

Data-Driven Prediction of The Bond Coefficient Between FRP Bars and Concrete

Nadia Nassif, M. Talha Junaid, Salah Altoubat, Mohamed
Maalej, and Samer Barakat



THE WORLD'S GATHERING PLACE FOR ADVANCING CONCRETE



Introduction

Fiber-reinforced polymer (FRP) bars are a type of reinforcing material used in construction to improve the structural performance and stability of concrete structures.

FRPs main benefits are:

- Corrosion resistance,
- High strength, and
- Low weight;



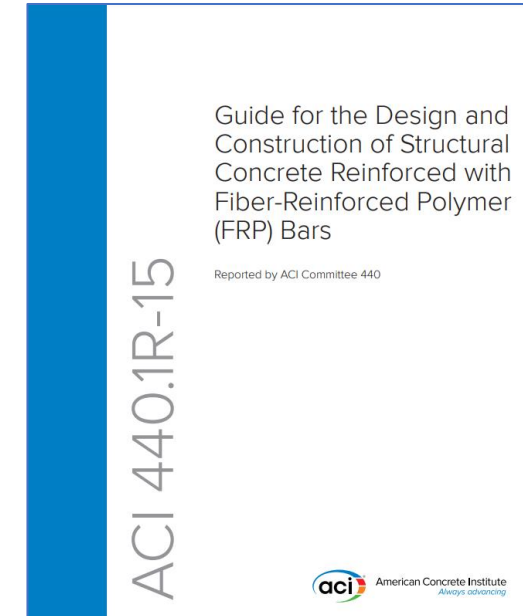
Sammen et al. (2019)

Background

With an aim to regulate the use of FRP as reinforcement in concrete structures,

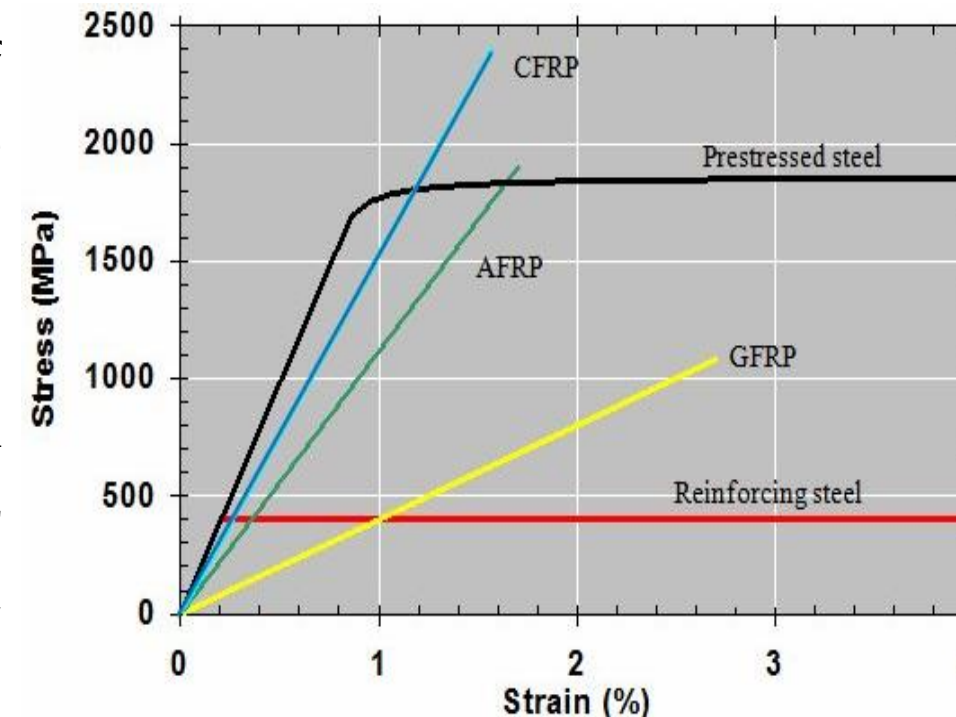
- American Concrete Institute (ACI) ACI 440.1R-15
- Canadian Standards Association (CSA) CSA S806-12

However, these guidelines are under continuous development following the recent advancements in the FRP field, in particular the durability and serviceability considerations of FRP concrete elements.



Background

- Serviceability requirements often control the design of FRP reinforced concrete flexural members due to the lower modulus of elasticity of FRP than of steel.
- ACI-440.1R crack control provisions for FRP-reinforced concrete mimic those from ACI-318, but with the addition of a bond-dependent coefficient (k_b), to account for differences in bond between FRP-concrete from steel-concrete.



$$w_c = 2 \frac{f_s}{E_s} \beta \sqrt{d_c^2 + \left(\frac{s}{2}\right)^2}$$

ACI-318 for steel reinforced concrete

$$w = 2 \frac{f_f}{E_f} \beta k_b \sqrt{d_{c+}^2 + \left(\frac{s}{2}\right)^2}$$

ACI-440.1R for FRP reinforced concrete

Background

An ACI Standard
An ANSI Standard

Building Code Requirements
for Structural Concrete
Reinforced with Glass Fiber-
Reinforced Polymer (GFRP)
Bars—Code and Commentary

