



Universidade do Minho
Escola de Engenharia

Durability assessment and prediction of fibre
polymer composites using artificial
intelligence

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artificial intelligence**



The European Master in Advanced Structural Analysis and Design using Composite Materials is a join initiative of:



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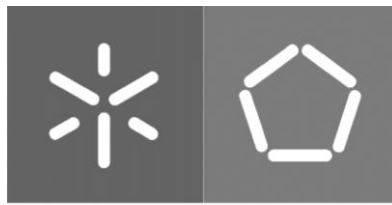


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Universidade do Minho
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Thammaiah Naganda Subbaiah

**Durability assessment and prediction
of fibre polymer composites using
artificial intelligence**



FRP++

Advanced structural analysis and
design using composite materials

Master Dissertation

European Master Advanced Structural Analysis
and Design using Composite Materials

Work developed under the supervision of
Professor Doctor José Sena Cruz
Doctor Amirhossein Mohammadi



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DECLARATION

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I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration.

I further declare that I have fully acknowledged the Code of Ethical Conduct of the University of Minho.

University of Minho, 01/09/2025

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RESUMO

Os compósitos de polímeros reforçados com fibras têm recebido crescente atenção como alternativas viáveis aos materiais de construção tradicionais, principalmente devido à sua superior relação resistência-peso, resistência à corrosão e durabilidade a longo prazo. Espera-se que sua utilização em aplicações estruturais continue a crescer, especialmente com a recente publicação da CEN/TS 19101:2022, uma especificação técnica europeia para o projeto de estruturas compósitas. Apesar das vantagens, a previsão do desempenho a longo prazo destes compósitos permanece um desafio significativo, particularmente devido à sua degradação sob condições ambientais. Para abordar esta questão, o presente estudo utiliza inteligência artificial (IA) para desenvolver modelos preditivos baseados em dados experimentais.

O objetivo principal deste estudo foi avaliar e prever o desempenho a longo prazo de compósitos de polímeros reforçados com fibras em aplicações estruturais, através de uma abordagem orientada por dados que abrange a recolha e análise sistemática de dados de durabilidade. Influências ambientais chave, como humidade, ciclos térmicos e exposição química, foram incorporadas no processo de modelação.

A metodologia de investigação inclui a análise exploratória de dados para identificar fatores críticos que influenciam a degradação, seguida da refinação dos parâmetros do modelo analítico através de análise inversa. Modelos preditivos baseados em IA foram desenvolvidos para estimar o desempenho a longo prazo dos compósitos sob diversas condições ambientais. Os resultados esperados incluem a criação de um conjunto de dados abrangente e a formulação de modelos robustos capazes de prever a retenção de resistência do material, orientando a seleção de compósitos e contribuindo para a normalização de materiais compósitos na engenharia estrutural, informando estratégias de projeto e manutenção para uma infraestrutura sustentável.

PALAVRAS-CHAVE: Compósitos poliméricos reforçados com fibras; Avaliação de durabilidade; Aprendizagem automática; Modelação preditiva.

ABSTRACT

Fiber polymer composites have gained increasing attention as viable alternatives to traditional construction materials, primarily because of their superior strength-to-weight ratio, resistance to corrosion, and long-term durability. Their use in structural applications is expected to grow further, especially with the recent publication of CEN/TS 19101:2022, a European technical specification for designing composite structures. Despite the advantages, predicting the long-term performance of these composites remains a significant challenge, particularly because of their degradation under environmental. To address this issue, the present study leverages artificial intelligence (AI), to develop predictive models based on experimental data.

The main objective of this study was to evaluate and predict the long-term performance of fibre polymer composites in structural applications. This involves a data-driven approach encompassing the systematic collection and analysis of durability data and the implementation of AI models to forecast the long-term behaviour of fibre polymer composites. Key environmental influences, such as humidity, thermal cycling, and chemical exposure, were incorporated into the modelling process.

The research methodology includes exploratory data analysis (EDA) to identify critical factors influencing degradation, followed by refinement of analytical model parameters through inverse analysis. AI-based predictive models were then developed to estimate the long-term performance of composites under various environmental conditions. The anticipated outcomes include the creation of a comprehensive dataset and the formulation of robust models capable of predicting material strength retention. These insights aim to guide the selection of composites and contribute to the standardization of composite materials in structural engineering, ultimately informing the design and maintenance strategies for sustainable infrastructure.

KEYWORDS: Fiber polymer composites, Durability assessment, Machine learning (ML), Predictive modelling.

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LIST OF ABBREVIATIONS AND SYMBOLS

ABBREVIATIONS

AI	Artificial Intelligence
EDA	Exploratory Data Analysis
ML	Machine Learning
FRP	Fibre Reinforced Polymers
TSR	Tensile Strength Retention
GFRP	Glass Fibre-Reinforced Polymers
CFRP	Carbon Fibre-Reinforced Polymers
ILSS	Interlaminar Shear Strength
T _g	Glass Transition Temperature
ANNs	Artificial Neural Networks
TVAE	Tabular Variational Autoencoder
RF	Random Forest
GB	Gradient Boosting
MAE	Mean Absolute Error
MSE	Mean Squared Error
RMSE	Root Mean Squared Error
R ²	R-squared

Symbols

A	Degradation rate constant
B	Material constant
c_0, c_1, c_2	Fitted Coefficients (in the Polynomial Degradation Model)
E_a	Activation Energy Associated with the Degradation Mechanism
k	Rate of Deterioration

A	Degradation rate constant
B	Material constant
k_{moist}	Moisture adjusted degradation rate constant
$P(t)$	Performance Attribute at Time t
η_c	Nominal Conversion Factor
η_{ct}	Conversion Factor for Temperature Effects
η_{cm}	Conversion Factor for Moisture Effects
P_o	Initial Performance
R	Universal Gas Constant
R^2	R-squared, Coefficient of Determination
T	Absolute Temperature in Kelvin
t	Time
x_{fit}	Thickness (in the Polynomial Degradation Model)
X	Input Variable for Linear Corrections
y	Predicted Value

INTRODUCTION

1.1. Background and Context

Fibre-reinforced polymer (FRP), comprising reinforcing fibres such as glass, carbon or basalt embedded in a polymer matrix has emerged as a cornerstone of modern structural engineering. Their remarkable properties, including high strength-to-weight ratio, corrosion resistance, and potential for long-term durability, position them as compelling alternatives to conventional materials such as steel and concrete [1]. Consequently, FRP is widely used as internal reinforcement in concrete for bridge beams and tunnel linings, in waterfront structures, bridge decks, and electrical substations. They are also used for the strengthening and retrofitting of existing structures, including historical buildings [2]. These possibilities are driving the adoption of FRP in applications ranging from bridge decks and wind turbine blades to marine structures and aerospace components [3]. The recent publication of CEN/TS 19101:2022, a European technical specification for designing all composite structures, underscores their growing acceptance and provides standardized guidelines for their use in critical infrastructure [4]. However, a significant challenge remains in ensuring the long-term durability of FRP under environmental effects, such as moisture, temperature fluctuations, ultraviolet (UV) radiation, and chemical exposure. These effects trigger complex degradation mechanisms such as matrix cracking, fibre-matrix debonding, hydrolysis, and photochemical breakdown that threaten the reliability of FRP over the 50–100 years lifespans expected of civil engineering structures [5]. The appeal of FRP lies in their versatility and high performance. However, their relatively recent adoption compared to traditional materials implies that long-term durability data are scarce [1]. Unlike steel or concrete, whose degradation are well known and documented, FRP exhibit significant variability owing to differences in resin types (e.g., unsaturated polyester vs. vinyl ester), fibre architectures, and manufacturing processes [4]. This variability complicates the development of universal predictive models, as degradation mechanisms are influenced by both the material characteristics and environmental conditions [6]. Environmental factors act synergistically, amplifying degradation in ways that are difficult to replicate in the laboratory.

1.2.Motivation

Civil engineering structures, where FRP composites are increasingly applied, are designed for long service lives, often exceeding 50 to 100 years. Unlike traditional materials such as steel and concrete, which have well-documented long-term performance data, FRP composites are relatively new, with limited comprehensive datasets on their behaviour over decades [7]. The durability of these materials is critical to ensure structural safety and reliability, as degradation can lead to reduced mechanical properties, such as tensile strength and stiffness, potentially compromising structural integrity.

The degradation of FRP composites is a complex, nonlinear, and multidimensional phenomenon driven by both external environmental and internal material factors. External environmental effects include exposure to moisture, alkaline solutions, acidic solutions, temperature variations, ultraviolet (UV) radiation, freeze-thaw cycles, and wet-dry cycles [8]. Material-dependent features such as fibre type, matrix type, fibre volume fraction, and manufacturing processes further influence degradation. These factors govern the material's response to environmental effects and its long-term performance. The complexity of FRP degradation is intensified by the synergistic effects of multiple environmental conditions acting concurrently [7].

A significant challenge in studying FRP composites durability is the limited availability of long-term test data. Unlike steel and concrete, which have been studied extensively over centuries, FRP composites lack comprehensive datasets spanning their intended service lives [7]. Accelerated aging tests, commonly used to simulate long-term exposure, may not fully replicate the synergistic effects observed in natural environments, leading to discrepancies between laboratory and field performance [9], [10].

1.3.Problem Statement

The increasing adoption of FRP composites in civil engineering applications necessitates accurate prediction of long-term mechanical properties, such as tensile strength retention (TSR), which is crucial for designers to establish appropriate environmental conversion factors in design codes [9]. The absence of such data often leads to overly conservative designs, increasing costs and reducing the economic competitiveness of FRP composites [10]. Existing predictive models for FRP degradation, such as those utilizing the Arrhenius equation and Fick's law, serve as valuable foundational tools for estimating material behaviour [11], [12].

These methodologies have been fundamental in providing initial insights into degradation rates and have been adapted to FRP composite systems due to their established mathematical rigor [13]. However, their applicability is constrained by certain limitations, which underscore opportunities for enhancement [14].

The effectiveness of traditional methods is largely contingent upon calibration factors derived from experimental tests, necessitating continual refinement as new data emerges [13]. This results in inefficiencies and potential inaccuracies. Moreover, these models often assume a singular degradation pathway, neglecting competing mechanisms or counteracting phenomena such as post-curing, which can enhance performance in the early stages of exposure while competing with deteriorative effects like moisture ingress. Although empirical reduction factors are beneficial, they risk underestimating or overestimating true durability, particularly in complex scenarios. This indicates that, while these traditional methods remain useful, their augmentation through parallel integration with advanced techniques could yield more comprehensive and flexible predictions.

Additional challenges arise in scaling and interpreting degradation phenomena from microscopic to macroscopic levels, as well as in addressing synergistic environmental effects. Although insightful, analytical studies at the molecular level are difficult to extrapolate to structural behaviours due to inherent simplifications and assumptions that may not hold true at other scales, potentially resulting in discrepancies between expected and observed outcomes [13]. There is a notable deficiency in comprehensive predictions of the overall performance of the material, as many studies only forecast one or two mechanical properties. Given that the combined effects differ from the linear summations of individual impacts, accurately modelling synergistic degradation under multiple environmental effects within conventional frameworks is challenging [15].

Collectively, these complex constraints reveal a significant research gap in the field of FRP composites durability, where the development of reliable design practices is impeded by the lack of standardized, long-term data and the limitations of current predictive tools. Innovative solutions that integrate extensive data curation, advanced modelling capable of capturing intricate interactions, and improved interpretability to bridge micro-macro divides are necessary to address this issue [10], [14].

1.4.Objectives

The research carried out in the scope of this MSc Dissertation is structured around a comprehensive set of objectives, each addressing a critical aspect of FRP composites durability prediction. The primary objective involves the compilation of a comprehensive dataset through the collection and curation of robust data from experimental tests documented in the literature. This dataset focuses on FRP composites durability under various environmental factors, including humidity, thermal cycling, UV exposure, and alkaline conditions. To achieve this, sources such as the DURABLE [16] database and other experimental studies on Glass and Carbon FRP composites will be utilized. Following data compilation, exploratory data analysis (EDA) will be conducted to identify key degradation factors through rigorous statistical analysis. This step is essential for uncovering patterns and relationships within the dataset that inform subsequent modelling efforts. Subsequently, Machine learning (ML) models will be developed and validated to predict short-term degradation. These models will undergo training, validation, and testing using the curated datasets to ensure accuracy and reliability. The outputs from the ML models will then be used to calibrate Arrhenius models, facilitating long-term durability forecasts over a 50-year lifespan and bridging the gap between short-term observations and extended service life projections. Finally, the research aims to support performance-based design by providing reliable predictions and recommendations that inform the design and maintenance of FRP structures. This aligns with established standards, such as CEN/TS 19101:2022, and contributes to sustainable infrastructure practices [4].

1.5.Structure of the Dissertation

The structure of this dissertation comprises six chapters. Chapter 1 provides an overview of the background, motivation, and context, delineating the research problem, specifying objectives, and establishing the scope and significance of the investigation. Following this, Chapter 2 provides a comprehensive review of existing literature on FRP, focusing on their durability under environmental exposure and associated degradation mechanisms, while also exploring the application of machine learning and the Arrhenius model in similar research contexts to identify gaps and opportunities for further exploration. The materials and data collection processes are detailed in Chapter 3, which details the FRP composites investigated, the sources of experimental and literature-based data, the environmental exposure conditions considered, and the data collection and preprocessing procedures, providing a comprehensive outline of key

variables and their descriptions. In Chapter 4, the dissertation delves into developing machine-learning models for predicting composite degradation over time, justifying the selection of specific algorithms, describing their training and testing within the experimental timeframe, and detailing how their outputs were integrated into an Arrhenius-based model to predict long-term degradation over a 50-year lifespan. Chapter 5 presents and interprets the key findings, starting with an exploratory data analysis to identify trends and significant variables affecting degradation, followed by the performance and outcomes of the machine-learning models and results from the Arrhenius-based extrapolation, with a discussion that compares these findings with existing literature, evaluates model reliability, addresses limitations, and considers practical implications. Finally, Chapter 6 summarises the primary findings and contributions, reflects on limitations encountered, and proposes directions for future research in AI-based durability modelling of composite materials.

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2. LITERATURE REVIEW

2.1. FRP Composites in Structural Applications

Fiber-reinforced polymer (FRP) composites or simply composites in contemporary standards such as CEN/TS 19101:2022, have become integral to modern civil engineering and infrastructure development. These FRP composites, which consist of a polymeric matrix reinforced with high-strength fibres such as glass or carbon, offer significant advantages over traditional construction materials like steel and concrete. Their lightweight nature, high strength-to-weight ratio, and resistance to corrosion make them particularly suitable for addressing modern infrastructure challenges, including the rehabilitation of aging structures and the construction of resilient new systems.

FRP composites are primarily classified according to the type of reinforcing fibres embedded within a polymeric matrix. The two predominant fibre types utilized in structural applications are glass and carbon, and the corresponding composites made of these fibres are called glass fibre-reinforced polymers (GFRP) and carbon fibre-reinforced polymers (CFRP), respectively. GFRP composites employ glass fibres as reinforcement, which are cost-effective and widely accessible. Industrialized during World War II, glass fibres exhibit high tensile strength and a moderate elastic modulus, rendering them suitable for applications necessitating durability and cost-efficiency [3]. GFRP composites generally possess an elastic modulus lower than that of CFRP but higher than many traditional materials such as concrete. Their ultimate strain is relatively high, often exceeding 2%, which contributes to their capacity to endure significant deformation prior to failure. However, as mentioned, GFRP composites are less stiff than CFRP, with an elastic modulus typically ranging from 20 to 40 GPa, contingent upon the fibre volume fraction and matrix type [17]. The primary limitation of GFRP is its susceptibility to environmental degradation, such as matrix weakening due to water uptake, although advancements in resin formulations have mitigated this issue to some extent. CFRP composites incorporate carbon fibres, renowned for their exceptional stiffness and strength. Developed in the 1960s, carbon fibres offer a high elastic modulus (often exceeding 200 GPa) and low elongation at failure, typically around 1-2% [3]. These properties render CFRP ideal for applications requiring high stiffness and strength, such as in long-span bridge cables or structural strengthening systems. CFRP composites exhibit excellent fatigue resistance in cyclic loading scenarios [3] which represents a substantial improvement over steel, which, despite its

ductility, is susceptible to fatigue and corrosion. Unlike steel, FRP composites are inherently resistant to corrosion, obviating the need for expensive protective coatings and maintenance in aggressive environments, such as those exposed to marine or de-icing salts [17]. CFRP composites as well have low thermal expansion coefficient making them suitable for demanding structural applications. However, the high cost and high carbon emission of carbon fibres has historically limited their widespread adoption, prompting research into hybrid configurations to balance performance and cost [18]. Additionally, the pseudo-ductile behaviour achieved through hybridization mitigates the brittleness of single-fibre composites, providing early warning of failure and enhancing structural safety [19].

