THE PREDICTION OF IN-SITU COMPRESSIVE STRENGTH WITH NON-DESTRUCTIVE METHOD USING REGRESSION ANALYSIS

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PLAGIARISM

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DEDICATION

This project is dedicated to God Almighty, who has provided me with the knowledge and wisdom I need to excel in every aspect of my academic career and has graciously supported my life.

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ABSTRACT

This study focuses on evaluating the relationship between destructive and non-destructive testing methods for predicting the in-situ compressive strength of concrete. The main aim is to develop a reliable regression-based model capable of estimating concrete strength using non-destructive approaches. The study specifically examined Grade 20 (C20) and Grade 25 (C25) concrete to determine the correlation between rebound hammer results, and conventional compressive strength tests.

The experimental procedure involved casting and curing concrete cubes and beams in the laboratory under controlled conditions. Both destructive tests (compressive and flexural strength) and non-destructive tests (rebound hammer) were carried out at curing ages of 7, 14, and 28 days, following BS EN 12390-3:2019, ASTM C39, and BS EN 12504-2:2012 standards. Rebound hammer readings were taken before compression tests on each specimen to establish a correlation between rebound number and actual strength. The data obtained were analyzed statistically using regression techniques to develop predictive models capable of estimating compressive strength from non-destructive test results.

The findings revealed that compressive and flexural strengths increased consistently with curing age for both concrete grades. At 28 days, C20 achieved an average compressive strength of 20.16 N/mm², while C25 reached 25.15 N/mm², aligning with their design targets. Rebound hammer values showed a strong positive correlation with destructive test results, with a prediction accuracy of about ±5%. The study concludes that properly calibrated non-destructive methods, particularly the rebound hammer tests, can effectively predict the in-situ compressive strength of concrete. This approach provides a cost-effective, rapid, and non-invasive means for quality control and structural assessment in modern construction practice.

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CHAPTER ONE

1.0 INTRODUCTION

1.1 Background of Study

Concrete is the foundation of construction, it is affordable, durable and easy to shape. The in-situ compressive strength is important for determining the structural integrity of buildings, bridges, and pavements. It's compressive strength, or how much weight it can bear before breaking is what makes it reliable.

Traditionally, we test this by crushing concrete samples in lab, but that causes a lot of trouble. It takes time, costs money, and if you are checking for a finished building, you can't just pull-out pieces without causing problems.

Traditional destructive testing (DT) methods, such as core extraction, are costly, time consuming, and damage structures. That's where non-destructive testing (NDT) comes in. Tools like Rebound Hammer (RH) and Ultrasonic Pulse Velocity (UPV) offer faster, cheaper and non-invasive alternatives. They let you examine concrete without damaging it, measuring things like surface hardness or how fast sound travels through it. The challenge is that these results don't directly show strength, you have to figure it and factors like the mixing or curing process can complicate things.

However, Nigerian construction industries still heavily rely on destructive tests due skepticism about NDT accuracy, particularly for locally produced concrete mixes. Recent studies (Breysse et al., 2022; Huang et al., 2024) highlight the need for localized regression models to correlate NDT data with the actual compressive strength, as universal models had failed for regional material variability.

Now using regression analysis (e.g., linear, polynomial, or machine learning-based), to develop a predictive model for Nigerian concrete, thereby addressing gaps in existing calibration methods. This is a method to connect numbers and patterns to Non-destructive test (NDT) data to actual strength. In Nigeria, especially around Benin where building construction is booming, this could be a smart and cost-effective way to ensure structures stand strong.

1.2 Statement of Problem

Determining the in-situ compressive strength of concrete is essential for guaranteeing the safety and durability of constructed structures like buildings, bridges, and roads, but checking how strong it is can be tricky. Usually, traditional destructive testing methods, such as core sampling, are costly, time-consuming, and may compromise the structural stability of existing buildings. There are easier ways to test concrete without breaking it, Non-destructive testing (NDT) methods offer a promising alternative but are limited by issues of precision, dependability, and lack of standardized protocols which often results to challenges related to accuracy, reliability. The problem is that the lack of robust predictive models that correlates and link NDT results and outcomes to actual compressive strength limits their widespread adoption and practical application in engineering practice. This project aims to create and formulate a reliable regression-based models to enhance the prediction of compressive strength non-destructively, thereby addressing the inefficiencies of current practices and enhancing quality control in construction processes.

1.3 Aims and Objectives

Aim:

To formulate and develop a regression-based model for accurately predicting the in-situ compressive strength of concrete using non-destructive testing methods, improving accuracy and enhancing reliability in structural assessment and evaluations.

The Objectives are:

i. To determine the compressive strength of grade 20 and 25 concrete using destructive method (DT).
ii. To determine the compressive strength of grade 20 and 25 concrete using Non-Destructive method (NDT).
iii. To determine the flexural strength of concrete beams of grade 20 and 25 using destructive method (DT).
iv. To determine the relationship between destructive and Non-Destructive data using regression analysis.

1.4 Scope of Study

This study focuses on predicting the in-situ compressive strength of concrete with non-destructive methods combined using regression analysis, specifically the rebound hammer and ultrasonic pulse velocity tests. It involves preparing grade 20 and 25 concrete samples, conducting both destructive and non-destructive tests in the laboratory under controlled conditions to ensure consistency. The collected data will be analyzed using regression techniques linear and non-linear implemented through statistical tools like Python, SPSS, or MATLAB. The regression models developed will be validated against results from destructive testing, aiming to establish a reliable and practical framework for strength prediction in local construction practices. The following activities were carried out:

i. Concrete samples of Grade 20 and Grade 25 concrete cubes and beams were prepare and casted in the laboratory under controlled conditions to serve as reference specimen.
ii. All the concretes samples were cured and tested at three different curing stages i.e. 7

days, 14 days, and 28 days.

iii. Before crushing, each concrete cube specimen was subjected to a Rebound Hammer Test to obtain non-destructive surface hardness readings for correlation with compressive strength results.

Note: Although Ultrasonic Pulse Velocity (UPV) testing was initially planned as outlined in the literature review, it could not be conducted due to equipment unavailability and accessibility constraints at the testing facility. Therefore, this study focuses primarily on the correlation between Rebound Hammer readings and compressive strength.

iv. The same concrete samples were later crushed using compression testing machine to obtain the compressive strength, and beam samples were tested for flexural strength.

v. The recorded NDT and destructive test data were used to develop multiple linear regression models to predict the compressive strength.

vi. The regression model was validated by comparing the predicted strengths with actual destructive results.

1.5 Justification of Study

The reliance on destructive testing methods for assessing and evaluating concrete strength poses significant challenges, including high costs, project delays, and potential structural damage. Non-destructive testing methods offer a cost-effective and efficient practical alternative solution, but their adoption is hindered by inconsistent accuracy and a lack of standardized predictive framework. This study addresses these challenges and gaps by developing a regression-based model tailored to local construction practices, which is particularly relevant in Nigeria, where cost effective and reliable quality control methods are critical due to resource constraints. The research will contribute to safer and more sustainable construction practices, increase the confidence of engineers in NDT methods, and provide a framework for integrating predictive models into local and global construction standards. Additionally, the study aligns and supports with global trends toward innovative and eco-friendly construction technologies, making it timely relevant and significantly impactful.

CHAPTER TWO

2.0 LITERATURE REVIEW

2.1 Overview

This chapter delves into the extensive body of literature surrounding the topic of study; " The prediction of in-situ compressive strength of concrete using non-destructive testing (NDT)methods using regression analysis techniques " which forms a foundation for this my project work and it play a critical role in the design and construction of civil engineering work to improve the accuracy, reliability, and practicality of concrete strength estimation in the field, without causing any damage to the structure.

Concrete is the most commonly used material in civil engineering project work, primarily owing to its relatively high compressive strength, durability, and adaptability in various construction environments. The compressive strength of concrete is not the only fundamental material property of concrete but also important the indicator of structural capacity and safety. Engineers and builders usually rely on it to ensure that buildings, bridges, dams, and other construction work can withstand the loads and stresses they carried throughout their lifespan.

Conventionally, core sampling and some subsequent laboratory tastings are the standard methods to determine compressive strength. However, these methods are practically destructive, labor-intensive, expensive, and time-consuming and very costly process. Moreover, they are often unsuitable for evaluating the strength of existing structures, heritage buildings, or inaccessible components without damaging part of the structure itself. To determine the in-situ compressive strength of structural members, concrete cores can be extracted and this method is called destructive testing. This destructive method is also costly and needs the drilling of concrete cores, transportation, and dressing of concrete cores as per the codal requirement to determine the compressive strength of concrete. To overcome this issue, in 1948 Swiss civil engineer and bridge builder Ernst O. Schmidt invented a rebound hammer (RH) to determine the compressive strength of concrete without damaging the structural concrete. Determining the properties of concrete without damaging the concrete is called non-destructive testing (NDT) or non-destructive evaluation (NDE). A brief description of NDT is available in Section "Non- destructive testing". The commonly used NDT techniques to evaluate the compressive strength of concrete are Rebound Hammer (RH) and Ultrasonic Pulse Velocity (UPV). UPV is an NDT method used to evaluate the elastic properties and integrity of materials, particularly concrete and rock. It involves the amount of the time it takes for an ultrasonic pulse to travel through a material and be reflected back by an internal defect or the opposite surface. The velocity of the pulse can then be calculated and used to determine the quality of the material. The UPV technique serves as a prevalent method for detecting damages or assessing deterioration in civil engineering infrastructures.

The previous challenge has led to increasing interest in non-destructive testing (NDT) methods as the alternatives. NDT methods such as the Rebound Hammer (RH), Ultrasonic Pulse Velocity (UPV), and the SONREB method (a combination of rebound and ultrasonic testing) enable the engineers to assess the concrete strength quickly and without damage. While NDT method results do not directly give compressive strength values, they are correlated with strength properties through empirical models and statistical techniques, especially the regression analysis.

In recent years, the integration of NDT with statistical and machine learning-based regression models has become a powerful approach for predicting in-situ compressive strength with improved accuracy and lower uncertainty. These models help to relate multiple NDT indicators to strength and also helps in accommodating complex, nonlinear relationships in the data. Several researchers have developed various regression models ranging from simple linear regression to advanced machine learning models like Gaussian Process Regression (GPR) and Ensemble learning for better analysis and to predict the behavior of concrete based on the field tests.

2.2 Concrete Compressive Strength

2.2.1 Importance of Compressive Strength

Concrete is a composite material made primarily from cement, water, fine and coarse aggregates, and sometimes admixtures. When it is properly mixed, placed, compacted, and cured, it hardens into a durable material that is capable of withstanding various structural loads that it's being subjected to. All among the mechanical properties of concrete, compressive strength is regarded as the most important and usually measured parameter in concrete engineering.