Reported by ACI Committee 440

ACI CODE-440.11-22



24.3.2.3 The bond factor for GFRP reinforcing bars k_b shall be taken as 1.35.

***R24.3.2.3** The bond factor k_b is a coefficient that accounts for the degree of bond between the GFRP bar and the surrounding concrete. Shield et al. (2019) found k_b values varied between 0.69 and 1.61 based on an examination of available crack width data in the literature. A k_b value of 1.35 was selected so that the crack widths would be no larger than 0.028 in. approximately 70% of the time for all GFRP bar surface types.*

$$w = 2 \frac{f_f}{E_f} \beta k_b \sqrt{d_{c+}^2 \left(\frac{s}{2}\right)^2}$$

where

w = crack width

f_f = stress in FRP reinforcement, MPa

E_f = modulus of elasticity of FRP bar, MPa

β = ratio of distance from neutral axis to extreme tension fiber to distance from neutral axis to center of tensile reinforcement

k_b = bond coefficient

d_c = thickness of concrete cover measure from the extreme tension fiber to center of bar, mm

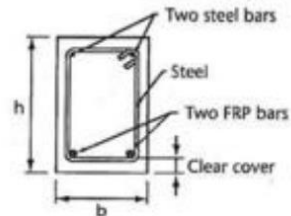
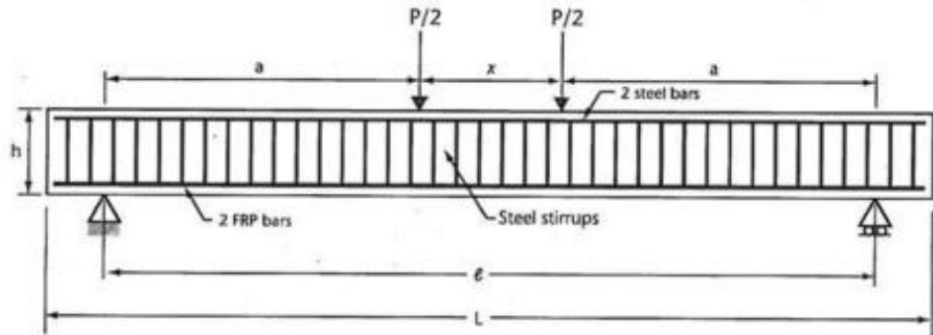
s = longitudinal FRP bar spacing, mm

Background on k_b test

© Canadian Standards Association

Design and construction of building structures with fibre-reinforced polymers

Annex S (normative) Test method for determining the bond-dependent coefficient of FRP rods



CSA
STANDARDS

5806-12
(reaffirmed 2017)

Design and construction of building structures with fibre-reinforced polymers

S.4.2

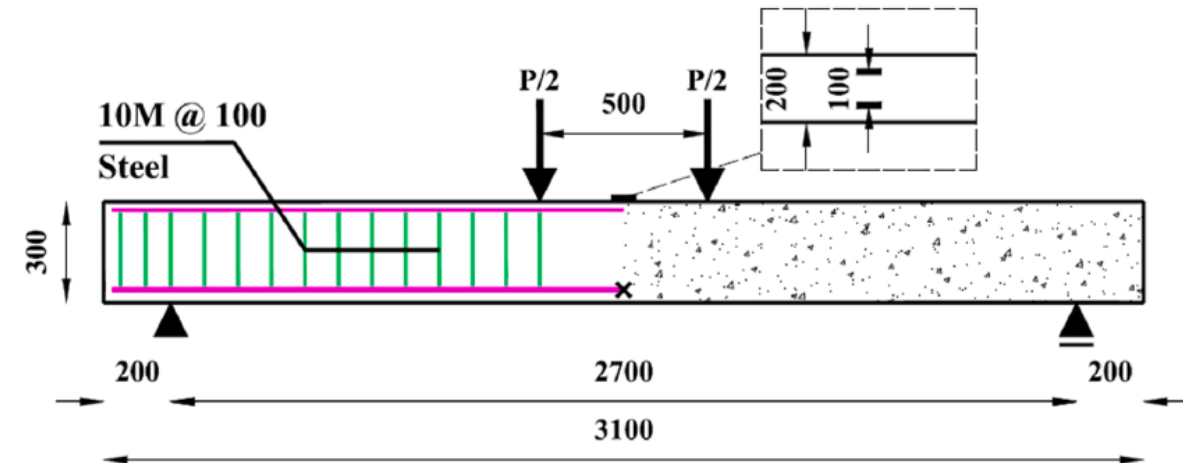
Beams dimensions should be close to $L = 3000$ mm, $b = 200$ mm, $h = 300$ mm.

S.4.12

FRP bars strain at mid-span should be measured with a minimum of two strain gages on each bar. Strain gages may be placed 10 mm apart from the centre line of the beam.

Literature review

- Mehany et al., (2022) studied the cracking behavior of 15 concrete beams reinforced with glass- and basalt-FRP (GFRP and BFRP) bars and evaluated the k_b values
 - Minimal difference in k_b , for different bars surface (sand-coated or grooved), recommended using 0.9-1.1 k_b for both surfaces