The mechanical properties of FRP composites are governed by the rule of mixtures, where the longitudinal elastic modulus and tensile strength depend on the volume fractions and properties of the constituent fibres and matrix. These properties can be tailored through careful fibre selection, volume fraction adjustments, and manufacturing techniques such as pultrusion or braiding, which influence fibre alignment and composite microstructure [20]. FRP composites have found extensive applications in civil engineering, particularly in the reinforcement, strengthening, and construction of infrastructure. Their adoption, though initially slower than in industries like aerospace, has grown significantly since the 1970s, driven by the need for lightweight, durable, and corrosion-resistant materials [7]. Their durability in harsh environments reduces lifecycle costs, making them economically viable for long-term infrastructure projects. The high strength-to-weight ratio of FRP composites compared to steel or concrete, facilitates the design of lighter structures, with comparable or superior load-bearing capacity, and easier handling and installation compared to heavy steel or concrete components. This attribute is particularly advantageous in applications such as bridge cables and pultruded profiles, where reduced weight simplifies construction and diminishes foundation requirements [7].

Techniques such as hand lay-up and pultrusion enable the rapid application of strengthening systems or the construction of structural profiles, thereby reducing construction time and costs [21]. FRP bars, typically embedded within concrete, offer superior corrosion resistance compared to steel, making them ideal for harsh environments such as highway bridge decks [17].

2.2. Durability of Composites

FRP composites, despite being an emerging material, face significant challenges regarding their long-term performance under environmental effects, which remains a critical concern for their widespread adoption in infrastructure projects. The durability of FRP composites is influenced by environmental factors such as moisture, temperature fluctuations, and UV radiation, which initiate physical and chemical degradation processes that can compromise mechanical properties and structural integrity. Understanding these environmental effects is essential for predicting the service life of FRP composite structures and developing mitigation strategies.

Moisture is one of the most pervasive environmental factors affecting FRP composites, particularly in marine environments and regions with high humidity. Water molecules penetrate the polymeric matrix through diffusion, capillary action along fibre-matrix interfaces, or microcracks, leading to matrix plasticization, swelling, and interfacial weakening [17]. GFRP composites are particularly susceptible to moisture-induced degradation due to the hydrophilic nature of glass fibres, which can absorb water and undergo hydrolysis, especially in alkaline environments like concrete pore solutions [22]. Studies have shown that prolonged immersion in water or alkaline solutions at elevated temperatures can reduce the tensile strength of GFRP bars by up to 20-30% over 20-30 months, primarily due to fibre degradation and interfacial debonding [1] [23]. CFRP composites although more resistant to moisture due to the inert nature of carbon fibres, are not fully immune to moisture effects, as water can degrade the epoxy matrix and weaken the fibre-matrix bond, reducing shear strength [7]. Ribeiro et al. [3] notes that moisture ingress is exacerbated in composites with poor manufacturing quality, such as those with voids or incomplete resin curing, which act as pathways for water penetration.

Temperature variations, including cyclic freeze-thaw conditions and elevated temperatures, significantly impact FRP composite durability. High temperatures accelerate chemical reactions within the matrix, such as hydrolysis and oxidation, and can cause thermal expansion mismatches between fibres and the matrix, leading to microcracking [21]. For instance, epoxy-based GFRP composites exposed to temperatures near or above their glass transition temperature (T_g , typically 100-150 °C for structural epoxies) experience a sharp decline in stiffness and strength due to matrix softening [17]. Conversely, subzero temperatures in freeze-thaw cycles can induce matrix embrittlement and microcracking, particularly in moisture-saturated composites, as water expansion during freezing generates internal stresses [3]. A study by Wu et al. [24] demonstrated that GFRP bars subjected to 300 freeze-thaw cycles (-20 °C to 20 °C) in a saline solution exhibited a 15% reduction in tensile strength, attributed to

matrix cracking and fibre-matrix debonding. CFRP composites, while more thermally stable due to higher thermal conductivity of carbon fibres, can still suffer from matrix degradation at elevated temperatures, compromising long-term performance at elevated temperatures [7].

UV radiation, commonly encountered in outdoor applications such as bridge decks and external strengthening systems, predominantly impacts the polymeric matrix of FRP composites. UV exposure induces photodegradation, resulting in the cleavage of molecular chains within the resin, which subsequently leads to surface discoloration, chalking, and microcracking [22]. These surface alterations expose the underlying fibres to further environmental degradation, thereby accelerating the deterioration process. In the case of GFRP composites, UV-induced matrix erosion diminishes the protective layer over glass fibres, heightening their vulnerability to moisture and chemical attack [17]. CFRP composites are less susceptible to UV radiation owing to the opacity of carbon fibres, which shield the matrix; however, prolonged exposure can still result in matrix embrittlement [3].

The synergistic effect of UV radiation, moisture, and temperature fluctuations, as frequently encountered in real-world conditions, exacerbates degradation, necessitating the use of protective coatings or UV-resistant resins in structural applications. In practice, FRP composites are rarely exposed to a single stressor but rather to a combination of moisture, temperature, and UV radiation, which interact synergistically to accelerate degradation. For instance, UV-induced surface microcracks facilitate moisture ingress, which, in turn, exacerbates hydrolysis and interfacial debonding under thermal cycling [7]. Ribeiro et al. [3] emphasize that accelerated aging tests incorporating wet-dry cycles, UV exposure, and temperature fluctuations result in more pronounced mechanical property losses than single-stressor tests, with GFRP composites exhibiting up to a 40% reduction in tensile strength after 6,000 hours of combined exposure. These synergistic effects underscore the necessity of realistic environmental testing protocols to accurately predict FRP durability in civil infrastructure. The environmental conditions delineated above initiate a range of chemical and physical degradation processes in FRP composites, affecting the matrix, fibres, and fibre-matrix interface. These processes alter the composite's microstructure and compromise its structural performance, necessitating a comprehensive understanding of their mechanisms. The polymeric matrix, typically epoxy or vinyl ester in structural FRP composites, is susceptible to chemical degradation through hydrolysis, oxidation, and chain scission. Hydrolysis occurs when water molecules react with ester or amide bonds in the resin, cleaving them and reducing molecular weight, which leads to matrix plasticization and loss of stiffness [17]. This process is accelerated in alkaline environments, such as concrete-encased GFRP bars, where high pH

levels (12-13) catalyse bond cleavage [23]. Oxidation, often induced by elevated temperatures or UV radiation, involves the reaction of polymer chains with oxygen, forming carbonyl groups and causing embrittlement [22]. UV-induced photodegradation further exacerbates matrix degradation by breaking carbon-carbon bonds, resulting in chain scission and surface erosion [21]. Ribeiro et al. [3] notes that vinyl ester matrices, while more resistant to hydrolysis than epoxies, remain vulnerable to UV-induced chain scission, leading to surface cracking after prolonged exposure. Delamination, the separation of composite layers, is particularly detrimental in laminated FRP structures like externally bonded strengthening systems, as it reduces load-carrying capacity and stiffness [3]. Physical degradation is often coupled with chemical processes, as cracks provide pathways for moisture and chemical ingress, creating a feedback loop that accelerates deterioration. The chemical and physical degradation processes described above have profound effects on the mechanical properties of FRP composites, including tensile strength, stiffness, shear strength, and fatigue resistance, ultimately influencing their long-term performance in structural applications. These impacts are critical for ensuring the safety and reliability of FRP-based infrastructure over their intended service life.

Sustained loading frequently accelerates the degradation rate of FRP composites, particularly when combined with adverse environmental conditions. This synergistic effect is notably pronounced in scenarios involving moisture and temperature cycles, where sustained loading can amplify cyclic thermal stresses at the fibre/matrix interface. This amplification promotes the formation of micro-cracks within the matrix and increases the rate of water ingress into the resin matrix. Empirical studies have demonstrated that GFRP sheets subjected to sustained loading during temperature cycles experience an approximate 20% reduction in tensile strength, while carbon fibre-reinforced polymer CFRP exhibits about a 10% reduction under similar conditions [25]. Prolonged exposure to elevated temperatures below the glass transition temperature of the resin can sometimes enhance mechanical properties due to post-curing effects; however, design practices conservatively exclude these positive effects from temperature conversion factors [4]. Conversely, very high sustained strain levels, such as 45% of the ultimate load, at elevated temperatures ranging from 40 °C to 60 °C, can precipitate premature failure in GFRP, resulting in tensile strength reductions exceeding 60%. These failures are attributed to mechanisms including hydrolysis, interfacial debonding, and delamination [26].

Research findings on the synergistic effects of mechanical loading and environmental exposure in FRP composites remain inconsistent. Some studies suggest that load levels representative of

typical civil engineering service conditions, generally limited to 20% to 30% of GFRP's short-term strength, do not significantly exacerbate the detrimental effects of environmental aging. However, when load levels substantially exceed these service limits, such as reaching 45% to 60% of the ultimate strength, the degradation of mechanical properties may be intensified by approximately 20 to 25% [5].

2.3.CEN/TS 19101:2022: Overview and how durability is addressed

The European standard CEN/TS 19101:2022 [9] offers guidelines for addressing the durability of composite structures, with a particular focus on environmental reduction factors and protective measures to mitigate degradation. According to CEN/TS 19101:2022 [9], environmental reduction factors are essential in accounting for the effects of moisture and temperature during the design phase of composite structures. Paragraph 6.2(4) of the standard specifies that for designated composite materials and environmental conditions, a set of conversion factor (η_c), as outlined in subclause 4.4.7 (Eq. 2.1), should be applied to adjust material properties for the effects of moisture and temperature [9].

$$\eta_c = \eta_{ct} \cdot \eta_{cm} \quad (2.1)$$

Where, η_{ct} is the conversion factor for temperature effects and η_{cm} is the conversion factor for moisture effects. These conversion factors were derived to reflect the degradation in stiffness and strength due to moisture absorption, which can induce mechanisms such as plasticization, hydrolysis, saponification, and swelling. The standard notes that these degradation processes are generally slow and depend on factors such as the type of polymer resin, fibre content, and the degree of resin cure (Paragraph 6.1(3)). For cases where the environmental conditions or composite materials are not covered by Subclause 4.4.7, the standard mandates testing under conditions representative of actual exposure to determine appropriate material properties [9]. This approach ensures that the design accounts for realistic degradation scenarios, particularly in moist environments. The permeability of composite materials to moisture is a significant factor influencing their durability. The standard recommends reducing moisture ingress by incorporating a resin-rich layer or surface veil, particularly in pultruded profiles, and enhancing the degree of resin cure through post-curing (Paragraph 6.3.2(2)) [9]. These measures help to isolate and protect the reinforcing fibres, thereby mitigating degradation at the fibre-matrix interphase. For composite structures permanently submerged in water, CEN/TS 19101:2022 advocates the use of protective systems such as barrier coats, gel coats, or other surface coatings to prevent direct contact with moisture (Paragraph 6.3.2(3)) [9]. Additionally, in marine or

moist environments, the application of anti-fouling coatings is recommended to minimize surface degradation caused by algae or fungal growth, which can compromise protective coatings over time (Paragraph 6.3.2(4)) [9]. The standard emphasizes that the durability of these protective systems must also be evaluated, as their effectiveness can diminish without regular maintenance (Paragraph 6.2(7)) [9]. The durability of composite structures in moist environments is governed primarily by the properties of the polymer resin and its interaction with reinforcing fibres. CEN/TS 19101:2022 highlights that the resistance to moisture is largely dependent on the type of resin used, with epoxy resins generally exhibiting superior durability compared to isophthalic and ortho phthalic polyesters (Paragraph 6.3.2(4)) [9]. Epoxy resins provide better protection to embedded fibres, reducing the rate of moisture-induced degradation. The standard also underscores the importance of the degree of resin cure, noting that post-curing can enhance durability by increasing the resin's resistance to moisture absorption (Paragraph 6.1, Note 1) [9]. Furthermore, the quality of the fibre-matrix bond, as measured by interlaminar shear strength (ILSS) per EN ISO 14130, is a critical indicator of a composite's ability to withstand moisture-related degradation (Paragraph 6.1(3), Note 3) [9]. In composite sandwich panels, the absorption of moisture can result in debonding between the core material and the composite face sheets, a concern specifically addressed in Paragraph 6.3.2(6) [9]. To mitigate this issue, the standard recommends the careful selection of materials to reduce the permeability of the face sheets and the implementation of construction detailing, such as sealing open edges and holes, to prevent moisture diffusion into the core. Regular surface cleaning and the application of protective coatings are also advised to minimize degradation in marine or moist environments (Paragraph 6.3.2, Notes 1 and 2) [9]. These measures collectively aim to preserve the structural integrity of composite sandwich panels throughout their design service life.

Beyond moisture, CEN/TS 19101:2022 addresses the durability of composite structures under thermal effects, chemical exposure, and UV radiation, acknowledging that these factors can act independently or in combination to exacerbate degradation. Thermal effects, as outlined in Subclause 6.3.1, include service temperature conditions, thermal cycles, and freeze-thaw cycles. Exposure to temperatures approaching or exceeding the glass transition temperature (T_g) of the polymer resin can significantly reduce stiffness and strength, primarily due to matrix softening (Paragraph 6.3.1, Note 2) [9]. The standard notes that fibre-dominated properties are less affected than matrix-dominated properties, with carbon and basalt fibres exhibiting superior performance at elevated temperatures compared to glass and aramid fibres (Paragraph 6.3.1, Note 4). For composite sandwich panels, thermal effects can induce curvature, internal

stresses, or interfacial damage due to differences in thermal expansion coefficients between the core and face sheets (Paragraph 6.3.1(3)) [9].

The interaction of multiple environmental factors can significantly amplify degradation, as noted in Subclause 6.4 of CEN/TS 19101:2022. Outdoor weathering involving moisture, thermal effects, and UV radiation can exacerbate degradation by promoting moisture ingress through UV-induced surface crazing and cracking (Paragraph 6.4, Note 2). The standard mandates testing under representative conditions to determine material properties for design when combined environmental effects are not covered by standard conversion factors (Paragraph 6.4(2)). This ensures that the design accounts for the worst-case scenarios, thereby enhancing the reliability of composite structures in complex environmental conditions.

2.4.Applications of Machine Learning

Machine Learning (ML) has emerged as a transformative tool in materials science, offering robust methodologies for predicting material properties and performance under various conditions. Among the most relevant ML techniques for materials prediction are (i) Decision Trees, (ii) Support Vector Machines (SVM), and (iii) ensemble methods such as Gradient boosting. Decision Trees and their advanced variants provide interpretable frameworks for regression tasks, offering equations that relate input parameters to mechanical properties, as demonstrated in studies predicting FRP-to-concrete bond strength [27]. Algorithms such as SVMs excel in high-dimensional spaces and are robust to overfitting, making them suitable for smaller data sets. Ensemble methods, which combine multiple models, enhance prediction accuracy by reducing variance in classifying FRP-to-concrete failure modes [28]. The selection of a machine learning technique depends on the size, quality, and nature of the dataset, as well as the specific prediction task. It also involves comparing the predictive performance of various algorithms. Challenges such as overfitting, poor data quality, and the need for comprehensive training datasets are critical considerations that necessitate careful algorithm selection and validation [28]. Recent advancements in deep learning and hybrid models (e.g. Deep Belief Network & Gene Expression Programming) have further expanded the potential of ML, enabling more accurate predictions of complex material behaviours under diverse environmental conditions. The application of ML in composite material research, particularly for FRPs, has revolutionized the prediction of mechanical properties and durability [20].

One significant application involves predicting the tensile strength retention of FRP composites subjected to adverse environmental conditions. Machello et al. employed Artificial Neural

Networks (ANNs), Decision Trees, and SVMs to forecast residual mechanical properties with high precision, surpassing the performance of linear models [28]. Machello et al. [29] also present a comprehensive investigation into the application of tree-based machine learning models for predicting the tensile strength retention of FRP composites subjected to elevated temperatures. The research underscores the susceptibility of FRP composites to thermal degradation, particularly when temperatures approach or exceed the resin's glass transition temperature, resulting in notable reductions in mechanical properties, including tensile strength and stiffness. The study utilizes three tree-based machine learning models, decision trees, M5P, and random forests which are optimized through Bayesian optimization and 10-fold cross-validation to improve predictive accuracy and robustness. Feature importance analysis identifies exposure temperature and T_g as the most critical factors affecting TSR, followed by other parameters such as sample thickness and exposure duration.