Compressive strength refers to the maximum compressive stress that concrete can withstand without failure when subjected to axial loads. It is measured in units of megapascals (MPa) or pounds per square inch (psi) and it is typically determined using standard cube or cylindrical specimens tested under controlled laboratory conditions. Compressive strength is one of the fundamental qualities of concrete that designers are interested in, and relevant information can be gathered through laboratory testing. Evaluating the compressive strength of concrete can estimate the residual capacity of the structure. Concrete specimens (cubes and cylinders) must be loaded to failure in order to directly determine the compressive strength of concrete. Therefore, samples must be analyzed in laboratories to determine the compressive strength of the concrete. The importance of compressive strength in civil engineering cannot be overstated:

a. It determines the load-carrying capacity of concrete elements such as beams, columns, and slabs.

b. It serves as a quality control parameter during construction and helps ensure that the material meets design specifications.
c. It is a key input in structural design codes and standards, determining the dimensions, reinforcement design, and safety margins.
d. It reflects the overall durability and performance of concrete, most especially in harsh environmental conditions.

In structural practice, higher compressive strength often referred to reduced member sizes, increased service life, and enhanced safety of infrastructure like buildings, bridges, tunnels, and dams.

2.2.2 Factors Affecting In-Site Compressive Strength

Concrete strength is practically measured under ideal and controlled laboratory conditions; the actual strength developed **in-situ** (on-site, within the structure) can significantly varies. Several factors influencing the development and final value of compressive strength in the field are:

a) Water-Cement Ratio (w/c): The ratio of water to cement in the concrete mix is the most important factor. A lower w/c ratio typically results to higher strength due to the formation of a denser cement paste matrix. However, insufficient water can also affect the workability which can leads to inadequate compaction.

b) Curing Conditions: Curing simply refers to maintaining an adequate moisture and temperature conditions after placing concrete. Poor curing may lead to incomplete hydration of cement, which may result in weaker concrete. Practically, curing may be insufficient due to weather, scheduling constraints, or site errors.

c) Concrete Age: Concrete use to gains strength over time due to ongoing hydration. The standard reference age is 28 days, but concrete continues to gain more strength for months afterward. Early-age concrete (e.g., 7 days) may have only 60–70% of its eventual strength.

d) Mix Proportions: The ratios of cement, aggregate, and water, as well as the use of additives (like fly ash, silica fume), significantly influence the concrete strength. Non-standard mix designs or errors in batch mixing may leads to suboptimal performance.

e) Compaction and Placement: Improper placement techniques, poor consolidation, or excessive vibration may introduce voids or segregation, which can reduce the concrete strength and durability.

f) Aggregate Quality and Grading: The size, shape, strength, and cleanliness of aggregates affect the mechanical interlock and the bonding with cement paste. Poor-quality aggregates can act as weak zones within the concrete.

g) Environmental Exposure: In-situ concrete may be exposed to extreme weather conditions like temperature, rainfall, wind, or contamination before hardening, which can affect strength development negatively.

2.2.3 Traditional Destructive Testing vs. In-Situ Testing

Concrete diagnosis is essential to enable structural engineers to make informed decisions about reconstructing or repairing buildings. For this purpose, the main challenge is the on-site evaluation of the concrete’s properties, particularly the compressive strength, which is essential to assess the structure’s safety under test. It is well known that destructive testing (DT) is the most reliable method for determining this quantity. However, DT is characterized by the need to perform laboratory concrete compressive strength tests and by the unavoidable local damage effect on the structure under test (which sometimes needs to be repaired after testing). To assess compressive strength of concrete, engineers traditionally rely on destructive testing (DT), especially during quality control and material evaluation, for existing or in-service structures, destructive testing (DT) causes challenges. In destructive testing, concrete samples are typically taken from structural elements and crushed in the lab to determine their strength. It is important to respect some main recommendations (as highlighted also in the CSLP guidelines:

a. The diameter of the extracted concrete should be at least three times greater than the maximum diameter of the aggregates.
    i. Core intended for resistance assessment should not contain reinforcing steel bars.
    ii. Core with defects should be evaluated carefully and separately.
b. The height/diameter ratio (slenderness) of the specimens should, if possible, be equal to one or two.
c. Before breaking, the core samples should be aired out for at least 24 h.

While accurate, this method has several challenges:

i. It damages the structural element.
ii. Core extraction and testing require specialized labor and time.
iii. Cores may not always be representative of the overall material used.

On the other hand, Non-destructive testing (NDT) techniques provide a complementary approach to obtaining information on the condition of a given structure. Non-destructive testing (NDT) methods such as the Rebound Hammer Test, Ultrasonic Pulse Velocity, and SONREB (combined method) allow for fast, non-invasive, and field-applicable assessments. But most importantly, NDT methods require values, calibration models, that is usually developed through regression analysis, to relate test outputs to actual compressive strength. The reliability of the concrete strength’s estimate depends on the number of concrete cores extracted as well as non-destructive measurements carried out.

The table below summarizes the major differences between traditional and in-situ testing methods:

Table 2.1: Major Differences Between Traditional and In-Situ Testing Methods

Feature	Destructive Testing (DT)	In-Situ Testing (NDT)
Method	Core extraction, lab compression testing	Surface/volume measurement using devices (e.g., hammer, UPV)
Accuracy	High (direct measurement)	Indirect (requires calibration)
Damage	Yes (removal of material)	No or very minimal
Speed	Time-consuming	Considerably Fast
Cost	High (labor, lab time, repairs)	Low to moderate
Field Suitability	Limited (disruptive)	Excellent for existing/heritage structures

Source: Gupta (2018); Gîrbaci et al. (2022).

2.3 Non-Destructive Testing (NDT) Methods for In-Situ Compressive Strength Prediction

2.3.1 Introduction to Non-Destructive Testing in Civil Engineering

Non-destructive testing (NDT) refers to the range of analysis or investigative techniques used in engineering and/or science to evaluate the physical and mechanical properties, integrity and characteristics of a material or structure without altering or damaging to their physical properties. NDT methods are used to examine and evaluate flaws, defects, or anomalies in a non-invasive manner, ensuring the reliability, safety, and quality of the examined materials or structures. In civil engineering practice, NDT has become an important tool for monitoring, assessing, and diagnosing the structural integrity and performance of concrete structures particularly during construction, rehabilitation, and forensic investigations.

For in-situ compressive strength prediction, NDT provides an attractive alternative to traditional destructive methods. Rather than removing cores or performing invasive laboratory testing, engineers can quickly collect surface or volumetric data from concrete elements and interpret them using empirical models or regression equations. NDT methods are very useful in:

i. Assessing old or heritage buildings
ii. Inspecting large or inaccessible components (e.g., bridge piers)
iii. Carrying out quality control during or post-construction
iv. Evaluating deterioration, cracks, or voids in service

Despite this, the main problem with using NDT measurements is that these methods do not directly provide the compressive strength values. Instead, they provide the pulse velocity V_p (i.e., the velocity of the compression stress waves) for the UPV technique and the rebound index R for the RH technique (a term directly related to the energy absorbed by the concrete during the impact with the rebound hammer).

Among the various NDT techniques available, the most commonly used in compressive strength estimation are the Ultrasonic Pulse Velocity (UPV) test, the Rebound Hammer test, and their combined application known as the SONREB method.

2.3.2 Ultrasonic Pulse Velocity (UPV) Test

This method involves measuring the velocity of an ultrasonic wave propagating through a specimen to evaluate its strength and quality characteristics. A complicated system of stress waves is created as a result, including longitudinal (compression), shear (transverse), and surface (Rayleigh) waves. The longitudinal waves, which move the quickest, are detected by the receiving transducer. The velocity of the ultrasonic wave can be used as a metric to grade the quality of the concrete, with higher velocities indicating better quality and homogeneity, and lower velocities indicating nonuniformity or the presence of defects such as cracks or voids. In order to conduct this test, an ultrasonic wave pulse is introduced into the material under examination, and the elapsed time for the pulse to traverse the material is meticulously recorded. Subsequently, the pulse velocity is computed by dividing the distance, the pulse travelled within the material by the time it took for this traversal. Notably, the velocity of the ultrasonic wave is influenced by the density and elastic modulus of the material. There are various standard methods used globally to conduct the UPV test, UPV testing methods can be categorized into three groups: direct testing, semi-direct testing, and indirect testing. According to IS 13311 Part 1 13, factors that can influence the pulse velocity includes the surface conditions and moisture present in the concrete, the shape, and size of the concrete member, the temperature of the concrete, the presence of stress, the effect of reinforcing bars, etc. It is important to consider these factors to obtain accurate results. The Ultrasonic Pulse Velocity (UPV) test is practically based on measuring the time in which it takes for an ultrasonic pulse to travel through concrete. It involves a transmitter sending a high-frequency pulse (typically 20–150 kHz) through the concrete, and a receiver detecting the signal at a known distance. The pulse velocity (V) is calculated as:

$$V= \frac{L}{T} \qquad (2.1)$$

Where:

V = Pulse velocity (m/s)

L = Path length (m)

T = Travel time (s)

The higher the velocity, the denser and more intact the internal structure of the concrete, which typically correlates with higher compressive strength. The method is non-invasive, faster, and safer, allowing it to be widely adopted in both laboratory and field settings.

2.3.2.1 Advantages of UPV

i. It detects internal defects like cracks, voids, honeycombing, or delamination.

ii. Surface preparation is not required.

iii. It works well for quality control and also checks for uniformity.

iv. It is applicable on both new and old concrete.

v. It provides consistent data when it is well-calibrated.

2.3.2.2 Limitations of UPV

a. It has indirect relationship with strength (it needs calibration).

b. The results is usually affected by moisture content, aggregate type, temperature, and path length.

c. It gives poor performance if access to both sides of a concrete member is limited.

d. It cannot differentiate between micro-cracks and material heterogeneity.

i. Rebound Hammer (Schmidt Hammer) Test

The RH test is one of the most widely used NDT techniques for determining the CS of concrete which offers a practical and reasonably priced method to determine the concrete CS. The RH test standards are provided by various nations like India, USA, China, UK, Russia, European Union, Switzerland, and Japan. It is commonly called the Schmidt Hammer test. The concept behind the hardness test is that an elastic mass's rebound is influenced by how hard the surface is that it impacts. The strength of concrete is inversely correlated with the amount of energy it can absorb. A spring-loaded mass impacts the concrete surface, and the distance the mass rebounds is measured as the rebound number (R-value). This value correlates with surface hardness, which is related to compressive strength. The method of testing starts with carefully choosing and preparing the concrete surface that will be tested. Abrasive stones should be used to smooth up the test surface after the surface has been chosen. To impart a specific amount of energy, the hammer is then driven on the test surface. Let the plunger make a perpendicular stroke to the surface. In the old RH, the inclination angle of the hammer has an impact on the results, but it is unimportant in the latest RH instruments. The rebound number should be recorded after the impact. The hammer is held perpendicular to the concrete surface and a plunger is pressed against the surface, releasing the mass while the rebound value is read off the scale. A minimum of ten readings must be taken in each area being analyzed. Although there is no unique relationship between concrete hardness and strength. However, according to IS 13311 Part 212, the rebound number is affected by factors such as cement type, aggregate type, carbonation of concrete, surface condition, concrete age, concrete moisture content, curing time, etc.