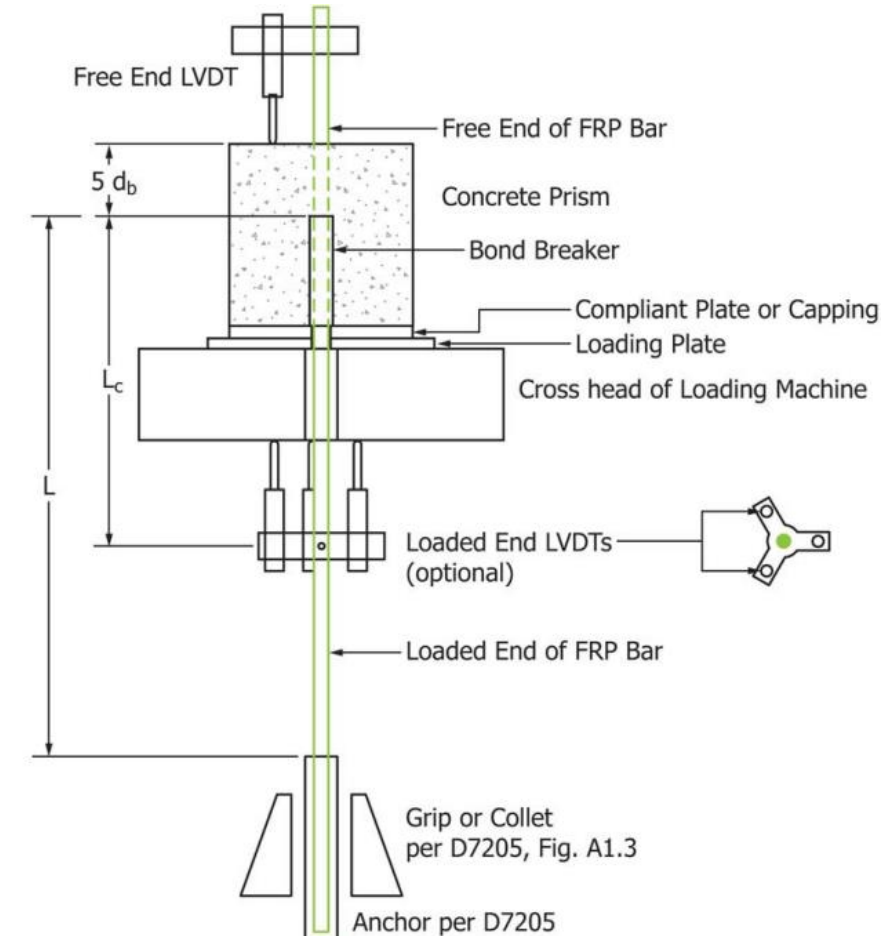


Beam ID	ACI 440X-XX [41]	Beam ID	ACI 440X-XX [41]
LS-GH-3#5	1.03	LS-GS-4#6	0.94
LS-GH-2#5	0.94	LS-GS-3#6	0.89
LS-BH-4#5	0.94	LS-GS-3#5	1.02
LS-BH-3#5	1.10	LS-GS-2#5	0.96
LS-BH-2#5	0.87	LS-BS-4#6	0.79
Overall	0.98 ± 0.09	LS-BS-3#6	0.81
Average		LS-BS-2#6	0.81
		Overall	0.89 ± 0.09
		Average	
	Sand-coated		Grooved

GFRP (G) and BFRP (B) bars. X#Y: X is the number of bars and Y is the number of FRP bars

Literature review

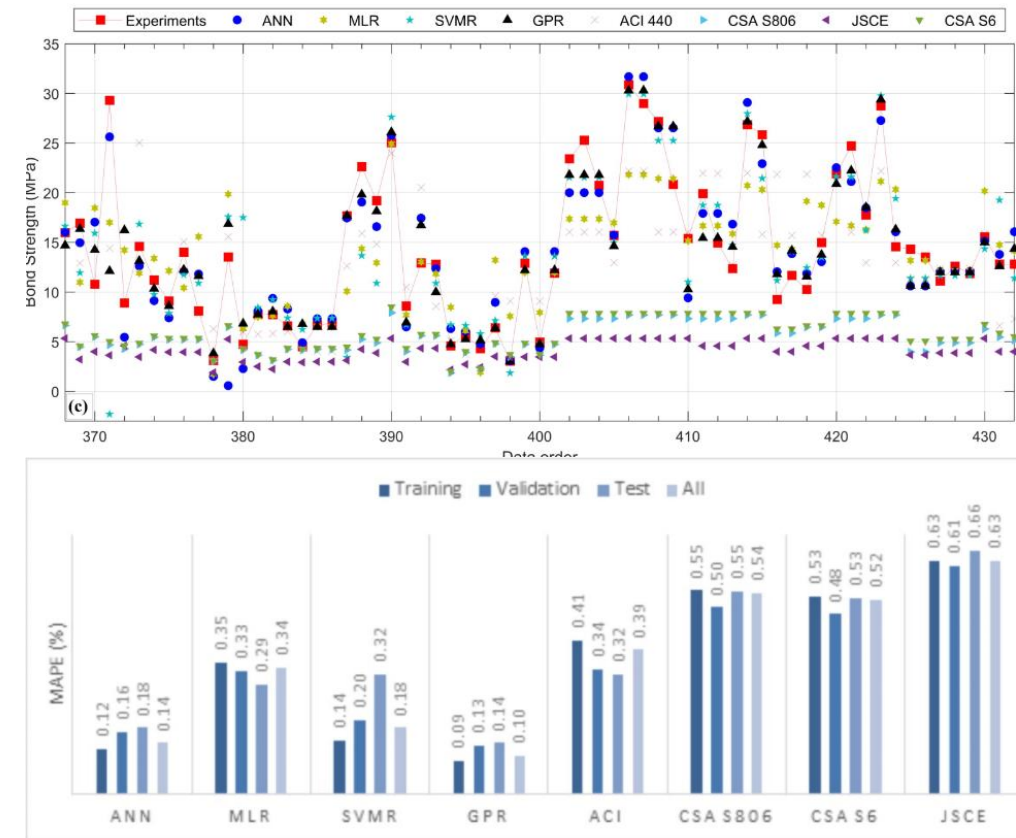
- Despite the attempts of previous studies to evaluate k_b from large-scale testing, minimal efforts were directed towards relating k_b to other FRP-concrete bond relations through more sustainable testing schemes.
- One of well-established FRP-concrete bonding tests that quantifies the bond strength (τ_u) for FRP-concrete bond is the FRP pull-out test (ASTM D7913) which is, relatively, a simpler standard test method compared to k_b large-scale testing.



