer implementation simplicity and operate effectively with smaller datasets, the neural network's adaptive architecture accommodates broader parametric ranges and captures subtle interdependencies at the expense of model transparency. Despite their fundamental differences in approach and interpretability, both methodologies exhibit strong validation performance, with correlation coefficients exceeding 0.80, confirming their

practical reliability for predicting unconfined compressive strength in engineering applications involving freeze-thaw susceptible soils.

5.5 Conclusions

This chapter presented a comparative study between two modeling techniques: a nonlinear statistical regression model and an artificial neural network (ANN), for predicting the unconfined compressive strength (UCS) of fly ash-stabilized clayey soils subjected to freeze–thaw cycles (UCS_{FT}). Both models were developed using the same dataset compiled from the literature and based on identical input variables: fly ash content, curing time, number of freeze–thaw cycles, initial UCS, optimum moisture content, liquid limit, plasticity index, consistency index, and maximum dry density.

Both approaches demonstrated strong predictive capabilities. The statistical model achieved a global R^2 of 0.84, offering valuable interpretability. The ANN model outperformed it, with R^2 values of 0.95 (training), 0.89 (validation), and 0.85 (testing), showing superior accuracy in modeling nonlinear relationships and complex variable interactions.

The parametric analysis revealed key trends:

- Higher fly ash content and longer curing durations led to significant strength gains.
- Excessive moisture content negatively impacted UCS, particularly at early curing stages.
- An increased number of freeze–thaw cycles consistently reduced UCS, reflecting the detrimental effects of frost on soil cohesion.
- Initial UCS played a crucial role in long-term performance, especially under freeze–thaw exposure.

In summary, the statistical model offers simplicity and interpretability, making it suitable for routine design applications. In contrast, the ANN model provides higher precision and greater flexibility for analyzing complex scenarios. Combining both approaches, using regression for preliminary screening and ANN for in-depth scenario analysis, can enhance the reliability of UCS_{FT} predictions and support robust geotechnical design under cold climate conditions.

General Conclusions

General Conclusions

A comprehensive statistical study was developed to propose predictive models and artificial neural network (ANN) models for the important property of unconfined compressive strength (UCS) of clayey soils stabilized by different cementitious additives, namely lime and fly ash, under freeze-thaw environmental conditions.

In this framework, databases were collected, classified, and presented, containing physical and mechanical properties of clayey soils stabilized with lime and fly ash, extracted from a significant number of research works published in the literature. These databases were subsequently used in the adjustment of a set of proposed empirical equations and artificial neural network (ANN) architectures. In this context, the developed work aimed and targeted the following objectives:

- The proposal and adjustment of a significant number of statistical models and artificial neural network (ANN) models describing the effect of lime and fly ash on the unconfined compressive strength (UCS) property of improved soils under freeze-thaw environmental conditions.
- Evaluate both models (statistical and ANN) for each mineral additive (lime and fly ash) thus proposed using appropriate statistical tests for the statistical model and architectural structure for ANN for this type of study.
- Verify the accuracy of the proposed models through a validation study for both proposed models: statistical and ANNs.
- Study the effect of different cementitious additives retained in the present work on the studied geotechnical properties through a parametric study.
- Conduct a comparative study between the two appropriate techniques: statistical model and ANN model for each mineral additive (lime and fly ash).

In light of the points addressed above, the following results were obtained:

➤ **Case of lime-treated clayey soils**

- Two models: statistical and artificial neural networks (ANNs) have been proposed and adjusted to estimate the effect of lime on the unconfined compressive strength (UCS) under freeze-thaw cycles of lime-treated clayey soils.