2.3.3.1 Advantages of Rebound Hammer

a. It is very easy to use and highly portable.

b. It provides immediate readings.

c. It is ideal for preliminary surveys or identifying strength variability

d. It is Non-invasive and does not require access to both sides of the member

e. Limitations of Rebound Hammer

f. It measures only surface hardness, not internal integrity

g. It accuracy is affected by surface texture and roughness, moisture content, age and carbonation of concrete, operator error.

h. Its results may be less accurate for very low or high-strength concretes.

2.3.4 The SONREB Method (UPV + Rebound Hammer)

To estimate the CS of concrete in building structures, the SONREB method, which combines the ultrasonic pulse velocity (UPV) and rebound hammer (RH) NDT techniques, is commonly employed by practitioners. SONREB method is a combined NDT method that uses the benefits of Ultrasonic Pulse Velocity (UPV) and Rebound

Hammer (RH) testing. It is a proven fact that, in most cases, the results provided by the SONREB method are more accurate than those offered by the individual UPV and RH methods, as the combined use of these techniques compensates for the weaknesses inherent in each method when applied individually. Since each method eliminates or reduces the other's limitations in which UPV assesses the internal integrity while RH assesses the surface hardness and the combined use allows for more accurate and reliable estimation of compressive strength. The validity of the SONREB method is derived from the compensation of the inaccuracies of the two non-destructive methods used. In fact, it has been noted that the humidity content underestimates the sclerometric index measurement, and overestimates the ultrasonic velocity. Moreover, as the age of the concrete increases, the sclerometric index increases while the ultrasonic speed decreases.

The available results from two different methods makes it possible to estimate the resistance through several correlations. Because the results of the NDT measurements are physical parameters for which the relationship with compressive strength is unknown, it is necessary to identify a suitable mathematical model, called the conversion model, to empirically relate these quantities in this method, multiple regression or machine learning models are developed using both RH and UPV values as input variables. These models are usually calibrated against core test results to achieve a reliable prediction equation.

2.3.4.1 Advantages of SONREB

a. It reduces uncertainty associated with single-method measurements.

b. It improves strength estimation across a wide range of concrete conditions.

c. It increases the model robustness by using both the surface and volume properties.

d. It is applicable for both new and aged concrete structures.

Finally, it is to note that between the non-destructive tests, rebound index test is less expensive compared to the ultrasonic test; however, the presented work shows that rebound index test has a weak relation with the concrete strength, while the ultrasonic test indicates a better relation with the concrete strength.

2.4 Regression Analysis for In-Situ Strength Prediction

Regression analysis is a statistical method used to understand the relationship between variables. It helps in predicting the value of one variable (dependent variable) based on the known values of one or more other variables (independent variables). The dependent variable is the compressive strength of concrete, and the independent variables are values obtained from non-destructive tests (NDTs) such as:

a. Rebound numbers from the Schmidt hammer

b. Ultrasonic pulse velocities from the UPV test

Because NDTs does not directly measure the strength, regression models are developed to translate test readings into predicted strength by values using real-world data (usually paired with destructive test results during calibration).

2.4.1 Reasons for using Regression Analysis

a. It helps in creating prediction equations that link NDT results to actual compressive strength.

b. It allows for combining multiple test results (e.g., UPV + Rebound Hammer) for better accuracy.

c. It supports data-driven decision-making in the field assessments, thereby reducing the need for expensive and invasive tests.

d. It is simple and easy to apply and more advanced when higher precision needed.

2.4.2 Types of Regression Techniques

There is various regression techniques used to predict in-situ concrete strength and these can be grouped into traditional and advanced/machine learning-based methods.

A. Linear Regression

This is the simplest form of regression, where a straight-line relationship is assumed between the test result (e.g., rebound number or UPV) and the concrete strength. Linear regression works well when there's a direct and consistent relationship between a test value and its strength. Linear regression is used to find the relationship between the equivalent in-situ (logarithm of) compressive concrete strength lnRc, and the (logarithm of) ultrasonic velocity, lnV. It is often used for individual NDT models (only rebound or only UPV) and simpler prediction tasks.

General Formula:

$$f_c = aX + b \qquad (2.2)$$

Where:

F_c = predicted compressive strength

X = NDT value (e.g., rebound number)

a, b = regression constants determined from calibration

Not suitable when the data relationship is nonlinear or influenced by many factors.

B. Multiple Linear Regression (MLR)

MLR extends linear regression by including two or more independent variables, such as rebound number and UPV velocity. It is used in SONREB methods, where both surface and internal properties are combined for better prediction.

Formula:

$$f_c = aX_1 + bX_2 + c \qquad (2.3)$$

Where:

X_1 = Rebound number

X_2 = UPV

a, b, c = regression coefficients

Advantages

a. It is more accurate than single-variable regression.

b. It accounts for more real-world complexity.

C. Nonlinear Regression

This is when the relationship between NDT values and strength does not follow a straight line, nonlinear regression is used. These models can include exponents, logarithms, or polynomial terms. It helps when test data curves or levels off (especially in old or variable concrete).

Formulas:

Power model: $f_c = a \cdot X_1^b \cdot X_2^c$ (2.4)

Logarithmic model: $f_c = a \cdot \ln(X_1) + b \cdot X_2 + c$ (2.5)

D. Gaussian Process Regression (GPR)

Gaussian Process Regression (GPR) is a machine learning-based method that predicts the strength based on a probabilistic model. Instead of giving just one result, it also gives a confidence interval, showing how certain the model is about the prediction.

Key Features

a. It captures complex relationships in the data.

b. It handles uncertainty better than classical regression.

c. It is useful when the data shows variability due to different environmental or material conditions.

E. Ensemble Learning (e.g., Random Forest, CatBoost)

Ensemble learning combines multiple models (called learners) to improve prediction performance. Popular methods include:

a. Random Forest
b. Gradient Boosting Machines
c. CatBoost

These models are built by training many decision trees and combining their outputs. They are known for handling noisy or complex datasets very well.

Advantages

a. It has high prediction accuracy

b. It can capture nonlinear, multi-variable relationships

c. It is less sensitive to over fitting if properly tuned

2.5 Empirical Framework

Concrete is a widely used material in structural engineering, but its quality varies significantly across construction sites. In Nigeria, many existing buildings and infrastructure projects have unknown or undocumented concrete quality due to the absence of strict quality control. This calls for reliable, fast, and affordable methods of assessing the concrete strength in-situ, particularly for retrofitting, rehabilitation, or quality assurance. In the assessment of existing reinforced concrete structures, understanding the in-situ compressive strength of concrete is critical for safety, rehabilitation and performance evaluations. Traditional destructive testing methods like core extraction, although being reliable, but are often invasive, costly and impractical in many real-life conditions. Non-destructive testing (NDT) methods such as the Ultrasonic Pulse Velocity (UPV) and Schmidt Rebound Hammer (RH) tests are alternatives due to their convenience and cost efficiency. To support this empirical model, data were sourced from laboratory tested concrete samples prepared under controlled conditions. The dataset includes samples with varied curing times (7, 14, and 28 days) for both Grade 20 and Grade 25 concrete, ensuring consistency in mix proportions, compaction, and curing conditions. The prediction of in-situ compressive strength with non-destructive methods have been considerably studied by some researcher.

Recent research studies have shown that relying solely on either UPV or RH has its limitations, especially when it comes to the influence of environmental and surface factors. However, combining both methods through SONREB provides more reliable results. For instance, Arora et al. (2024) with721 samples from lab and field sites, demonstrated that while UPV alone gave R^2 value of 0.78, RMSE=4.2 MPa, when combined with rebound hammer R^2 improved to 0.92 using ensemble machine learning models like CatBoost, XGBoost, Random Forest. Showed machine learning handles UPV data better than linear models.

Sharma and Sethi (2021) examined the strength development of concrete with 50–60% fly ash replacement using UPV testing as a non-destructive indicator across 90 cylindrical samples, readings were collected at 3, 7, 28, and 90 days and correlated them with compressive strength using quadratic regression models. The results showed that although early-age strength prediction had moderate accuracy (R^2 = 0.82), long-term prediction at 90 days reached an R^2 of 0.94. The research demonstrated that the UPV method is highly effective for monitoring long-term pozzolanic activity and strength gain in fly ash concrete, particularly in sustainability-oriented designs.

Tran et al. (2021) study investigated the predictive potential of ultrasonic pulse velocity (UPV) when used in combination with artificial intelligence for strength estimation in concrete made with recycled aggregates and ground granulated blast-furnace slag (GGBFS). A total of 120 cylindrical specimens were tested at 7, 28, and 56 days. Using UPV data and material proportions as inputs, the researchers trained an artificial neural network (ANN) and a support vector regression (SVR) model. The ANN achieved an R^2 of 0.94, while the SVR model trailed slightly with 0.91. Notably, the use of eco-materials resulted in lower early-age strength but demonstrated strength parity with traditional concrete at 56 days. It emphasizes that non-destructive testing, paired with AI, is highly effective in evaluating sustainable concrete performance while reducing the environmental impact of traditional sampling methods.

Ogunwale et al. (2023) research studies applied the SONREB method combining ultrasonic pulse velocity (UPV) and rebound hammer readings to estimate the compressive strength of concrete cylinders. A total of 100 samples were cast with three different water–cement ratios and tested at 7, 14, 28, and 56 days. They used a feature fusion technique, where statistical features from both NDT methods were merged before regression analysis. Multiple linear regression and support vector regression models were developed. The feature-fused SVR model achieved the highest accuracy, with an R^2 value of 0.95 and mean absolute error of 2.3 MPa. The research concluded that enhancing raw NDT readings with statistical feature extraction significantly improves the reliability of SONREB predictions, especially when variability in test surfaces is present.