(ASTM D7913)

Literature review

- Recent studies have utilized Machine Learning (ML) techniques to model bond strength of FRP-concrete. have shown relatively better prediction accuracy when compared to ACI440.1R-15 bond-strength formulation
- Yan et al. and Golafshani et al. utilized artificial neural network (ANN) ML technique, while Basaran et al. tested several ML techniques including ANN, Gaussian process regression (GPR) and regression trees. Barsan et al. stated that using GPR will better mimic the expected mechanical behaviour of FRP-concrete system.



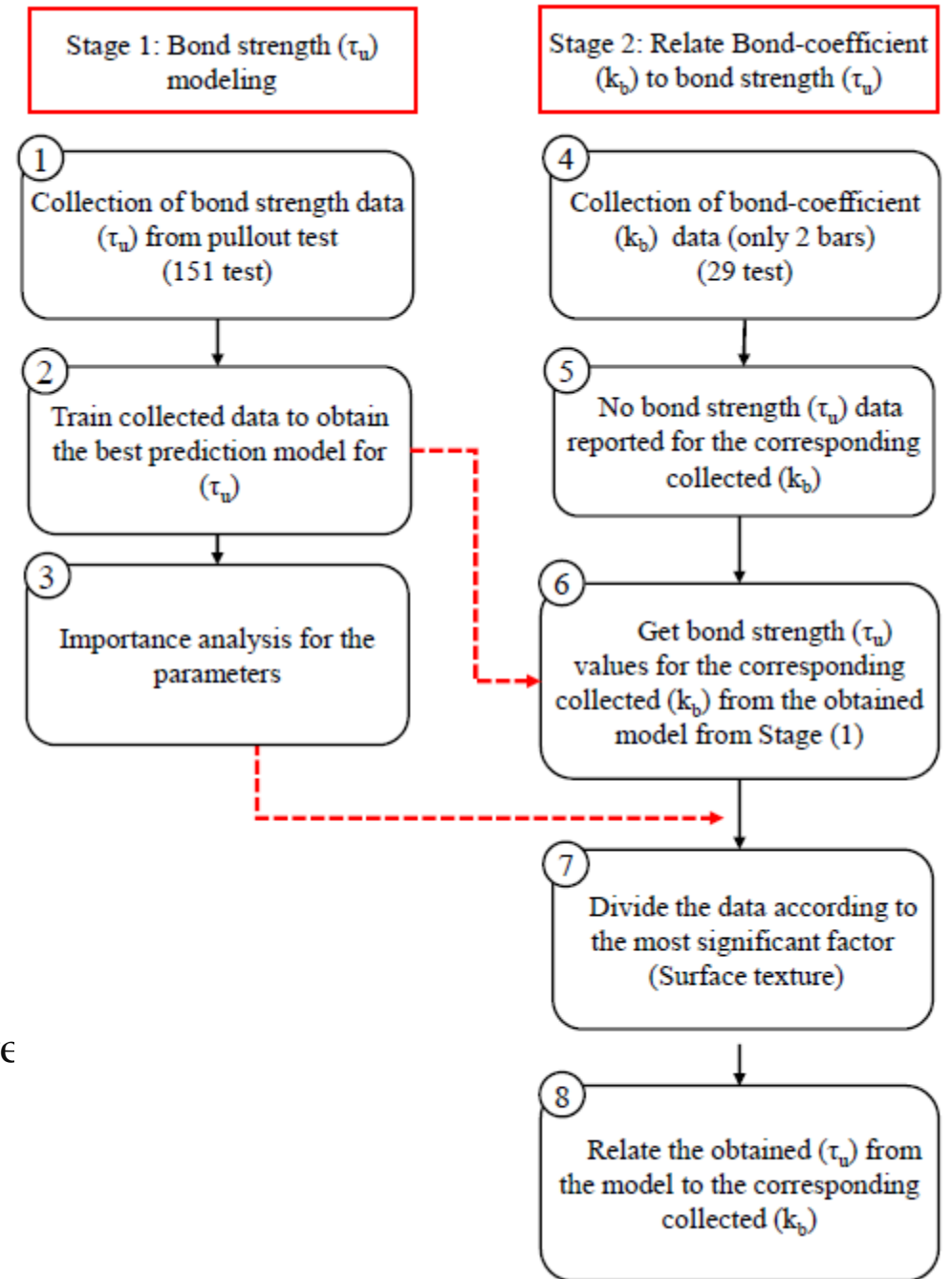
Barsan et al. 2021

Research Gap and Objective

- In light of discussed literature, the employment of ML was limited to understanding the effect of parameters on τ_u .
- Due to the complex nature of the bond behaviour, it has been challenging to establish a correlation between k_b and τ_u .
- This study aims to relate the experimental k_b obtained from large-scale testing to a relatively simpler τ_u obtained from smaller scale FRP pull-out test.
- The relation was established utilizing data-collection for both tests, then applying three machine learning techniques in an attempt to understand the complex bond behaviour at varying FRP and concrete properties.