Baghaei et al. [27] developed an M5P decision tree model to estimate the bond strength of FRP-to-concrete joints under wet conditions, utilizing a database of 429 durability tests. This model yielded a physics-based equation that integrates mechanical, geometrical, and environmental parameters, demonstrating superior performance compared to traditional empirical models [28]. ML has also been applied to less-explored areas, such as the bond strength between FRP laminates and timber, to address sustainability challenges in construction. Although limited, studies such as those by Jia et al. [30] have employed ML to analyse the fatigue behaviour of timber-FRP composites, underscoring the potential for further research. Additionally, ML techniques have been explored for predicting the durability of GFRP rebars in alkaline conditions, using non-linear genetic algorithms to model complex degradation mechanisms [31]. These applications highlight the versatility of ML in managing diverse composite systems and environmental conditions, paving the way for more reliable structural design.

Despite its advancements, ML-based durability prediction for composite materials encounters several challenges. A primary limitation is the quality and comprehensiveness of available datasets. The accuracy of machine learning models heavily relies on the training data, which, in the case of FRP composites, are often limited, scattered, or inconsistent owing to variations in testing protocols, material compositions, and environmental conditions [28]. Enhancing datasets for durability of FRP composites through additional experimental studies and accessible databases is crucial for improving prediction reliability. Mohammadi et al. [32] addressed the limitations of a constrained experimental dataset by incorporating synthetic data generation. The original dataset in their study suffered from data scarcity and gaps, which hindered the predictive performance of machine learning models. To overcome this, the authors

employed a Tabular Variational Autoencoder (TVAE), a generative artificial intelligence technique, to create a synthetic dataset of 20,000 specimens. The TVAЕ model, consisting of probabilistic encoder and decoder neural networks with three hidden layers each, was designed to learn the joint probability distribution of the dataset's continuous and categorical variables, capturing complex, non-Gaussian distributions and imbalanced categorical features. The synthetic dataset's ability to provide a larger and more diverse set of samples enabled the model to better capture the complex nonlinear relationships governing shear resistance, particularly for underrepresented configurations, thus improving generalization and predictive accuracy [32].

Another challenge is the extrapolation of short-term accelerated aging data to long-term service-life predictions. Comparative studies between traditional algorithms and ML-based models are necessary to validate extrapolation ranges and ensure realistic outcomes. Additionally, selecting appropriate ML algorithms is challenging, particularly for structural engineers with limited ML expertise. Sensitivity analyses revealed that different algorithms assigned varying weights to the input variables, complicating the model selection. Comprehensive comparisons of algorithm performance, considering both statistical metrics and aging protocols, are essential for guiding researchers [31].

Insufficient training data further complicate ML applications, potentially leading to overfitted models that perform well on training data but poorly on the unseen datasets. Incorporating background knowledge of FRP degradation mechanisms can mitigate these issues by informed data selection and algorithm tuning and reducing the risk of overfitting [29]. The cautious adoption of ML by structural engineers, driven by concerns regarding structural safety, highlights the need for rigorous validation and transparency in model development.

The opportunities for ML in durability prediction are vast. Expanding research to include understudied mechanical properties, such as interlaminar shear strength, and environmental conditions, such as UV radiation and fire, can broaden the applicability of ML models [28]. Leveraging existing databases and developing models using ML algorithms offers promising avenues for enhancing predictive accuracy. Furthermore, combining ML with physical models, such as those based on degradation kinetics, could combine the strengths of data-driven and mechanistic approaches and improve interpretability and robustness [10]. The growing availability of computational resources and open-access data repositories presents an opportunity to overcome data limitations, foster collaborative research, and advance ML applications in composite materials.

2.5. Arrhenius Model for Long-Term Extrapolation

The Arrhenius model, grounded in chemical kinetics, has become a prevalent method for extrapolating short-term experimental data to forecast long-term material property retention in FRP composites. This model is predicated on the Arrhenius equation, which delineates the temperature dependence of reaction rates. In the realm of material degradation, it is employed to model the rate of deterioration of material properties as a function of temperature. The model presupposes that the degradation process adheres to a first-order kinetic reaction, expressed as:

$$k = A \times \exp \left[\frac{-E_a}{RT} \right] \quad (2.2)$$

where (k) represents the rate of deterioration, (A) is a pre-exponential factor, (E_a) denotes the activation energy associated with the degradation mechanism, (R) is the universal gas constant, and (T) is the absolute temperature in Kelvin [33]. This equation enables researchers to estimate the rate of property loss under specific environmental conditions by accelerating degradation through elevated temperatures and extrapolating results to lower, service-relevant temperatures. In the study by Karbhari et al. [33], the Arrhenius model was utilized to predict the long-term deterioration of tensile, flexural, short-beam-shear, and in-plane shear strengths of carbon/epoxy composites subjected to water immersion at 23°C. The model employs data from accelerated tests at higher temperatures to derive deterioration rates, if the degradation mechanisms remain consistent across temperature ranges. This assumption is essential, as it underpins the validity of long-term extrapolations but is often contested by changes in degradation mechanisms at different temperatures [34]. Karbhari et al. [33] employed this approach to predict the service life of carbon/epoxy laminates with varying thicknesses over a 100-year period. Their methodology involved measuring property retention after immersion in deionized water at different temperatures, and using these data to derive Arrhenius-based predictive equations of the form:

$$P(t) = \frac{P_0}{100} [A \ln(t) + B] \text{ for } t > 0 \quad (2.3)$$

Where, $P(t)$ is the performance attribute at time t ; P_0 is the initial performance, A is a degradation rate constant, and B is a material constant reflecting initial post-cure effects. The study found that tensile strength and modulus exhibited excellent durability for thinner laminates (2 layers), with design values not reached within 100 years, while thicker laminates

(6 and 12 layers) demonstrated faster deterioration due to increased interlaminar and intralaminar degradation [33].

Similar applications of the Arrhenius model have been documented in other studies. Litherland et al. [35] and Proctor et al. [34] utilized the model to forecast the service life of glass fibre-reinforced composites, employing time-temperature superposition to extrapolate short-term data. Chin et al. [36] applied the model to E-glass/vinyl ester systems, demonstrating its efficacy in predicting strength retention under aqueous exposure. These studies underscore the model's versatility across various composite systems while highlighting the necessity for careful consideration of material-specific degradation mechanisms. The Arrhenius model's predictions are frequently employed in conjunction with safety factors to determine design allowable, as prescribed by guidelines such as CEN/TS 19101:2022 [9]. These guidelines apply environmental reduction factors to account for degradation. However, Karbhari et al. [33] noted that these factors are time-invariant and do not account for changes in material variability over time, potentially leading to a false sense of reliability. For instance, their study demonstrated that while the tensile strength of 2-layer specimens remained above the design allowable for over 100 years, 6-layer specimens reached these thresholds much earlier owing to increased interlaminar degradation.

The equivalent temperature approach proposed by Karbhari et al. [33] is a step toward accounting for time-varying conditions; however, its practical implementation requires extensive field data. Other studies have explored ML techniques to predict long-term behaviour by identifying patterns in experimental data, potentially overcoming the Arrhenius model's reliance on simplistic assumptions [37].

2.6. Conclusions

This chapter provides a comprehensive literature review on FRP composites, specifically GFRP and CFRP, in structural applications within civil engineering. It outlines their superior properties, including high strength-to-weight ratios, corrosion resistance, and suitability for infrastructure rehabilitation and new construction, compared to traditional materials like steel and concrete. The review details the mechanical properties of FRP composites, governed by the rule of mixtures, and their susceptibility to environmental degradation from moisture, temperature fluctuations, UV radiation, and synergistic effects, which lead to matrix plasticization, fibre degradation, interfacial debonding, and reduced mechanical performance. The CEN/TS 19101:2022 standard is discussed, providing guidelines on environmental

reduction factors, protective measures, and testing to ensure durability. The chapter also explores ML applications, such as decision trees, support vector machines, and ensemble methods, for predicting FRP mechanical properties and durability, alongside the Arrhenius model for extrapolating short-term degradation data to long-term performance.

Several knowledge gaps are identified that justify further research. Firstly, ML-based durability predictions are constrained by limited, scattered, or inconsistent datasets due to variations in testing protocols, material compositions, and environmental conditions, often necessitating synthetic data generation. Secondly, extrapolating short-term accelerated aging data to long-term service life remains challenging due to potential changes in degradation mechanisms across temperature ranges. Thirdly, understudied areas, such as interlaminar shear strength, UV radiation and fire effects, require further exploration to broaden ML applicability. Finally, the reliance on time-invariant environmental reduction factors in standards like CEN/TS 19101:2022 overlooks evolving material variability, highlighting the need for dynamic, data-driven predictive models to enhance the reliability of FRP composite applications in structural engineering.

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3. DATA COLLECTION

The establishment of a comprehensive database is an essential step in utilizing ML techniques to forecast the long-term performance of FRP composites under various aging conditions. The creation of the durability database involved a systematic literature review of experimental studies on FRP composites, with data extracted from peer-reviewed journals. Each study was selected for its detailed reporting of experimental conditions, material properties, and mechanical test results, ensuring data reliability. Data collection focused on extracting quantitative metrics such as tensile modulus, tensile strength, flexural modulus, compressive strength, and interlaminar shear strength, alongside ageing conditions and material characteristics. The dataset containing 969 records of data, was parsed to create a structured dataset. Each record corresponds to a unique combination of composite material, ageing protocol, and test condition, with columns representing variables like fibre type, matrix type, ageing duration, and mechanical properties.

3.1. Structured Dataset Collected from Literature

The database constitutes a rigorously organized repository engineered to underpin the systematic evaluation of FRP composites' durability across a spectrum of environmental and ageing regimes. The database is systematically divided into primary sections as shown in Figure 3.1, each defined by specific parametric fields:

General Metadata: This section includes fields such as Title, DOI, and short name, providing essential identifiers for traceability and bibliographic referencing.

Composite Material Specifications: This segment comprises descriptors such as Composite Name, Composite Type, Fibre Type, Matrix Type, Fibre Layup, Production Method, Thickness, Fibre Content Type, and Fiber Content. These parameters collectively elucidate the main characteristics and fabrication of the composites analysed, as well as the materials' long-term performance.

Ageing Protocols: Subdivided into categories such as Hygrothermal Ageing Protocol, Freeze-Thaw Cycle Ageing Protocol, etc.; these fields specify the environmental conditions applied to the materials.

Mechanical Performance Metrics: Encompassing test categories such as Tensile Test or Flexural Test; this section records the mechanical properties including modulus and strength,

both pre- and post-ageing, along with retention metrics, thereby providing quantifiable indices of durability.

The database exhibits a hierarchical progression from overarching descriptors to specific test outcomes, fostering a relational comprehension of the interplay between material constitution, ageing conditions, and resultant mechanical behaviour.

General Metadata	Composite Material Specifications	Ageing Protocols	Mechanical Performance Metrics
Title	Composite Name	Hygrothermal Ageing	Tensile Test
DOI	Composite Type	Freeze-Thaw Cycle Ageing	Flexural Test
Short-name	Fibre Type		Modulus Pre/Post Ageing
	Matrix Type		Strength Pre/Post Ageing
	Fibre Layup		Retention Metrics
	Production Method		
	Thickness		
	Fibre Content Type		
	Fiber Content		

Figure 3.1. Structure of dataset

3.2. Aging Protocol

As explained in Chapter 2, the durability of FRP composites is significantly affected by environmental exposure conditions, which the database categorizes into several ageing protocols: hygrothermal ageing, constant temperature ageing, chemical ageing, natural weathering, and freeze-thaw cycles. Each protocol simulates specific environmental condition to evaluate material degradation over time.

Hygrothermal ageing, as explored in [1], [11], [38], [39], [40], [41], [42], [43], [44], [45], involves immersion in demineralized water or tap water at controlled temperatures and relative humidity (up to 100%) for long durations. This protocol assesses moisture absorption and its impact on mechanical properties, such as tensile and flexural strength. Constant temperature ageing, as explored by [41], [42], [46], [47] subjects composites to elevated temperatures for short durations. This protocol is critical for understanding thermal degradation, particularly in fire-resistant applications.

Chemical ageing, documented in [1], [11], [43], [44], involves immersion in solutions like sodium chloride (NaCl) to simulate corrosive environments. Natural weathering, as in [38],

[41], [48] exposes composites to real-world climatic conditions at various geographic locations, at varying temperatures and relative humidity. This protocol captures the combined effects of UV radiation, temperature fluctuations, and precipitation over long durations.

Freeze-thaw cycles [2], [8], [49], [50], [51], [52], [53], [54], [55], [56], [57] simulate alternating temperature extremes, critical for composites in cold climates.

These diverse exposure conditions ensure the database captures a broad spectrum of degradation mechanisms, enabling robust machine learning model development

3.3.Data Preprocessing

Preprocessing was a critical step to ensure data quality for machine learning applications. The dataset was cleaned to address missing values, inconsistencies, and formatting errors. Some studies reported fibre content as “not specified” which was flagged for imputation or exclusion based on the variable’s importance. Missing values in mechanical properties, such as tensile modulus in Khalifa [58], were handled using mean imputation or excluded if deemed non-representative. Standardization was applied to units to ensure consistency. Categorical variables, such as fibre type and ageing protocol, were encoded using one-hot encoding to facilitate model training.

3.4.Description of Key Variables

The database includes a comprehensive set of variables critical for understanding composite durability and developing predictive models. These variables are grouped into material characteristics, ageing conditions, and mechanical properties, each described below.

3.4.1. *Material Characteristics*

3.4.1.1. Fibre Type

Figure 3.2 presents a pie chart illustrating the distribution of reinforcing fibre types, which include carbon, glass, and basalt fibres. Glass fibres predominate, constituting 81.8% of the samples. This dominance is likely attributable to the cost-effectiveness and satisfactory mechanical properties of glass fibres. Carbon fibres, comprising 12.3% of the samples, are employed in contexts necessitating exceptional strength-to-weight ratios, despite their higher cost. While Basalt accounted for 4.4%, hybrid alternatives, accounting for a mere 0.9% suggest

a minor yet specialized role, potentially in applications that benefit from the combined properties of different fibres.

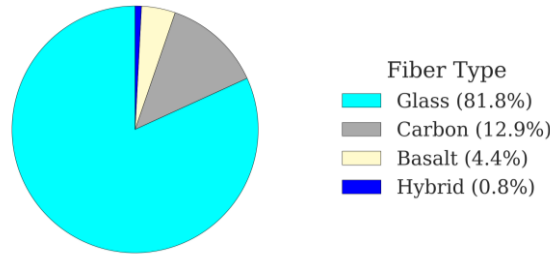


Figure 3.2. Distribution of fibre type from the database

3.4.1.2. Matrix Type

Figure 3.3 illustrates the distribution of matrix types within the FRP dataset, with vinyl ester emerging as the most prevalent matrix material at 55.6%. Isophthalic polyester follows at 15.5%, likely chosen for its balance of cost and performance in less demanding conditions. Epoxy, representing 22.8%, is notable for its excellent adhesion and chemical resistance, making it a preferred choice for high-performance applications. In contrast, Orthophthalic polyester accounts for only 1.2%, indicating its limited adoption, possibly due to inferior durability compared to other alternatives.