Owolabi and Falade (2022) study focused on evaluating the practicality of using only rebound hammer tests for mass concrete structures in hot climates, where internal curing differs from laboratory conditions. A total of 75 core-drilled samples were extracted from dam foundation blocks in Nigeria and tested alongside surface rebound values. The correlation between hammer readings and lab-based compressive strength was analyzed using linear and logarithmic regression models. The results indicated that the rebound hammer alone could produce moderately reliable predictions ($R^2 = 0.76$), but accuracy improved significantly ($R^2 = 0.88$) after applying temperature-correction and core-depth adjustment factors. The authors concluded that rebound hammer testing, when adjusted for field-specific conditions, remains a cost-effective and useful tool for mass concrete evaluation in developing regions.

Mehta et al. (2023), presented their findings by evaluating the compressive strength of pervious concrete made with large aggregate gaps and low cement paste. Sixty cylindrical samples were prepared with varying aggregate sizes and porosities and tested using rebound hammer and ultrasonic pulse velocity methods at 7, 14, and 28 days. The UPV readings were more consistent than rebound values due to the surface irregularity of pervious concrete. Regression models including multiple linear regression and decision tree regression were developed. The decision tree model showed the best performance with an R^2 of 0.88. It was concluded that while UPV was the better single predictor, combining both NDT methods in regression tree framework improved robustness, especially in porous materials where standard NDT assumptions are challenged.

Karthik and Kumar (2020) explored the use of regression tree models for predicting compressive strength from rebound hammer and ultrasonic pulse velocity data. It involved 120 concrete cube samples made from three different mix designs and tested at 7, 28, and 56 days. It was found that regression trees provided simple yet powerful predictive models with R^2 values around 0.90. The models clearly visualized how strength varied across ranges of UPV and rebound readings. Unlike black-box models like ANN, regression trees offered transparency and interpretability. The findings suggest that tree-based methods can help engineers understand the influence of different NDT readings on strength prediction and support field decision-making with visual clarity.

Salim et al. (2021), Applied Sciences (MDPI), a study investigation combined the use of ultrasonic pulse velocity (UPV) and rebound hammer (RH) readings to predict the compressive strength of ordinary Portland cement concrete cubes. A total of 120 specimens were cast and cured for 7, 14, 28, and 56 days. Multiple linear regression (MLR) and support vector regression (SVR) models were trained on the NDT data. The

SVR approach achieved an R^2 of 0.92, outperforming MLR ($R^2 = 0.85$). UPV emerged as the most influential predictor, while the rebound hammer added complementary information. They concluded that concluded that integrating these two NDT techniques with SVR provides a robust, non-destructive method to estimate in-situ strength, reducing the need for core drilling in field evaluations.

Zhao et al. (2022), In this work, the Schmidt rebound hammer was used to obtain surface hardness measurements on recycled aggregate concrete (RAC) specimens with replacement ratios of 25%, 50%, 75%, and 100%. Samples were cured for 28 days. Extreme gradient boosting (XGBoost) and random forest regression models were trained to predict compressive strength from the rebound data and mix parameters (water–cement ratio and aggregate content). XGBoost yielded the best performance with an RMSE of 2.1 MPa. Feature-importance analysis showed that water–cement ratio and replacement ratio were the key inputs. This demonstrates that ML models can effectively turn simple rebound readings into reliable strength estimates for sustainable concrete.

Akinpelu et al. (2021), it involves casting 90 self-compacting concrete (SCC) cubes and conducted ultrasonic pulse velocity and rebound hammer tests at 7, 14, and 28 days. They developed an artificial neural network (ANN) using the Levenberg–Marquardt training algorithm to predict compressive strength. The ANN achieved an $R^2 > 0.93$ and MAE below 2 MPa, significantly outperforming traditional linear regression. This study highlights that merging multiple NDT inputs in an ANN framework delivers high-accuracy, non-invasive strength predictions critical for SCC applications where flow characteristics and early age strength both influence performance.

Bakri and Alhajjar (2020), sought to refine strength predictions in old buildings using a combination of rebound hammer testing and selective core samples. The focused was on 60 buildings ranging from 10 to 40 years old. Rebound hammer tests were conducted at multiple points on walls and columns, and cores were extracted selectively from locations where readings were consistent. The combined dataset was analyzed using simple linear regression and calibration equations. It was then found out that core strength could be predicted with an R^2 of 0.88 when corrected rebound hammer values were used alongside building age and location. This method provides a reliable way to assess structural integrity in aging infrastructure, helping reduce the number of cores needed for accurate strength estimation.

Daramola and Adeyemi, (2020), investigated how response surface methodology (RSM) could be used to model concrete strength from non-destructive test data. Ninety cylindrical concrete samples were produced with three different mix designs and tested using rebound hammer and ultrasonic pulse velocity techniques at curing ages of 7, 14, 28, and 56 days. Using RSM, the authors built second-order polynomial models for strength estimation and validated them with actual compressive test data. The combined NDT-based RSM model had an R^2 value of 0.91. The research found that the interaction between UPV and RH readings was statistically significant and improved the overall accuracy of predictions. It concluded that RSM is a reliable and practical tool for strength estimation, especially where computational resources are limited.

Ismail et al. (2022), explored advanced machine learning integration with traditional NDT techniques. The researchers created a dataset from 110 concrete cubes tested using both UPV and rebound hammer at 7, 14, 28, and 90 days. Alongside standard SONREB correlations, the team implemented Light Gradient Boosting Machine (LightGBM), a powerful tree-based model, to estimate compressive strength. LightGBM achieved an R^2 of 0.97, outperforming SVM and ANN models developed on the same dataset. The model was particularly effective at detecting hidden relationships between curing age, NDT readings, and strength development. This demonstrates how merging modern machine learning with classical NDT techniques can improve the accuracy of in-situ strength evaluation significantly, especially in high-volume construction sites where speed and accuracy are both critical. Shetty et al. (2021) experiment UPV and rebound hammer separately using Multi linear regression on 400 mixed-design concrete cubes sample, the rebound only and SONREB (combined) $R^2$is 0.66 and 0.89 respectively. It was found that moisture and curing time strongly affected the prediction accuracy.

Nasrullah et al. (2022), introduced an intelligent modeling approach for strength prediction. Rebound hammer test data from 96 concrete cube specimens prepared with various water–cement ratios and aggregate sizes was gathered. They proposed a hybrid model combining an artificial neural network (ANN) and a genetic algorithm (GA) to optimize prediction performance. The hybrid model achieved superior accuracy with an R^2 value of 0.96 and a mean squared error of less than 2 MPa. Sensitivity analysis indicated that rebound number and curing age were the two most influential features. The model's robustness was validated on an independent test set. The research demonstrates the ability of intelligent hybrid models to significantly enhance the usability of basic NDT tools like the rebound hammer, especially in complex or variable concrete mixtures. Khatib and Bayomy (2021) with sample size of 300 concrete cubes of varying mix ratios, using UPV method and simple linear regression type, resulting to correlation coefficient of R^2 = 0.77, the key result noted better prediction in dense and well-cured concrete and thus developing this equation; f_c=0.0045V−3.2f_c = 0.0045V - 3.2f_c =0.0045V−3.2. Overestimated strength in porous or cracked concrete is the only it has.

Kwon et al. (2022) and Gupta et al. (2022) work on Rebound hammer and UPV respectively. Kwon et al. (2022) incorporate rebound hammer with simple linear regression using 250 field test point on aging bridges to obtain weak correlation R^2 of 0.63 and RMSE of 5.6 MPa, it is observed that carbonation and weathering significantly reduced accuracy, it is recommended to be using RH only for preliminary assessment, while Gupta et al. (2022) observed that using UPV only with support vector regression (SVR) on 600 cylindrical specimens obtain the result for R^2as 0.87 and RMSE as 3.2MPa. It was found that SVR is more effective than linear regression for medium-strength concrete.

Musa and Muhammad (2022) explored the behavior of nano-silica-modified concrete using non-destructive methods. The research involved casting 80 concrete specimens with nano-silica dosages of 0%, 1%, 2%, and 3%. The Schmidt rebound hammer was used to assess surface hardness at 7, 14, and 28 days. The rebound numbers were correlated with compressive strength using exponential regression models. The highest R^2 value (0.89) was obtained with 2% nano-silica replacement, suggesting optimal particle dispersion at that dosage. The study revealed that nano-silica not only improves compressive strength but also enhances the consistency of rebound readings due to a denser matrix structure. The findings support the use of rebound hammer as a valid technique for monitoring nano-enhanced concrete, especially in early-age performance assessment.

Moreno et al. (2025), gave their observation on Polynomial Chaos Expansion for Self-Healing Concrete Using UPV by casting of 70 self-healing concrete specimens embedded with bacterial capsules. Ultrasonic pulse velocity tests were conducted at 7, 28, 56, and 90 days to track strength recovery. A polynomial chaos expansion (PCE) model was used to relate UPV readings to compressive strength, achieving $R^2 = 0.88$ and capturing uncertainty in self-healing performance. The findings demonstrate that probabilistic PCE with UPV data offers a non-destructive way to monitor and predict self-healing concrete behavior over time.

Suleiman and Musa (2022), explored how non-destructive testing can be used to evaluate concrete incorporating silica fume. A total of 90 cube specimens with silica fume dosages ranging from 5% to 15% were tested at 7, 14, and 28 days using the Schmidt rebound hammer. The rebound values were then correlated with compressive strength using polynomial regression. The resulting model had an R^2 of 0.89, with prediction errors below 5 MPa. This study also revealed that silica fume improved the uniformity of rebound results, possibly due to its densifying effect on the concrete matrix, it was concluded that regression-based models developed from rebound hammer data are useful tools for field engineers seeking to monitor strength development in silica-fume-enhanced concrete without damaging the structure.

Additionally, studies such as Al-Bayati et al. (2023) and Angiulli et al. (2024) confirm that combining NDT techniques with multiple regression models significantly enhances predictive accuracy. Al-Bayati et al. uses multiple linear regression on SONREB with 372 specimens with cores achieved an R^2value of 0.75 for rebound only, 0.80 for UPV only and 0.91 with RMSE value of 3.1 MPa for SONREB using multiple linear regression demonstrated superior accuracy when combining both tests, while Angiulli et al. using SONREB on concrete walls with varying age and conditions achieved an even higher R^2 of 0.93 and RMSE of 2.8 MPa using Gaussian Process Regression (GPR). GPR model accounted for uncertainty, providing a confidence range and particularly effective in non-uniform or aged concrete. Furthermore, Tufekcioglu and Sari (2022) the SONREB with exponential nonlinear regression on 12o core-tested columns resulting in R^2value of 0.88 and noted high reliability in mid-strength concrete (25-40 MPa), a model is being developed $f_c = a \cdot V^b \cdot R^c$ but it is less accurate in very high or low strength regions.