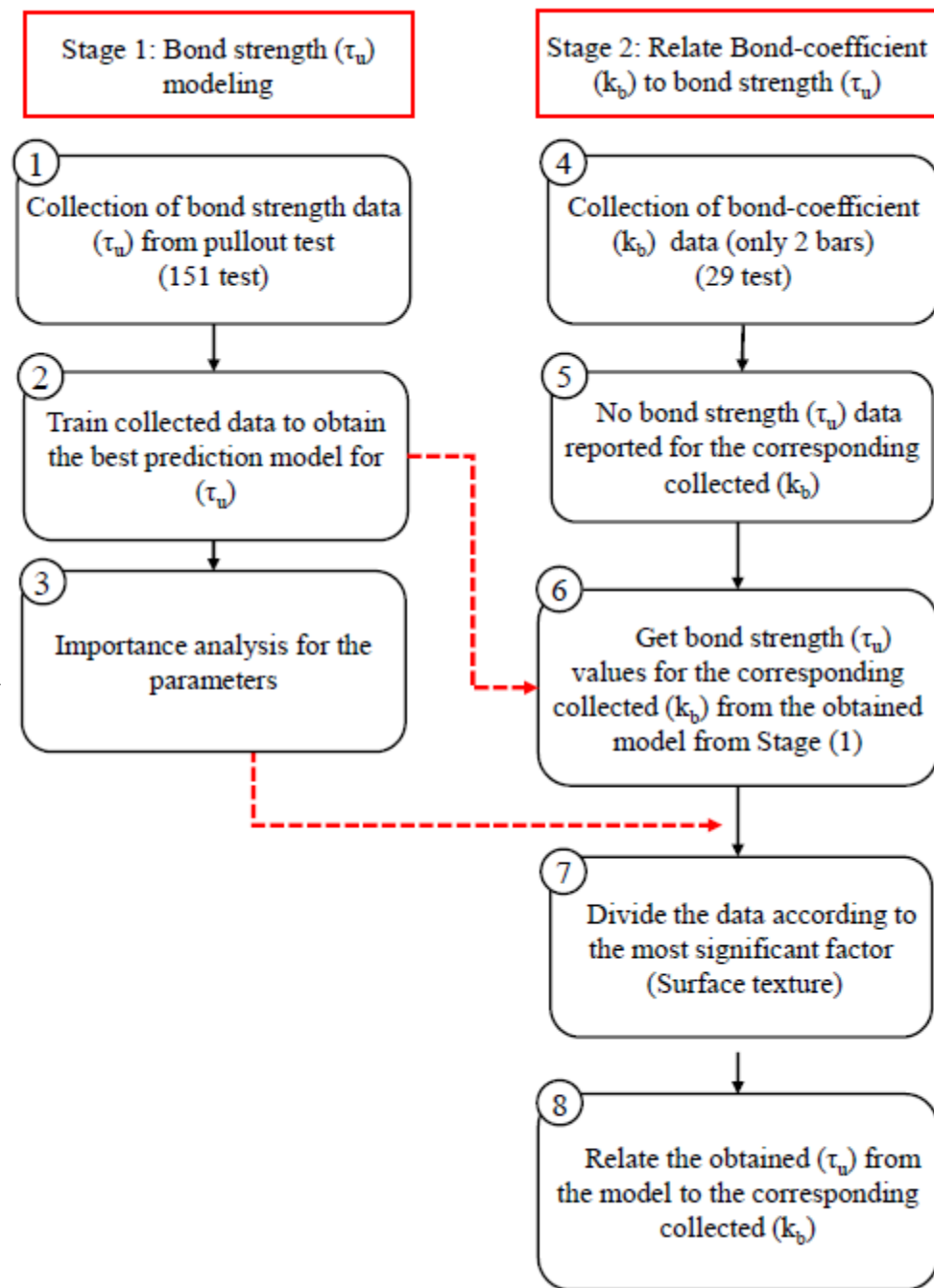
Methodology

- Two-Stage Approach to Understanding FRP-Concrete Bond Strength
- **Stage 1: Data Collection and Model Training**
 - Collected a dataset of 151 τ_u (bond strength) tests.
 - Utilized three machine learning models for prediction: Ensembled Trees (ET), Artificial Neural Network (ANN), and Gaussian Process Regression (GPR).
 - Dataset split: 70% training, 15% validation (to avoid overfitting), and 15% testing (for generalization).
 - Identified the best model based on the highest R^2 and low RMSE for further analysis.



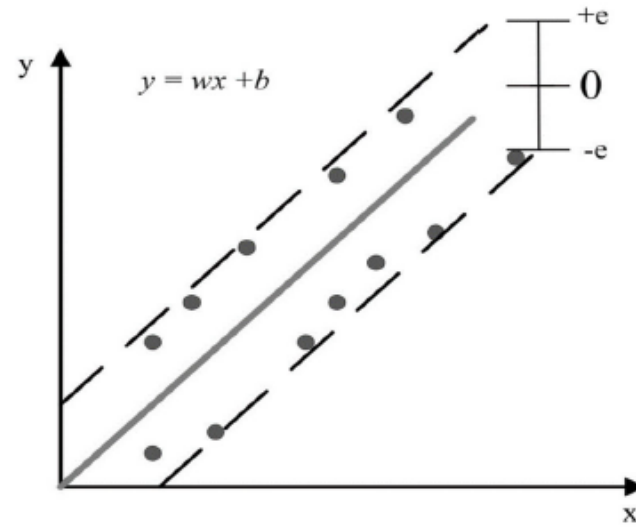
Methodology

- **Stage 2: Bridging τ_u and k_b**
- Gathered data from 29 large-scale k_b tests, where traditional studies often lack corresponding τ_u data.
- Applied the best-performing model from Stage 1 to estimate τ_u values for the collected k_b dataset.
- Conducted significance analysis to identify the most impactful variables affecting τ_u .