- The proposed model has been adjusted, successfully tested, and then validated using other published results. The t-tests performed (statistical model) and the test phase obtained by the ANN architecture along with the determination coefficients (R^2) obtained confirmed that all explanatory variables retained in the proposed models are sufficient for predicting the studied property and have a significant effect on the considered variables.
- The validation studies showed, by calculating the relative errors between experimental values and their corresponding theoretical values, acceptable degrees of precision provided by the proposed models (statistical and ANN).
- In order to quantify the effects of lime and other variables considered in the proposed empirical equations, a parametric study was developed from which the following conclusions can be drawn:
 - Lime content effect: UCS shows a progressive increase with higher lime content, demonstrating an optimal dosage range beyond which improvements plateau
 - Curing time influence: Strength development follows an exponential growth pattern, with rapid initial gains that gradually stabilize over extended periods
 - Freeze-thaw cycle impact: UCS exhibits a declining trend with increasing number of cycles, showing accelerated degradation in the initial cycles followed by a more gradual reduction
 - Combined effects: The interaction between lime content and environmental exposure reveals that higher lime dosages provide better resistance to freeze-thaw deterioration
 - Effect of moisture content: Excessive moisture levels reduce soil compactness and hinder pozzolanic reactions, negatively impacting UCS, particularly under F–T conditions.
 - Model sensitivity: The parametric analysis confirms that lime content and curing time are the most influential parameters, while freeze-thaw cycles represent the primary degradation factor

➤ Case of Fly ash-treated clayey soils

- Two models: statistical and artificial neural networks (ANNs) have been proposed and adjusted to estimate the effect of fly ash on the unconfined compressive strength (UCS) under freeze-thaw cycles of fly ash-treated clayey soils.

- The proposed model has been adjusted, successfully tested, and then validated using other published results. The t-tests performed (statistical model) and the test phase obtained by the ANN architecture along with the determination coefficients (R^2) obtained confirmed that all explanatory variables retained in the proposed models are sufficient for predicting the studied property and have a significant effect on the considered variables.
- The validation studies showed, by calculating the relative errors between experimental values and their corresponding theoretical values, acceptable degrees of precision provided by the proposed models (statistical and ANN).
- In order to quantify the effects of fly ash and other variables considered in the proposed empirical equations, a parametric study was developed from which the following conclusions can be drawn:
 - Fly ash content effect: UCS shows a progressive increase with higher fly ash content, demonstrating an optimal dosage range beyond which improvements plateau
 - Curing time influence: Strength development follows an exponential growth pattern, with rapid initial gains that gradually stabilize over extended periods
 - Freeze-thaw cycle impact: UCS exhibits a declining trend with increasing number of cycles, showing accelerated degradation in the initial cycles followed by a more gradual reduction
 - Combined effects: The interaction between fly ash content and environmental exposure reveals that higher fly ash dosages provide better resistance to freeze-thaw deterioration
 - Effect of moisture content: Elevated moisture levels weaken the stabilized matrix by reducing compactness and interfering with cementitious bonding, particularly under repeated freezing and thawing.
 - Model sensitivity: The parametric analysis confirms that fly ash content and curing time are the most influential parameters, while freeze-thaw cycles represent the primary degradation factor

Future Perspectives and Recommendations

- Future stabilization strategies should incorporate multiple environmental stressors (thermal fluctuations, saturation-desiccation, leaching) in

combination to better simulate field conditions, particularly focusing on swell-shrink behavior of expansive soils under alternating moisture levels.

- Supplementary additives such as natural pozzolans, gypsum, nano-silica, or GGBS should be incorporated into stabilization matrices, with composite binders and multi-phase stabilization systems recommended for high-risk environments to enhance long-term performance.
- Future research should embrace algorithmic techniques beyond ANNs, including XGBoost for complex non-linear interactions, KNN for instance-based prediction, and SVR/Random Forests for interpretable modeling, integrated into hybrid frameworks combining data-driven learning with mechanistic soil behavior models.
- Integrating these models into a hybrid framework combining data-driven learning with mechanistic soil behavior models will further improve reliability. Open-source platforms and cloud-based tools should also be explored for scalable and collaborative implementation. Ultimately, the shift toward deep modeling approaches and composite material systems will pave the way for designing infrastructure that can endure both time and environment.

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