Marquez et al. (2023), made an advanced study combined ultrasonic pulse velocity, rebound hammer, and acoustic emission test data into a hybrid input dataset. Over 100 concrete cubes and prisms were evaluated across 7, 28, and 56 days. A deep neural network (DNN) was trained using Tensor Flow, with input features standardized and filtered through a dimensionality reduction algorithm. The DNN achieved an R^2 of 0.96 and significantly outperformed traditional machine learning models like random forest and support vector regression. The model also provided insight into which NDT features contributed most to prediction accuracy UPV amplitude and AE frequency were the top variables. This work demonstrates the cutting-edge potential of deep learning when combined with multi-source non-destructive testing for robust in-situ concrete strength estimation.

Ghosh and Chatterjee (2021), was focused on the challenge of estimating compressive strength in concrete mixtures enhanced with different fiber types. Ninety cube specimens were prepared using steel, glass, and hybrid fiber combinations. Ultrasonic pulse velocity tests were conducted at 3, 7, and 28 days, and the data were analyzed using multiple nonlinear regression and artificial neural networks. The ANN model provided the highest prediction accuracy with $R^2 = 0.92$. Interestingly, the presence of glass fibers caused slight scattering in UPV results, while steel fibers enhanced pulse velocity due to better matrix compaction. It was then confirmed that the UPV method remains effective for strength prediction in fiber-reinforced concrete, especially when supported by non-linear or machine learning-based models that can capture subtle material interactions. Idris et al. (2023) applied a second-degree polynomial regression (nonlinear) to rebound hammer data with 360 samples tested in lab and on-site, the results are RMSE of 3.9MPa and improved the R^2value from 0.63 to 0.83, Nonlinear significantly improved fit over linear regression.

Similarly, Nuruzzaman et al. (2020) used both linear and polynomial regression and found that polynomial models yielded better results, especially when tailored to local conditions. Rebound Hammer was used with 180 cube samples, the linear model give R^2 value of 0.71 while the value for Polynomial model is 0.81

Machine learning techniques have also demonstrated improve performance in handling complex and noisy datasets. Yilmaz et al., (2023) used Artificial Neural Networks (ANN) on SONREB data with 250 test points from old infrastructure and achieved an R^2value of 0.96 with an RMSE of 2.1 MPa. These methods provide the flexibility to capture nonlinear interactions between input variables like UPV, RH, and concrete strength. Model captured complex interactions better than MLR and especially good for non-standard concrete mixes. However, despite the superior accuracy of machine learning models, their practical application in field environments may be limited by accessibility to computational resources and expertise. Therefore, this study emphasizes methods that balance predictive strength with ease of use, especially for engineers working in resources-limited settings.

It is clear that non-destructive testing (NDT) methods like the rebound hammer and ultrasonic pulse velocity can be used to predict how strong concrete is without breaking or damaging it. When these tests are used together and analyzed with regression methods, they give much better and more accurate results. This makes them a useful and smart option, especially when dealing with existing buildings or structures where we don't want to cause any harm. Several studies being look all agreed on one: the accuracy of these methods depends a lot on how the data is collected and how the models are built. If these tests are done carefully and the analysis is also done properly, the predictions can be trusted for real construction decisions. It's a faster and cheaper way to get useful information without taking out physical samples all the time.

NDT method like UPV and rebound hammer alone offer moderate accuracy, but are more powerful when combined (SONREB). Simple regression models are suitable for preliminary predictions but are sensitive to variability and local conditions. Machine learning and advanced regression techniques such as GPR, CatBoost, and ANN significantly improve prediction accuracy and robustness, especially in complex or uncertain concrete environments.

2.6 Literature Gap

Despite the numerous extensive research and studies that has been conducted out on the use of non-destructive testing (NDT) methods to predict in-situ compressive strength of concrete in combination with statistical or machine learning models, most of the studies utilized rebound hammer and ultrasonic pulse velocity (UPV) either separately or in combination, but few explored newer NDT tools such as acoustic emission or electrical resistivity for regression-based predictions. Many existing studies are conducted in controlled laboratory environments using standard cube or cylinder specimens. This limits the generalization of the results to real field conditions, where concrete may vary in mix design, compaction, curing, and exposure. Only a small portion of the researcher's validates models on real in-situ structural elements such as columns, slabs, or foundation blocks.

Although the SONREB method has gained popularity due to its dual-parameter approach, its limitations in capturing the influence of internal micro-cracks, curing effects, and surface roughness remain under-investigated. As a result, the current models often struggle to generalize beyond standard specimens tested under controlled conditions.

Another consistent issue across is the narrow focus on traditional concrete types, high-performance concrete and recycled aggregate concrete have received some attention, but there still remains limited research on using NDT for modern and sustainable materials like geopolymer concrete, nano-silica-enhanced concrete, fiber-reinforced concrete and self-healing concrete. The behavior of these new innovated materials under NDT is still not fully understood, especially when tested at early ages, they respond differently to wave propagation and rebound, making existing models potentially unreliable if directly applied.

Additionally, most study work utilized standard cube or cylinder specimens, which do not accurately reflect the complex geometries or boundary conditions found in real structural elements such as beams, slabs, and columns. This presents a challenge in transferring laboratory models to actual on-site applications. Another challenge exists in the limited comparison of NDT-based predictions with actual destructive test results obtained from field cores. While several models were validated in laboratory settings, only a few findings tested the reliability of NDT regression models in real construction environments. This raises concerns about the generalize ability and transferability of those models from controlled lab conditions to practical field conditions, where variability in temperature, curing conditions, and surface texture can significantly influence the test outcomes.

Moreover, many researchers relied heavily on linear or multiple linear regression methods, even when the relationship between strength and NDT measurements was non-linear. Although some progress has been made using support vector machines, artificial neural networks, and decision trees, few studies have explored deep learning models or hybrid techniques combining multiple machine learning algorithms. This suggests a clear opportunity for future work to apply more advanced predictive systems that can better capture the hidden patterns in complex datasets, especially where multiple variables interact dynamically over time.

A further research gap lies in the inconsistency of test protocols and calibration practices. There is no standardization across studies regarding the exact position of NDT testing, the number of readings averaged per sample, or how environmental conditions are accounted for in the models. These inconsistencies lead to difficulties in comparing outcomes across different research works and hinder the formulation of universally applicable regression models. Also, some studies failed to explain how outliers or noisy data were handled, which can affect model integrity in practical field applications.

Finally, while many studies achieved high R^2 values in their predictions, few discussed the practical usability of their models in field inspection scenarios. Engineering applications demand models that are not only accurate but also easy to use with limited data, requiring minimal calibration. Few studies provided simplified model equations or field-applicable charts that engineers can use directly during structural assessments. Without these tools, the implementation of even the most accurate models becomes limited to academic or specialized environments.

Coming to conclusion, although the much research work being has been done and showing promising advancements in predicting concrete strength using NDT and regression techniques, but several important gaps still remain and these include; the lack of full-scale, on-site validation and strong need for more field-oriented research, under-representation of new-generation concrete materials, insufficient exploration of hybrid AI approaches and application of modern tools, and limited consideration of environmental and operational variability, exploration of alternative NDT methods, and development of practical and user-friendly models. Addressing these issues would help transition NDT-based prediction from academic theory modeling into everyday on-site engineering application and practice.

CHAPTER THREE

METHODOLOGY

3.1 Location of Study

The research methodology in this study was based on experimenting and testing Grade 20 and 25 concretes for compressive and flexural strength using destructive methods, while non-destructive tests were carried out using the Rebound Hammer and Ultrasonic Pulse Velocity (UPV) devices. All samples were prepared in the laboratory at the University of Benin, Benin City, Ovia North-East Local Government Area of Edo State, Nigeria (6.64° N latitude and 5.58° E longitude). This laboratory-based approach provided controlled conditions necessary for developing reliable regression models for predicting condition of in-situ concrete strength.

3.2 Sample Collection

All concrete samples used in this study were prepared in the Civil Engineering Laboratory of the University of Benin under strictly controlled conditions. This approach is being considered in order to eliminate variability that is associated with field conditions such as inconsistent mixing, environmental exposure which is commonly encountered at construction sites. The Grade 20 and Grade 25 concrete specimens were batched, mixed, and cast by following the standard procedures as outlined in BS EN 12390-1:2012. The controlled environment of the laboratory ensured:

a. Accurate proportion for cement, aggregates, and water

b. Uniform mixing and proper workability

c. Consistent compaction and finishing

d. Standard curing conditions

The cube sample specimens (100mmx100mmx100mm) for compressive strength testing and beam sample specimens (100mmx100mmx500mm) for flexural strength testing were prepared, all samples were properly labeled to indicate the concrete grade and testing age (i.e. 7, 14, and 28 days).

This provide a reliable baseline for comparing destructive and non-destructive test results, and also for developing regression models that can later be validated for field application.

3.3 Materials and Mix Design

3.3.1 Materials Used

The following materials were used in the preparation of concrete specimens;

3.3.1.1 Cement

The type used is Ordinary Portland Cement (OPC) conforming to BS EN 197-1 and ASTM C150 which is source from local supplier in Benin City.

3.3.1.2 Aggregate

3.3.1.2.1 Fine Aggregate

Natural river-sand conforming to BS EN 12620, with maximum size of 4.75mm, Grading zone II, which is source from local quarry.

3.3.1.2.2 Coarse Aggregate

This is crushed granite with maximum size of 20mm, also sourced from local quarry.

3.3.1.3 Water

Good portable water conforming to BS EN 1008, that is free organic matter and harmful chemicals

3.3.1.4 Admixtures

No chemical admixture is used in this study.

3.3.2 Mix Design

The concrete mix design for this study was developed and prepared using the OP-020 Concrete Mix Design procedure of GandP Geotechnics SdnBhd, which served as the official reference document for all laboratory trials (GandP Geotechnics, 2003), to ensure the production of Grade 20 (C20) and Grade 25 (C25) concrete with adequate workability, strength, and durability, the OP-020 procedure provided detailed guidance on the determination of target workability, selection of water content, and calculation of binder and aggregate proportions based on density relationships and specific gravities of constituent materials . The design procedure was guided by BS EN 206:2013 for concrete specification, BS 8500-1:2015 for complementary British Standard to BS EN 206, and the fundamental mix design methodology outlined by Neville and Brooks (2010) in Concrete Technology.