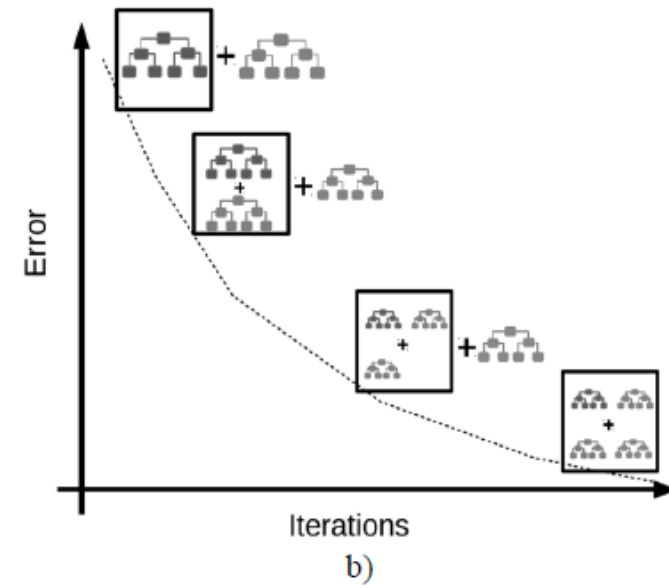


Methodology

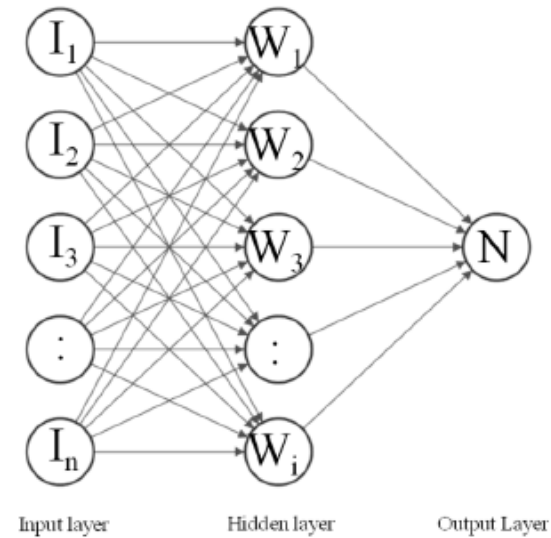
- A general description of ML models used a) GPR, b) ET, and c) ANN



a)



b)



Input layer

Hidden layer

Output Layer

c)

Methodology

Table 1— Statistics of 151 FRP pull out test for τ_u [11-25].

	D (mm)	fc' (MPa)	L (mm)	c/D (-)	τ_u (MPa)
Min	6.0	32.0	20.0	4.2	0.4
Max	12.7	62.9	784.0	12.5	16.2
Average	8.5	42.6	177.0	8.8	9.2
q1	8.0	33.7	40.0	5.8	3.2
q2	8.5	40.0	47.5	7.4	8.3
q3	9.5	50.7	249.5	12.0	15.4
Range	6.7	30.9	764.0	8.3	21.2

Table 2— Statistics of 29 large-scale FRP reinforced beams for k_b [1-4,10].

	D (mm)	fc' (MPa)	L (mm)	c/D (-)	k_b (-)
Min	8.0	29.0	50.0	1.97	0.49
Max	12.7	78.0	500.0	6.25	1.55
Average	16.1	41.6	265.8	3.38	1.00
q1	4.6	13.7	100.0	1.02	0.26
q2	12.7	32.0	225.0	2.62	0.80
q3	15.9	37.0	350.0	3.14	1.00
Range	19.1	42.5	450.0	3.94	1.12

Results and Discussion

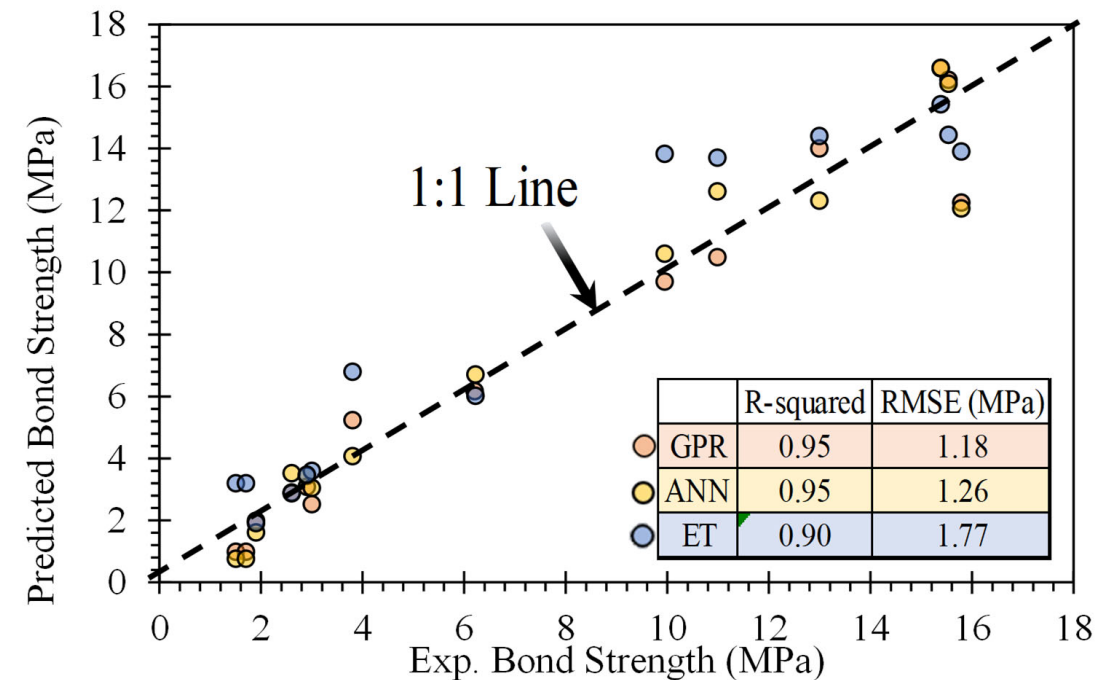
- **Gaussian Process Regression (GPR)**

Outperforms:

Achieved the highest accuracy with $R^2 = 0.95$ and the lowest RMSE = 1.18 MPa, surpassing ANN and ET models.