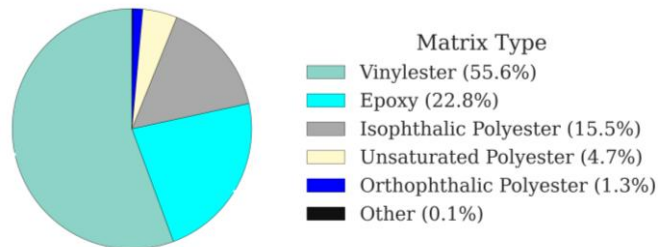


Figure 3.3. Distribution of matrix type from the database

3.4.1.3. Fiber Thickness (mm)

Figure 3. illustrates the distribution of thickness ranges within the dataset, expressed both as counts and percentages, which is critical for understanding material characteristics in the context of this academic thesis. The data is segmented into six categories: NA (4 items, 0.4%), 0-1 mm (95 items, 9.8%), 1-2 mm (326 items, 33.7%), 2-3 mm (230 items, 23.8%), 3-5 mm (187 items, 19.3%), 5-10 mm (111 items, 11.5%), and 10-20 mm (14 items, 1.4%). The largest proportion of the dataset falls within the 1-2 mm range, accounting for 33.7% of the total, indicating a predominance of thinner materials. Conversely, the 10-20 mm range represents the

smallest segment at 1.4%, suggesting that thicker materials are less common. The NA category, with only 0.4%, indicates minimal missing or unclassified data, ensuring the reliability of the overall distribution. This analysis underscores the variability in thickness and provides a foundation for further statistical evaluation in the study.

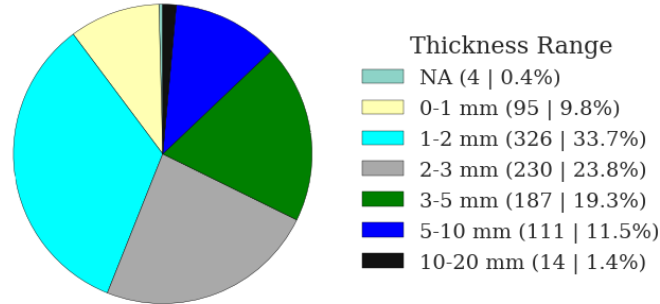


Figure 3.4. Distribution of thickness of FRP from the database

3.4.1.4. Fibre Content (%)

The fibre content in the FRP dataset ranges from 0.0% to 100.0%, with a notable concentration between 60.0% and 70.0%. The most frequent fibre content range is 60.0% to 70.0%, exhibiting the highest count, followed by the 50.0% to 60.0% range and the 0.0% to 10.0% range, each with significant but lower counts. This distribution, as illustrated in the histogram in Figure 3.4, suggests a focus on moderate to high fibre volume fractions, which is consistent with efforts to enhance mechanical properties such as stiffness and strength, crucial for structural performance. Lower fibre content ranges, such as 0.0% to 10.0%, may indicate an emphasis on matrix-dominated properties, while the sparse representation of higher ranges, like 90.0% to 100.0%, highlights a lesser focus on extreme fibre reinforcement.

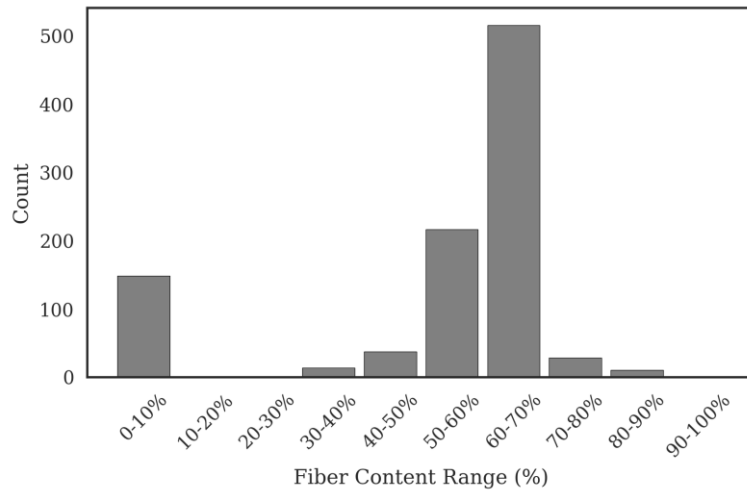


Figure 3.5. Distribution of fibre content percentage from the collected database

3.4.1.5. Production Method

According to the pie chart in Figure 3.6, pultrusion is the predominant production method, representing 55.2% of the samples. This method's widespread use can be attributed to its ability to efficiently produce continuous, high-strength profiles, which is advantageous for structural components. Resin infusion moulding, at 31.4%, ranks as the second most common technique, valued for its capacity to achieve uniform resin distribution in complex geometries. Less frequently used methods include wet hand lay-up (8.5%) and filament winding/resin transfer moulding (0.9%).

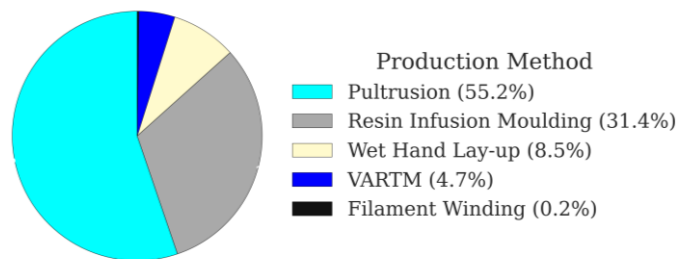


Figure 3.6. Distribution of production method involves in the samples studied

3.4.2. Ageing Conditions

3.4.2.1. Ageing Protocols

The distribution of ageing protocols, as depicted in Figure 3.7, reveals a diverse array of testing methodologies employed to simulate environmental conditions. Hydrothermal ageing represents the largest proportion at 38.3%, indicating a significant emphasis on evaluating the combined effects of moisture and temperature. This is followed by freeze-thaw cycles at 19.9%,

constant temperature ageing at 18.3%, chemical ageing at 19.9%, and natural weathering at 3.6%. The predominance of hydrothermal ageing underscores its perceived importance in replicating real-world conditions, whereas the minimal representation of natural weathering may suggest a preference for controlled laboratory conditions or a limitation in long-term exposure data [38].

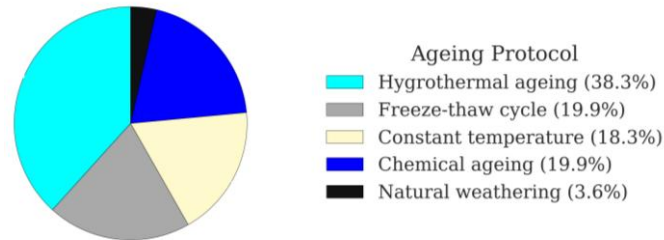


Figure 3.7. Distribution of ageing protocol studied

3.4.2.2. Temperature

The temperature distribution in hydrothermal ageing protocol, another critical variable, encompasses a wide range of conditions under which the FRP materials were tested, as detailed in Figure 3.8. The majority of tests were conducted at 60.0°C, accounting for 34.7% of the dataset, followed by 20.0°C (17.6%), 23.0°C (18.7%), 30.0°C (17.4%), 25.0°C (1.0%), 40.0°C (17.4%), 45.0°C (2.1%), and 80.0°C (6.7%). This distribution highlights a concentration of testing around moderate to elevated temperatures, with 60.0°C emerging as a focal point, likely due to its relevance in accelerated ageing studies. The inclusion of both low (20.0°C) and high (80.0°C) [46].

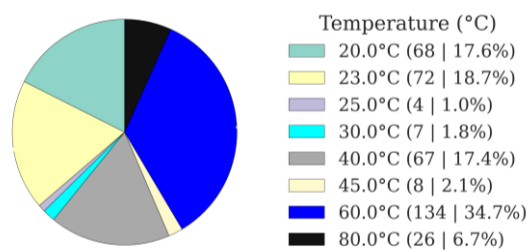


Figure 3.8. Distribution of temperature across different categories

3.4.2.3. Relative Humidity

Relative humidity levels, as presented in Figure 3.9, are predominantly high, with 100% humidity comprising 75.7% of the tests, followed by 95.0% at 11.9%, and 99.0% at 22.3%. This skewed distribution towards near-saturation conditions suggests an emphasis on evaluating the impact of moisture ingress, a critical factor in the degradation of FRP materials.

The limited representation of lower humidity levels (e.g., 95.0%) may reflect a research focus on worst-case scenarios, where maximum moisture exposure is intended to accelerate ageing processes [1].

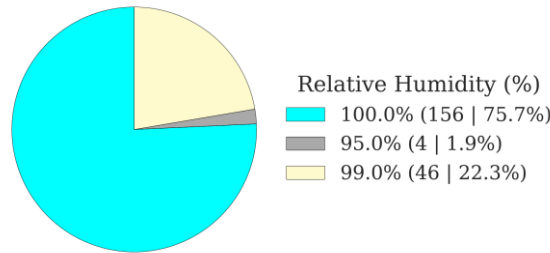


Figure 3.9. Distribution of relative humidity across different categories

3.4.3. Mechanical Properties

In the scope of this study, the mechanical properties analysed were tensile, flexural and interlaminar shear properties. These mechanical properties were selected as key variables due to their direct influence on the material's performance in practical applications. By systematically evaluating these parameters, this study due time constraints aims to provide a comprehensive understanding of the material's tensile behaviour only under various loading conditions, thereby facilitating informed decisions in material selection and design optimization.

Figure 3.10 presents a pie chart illustrating the proportion of tests conducted on various mechanical properties. Tensile testing dominates with 1526 tests (69%), reflecting its critical role in assessing resistance to axial loads. Flexural strength testing, with 346 test records (15.2%), evaluates bending resistance, while interlaminar shear stress testing, comprising 410 test records (18.0%), focuses on layer adhesion integrity.

The heavy weighting towards tensile testing suggests a research emphasis on load-bearing capacity, essential for applications like structural reinforcement. Flexural and interlaminar shear tests complement this by addressing transverse and interlayer behaviours, respectively, providing a comprehensive mechanical profile. However, the lower frequency of flexural and shear tests may indicate gaps in exploring other properties like compressive strength.

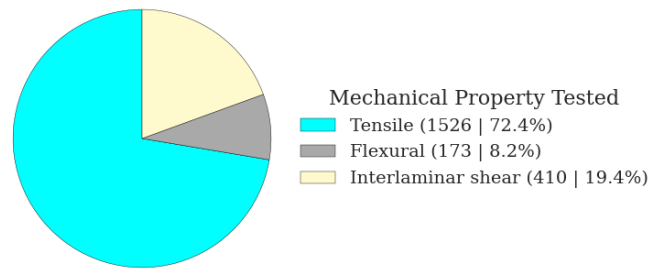


Figure 3.10. Distribution of mechanical property tested across different categories

3.4.4. *Derived Variables*

Retention ratios are calculated as the ratio of aged to unaged mechanical properties, such as the tensile strength retention. These ratios quantify the extent of degradation and are key targets for machine learning models [38].

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4. PREDICTIVE MODELLING

4.1. Overview of Research Approach

The development of predictive models for assessing the long-term durability of FRP composites under various ageing conditions represents a major advancement in materials science and structural engineering. This chapter delineates the comprehensive methodology employed to construct a ML framework that leverages the durability database described in Chapter 3. The primary objective is to predict the mechanical performance of FRP composites over extended timeframes (50–100 years) based on experimental data aggregated from literature sources. The research approach integrates systematic data collection, rigorous preprocessing, model development, evaluation, and long-term extrapolation, ensuring robust and reliable predictions. By employing advanced ML algorithms, this study addresses the challenges of inconsistent test methods and limited standardised durability data. Model Training, Validation, and Testing. An overview of the process followed is detailed in the figure below.

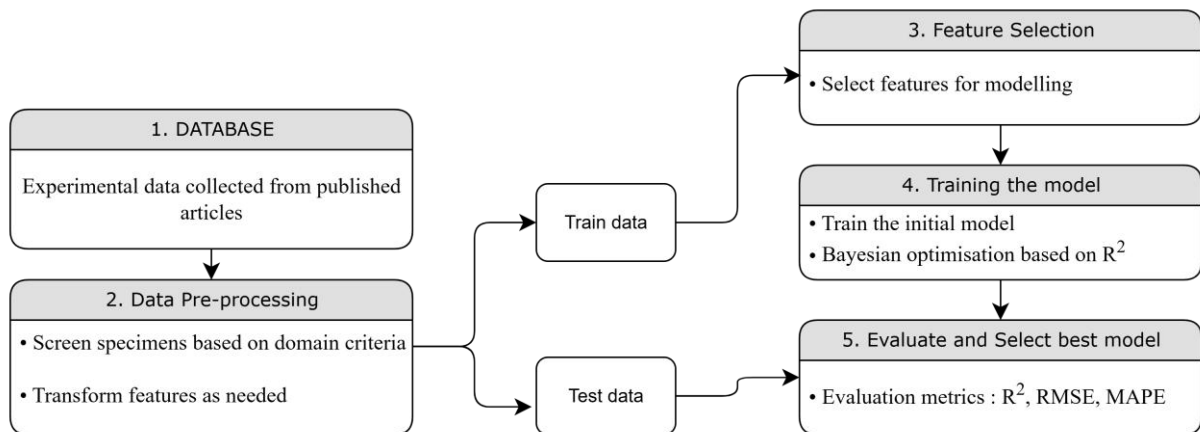


Figure 4.1. Overall framework of ML process

The initial phase involved creating the database which is already discussed in the previous section. The second step is the loading and preprocessing of the dataset utilizing the python library pandas for data handling. Considering the dataset's complexity, which includes multiple ageing protocols (e.g., hygrothermal, freeze-thaw cycle, chemical) and test types (e.g., tensile test, flexural test) a sub dataset that filters the data of a particular ageing protocol and test type from the rest of the dataset was created. This facilitates targeted data selection, essential for concentrating on specific ageing conditions and material test outcomes, which are vital for evaluating composite performance in different environments.

Feature selection is an essential phase in the development of ML regression models aimed at predicting tensile strength retention in composite materials subjected to hygrothermal aging. Tensile strength preserved post-aging, is influenced by material composition, processing, initial properties, and aging conditions. Features were selected using domain expertise and correlation analyses to ensure model accuracy, efficiency, and interpretability while mitigating overfitting and multicollinearity. Material-centric features like "Matrix Type" "Fibre Type" "Composite Type" "Fiber content" "Production method" and "Thickness" captured intrinsic properties critical to hygrothermal degradation. Initial mechanical properties such as "Tensile modulus of unaged specimen" and "Tensile strength of unaged specimen" served as reference points for retention calculations, exhibiting high feature importance, as they reflect baseline fibre-matrix integrity critical for tensile testing outcomes.

Hygrothermal aging parameters like "Ageing duration" "Temperature" "Relative humidity" "Type of medium" and "Test direction" addressed environmental conditions.

The literature offers a wide range of machine learning algorithms for building prediction models with tabular data, where a collection of random variables is used as input to forecast one or more target values [59]. In this study, several models like CatBoost [60], Random forrest (RF) [61], Gradient Boosting [62], XGBoost [63], Decision Tree [64] and LightGBM [65] were used. The objective of creating multiple machine learning methods for predictive modelling is to adopt the most effective prediction model.

To ensure model generalisability, the dataset was split into training and testing sets, typically following an 80% training and 20% testing ratio. The training set was used for parameter fitting, while the testing set was reserved for final evaluation. Each ML algorithm is characterized by a set of parameters, commonly referred to as hyperparameters, which are set before the learning process begins. Optimization of these hyperparameter is a critical process for obtaining the highest possible predictive accuracy [32].

In this study Bayesian optimization is employed for fine tuning parameters that significantly impact model performance. It is particularly effective for functions, where the relationship between hyperparameters and model performance is complex and lacks a closed-form expression. Unlike manual or grid search methods, which are computationally intensive or rely on expert intuition, Bayesian optimization leverages a probabilistic model, typically a Gaussian process, to model the unknown objective function [66]. The process involves setting a prior distribution over the function, updating it with observed data to form a posterior distribution, and using an acquisition function to select the next hyperparameter set to evaluate [67]. Bayesian optimization outperforms traditional methods like grid or random search, particularly

in high-dimensional spaces, by reducing the number of evaluations needed to identify optimal hyperparameters [66].

4.2.Evaluation Metrics

Model performance was assessed using a comprehensive array of metrics to quantify predictive accuracy and goodness-of-fit. These metrics comprised Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), R-squared (R^2). A comparative analysis of multiple regression models was undertaken. For prediction of tensile strength retention of a composite material subjected to hygrothermal ageing, the CatBoost Regressor model produced an MAE of 0.06, MSE of 0.01, RMSE of 0.07, R^2 of 0.88, RMSLE of 0.04, and MAPE of 0.08, with a training duration of 0.47 seconds.