The mix design approach adopted in this study followed a systematic procedure that considered the target compressive strength, desired workability, maximum aggregate size, and water-cement ratio requirements. Both concrete grades were designed to achieve their characteristic strengths at 28 days while maintaining practical workability suitable for laboratory casting and compaction.

3.3.2.1 Design Parameters and Material Properties

The design was based on the following key parameters and material characteristics:

Grade 20 (C20) Concrete, Target characteristic strength: 20 N/mm² at 28 days, Target mean strength (fm): Calculated using:

$$f_m = f_{ck} + k \cdot s \quad (3.1)$$

Where:

f_{ck} = characteristic strength = 20 N/mm²

k = margin factor = 1.64 (for 5% defective proportion)

s = standard deviation = 4 N/mm²

$f_m = 20 + (1.64 \times 4) = 26.56$ N/mm² ≈ 27 N/mm²

Water-cement ratio: 0.62 (selected based on strength requirements and durability considerations per BS 8500-1:2015)

Cement type: Ordinary Portland Cement (OPC) conforming to BS EN 197-1:2011

Nominal maximum aggregate size: 20 mm

Target slump: 30-60 mm (low workability suitable for cube and beam specimens)

Grade 25 (C25) Concrete:

Target characteristic strength: 25 N/mm² at 28 days

Target mean strength (fm): Calculated similarly:

$fm = 25 + (1.64 \times 4) = 31.56$ N/mm² ≈ 32 N/mm²

Water-cement ratio: 0.55 (reduced w/c ratio to achieve higher strength)

Cement type: Ordinary Portland Cement (OPC) conforming to BS EN 197-1:2011

Nominal maximum aggregate size: 20 mm

Target slump: 30-60 mm

Aggregate Properties:

Coarse Aggregate:

Type: Crushed granite

Nominal maximum size: 20 mm

Relative density (SSD): 2.7

Grading: Single-sized, conforming to BS EN 12620:2013

Fine Aggregate:

Type: Uncrushed natural sand

Grading zone: Zone II (per BS 882:1992)

Relative density (SSD): 2.65

Fineness modulus: Approximately 2.8

3.3.2.2 Mix Design Calculations

For Grade 20 (C20) Concrete:

Using the design methodology and referring to standard mix design tables:

Step 1: Free Water Content

For 20 mm maximum aggregate size and 30-60 mm slump:

Free water content = 210 kg/m^3 (from Table 3, standard mix design tables)

Step 2: Cement Content

Using the selected water-cement ratio of 0.62:

Cement content = Water content ÷ w/c ratio

Cement content = 210 ÷ 0.62 = 339 kg/m^3 ≈ 340 kg/m^3

This satisfies the minimum cement content requirement of 300 kg/m^3 for normal exposure conditions (BS 8500-1:2015).

Step 3: Total Aggregate Content

Assuming concrete density of 2400 kg/m^3:

Total aggregate = Concrete density - (Cement + Water)

Total aggregate = 2400 - (340 + 210) = 1850 kg/m³

Step 4: Fine and Coarse Aggregate Proportioning

Based on BS 882 grading Zone II for fine aggregate and 20 mm maximum size coarse aggregate, the proportion of fine aggregate is approximately 32% of total aggregate content (from standard proportioning charts):

Fine aggregate content = 1850 × 0.32 = 592 kg/m³

Coarse aggregate content = 1850 × 0.68 = 1258 kg/m³

Mix ratio by mass: 1: 1.74: 3.70: 0.62 (Cement: Fine aggregate: Coarse aggregate: Water)

For Grade 25 (C25) Concrete:

Step 1: Free Water Content

For 20 mm maximum aggregate size and 30-60 mm slump:

Free water content = 210 kg/m³

Step 2: Cement Content

Using the selected water-cement ratio of 0.55:

Cement content = Water content ÷ w/c ratio

Cement content = 210 ÷ 0.55 = 382 kg/m³ ≈ 380 kg/m³

Step 3: Total Aggregate Content

Assuming concrete density of 2400 kg/m³:

Total aggregate = 2400 - (380 + 210) = 1810 kg/m³

Step 4: Fine and Coarse Aggregate Proportioning

Using the same proportioning approach:

Fine aggregate content = 1810 × 0.32 = 579 kg/m³

Coarse aggregate content = 1810 × 0.68 = 1231 kg/m³

Mix ratio by mass: 1: 1.52: 3.24: 0.55 (Cement: Fine aggregate: Coarse aggregate: Water)

3.4 Sample Curing and Storage

After the concrete samples were cast, all concrete specimens were properly and carefully demolded after 24 hours and immediately transferred to a curing tank that maintained a room temperature (approximately 25ºC ± 2º) in the laboratory, allowing the concrete specimens to be properly cured and stored, for them to gain consistent development strength across all samples before testing. The curing periods were set at **7, 14, and 28 days,** representing the early-age, intermediate, and standard maturity stages respectively, depending on when each sample was planned and scheduled to be tested. All the samples are being kept fully submerged in water throughout their respective curing stages, and the water is also maintained above the specimen surfaces.

Each specimen was clearly labeled with waterproof markers to indicate; Concrete grade, Specimen type (cube or beam), and Scheduled testing date.

This standard curing and storage method helped to make sure that all the samples developed strength under similar moisture and environmental conditions, so that the results from both destructive and non-destructive tests would be more accurate, consistent and reliable.

3.5 Experimental Test and Analysis

This stage focused on conducting practical tests on the concrete samples and analyzing the results to build models that can predict strength without causing damage to the structure. Both destructive and non-destructive testing methods were applied to assess the compressive and flexural strength of Grade 20 and 25 concrete. This was done to gather the necessary data for comparing test results and developing accurate regression models.

3.5.1 Destructive Testing

Destructive testing was carried out to determine the actual strength of the concrete by crushing the samples under controlled conditions. This process involves applying load to the concrete until it fails, and it helps in obtaining their actual and reliable strength values that were later used as benchmark and reference for evaluating and assessing the non-destructive test results. Destructive tests were carried out on both cube and beam specimens to evaluate compressive and flexural strength, respectively.

3.5.1.1 Compressive Strength Test

The compressive strength test was performed on concrete cubes according to BS EN 12390-3 with standard dimensions of 100 mm × 100 mm × 100 mm. These samples were tested at 7, 14, and 28 days after casting, which are commonly used ages for monitoring strength development in concrete. The test was done using a compression testing machine available in the lab in accordance with the guidelines of BS EN 12390-3. Each cube was placed centrally on the testing machine, and load was applied steadily at a constant rate until the sample failed. The highest maximum load it could carry before breaking was recorded. To calculate the compressive strength, the load was divided by the surface area of the cube. This gives the strength in Megapascals (MPa). For each group (based on age and concrete grade) to ensure consistency and reliability of the results, at least three cubes were tested, and their average was used for analysis. The formula to calculate the compressive strength:

Compressive Strength (MPa) = Cross-sectional Area (mm2) / Maximum Load (N)

$$f_c = \frac{P}{A} \tag{3.2}$$

Where:
f_c = compressive strength of the concrete (MPa or N/mm^2).

P = maximum load applied to the specimen at failure (N).

A = cross-sectional area of the specimen (mm^2).

3.5.1.2 Flexural Strength Test

In addition to compressive strength, beam specimens were tested to measure how well the concrete could resist bending. This is important because many concrete elements like slabs and beams are often subjected to bending forces in real structures.

The beam prismatic beam samples used were typically around 100 mm × 100 mm × 500 mm in dimension. The flexural test was performed following BS EN 12390-5 with a two-point loading method, where the load was applied gradually at two third-points along the beam span using a flexural testing machine until failure occurred and the breaking point load was recorded. The failure load was then used to calculate the flexural strength using the appropriate formula for two-point loading:

$$\text{Flexural Strength (MPa), } f_r = \frac{P \cdot L}{b \cdot d^2} \tag{3.3}$$

Where:

f_r = flexural strength or modulus of rupture (MPa).

P = Applied load at failure (N)

L = Span length (mm)

b = Width of the beam (mm)

d = Depth of the beam (mm)

Just like in the compressive strength test, multiple beams were tested for each category, and the average result was recorded. The flexural test helped to assess the concrete's resistance to bending forces, which is critical for structural elements like slabs and beams. These destructive tests provided the actual strength values required for model development and served as the reference against which the predictions from the non-destructive tests were compared. This made it easier to see how accurate the prediction models would be.

3.5.2 Non-Destructive Testing

Non-destructive testing (NDT) was carried out on the same concrete samples before applying any load or damage to them. The goal was to estimate the strength of the concrete without altering or destroying the structure. These tests are very useful in real-life situations where it is important to check the condition of concrete in existing buildings without taking out samples or causing damage. The non-destructive testing method carried out in this study was the Rebound Hammer test. Although Ultrasonic Pulse Velocity (UPV) testing was initially proposed, it was not executed due to equipment unavailability**.** These tests were carried out on all samples before any destructive testing was performed. This ensures that NDT readings were taken on undamaged concrete surfaces, which provides accurate baseline data for correlation with the obtained compressive and flexural strength values.

3.5.2.1 Rebound Hammer Test

The Rebound Hammer test, also known as the Schmidt Hammer test, the test was performed following IS 13311 part 1. It is used to assess and measure the surface hardness of concrete, which is related to its compressive strength. The hammer has a spring-loaded plunger that, when pressed against the concrete surface, releases and rebounds. The distance of the rebound (called the rebound number) is shown as a number on the scale of the device which is recorded and used to estimate the strength of the concrete.

For each concrete specimen, rebound readings were taken at several points on the surface to ensure accuracy. Rebound numbers were recorded at different points and the average of these values was used as the final rebound number for that sample. It is important to perform this test on a smooth, clean, and dry surface to avoid inaccurate readings. This test was performed before the destructive test, to make sure the surface was still intact and undamaged.

3.5.2.2 Apparatus for Rebound Hammer Test

i. Schmidt Rebound Hammer (Rebound Hammer Device)

ii. Concrete Specimens

iii. Measuring Tape or Ruler

iv. Steel Wire Brush

v. Permanent Marker or Chalk

vi. Data Recording Sheet or Logbook

vii. Protective Gloves and Safety Goggles

viii. Tripod Stand (optional)

3.5.2.3 Procedures

i. Clean each concrete sample using wire brush to remove dust and debris. A smooth and dry surface will ensure accurate readings.

ii. Held the hammer in right angle (90) to the surface either vertical or horizontal depending on the sample orientation

iii. Press the plunger against the surface until it rebounded, displaying a number. This is done at several points on each sample with a minimum of 10.

iv. All rebound values were noted and recorded. Their average was taken as final rebound number for each sample to ensure good reliability.

v. These tests are not performed near edges, cracks, or damp surfaces, because these could affect the result.

vi. Gloves and goggles were used throughout and the hammer was also checked and calibrated to ensure it functioned properly.