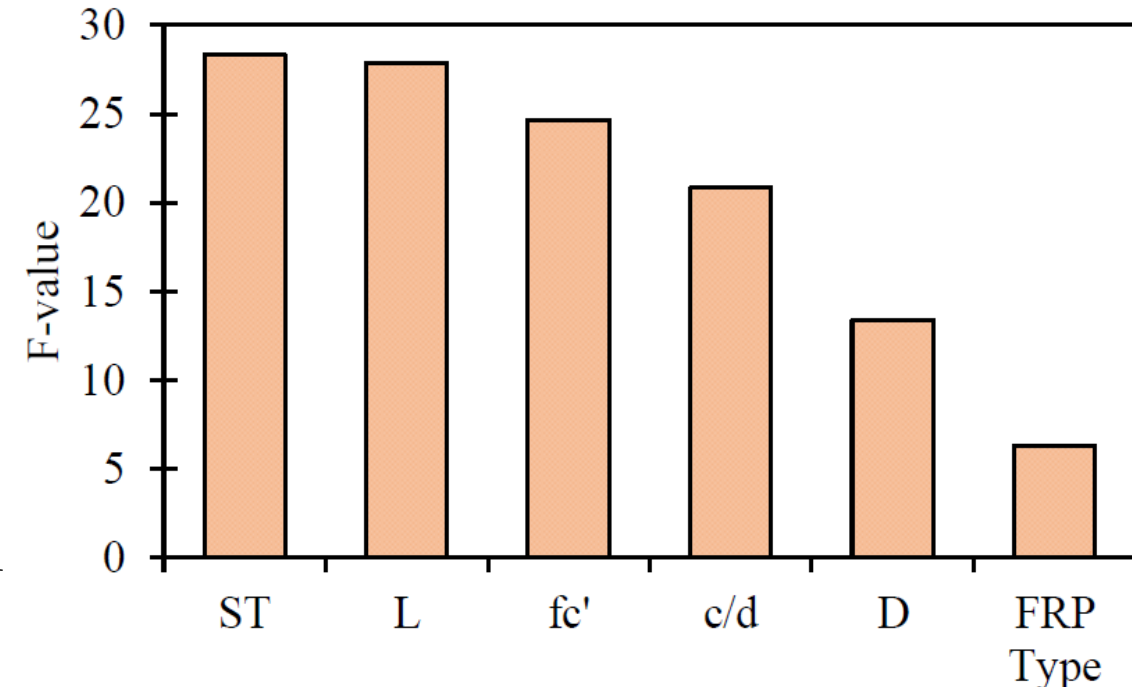
- **Comparative Analysis:**

GPR and ANN showed conservative predictions with GPR having a 28.9% lower RMSE than ANN, highlighting its superior predictive capability for τ .



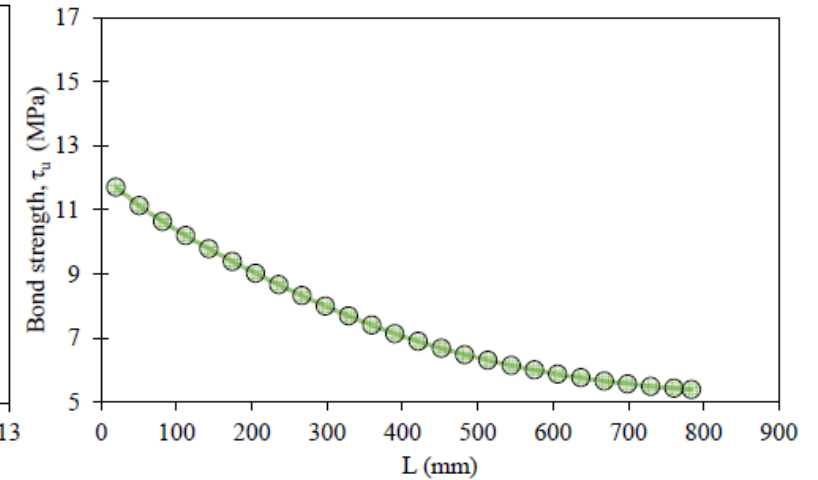
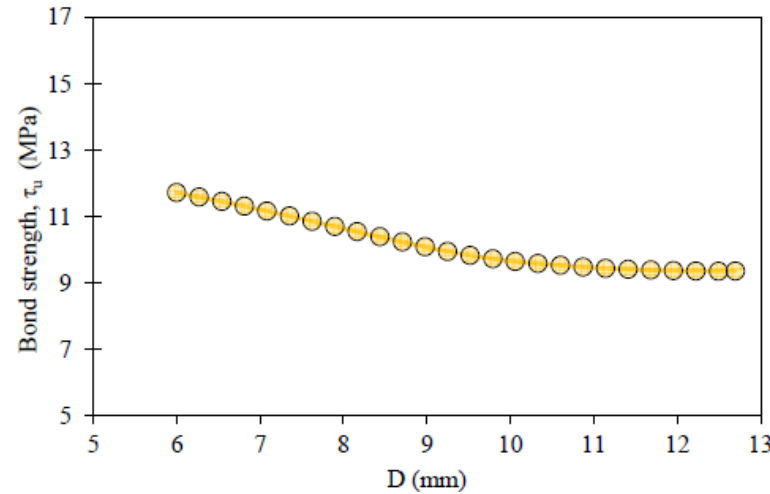
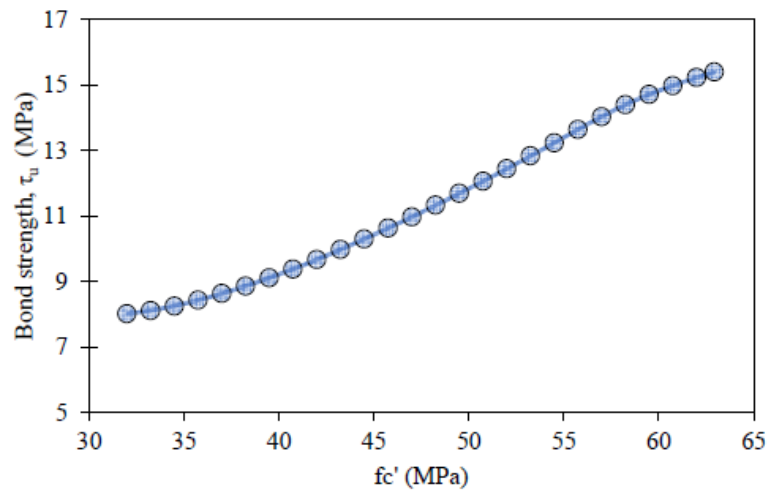
Results and Discussion