The Random Forest Regressor (MAE: 0.0639, R^2 : 0.8535) and Gradient Boosting Regressor (MAE: 0.0649, R^2 : 0.8471) followed, leveraging ensemble techniques to improve accuracy. However, their higher error metrics suggest a lesser ability to capture data nuances compared to CatBoost. The high R^2 values, generally exceeding 0.88, indicate that all models accounted for a substantial portion of the variance in the tensile strength retention data. The CatBoost Regressor's efficiency suggests its potential for practical applications, while the consistent performance across metrics underscores the robustness of the modelling approach for predicting degradation in composite materials.

The dataset was firstly prepared using a custom filter, with categorical variables such as material composition, manufacturing methods, and exposure conditions encoded into numerical variable with values ranging from 1 to n with n as the length of unique values in that categorical variable [68]. This transformation facilitated the integration of diverse material and environmental factors into the modelling process, ensuring a comprehensive representation of the factors influencing degradation.

Then the coefficients A (representing the logarithmic degradation rate) and B (the intercept adjusted by initial tensile strength) for logarithmic model describing tensile strength retention (refer to Eq. 2.3) at different temperatures were obtained. Then, two models were fitted to A and B against different temperatures. Therefore, a model will be obtained that can predict the stress retention for different times and temperatures. The optimization process employed the `scipy.optimize.curve_fit` [69] to fit the logarithmic degradation model to tensile strength retention data across different temperature conditions. This method utilized a non-linear least squares technique to iteratively adjust A and B , minimizing the error between observed and

predicted values. The logarithmic model was selected for its ability to capture the non-linear decay of tensile strength over time, a common characteristic of hygrothermal ageing in composites. Subsequently, a secondary optimization step modelled A and B as linear functions of temperature, enabling the prediction of degradation behaviour under varying thermal conditions. This approach provided a structured method to quantify how temperature influences the rate and extent of material degradation, offering valuable insights for material design and performance prediction.

4.3. Long-Term Extrapolation Using Arrhenius Model

4.3.1. Model Formulation and Calibration

The Arrhenius model, a cornerstone of chemical kinetics, is extensively utilized in materials science to predict the long-term durability of FRP composites under hygrothermal ageing. This model facilitates the extrapolation of short-term accelerated ageing data to estimate long-term mechanical property retention, particularly tensile strength, at service conditions. The Arrhenius model is applied to experimental data from the Durable [16] dataset, which includes tensile strength retention measurements for laminates of varying thicknesses exposed to hygrothermal conditions. The conventional approach involves plotting the natural logarithm of the time required to reach a specific level of normalized tensile strength retention against the inverse of temperature ($1/T$) to extrapolate long-term behaviour. The code implements two Arrhenius-based functions: the standard `arrhenius_retention_scaled` and the enhanced `arrhenius_retention_scaled_enhanced`. The former model's retention as:

$$r(t, T) = \text{scale} \cdot \exp(-k \cdot t) \quad (4.1)$$

where (k) is the temperature-dependent rate constant. The enhanced version incorporates a baseline retention value to account for residual strength, particularly in thicker laminates with fibre-dominated properties.

$$r(t, T) = \text{baseline} + (1 - \text{baseline}) \cdot \text{scale} \cdot \exp(-k \cdot t) \quad (4.2)$$

These models are fitted to experimental data using the `curve_fit` function from `scipy.optimize`, optimizing parameters $\log A$, E_a , `scale` and `baseline`, for the enhanced model to minimize the error between predicted and experimental retention values. The enhanced model is particularly effective for thicker laminates, where fibre-dominated properties result in non-zero residual strength after prolonged exposure.

To enhance predictive accuracy, a polynomial degradation model (`degradation_model_poly`) is developed to predict tensile strength retention based on time and temperature. This model is refined through sequential corrections, including a quadratic function for laminate thickness.

$$y_{pred_modified} = y_{pred_poly} \cdot (c_0 + c_1 \cdot x_{fit} + c_2 \cdot x_{fit}^2) \quad (4.3)$$

where x_{fit} is the thickness and c_0, c_1, c_2 are fitted coefficients. Additional linear corrections, defined as

$$\text{linear_func}(X, a, b) = a \cdot X + b \quad (4.4)$$

are applied to account for material and environmental parameters such as composite type, fibre content, initial tensile strength, temperature, and test direction.

Model accuracy is evaluated using the coefficient of determination (R^2) and error analysis is conducted by plotting the ratio of true to predicted retention against exposure time using seaborn's `regplot`. This integrated methodology, combining Arrhenius-based models with polynomial corrections, enables robust projections of tensile strength retention over extended periods, effectively accounting for the complex interplay of material and environmental factors.

4.3.2. Long-Term Durability Projection

The long-term durability assessment of composite materials subjected to hygrothermal aging employed the calibrated Arrhenius model to forecast tensile strength retention over extended periods, surpassing the limitations of experimental data. By utilizing the activation energy and pre-exponential factor derived from the Arrhenius plot, the model facilitated the estimation of degradation rates at lower, service-relevant temperatures. This extrapolation was crucial for predicting the service life of composite structures, thereby reducing the necessity for costly long-term experimental testing. The dataset's comprehensive coverage of aging conditions, including temperature, humidity, and duration, ensured that the projections were grounded in a diverse set of experimental observations, thereby enhancing their applicability to real-world scenarios.

Challenges in long-term durability projection included the assumption of a constant activation energy across temperatures, which may oversimplify the complex interplay of environmental factors in hygrothermal aging. To mitigate this, the numerical encoding of categorical variables allowed the model to account for variations in material composition and manufacturing processes. The code's suggestion to explore non-linear models if residuals indicate deviations from linearity underscores the need for further refinement. Sensitivity analyses could elucidate

the impact of input variables, such as humidity or material properties, on long-term predictions, thereby enhancing model robustness.

5. RESULTS AND DISCUSSION

5.1. Exploratory Data Analysis

This EDA examines the degradation behaviour of FRP composite. The dataset analysed in this study comprises an extensive array of experimental results from various studies on FRP composites, with a focus on their mechanical properties under diverse aging protocols. The analysis seeks to discern key trends and patterns in FRP degradation, identify critical environmental factors affecting durability, and conduct a comparative analysis of different types and compositions.

5.1.1. Statistical Trends and Distributions

Impact of Ageing Protocols

The scatter plot in Figure 5.1 illustrates the retention of tensile strength as a function of the of aging duration (in hours) across three protocols, providing a visual depiction of degradation dynamics. Hygrothermal aging, represented by red data points, predominates the dataset with a broad distribution from approximately 1 to 20,000 hours. At shorter durations (<5,000 hours), retention values span between 0.8 and 1.0, indicating minimal initial degradation. However, as aging extends beyond 10,000 hours, a significant decline is observed, with retention values decreasing to 0.4–0.6. This trend, appearing more gradual on the log scale, suggests that the combined effects of elevated temperature and humidity accelerate matrix degradation, likely through moisture-induced plasticization or hydrolysis, which compromises the fibre-matrix interface and diminishes the composite's load-bearing capacity.

In contrast, samples which were aged under freeze-thaw cycles, depicted by blue data points, exhibit less dispersed pattern across 0–18,000 hours, with retention values predominantly ranging from 0.8 to 1.2. Notably, several points exceed 1.0, particularly at shorter durations, suggesting an initial stiffening effect. Beyond 10,000 hours, the retention stabilizes at approximately 0.8–1.0, with infrequent drops to 0.6, indicating a gradual onset of degradation. Values above 1.0 warrant scrutiny, as they could indicate measurement inconsistencies or a genuine material response, such as stress-induced densification, which requires validation through additional testing.

Chemical aging, represented by green data points, is the least represented, with durations ranging from 0 to 15,000 hours and retention values generally between 0.8 and 1.2, with an average around 1.0 up to 10,000 hours. Beyond this threshold, the sparse data suggest a slight decline to 0.6–0.8. This moderate impact implies that chemical exposure, potentially involving corrosive media, affects the matrix or fibre surface selectively. The limited data points restrict robust conclusions, but the trend suggests that chemical aging may be less aggressive than hygrothermal conditions for the tested composites.

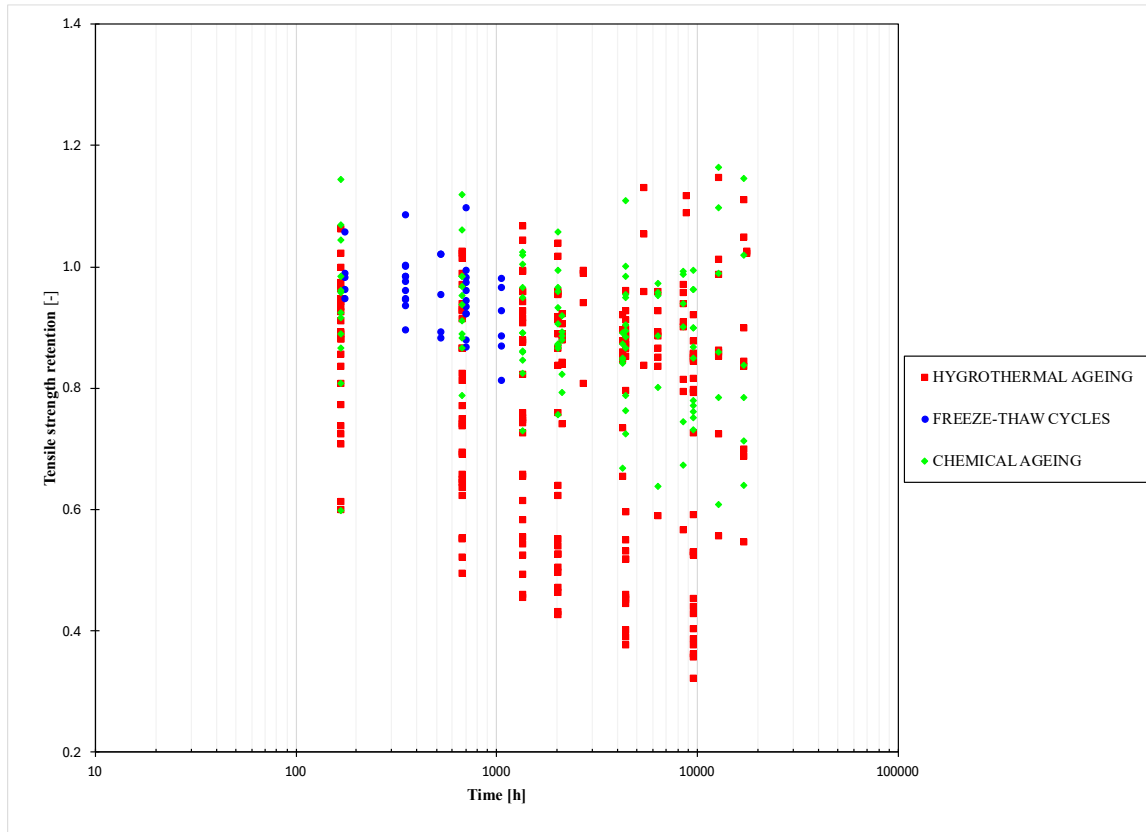


Figure 5.1. Plot of tensile strength retention vs. ageing duration

Role of Fiber Type in FRP Degradation

The scatter plot illustrated in Figure 5.2 depicts the retention of tensile strength as a function of ageing duration (in hours) for four types of fibres: glass (green), carbon (blue), basalt (red), and hybrid (pink). This visualization offers a comparative framework to evaluate how different fibre types influence degradation under extended exposure. GFRP composites, indicated by green data points, demonstrate a dense clustering at shorter durations with retention values predominantly between 0.7 and 1.1. Beyond a duration of 100,000 hours, the data become sparser, with retention stabilizing around 0.7–0.9, suggesting a moderate decline. This behaviour indicates that glass fibres, known for their cost-effectiveness and moderate

mechanical properties, undergo gradual degradation, likely due to moisture ingress and matrix weakening over time. Carbon fibre-reinforced composites, represented by blue data points, exhibit a more variable distribution across durations of 0 to 100,000 hours, with retention values initially ranging from 0.8 to 1.4 at shorter durations (0–5,000 hours) and declining to 0.3–0.8 at longer durations (10,000–100,000 hours).

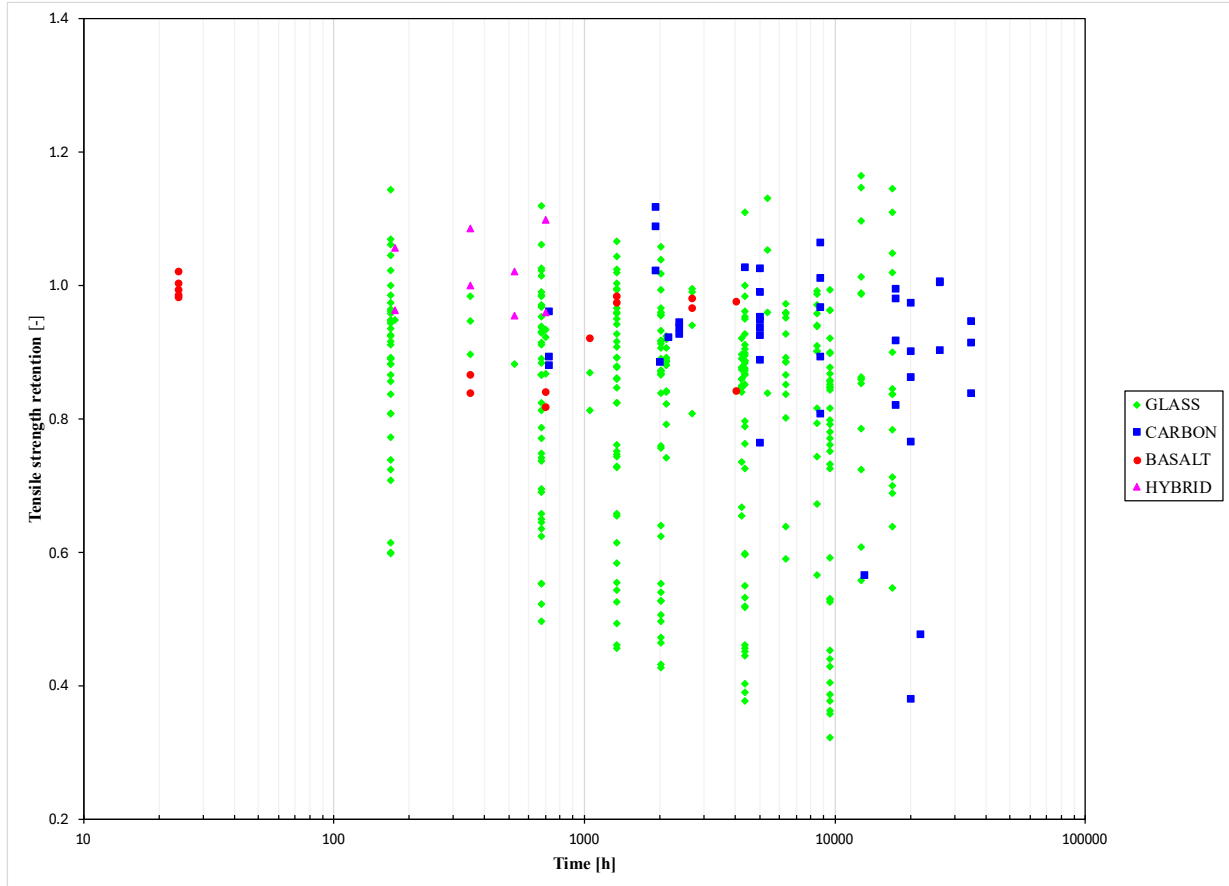


Figure 5.2. Plot of tensile strength retention by fibre type

The presence of retention values exceeding 1.0 at early stages may reflect an initial stiffening effect or measurement variability, while the subsequent decline highlights significant degradation. Carbon fibres, valued for their high strength and stiffness, appear susceptible to long-term environmental exposure, possibly due to interfacial degradation or matrix cracking under sustained stress. The wide range of retention values suggests that carbon-based FRP may respond differently depending on specific ageing conditions or composite formulations. Basalt fibre-reinforced composites, marked by red data points, are less numerous but show retention values between 0.6 and 1.2 across durations of 0 to 15,000 hours, with a slight decline to 0.6–0.8 beyond a duration of 10,000 hours. This trend indicates that basalt fibres, an emerging alternative with good thermal and chemical resistance, maintain relatively stable tensile strength retention compared to glass and carbon, particularly at intermediate durations. The

limited data points restrict definitive conclusions, but basalt's performance suggests potential resilience, possibly due to its inorganic nature and resistance to moisture-induced degradation. Hybrid fibre composites, represented by pink data points, are the least represented, with retention values ranging from 0.7 to 1.1 over durations of 0 to 10,000 hours, showing minimal decline. This stability may reflect the synergistic effects of combining different fibre types (e.g., glass and carbon), though the sparse data necessitate caution in interpretation.