3.6 Data Collection Approach

Both the Rebound Hammer and UPV tests were carried out before destructive tests, so that their true condition could be measured to avoid any interference caused by cracking or micro-damage. After these non-destructive tests, the same cubes were crushed using a compression testing machine to determine their actual compressive strength. Additionally, concrete beams were tested using flexural strength method to assess their bending resistance. The results from these non-destructive methods were later compared with the values obtained from destructive testing to see how closely they matched. The main purpose of this was to find out how accurately strength can be predicted without breaking the concrete, which is especially useful in real-life construction and structural maintenance. All the NDT results collected during this process were used in the next stage of the project, where regression models were developed to predict the compressive and flexural strength of concrete based on RH and UPV readings.

3.7 Regression Model Application Process

After the collection of all the necessary data, the next step is the application of regression analysis in order to develop a model that can predict the compressive strength of the concrete using non-destructive test (NDT) results. This stage is important because it forms the mathematical relationship between the actual strength and the NDT values.

The recorded data from the rebound hammer and UPV tests were arranged alongside the corresponding compressive strength values for each concrete tube. The main goal was to identify how well the NDT results could estimate the actual strength without needing to crush the concrete and to achieve this, a multiple linear regression technique was used. This method helped to analyze how two independent variables, which is the rebound hammer and pulse velocity could be used to predict the dependent variable, which is compressive strength.

Using Microsoft Excel and statistical tools like SPSS or MATLAB, the data was inputted into the software, and the regression was run. The software generated the regression equation in the form:

$$f_c = a + b_1 R + b_2 V \qquad (3.3)$$

Where:

f_c = predicted compressive strength

R = rebound number

V = pulse velocity

a, b_1, and b_2 = regression constants determined by the software

The output also includes important indicators such as the coefficient of determination (R^2), standard error, and or p-values, which helped assess how reliable the model was. A high R^2 value mean that the model has a good fit and could accurately estimate the compressive strength from NDT values.

Once the model was developed, it was tested by comparing the predicted strength values with the actual values from the destructive tests. This helped confirm the effectiveness of the regression hammer and UPV readings can be used to predict in-situ concrete strength with reasonable accuracy.

3.8 Statistical Analysis Technique

Statistical analysis was conducted after completing the tests to interpret the results and explore the relationship between NDT results and actual compressive strength values. Microsoft Excel and IBM SPSS were used to carry out this analysis due to their ease use and wide acceptance in engineering research. Descriptive statistic like mean, standard deviation, minimum, and maximum were used to understand the distribution and consistency of the data. This was followed by correlation analysis using Pearson's coefficient to measure how strongly and in what direction the NDT values relate to compressive strength.

Then multiple regression analysis was applied to develop a predictive model for estimating compressive strength using NDT results. The performance of the model was evaluated using R^2 to measure its explanatory power, while p-values and standard error were used to assess its reliability. Additional checks like residual analysis and normality tests were also carried out to ensure the model followed linear regression assumptions. Finally, this statistical approach helped to turn raw test data into a dependable model for predicting in-situ compressive strength based on the NDT outcomes.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents, analyses, and discusses the experimental results obtained from both destructive and non-destructive tests (NDT) carried out on concrete specimens of grades 20 MPa and 25 MPa. The main purpose was to establish a correlation between destructive and non-destructive results and subsequently develop a regression-based model capable of accurately predicting the in-situ compressive strength of concrete.

Although both Rebound Hammer and Ultrasonic Pulse Velocity tests were initially proposed, only the Rebound Hammer test was successfully conducted due to the unavailability of UPV equipment during the testing period. Consequently, all results, analyses, and regression models presented in this chapter are based solely on Rebound Hammer data

Results are presented in tabular and graphical formats, with detailed interpretation of their significance in assessing the mechanical performance of concrete and the effectiveness of regression analysis for predictive modeling. It should be noted that due to equipment constraints, only Rebound Hammer tests is performed as the NDT component of this study. Consequently, the regression models developed are based mainly on the correlation between Rebound Hammer readings and compressive strength, rather than the combined SONREB approach initially mentioned.

4.2 Comparison of Rebound Hammer and Compressive Strength Results

The rebound hammer test was conducted in accordance with BS EN 12504-2:2012 and ASTM C805, on the cured specimens at 7, 14, and 28 days. The rebound number obtained was used to estimate equivalent compressive strength. The average results are presented in Table 4.2. The compressive strength test was performed in accordance with

BS EN 12390-3:2019 and ASTM C39, using a calibrated compression testing machine. Three cubes were tested for each mix at each curing age, and the average values are presented in Table 4.2.

4.2.1 Compressive Strength of concrete

The results of the compressive strength test at 7, 14, and 28 days are presented in the tables 4.1-4.3:

Table 4.1: Comparison of Average Compressive Strength Results from Destructive Compression Tests (DT) at Different Curing Ages (7 Days)

COMPRESSIVE STRENGTH (7 DAYS)								
Grade of Concrete	**Cube No. (kN)**			**Average Strength (kN)**	**Weight of Cube (kg)**			**Strength =F/A (N/mm^2)**
	1	2	3		1	2	3	
C20	157.946	137.338	137.722	144.34	2.524	2.522	2.543	14.43
C20	123.423	144.610	116.996	128.34	2.539	2.539	2.520	12.83
C20	111.676	144.007	130.243	128.64	2.575	2.531	2.554	12.86
C25	182.036	170.584	187.502	180.04	2.522	2.560	2.593	18.00
C25	188.871	170.583	174.727	178.06	2.539	2.548	2.514	17.81
C25	180.765	173.550	160.853	171.72	2.531	2.575	2.549	17.17

Table 4.2: Comparison of Average Compressive Strength Results from Destructive Compression Tests (DT) at Different Curing Ages (14 Days)

COMPRESSIVE STRENGTH (14 DAYS)								
Grade of Concrete	**Cube No. (kN)**			**Average Strength (kN)**	**Weight of Cube (kg)**			**Strength =F/A (N/mm^2)**
	1	2	3		1	2	3	
C20	177.589	197.584	138.220	171.13	2.549	2.520	2.574	17.11
C20	137.722	128.996	116.996	127.90	2.587	2.554	2.561	12.79
C20	159.561	142.543	130.214	144.11	2.515	2.593	2.577	14.41
C25	180.947	193.550	215.879	196.79	2.541	2.514	2.552	19.68
C25	227.564	232.502	204.947	221.67	2.543	2.549	2.532	22.17
C25	187.589	174.727	221.564	194.63	2.529	2.535	2.546	19.46

Table 4.3: Comparison of Average Compressive Strength Results from Destructive Compression Tests (DT) at Different Curing Ages (28 Days)

COMPRESSIVE STRENGTH (28 DAYS)								
Grade of Concrete	**Cube No. (kN)**			**Average Strength (kN)**	**Weight of Cube (kg)**			**Strength =F/A (N/mm^2)**
	1	2	3		1	2	3	
C20	180.029	162.579	198.220	180.28	2.582	2.565	2.579	18.03
C20	171.778	196.587	186.996	195.12	2.544	2.562	2.557	19.51
C20	188.995	194.537	183.214	188.92	2.586	2.507	2.565	18.89
C25	241.934	269.597	223.565	245.03	2.866	2.512	2.529	24.50
C25	240.062	230.576	218.597	229.75	2.572	2.531	2.013	22.98
C25	230.570	244.658	251.598	242.27	2.522	2.519	1.888	24.23

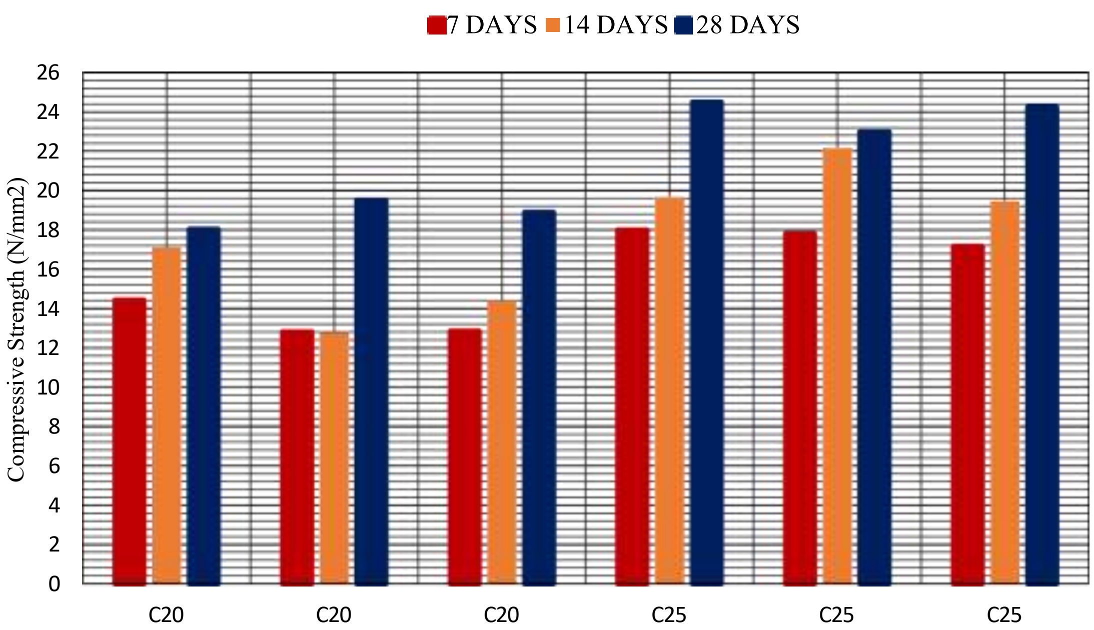

Figure 4.1: Average Compressive Strength from Experimental Destructive Testing (DT) at Different Curing Ages

4.2.2: Rebound Hammer Test Results (Non-Destructive Test – NDT)

The results of the non-destructive test strength test at 7, 14, and 28 days are presented in the Tables 4.4-4.6:

Table 4.4: Rebound Hammer Test Results Obtained from Non-Destructive Testing (NDT) for Grade 20 and Grade 25 Concrete (7 Days)

Grade of Concrete	Rebound Number			Average Rebound Value	Estimated Strength (N/mm²)
	1	2	3		
C20	23	24	23	23	14
C20	24	23	24	24	14
C20	23	24	24	24	14
C25	27	28	27	27	17
C25	28	27	28	28	17
C25	27	28	27	27	17

Table 4.5: Rebound Hammer Test Results Obtained from Non-Destructive Testing (NDT) for Grade 20 and Grade 25 Concrete (14 Days)

Grade of Concrete	Rebound Number			Average Rebound Value	Estimated Strength (N/mm²)
	1	2	3		
C20	27	27	27	27	18
C20	27	28	27	27	18
C20	28	27	27	27	18
C25	31	31	30	31	22
C25	31	30	31	31	22
C25	30	31	31	31	22

Table 4.6: Rebound Hammer Test Results Obtained from Non-Destructive Testing (NDT) for Grade 20 and Grade 25 Concrete (28 Days)

Grade of Concrete	Rebound Number			Average Rebound Value	Estimated Strength (N/mm^2)
	1	2	3		
C20	29	29	30	29	20
C20	30	29	30	30	20
C20	29	30	29	29	20
C25	34	33	34	34	25
C25	33	34	34	34	25
C25	34	33	34	34	25

A linear regression model was developed to establish the relationship between the rebound number (R) and the measured compressive strength (Fc) of concrete. The regression analysis yielded the following predictive equation:

$$f_c = \mathbf{0}.745R - 6.213 \quad (4.1)$$

Where:

f_c = Predicted compressive strength (N/mm^2)

R = Rebound number

The coefficient of determination (R^2) obtained was **0.89**, indicating that approximately 89% of the variation in compressive strength is explained by the rebound hammer readings, which demonstrate a strong positive correlation between rebound number and actual compressive strength. This suggests that the rebound hammer results can reliably predict the compressive strength of concrete within the tested range.