- **Key Variables Impacting τ :**
 - Surface Texture (ST) and Anchorage Length (L) were found to have the most significant impact on τ .
 - FRP Type had the least impact, suggesting other factors play more critical roles in bond behavior.



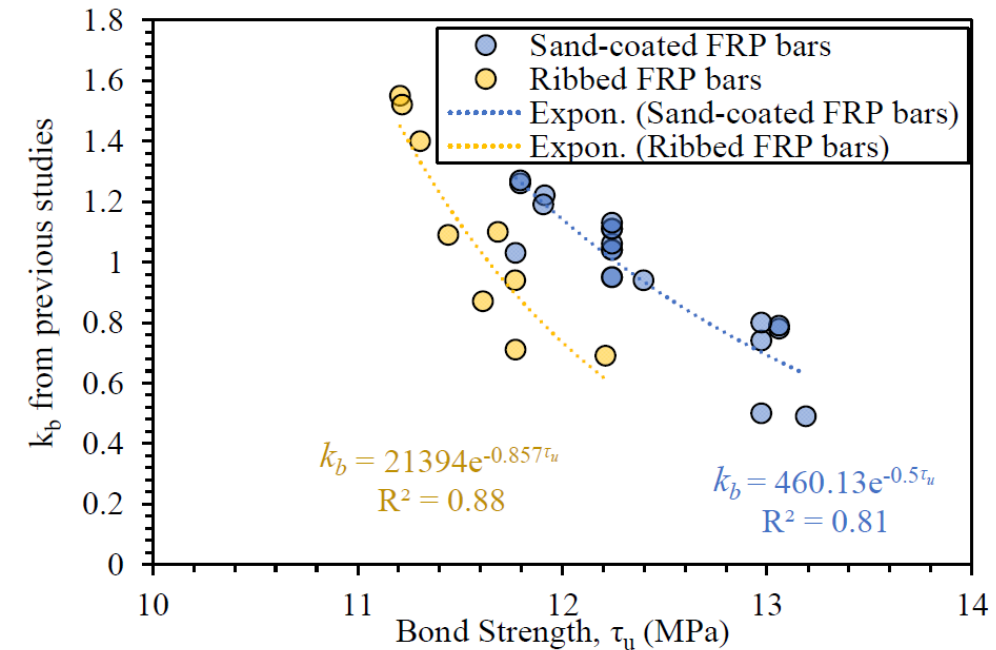
Results and Discussion

- **Model Robustness:**
 - Conducted sensitivity analysis confirming the model's robustness; τ_u predictions remained accurate across varied input conditions.



Results and Discussion

- **Strong Relation Established:**
 - related τ_u to k_b , especially for sand-coated and ribbed bars, with $R^2 > 0.80$, indicating a robust correlation.
- **Implications for FRP-Concrete Bonding:**
 - Increased τ_u correlates with reduced k_b , enhancing FRP-concrete bond performance.
 - The findings underscore the potential of using simpler pull-out tests to predict complex k_b values accurately, guided by ML models.



SUMMARY AND CONCLUDING REMARKS

- Developed a machine learning model to establish a relationship between the bond-dependent coefficient (k_b) from large-scale tests and bond strength (τ_u) from simpler pull-out tests for FRP-reinforced concrete.
- Identified surface texture (ST) as the most significant variable affecting the bond strength, leading to a robust correlation between k_b and τ_u with $R^2 > 0.8$ across various surface textures and fiber types.
- Emphasized the need for expanding the dataset for future research to explore beyond the current study's limitations and enhance the model's applicability and accuracy.
- Highlighted the importance of standardizing testing protocols for FRP-concrete bond strength to ensure consistency across studies and contribute to the development of structural codes.

Thanks for listening