Role of Matrix Type in Tensile Strength Degradation

The type of matrix is crucial in influencing the mechanical properties and durability of composite materials. Epoxy, denoted by red data points, is renowned for its superior adhesion, chemical resistance, and high mechanical strength, making it a favoured choice in aerospace and marine applications. Isophthalic Polyester (blue) and Unsaturated Polyester (cyan) are thermosetting resins widely used in the construction and automotive sectors due to their cost-effectiveness and ease of processing, though they may show varying degradation resistance. Vinyl Ester (green), a hybrid of polyester and epoxy traits, provides enhanced toughness and corrosion resistance, making it versatile for challenging environments. The scatter plot reveals distinct degradation trends over time, up to 25,000 hours, with the y-axis showing tensile strength retention. Initially, all matrix types exhibit tensile strength retention near or above 1.2, indicating strong initial performance. Over time, a noticeable decline occurs, with degradation rates and extents differing. Epoxy (red) shows a sharp drop, with some points below 0.3 after around 6,000 hours, suggesting susceptibility to long-term degradation. This rapid decline may stem from high cross-linking density, which boosts initial strength but may cause micro-cracking under sustained stress. Conversely, Vinyl Ester (green) and Isophthalic Polyester (blue) show gentler declines, stabilizing around 0.7–0.9 even after 18,000 hours, reflecting a more resilient structure with fewer outliers. Unsaturated Polyester (cyan) displays the most scattered data, with retention varying from 0.5 to 1.2, indicating inconsistent performance possibly due to formulation or curing variations.

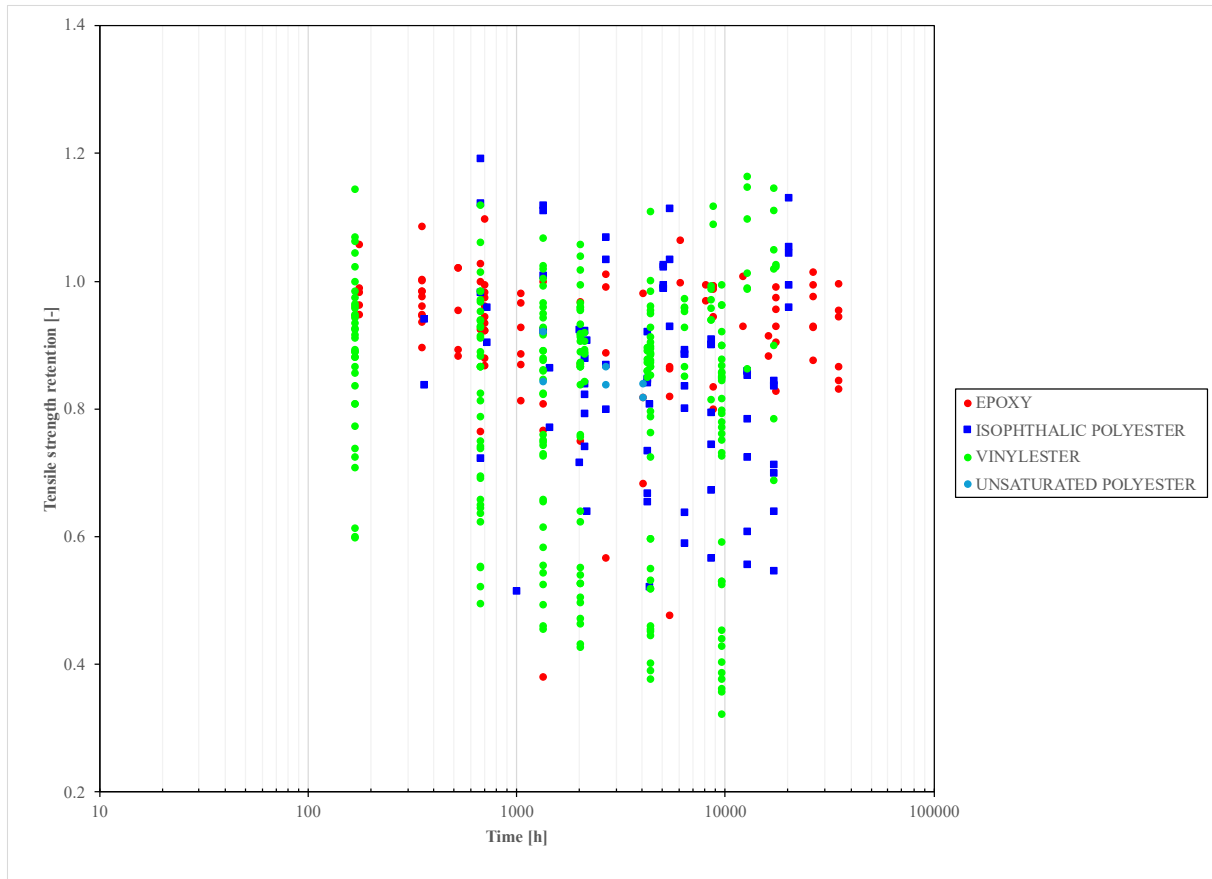


Figure 5.3. Plot of tensile strength retention by matrix type

5.2. Machine learning model results

5.2.1. Training and Validation Performance

The performance of machine learning models designed to predict the short-term degradation of materials is analysed, with a particular focus on tensile strength retention as a critical indicator of material durability. The primary objective is to evaluate the accuracy and reliability of these models in forecasting short-term degradation under various environmental conditions, as well as to identify their strengths and limitations in practical applications. The accuracy of short-term degradation predictions is crucial for assessing material durability under diverse environmental conditions, such as temperature and exposure time. In this study, machine learning models were trained on a dataset capturing tensile strength retention over short timeframes.

The evaluation of various machine learning models as seen in Figure 5.4 for predicting short-term degradation of materials revealed significant insights into their performance metrics. The analysis, conducted using a range of regression algorithms including CatBoost Regressor, Random Forest Regressor, Gradient Boosting Regressor, Extreme Gradient Boosting, and Extra Trees Regressor, yielded a comprehensive comparison based on metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), R^2 score, Root Mean Squared Logarithmic Error (RMSLE), Mean Absolute Percentage Error (MAPE).

	Model	MAE	MSE	RMSE	R^2	RMSLE	MAPE
catboost	CatBoost Regressor	0.0562	0.0054	0.0717	0.8829	0.0402	0.0788
rf	Random Forest Regressor	0.0639	0.0068	0.0808	0.8535	0.0459	0.092
gbr	Gradient Boosting Regressor	0.0649	0.0071	0.0823	0.8471	0.0465	0.0925
xgboost	Extreme Gradient Boosting	0.0652	0.007	0.0827	0.8467	0.0466	0.0919
et	Extra Trees Regressor	0.0677	0.0074	0.0848	0.8396	0.0478	0.0957
dt	Decision Tree Regressor	0.0731	0.0093	0.0952	0.7938	0.0538	0.1037
lightgbm	Light Gradient Boosting Machine	0.0805	0.0108	0.1024	0.7696	0.0617	0.1315
knn	K Neighbors Regressor	0.0799	0.0114	0.1043	0.7601	0.0612	0.1239
ada	AdaBoost Regressor	0.0889	0.0117	0.107	0.7504	0.064	0.1468

Figure 5.4. Comparison of ML model performance

Among these, the CatBoost Regressor emerged as the top performer, as illustrated in Figure 5.5 achieving an MAE of 0.0562, MSE of 0.0054, RMSE of 0.0717, R^2 of 0.8829, RMSLE of 0.0402, and MAPE of 0.0788, with a training time of 0.4720 seconds. This superior performance indicates that the CatBoost Regressor effectively captures the underlying patterns in the tensile strength retention data, offering high accuracy and reliability for short-term degradation predictions.

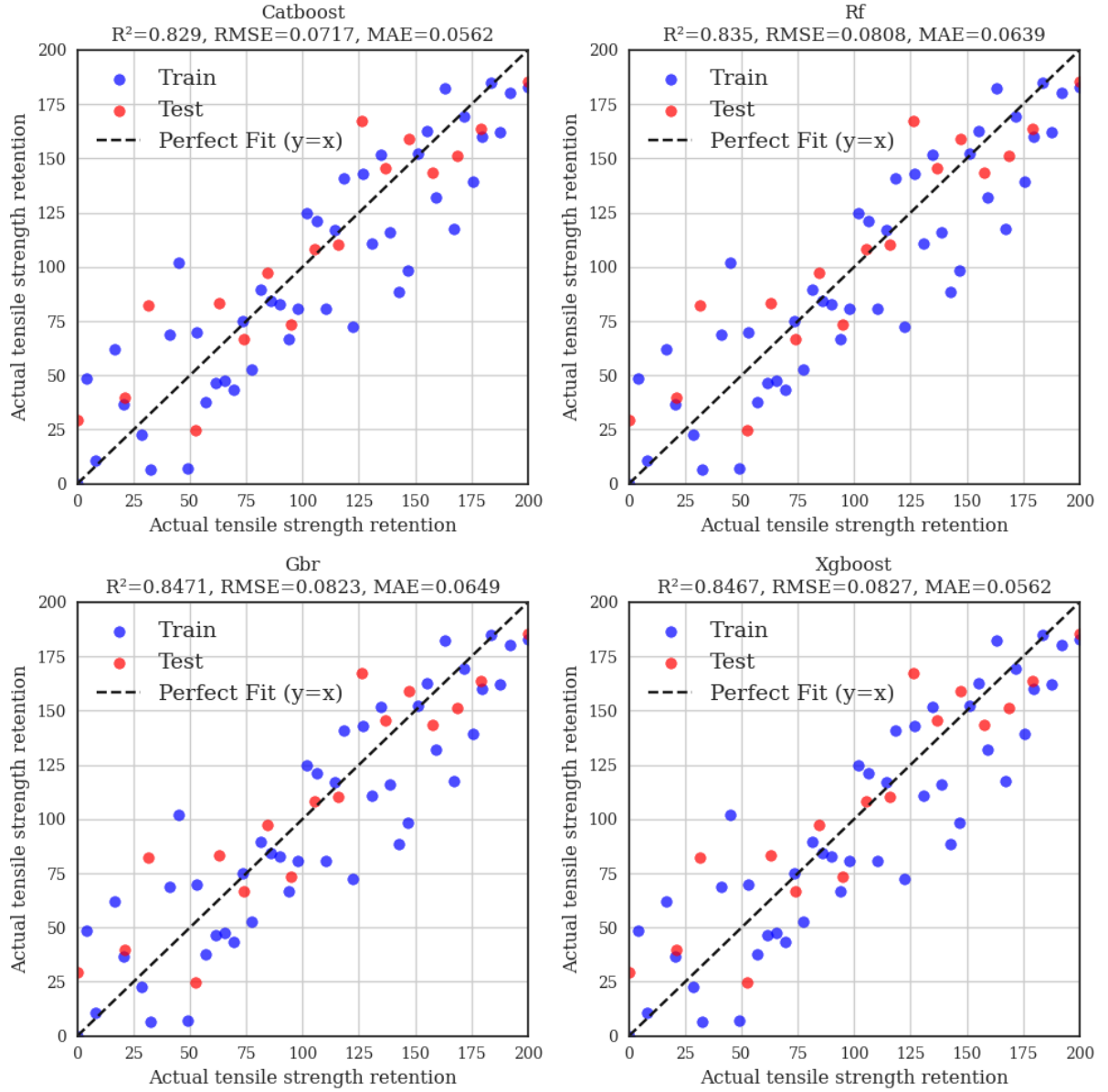


Figure 5.5. Comparison of the experimental and predicted values of TSR for the ML models trained.

The significance of these results lies in their ability to guide the selection of an optimal model for practical applications in materials science, particularly where early-stage degradation forecasts are critical. Compared to other models, the CatBoost Regressor demonstrates highest value of R^2 across all configurations, indicating superior accuracy and reliability. The relatively short training time further enhances its feasibility for iterative development and real-time applications.

5.2.2. Feature Importance and Model Interpretation

The machine learning model developed for predicting tensile strength retention in composite materials offers a comprehensive framework for elucidating the relative contributions of various features to the degradation process. This model is iteratively refined through linear adjustments for features such as composite thickness, composite type, fibre content, tensile strength of unaged specimens, temperature, and test direction. The interpretability of this approach is significantly enhanced by the feature importance analysis conducted using the CatBoost algorithm, with results depicted in Figure 5.5.

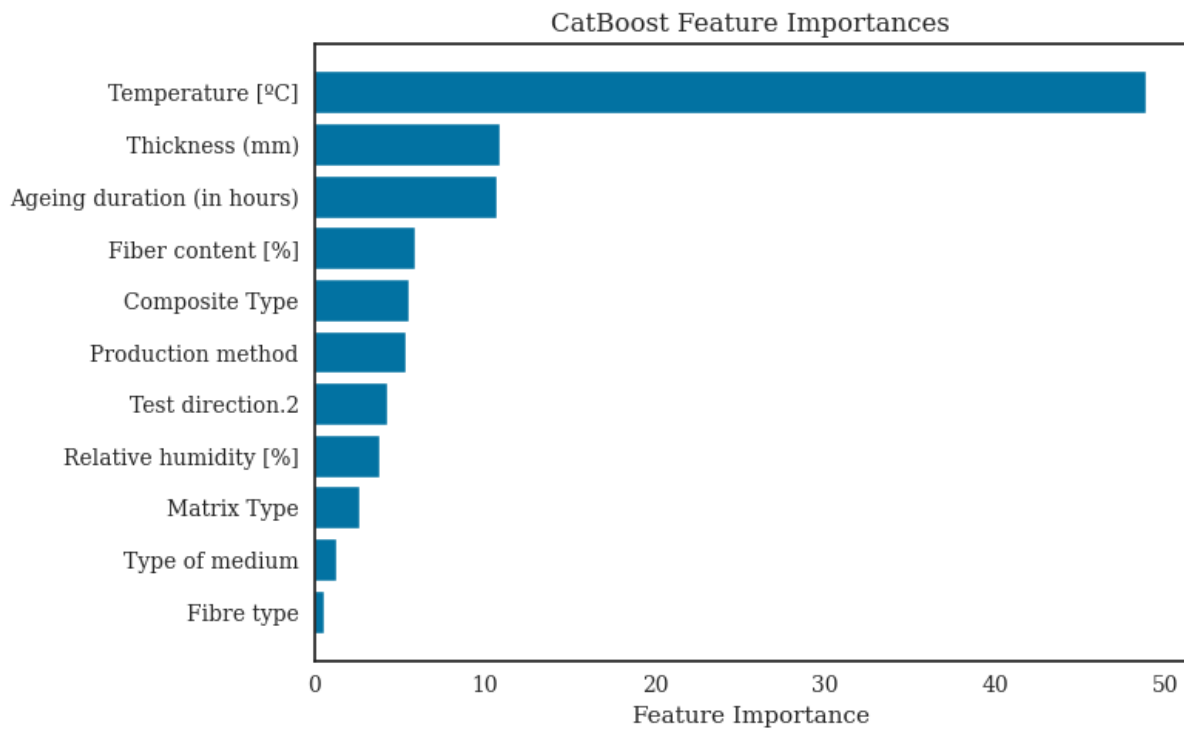


Figure 5.6. Feature Importance plot of the model

The feature importance plot in Figure 5.5 indicates that temperature and ageing duration (in hours) are the most influential factors with feature importance scores of 50 and 35, indicating it has the most significant impact on the model's predictions. This finding aligns with the model's foundational reliance on a polynomial degradation model that incorporates time and temperature as primary variables, reflecting their critical roles in driving degradation mechanisms. The prominence of ageing duration suggests that cumulative exposure time is a key determinant of material degradation, while the dominant influence of temperature underscores its role as a catalyst for accelerating chemical and physical deterioration processes. Following temperature and ageing duration, the tensile strength of unaged specimens emerges as the next most significant feature. This indicates that the initial mechanical properties of the

composite serve as a baseline that strongly influences its degradation resistance. The thickness of the specimen also ranks relatively high, suggesting that geometric factors play a notable role, potentially due to variations in surface area exposure or internal stress distributions that affect degradation rates. These findings suggest that pre-ageing material properties and geometry are critical secondary factors that modulate the degradation process beyond the primary effects of time and temperature. Features such as fibre content, production method, composite type, and matrix type exhibit intermediate importance scores, indicating their moderate but non-negligible influence on tensile strength retention. The ranking of fibre content highlights the role of reinforcement in maintaining structural integrity, with higher fibre contents potentially enhancing resistance to degradation through improved load transfer. The production method and composite type reflect process and material-specific effects, such as curing conditions or chemical composition, which may influence the material's susceptibility to environmental ageing. matrix type, while less dominant, suggests that the polymer matrix's chemical stability or interaction with the reinforcement impacts degradation behaviour. These intermediate features collectively contribute to a nuanced understanding of how manufacturing and material selection influence long-term performance, warranting further investigation into their specific interactions.

Features with lower importance scores, such as relative humidity, type of medium and test direction, suggest a lesser yet still pertinent influence on the model's predictions. The minimal impact of relative humidity and type of medium indicates that, within the dataset, these environmental factors may not exhibit sufficient variability to exert a strong effect or may be overshadowed by temperature and duration. Similarly, the test direction's low importance aligns with the model's correction approach, where its effect is accounted for as a linear adjustment but does not emerge as a primary driver compared to other factors. This hierarchy of importance provides a clear prioritization for experimental design, focusing on optimizing temperature, duration, and initial material properties.

5.2.3. Implementation of Arrhenius Framework

The utilization of the Arrhenius framework for predicting tensile strength retention is explored in this subsection, with the results graphically represented in Figure 5.6. This figure depicts a scatter plot comparing the predicted tensile strength retention against the true values, accompanied by an R^2 value of 0.5334, which quantifies the model's explanatory power. The concentration of data points within the 0.4 to 0.8 range on both axes, reflecting a region where

the model's predictions align relatively well with the experimental outcomes. However, the distribution of points exhibits significant dispersion, with notable deviations above and below the ideal diagonal line. Specifically, instances of overprediction are observed at higher retention values, where some predicted values exceed 1.0 while the corresponding true values do not, suggesting potential limitations in the model's ability to accurately extrapolate beyond certain thresholds. Conversely, underpredictions are evident at lower retention levels, further highlighting the framework's inconsistent performance across the full spectrum of data.

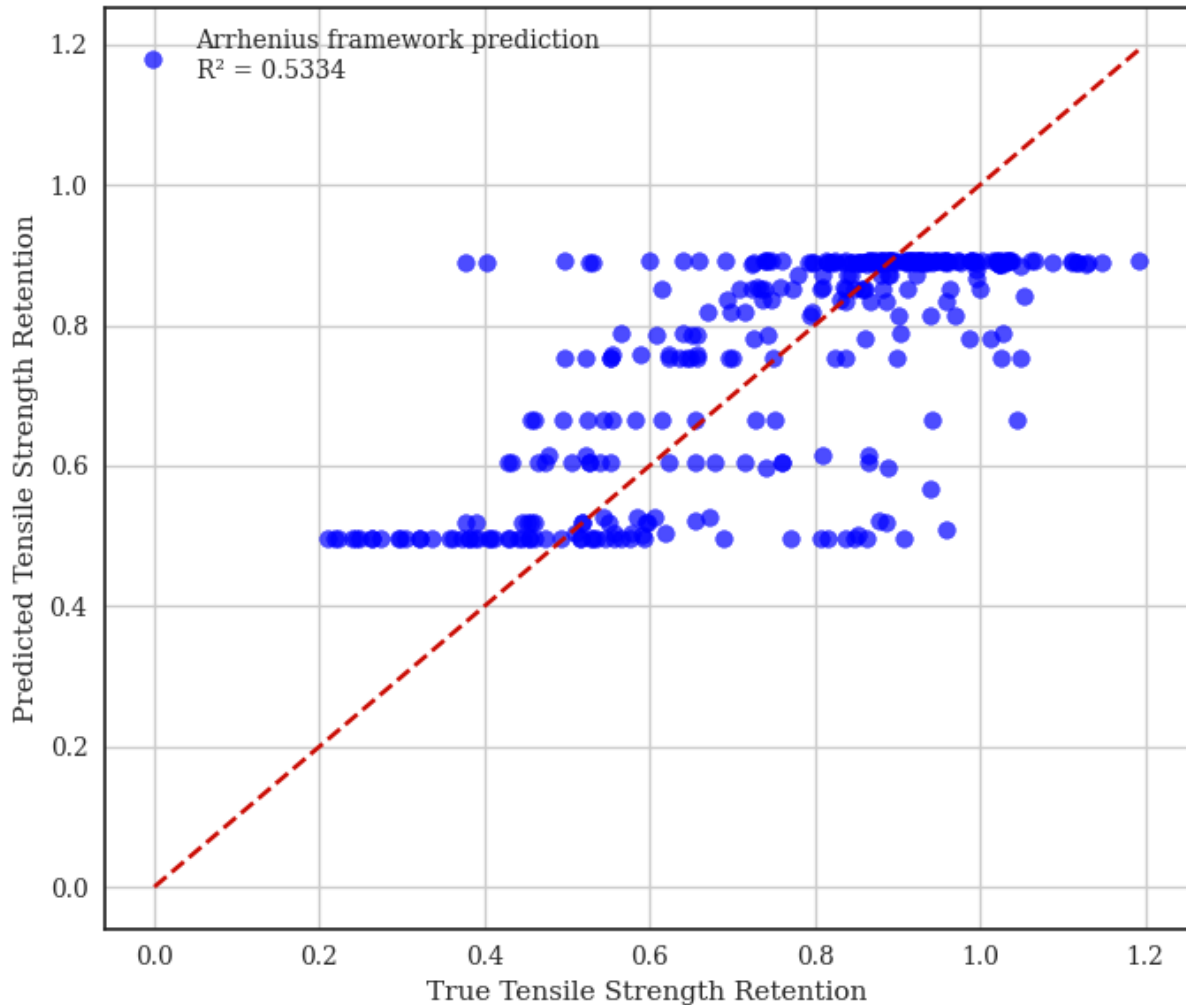


Figure 5.7. Plot of predicted vs. true tensile strength retention by Arrhenius framework

The framework, predicated on a linear relationship between the logarithm of the rate constant and the inverse of temperature, may not fully capture the multifaceted degradation processes affecting tensile strength retention. Consequently, these results suggest that while the Arrhenius framework serves as a useful initial tool for prediction and can extrapolate based on the presented data, its accuracy is constrained under the current experimental conditions, with a low level of reliability. This poor predictive performance could be attributable to the model's

approximations and the influence of multiple interacting factors, compounded by dataset's limited size, which restricts its ability to support reliable extrapolation.

5.2.4. Degradation Curve Fitting and Long-Term Trends

The examination of degradation curve fitting for composite materials under varying thermal conditions has yielded significant insights into the retention of long-term tensile strength. The findings reveal a clear temperature-dependent degradation trend, with distinct performance outcomes observed at the tested temperatures of 40°C, 60°C, and 80°C. The logarithmic model, as shown in Figure 5.7 produced R^2 values of 0.15, 0.25, and 0.92 for 40°C, 60°C, and 80°C, respectively. These results suggest that the model's predictive accuracy enhances with increasing temperature, with the 80°C data exhibiting the closest fit, as illustrated in the logarithmic plot of tensile strength retention versus time.

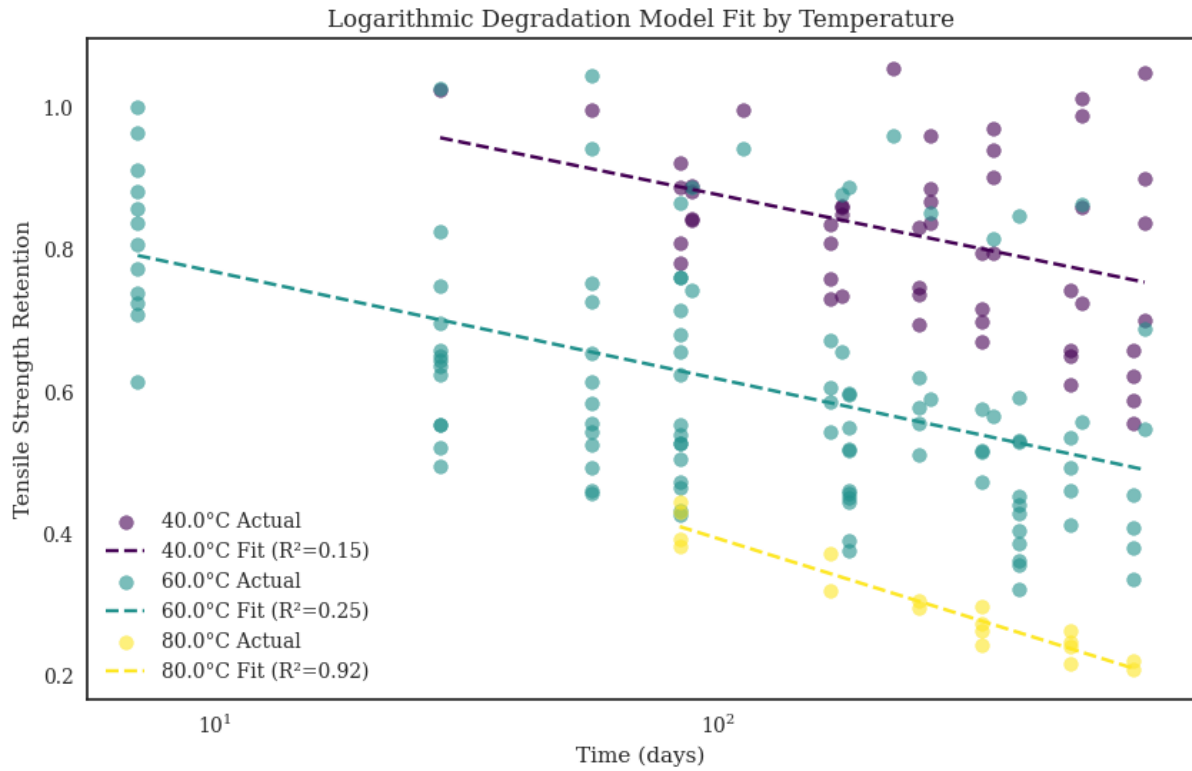


Figure 5.8. Logarithmic degradation model fit by temperature

Analysis of the fitted curve ($R^2 = 0.15$) at 40°C reveals considerable scatter around the predicted line, indicating limited explanatory power for degradation at lower temperatures. Conversely, the 60°C dataset achieved an R^2 of 0.25, signifying a moderate improvement in fit, albeit with noticeable deviations. The most notable result was observed at 80°C, where the model attained an R^2 of 0.92, reflecting an excellent fit with the data points closely aligning with the fitted

curve. This temperature-dependent enhancement suggests that higher thermal exposure amplifies the logarithmic degradation mechanism, potentially due to accelerated chemical or physical processes within the composite matrix.

Further analysis of the logarithmic model, parameters (A) and (B) provided additional insights into the degradation behaviour. The fitted values for (A) and (B) at each temperature reveal a trend of decreasing (B) and increasingly negative (A) with rising temperature. This indicates a steeper decline in retention over time at higher temperatures, consistent with Arrhenius degradation kinetics. To capture this trend, second-degree polynomial fits were applied to (A) and (B) as functions of temperature, and these polynomial fits, plotted against temperature, demonstrate a non-linear relationship, with (A) becoming more negative and (B) decreasing more rapidly at higher temperatures, reinforcing the enhanced degradation rate observed in the 80°C data.

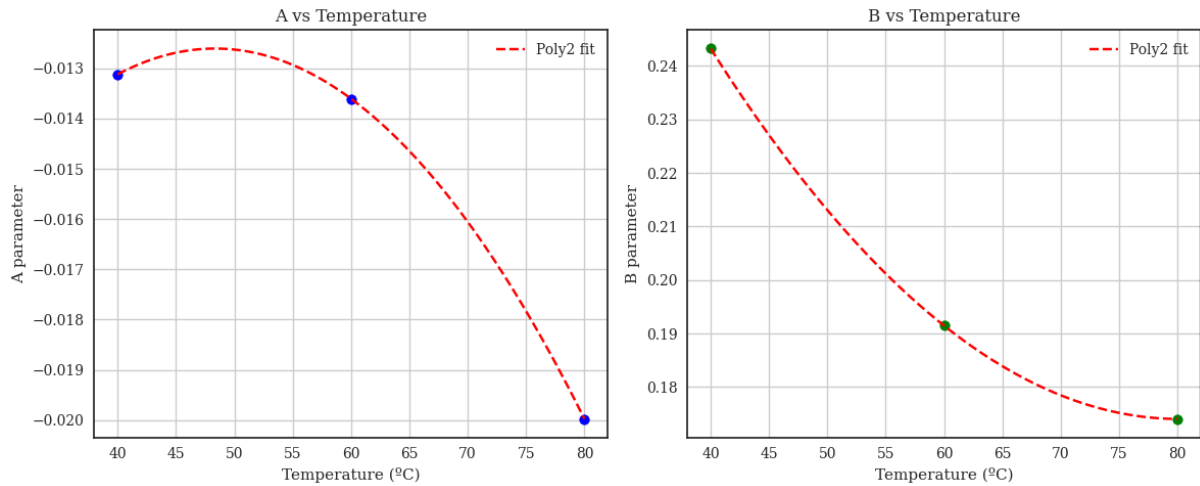


Figure 5.9. Polynomial fit of parameters A and B vs. temperature

The long-term trends inferred from these results suggest that temperature is a critical driver of composite degradation, with implications for service life prediction under elevated thermal conditions. The high R^2 value at 80°C (0.92) indicates that the logarithmic model effectively captures the degradation kinetics at this temperature, potentially serving as a reliable predictor for accelerated aging scenarios.

The relationship between material thickness and the predictive accuracy of the tensile strength retention model was explored through a detailed visualization of model error, defined as the ratio of true tensile strength retention to predicted values, plotted against thickness in millimetres. The resulting plot, as depicted in Figure 5.8 demonstrated a clear trend wherein the model error increases as thickness ranges from approximately 2 mm to 6 mm. At lower thicknesses, the error remains close to 1, indicating a satisfactory alignment between predicted

and actual retention values. However, as thickness increases, the error rises, signifying that the model tends to underpredict tensile strength retention at higher thicknesses. This systematic deviation highlights a potential limitation in the current quadratic correction applied to the polynomial degradation model, suggesting that the model may not fully capture the complex influence of thickness on material durability.

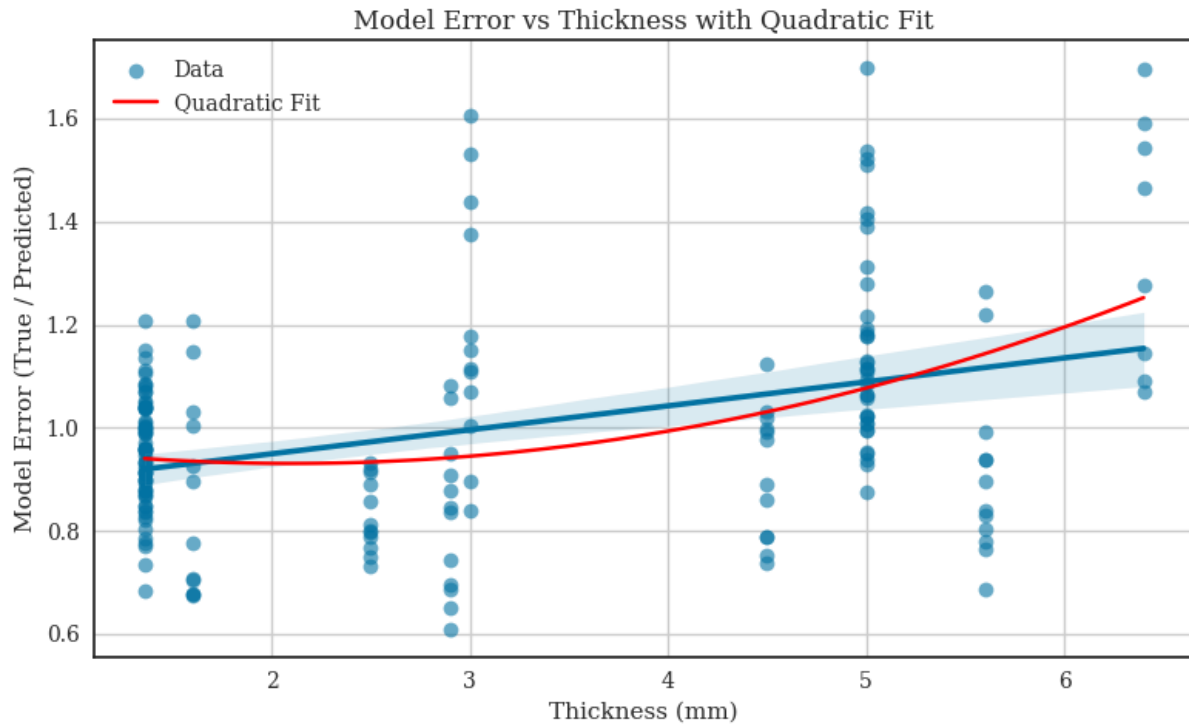


Figure 5.10. Model error vs thickness with quadratic fit

The quadratic fit, depicted as a red dashed line, exhibits a slight upward curvature, indicating a non-linear relationship between thickness and model error, which diverges from the blue linear regression line, particularly at thicknesses exceeding 5 mm. These observations imply that while the quadratic correction enhances model performance, its effectiveness could be improved through the integration of higher-order polynomial terms or interaction effects with variables such as temperature or composite type. Additionally, the observed underprediction at higher thicknesses underscores the need for expanded experimental data to refine the model, ensuring its predictive accuracy across the full spectrum of material thicknesses and enhancing its applicability in practical durability assessments.

The scatter plot shown in Figure 5.10 evaluates the performance of a logarithmic-polynomial model for predicting tensile strength retention in composite materials, plotting predicted values against true observed retention. The base log-poly model yields an R^2 of 0.6053, which improves to 0.7544 following the application of corrections, indicating enhanced predictive

accuracy. The corrections applied to the logarithmic-polynomial model involve multiplicative factors fitted via curve fit. Initially, a quadratic correction for thickness and subsequent linear corrections address composite type, fibre content (%), tensile strength of unaged specimens (MPa), temperature (°C) again, and test direction, each computed by fitting a linear function to the ratio of true retention to the current modified prediction, then multiplying back. This iterative process boosts R^2 by incorporating domain-specific influences based on feature importance analysis performed earlier.

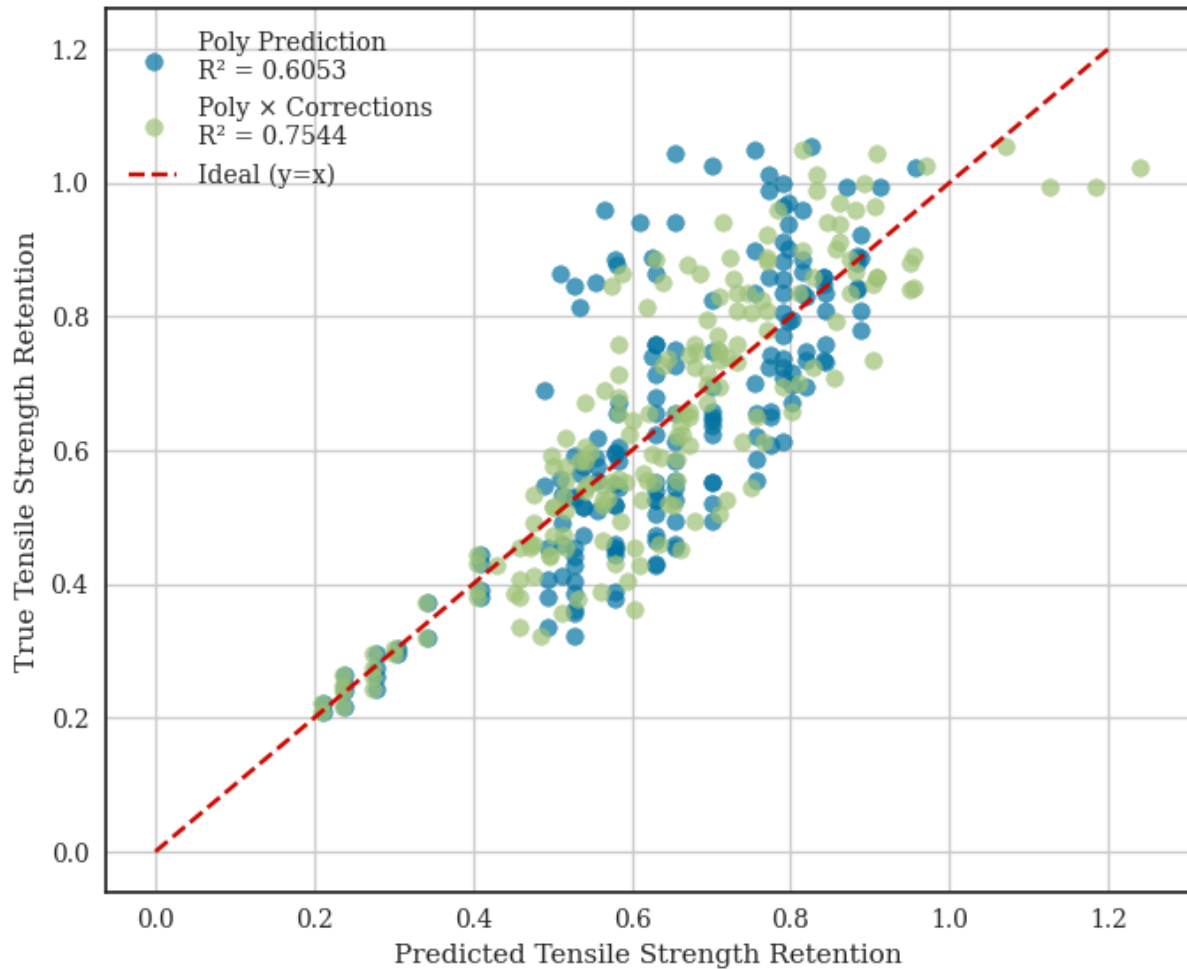


Figure 5.11. Predicted vs true retention of Log-Poly model

The analytical modelling strategy utilized here presents unique strengths, leveraging precise parameter tuning to deliver clear, physics-based enhancements distinct from the opaque outputs of machine learning approaches. This approach suits potentially limited datasets in materials science, enabling extrapolation, error analysis, and alignment with theoretical degradation mechanisms.

5.3.Discussion

5.3.1. *Alignment with Existing Literature*

The logarithmic degradation model employed in this study aligns well with the study of Karbhari et al. [33] which extrapolated short-term data to predict long-term property retention, emphasizing the logarithmic relationship between time and degradation. The current results extend this by showing temperature-dependent fits, with R^2 values increasing from 0.15 at 40°C to 0.92 at 80°C, indicating improved model fidelity at elevated temperatures. Machello et al. [29], in their tree-based machine learning study, similarly highlighted the susceptibility of FRP composites to thermal degradation at higher temperatures, where exposure temperature emerges as a critical factor influencing TSR.

Traditional models, such as the Arrhenius-based approaches frequently cited in the literature [51], [70], emphasize the exponential decay of mechanical properties under hygrothermal aging, where activation energy governs the rate of degradation. The Arrhenius framework predicted tensile strength retention with an R^2 value of 0.5334, indicating moderate explanatory power. While it serves as a useful initial tool for prediction and extrapolation, significant dispersion and deviations, including overpredictions at higher values and underpredictions at lower ones, reveal the model's limitations in capturing complex degradation processes. The framework's reliance on a linear relationship and the dataset's small size contribute to its inconsistent performance and low reliability for extrapolation.

The analysis of model error *versus* specimen thickness, further reinforces literature on thickness-dependent degradation. This quadratic trend indicates that prediction accuracy diminishes for thicker samples, likely due to enhanced interlaminar and intralaminar degradation mechanisms, as reported by Karbhari et al. [33]. This thickness effect is also implicit in machine learning applications, where sample thickness ranks as a key feature in predicting TSR in the study of Machello et al. [29].

Finally, the polynomial prediction yielding an R^2 of 0.6053, demonstrates predictive performance that surpasses simple linear models and aligns with advanced machine learning techniques in the literature. The improved R^2 post-corrections in this study reflects the enhanced accuracy achieved through ensemble methods and use of knowledge-based corrections to enable robust predictions of complex behaviours as advocated by [28]. Similarly, Machello et al. [29] optimized tree-based models via Bayesian optimization, identifying temperature and thickness as dominant factors, which parallels the current model's emphasis on

these variables for better alignment with actual data. Overall, these results affirm the literature's consensus on the interplay of environmental factors, as detailed in CEN/TS 19101:2022 (Subclause 6.4), where combined thermal and moisture effects amplify degradation beyond isolated conditions, necessitating representative testing for reliable design [9].

5.3.2. Limitations of the Study and Modelling Approach

While the polynomial model with corrective factors exhibits improved predictive capability for tensile strength retention, it is imperative to acknowledge several inherent limitations in the study design and modelling methodology to appropriately contextualize the results. The primary limitation arises from the dataset's composition, which aggregates experimental data from diverse sources; this heterogeneity introduces potential inconsistencies in testing conditions, specimen preparation, and measurement precision, as highlighted in comprehensive reviews of accelerated ageing methodologies [71]. Such variability may manifest as unexplained residuals in the model, particularly evident in the scatter observed beyond moderate exposure durations, where the polynomial form adequately captures initial non-linear decay but struggles with asymptotic behaviours in prolonged ageing, reminiscent of challenges in kinetic models for epoxy hydrolysis [70]. Furthermore, the reliance on linear corrections for influential parameters such as thickness and fibre content assumes a straightforward proportionality that may oversimplify complex interactions; for instance, at elevated fibre volumes, interfacial effects could introduce non-linearities due to altered moisture diffusion paths, aligning with observations on humidity-induced weakening in fibre-matrix bonds [72], thereby risking underestimation of degradation in densely reinforced composites.

The exclusive focus on static tensile testing further narrows applicability, neglecting dynamic or multi-axial loading scenarios that exacerbate anisotropic degradation in orthotropic laminates, as documented in studies on hygrothermal influences [73]. These shortcomings collectively underscore the need for cautious interpretation, particularly when applying the model to novel materials or untested protocols.

5.3.3. Practical Implications of the Results

The refined polynomial model, which achieves an R^2 of 0.75 through targeted corrections, offers significant practical value for advancing the engineering of durable composite systems in sectors exposed to environmental effects. By quantifying the interplay of time, temperature,

and material attributes on tensile strength retention, the model enables designers to optimize laminate configurations, such as increasing fibre content to enhance resistance against hygrothermal degradation, potentially extending operational lifespans in applications like wind turbine blades, where moisture ingress and thermal fluctuations are prevalent. This predictive insight facilitates material selection processes that prioritize high-retention composites, thereby reducing the frequency of costly replacements and aligning with sustainability goals by minimizing resource-intensive manufacturing cycles for carbon fibre reinforcements [74].

Beyond design, the framework's integration into digital tools offers transformative potential for predictive maintenance and structural health monitoring, where real-time inputs of exposure parameters could forecast residual strength, triggering pre-emptive interventions in critical assets like aircraft components [75]. This capability extends to digital twin platforms, allowing virtual replication of aging scenarios to evaluate service-life extensions without extensive physical testing, thereby accelerating innovation in composite-intensive industries while mitigating risks associated with anisotropic property loss. Economically, these implications translate to reduced downtime and lifecycle costs, particularly in harsh environments, by guiding the adoption of robust protocols that account for multifactorial influences, as evidenced in durability studies of glass fibre-reinforced polymers[1]. However, successful implementation necessitates calibration with application-specific data to address model biases, ensuring that predictions inform reliable decision-making across diverse operational contexts.

5.3.4. Calculation of Conversion Factors for Temperature and Moisture

To assess the long-term durability of FRPs, conversion factors for temperature and moisture were derived. A representative sample from the database, reported by Heshmati et al. [43], with a thickness of 1.25 mm and fibre content of 82% by mass, was selected from the database. This sample was immersed in distilled water at 100% relative humidity and exposed to 45 °C for 20,160 hours, resulting in a tensile strength retention of 0.57. The aim was to project this behaviour to a target service life of 50 years (438,312 hours).

The degradation rate was estimated by fitting the observed retention data. A moisture-adjusted rate constant k_{moist} was then used in Eq. 4.3 to extrapolate the retention to 438,312 hours at 45 °C. The results indicated that the tensile strength retention would decline to approximately 0.11. By comparing this projected value with the observed retention of 0.57 at the initial exposure

period, the temperature conversion factor η_{ct} was determined to be 0.2. This factor represents the relative reduction in durability over the service life under the specified temperature conditions.

Moisture effects were evaluated by comparing the projected retention in moist and dry conditions. The experimental dry retention of the sample was reported as 0.8 after 20,160 hours [43], the corresponding degradation rate constant k_{dry} was calculated and used to project the long-term dry retention, which was found to be about 0.1185. From k_{moist} , the moist retention was estimated at 0.11. The ratio of these values yielded a moisture conversion factor of 0.96, indicating that moisture contributes causes a marginal additional reduction in tensile strength retention compared to dry conditions.

The nominal conversion factor, η_c from Eq. 2.1 would be 0.19. These conversion factors η_{ct} and η_{cm} provide a quantitative basis for incorporating temperature and moisture effects into durability predictions for FRP composites over extended service lifetimes.

6. CONCLUSION AND FUTURE WORK

6.1. Conclusions

This study aimed to advance the prediction of long-term durability for FRP composites in civil engineering by developing an integrated, data-driven modelling framework. Through the curation of a comprehensive dataset from experimental literature, detailed exploratory data analysis to uncover key degradation factors, and the application of machine learning models calibrated with Arrhenius methodologies, the research established a robust approach for forecasting mechanical property retention over a 50-year lifespan. This methodology bridges short-term experimental insights with long-term performance projections, enabling more accurate and efficient design practices that enhance the adoption of FRP materials in sustainable infrastructure.

The exploratory data analysis and modelling efforts in this study offer a comprehensive understanding of the degradation behaviour of FRP composites under various aging protocols, with a particular emphasis on tensile strength retention. The CatBoost Regressor emerged as the most effective model for predicting short-term degradation, surpassing other regression algorithms. For short durations, the CatBoost model accurately predicted tensile strength retention values, capturing minimal initial degradation. Despite the CatBoost model's robust predictive capabilities for short-term degradation and the polynomial model's improved accuracy post-corrections, limitations in the study design, including dataset heterogeneity and reliance on static tensile testing, necessitate cautious interpretation. The Arrhenius framework's moderate performance and its inconsistent predictions across retention ranges indicate challenges in modelling multifaceted degradation processes using traditional methods, particularly with limited data.

The practical implications of these findings are significant for industries reliant on durable composites, such as aerospace, marine, and renewable energy. The refined polynomial model and machine learning insights enable optimized material selection and laminate design, enhancing resistance to hygrothermal degradation and extending service life in applications of composites.

The findings of this study collectively address the primary research objectives, which encompass the development of an accessible predictive tool for assessing material strength retention, the quantification of key variables influencing degradation trajectories, and the

evaluation of model performance under real-world dataset constraints. This research contributes to a deeper understanding of long-term composite material behaviour, highlighting the potential for customized aging protocols to optimize lifecycle performance across critical applications, including aerospace and renewable energy infrastructure.

6.2.Recommendations for Future Research

Building upon the foundations established in this thesis, future research should prioritize expanding the dataset to encompass a broader spectrum of composite systems and aging conditions, thereby addressing the current limitations imposed by data heterogeneity and scope. Standardizing data collection across sources, potentially through collaborative databases, would reduce heterogeneity and enhance preprocessing robustness, as advocated in reviews of polymeric lifetime prediction techniques. Furthermore, exploring hybrid datasets that combine laboratory results with field exposure data would improve model generalizability, allowing for validations against real-service conditions where factors such as UV radiation or mechanical fatigue interplay with hygrothermal stressors.

Modelling enhancements are recommended to incorporate non-linear or adaptive corrections, such as through neural networks that capture complex interactions between fibre content and temperature, potentially surpassing the linearity assumptions of the current. Embedding physics-based constraints, like Arrhenius kinetics, into machine learning architectures would yield mechanistically informed predictions, improving uncertainty handling. Extending the model to encompass multi-property forecasts, would facilitate holistic durability metrics, informed by standards like CEN/TS 19101:2022 for informed design decisions. To bridge the gap between modelling and practical deployment, experimental validation campaigns are recommended, focusing on controlled aging trials with varied composite architectures to test the model's forecasts empirically. These steps would propel the field toward more versatile and impactful durability solutions.

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