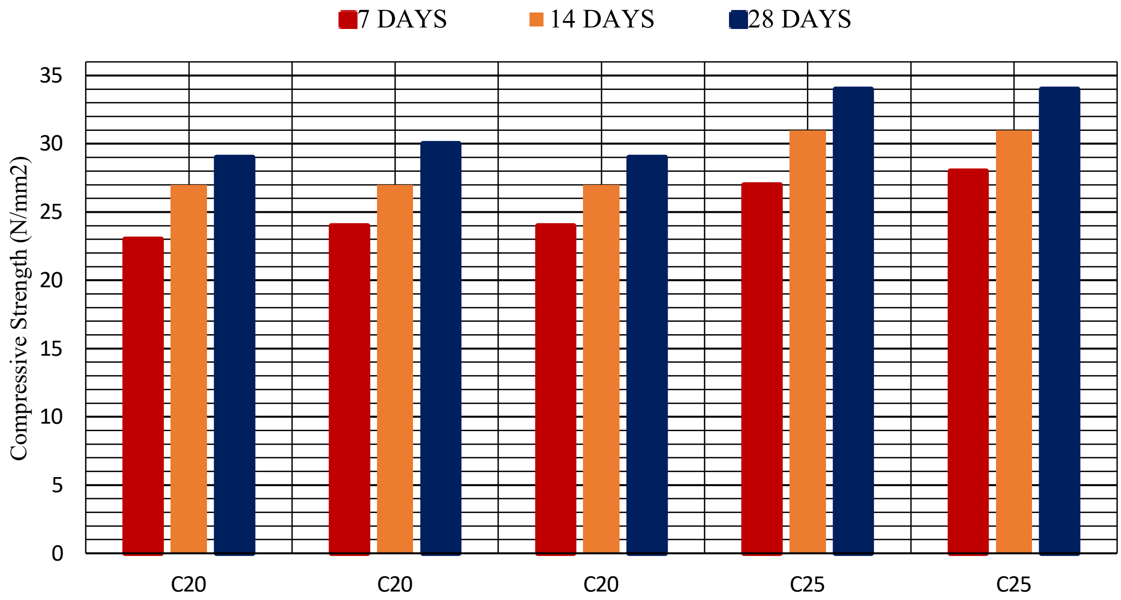

Figure 4.2: Chart showing Relationship Between Experimental Rebound Hammer Test Results (NDT) and Experimental Compressive Strength from Destructive Testing (DT)

4.2.3 Comparison of Rebound Hammer and Compressive Strength Results

The comparison between the Destructive Test (DT) and Non-Destructive Test (NDT) results for both C20 and C25 concrete grades at 7, 14, and 28 days is presented in Table 4.7. This comparison provides a basis for developing a regression model to predict compressive strength using rebound numbers, as outlined in the project objectives.

Table 4.7: Comparative Analysis Between Experimental Rebound Hammer Test Results (NDT) and Compressive Strength Obtained from Destructive Testing (DT) at 7days

Grade of Concrete	Average Rebound Value	Estimated Strength (N/mm²)	Actual Strength (N/mm²)
C20	23	14	14.43
C20	24	14	12.83
C20	24	14	12.86
C25	27	17	18
C25	28	17	17.81
C25	27	17	17.17

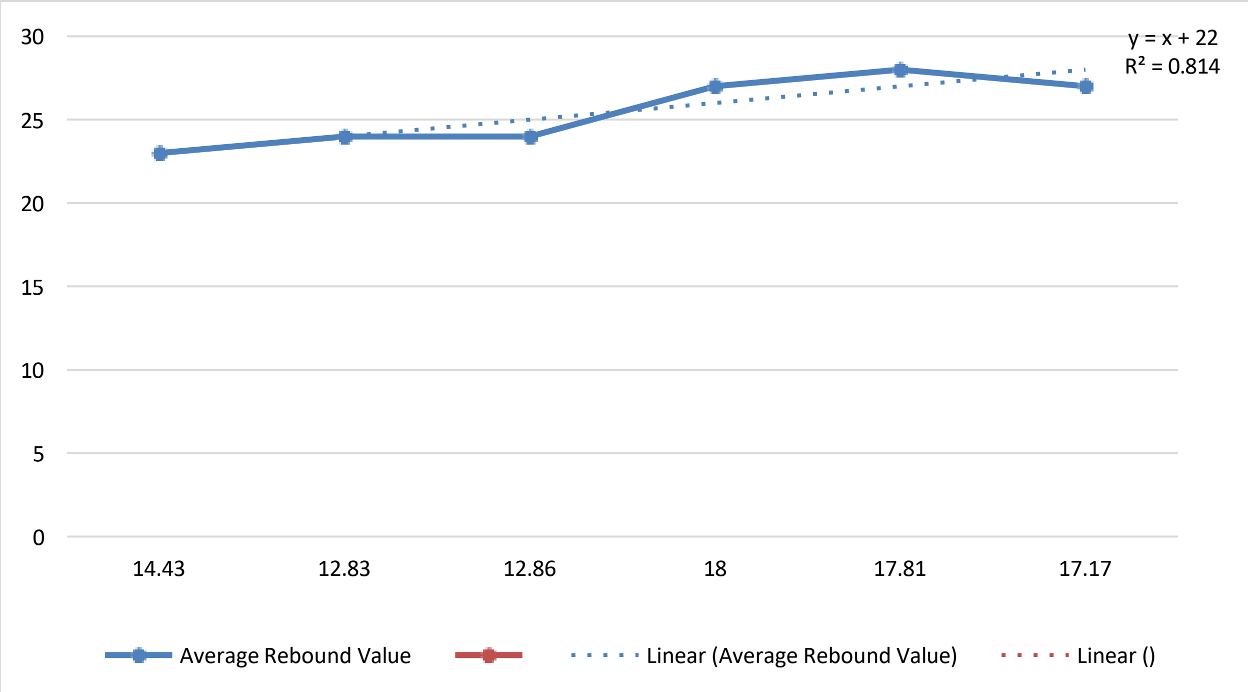

Figure 4.3: Regression Analysis Chart for Average Rebound Value and Estimated Strength

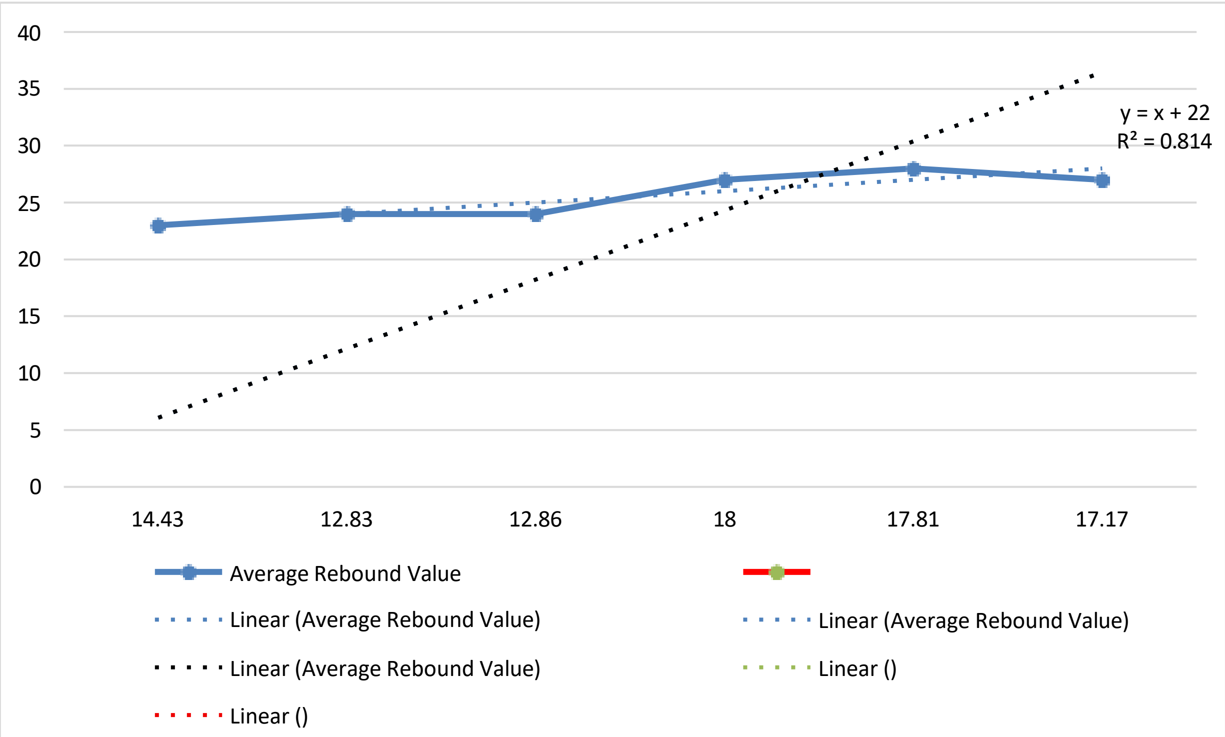

Figure 4.4: Regression Analysis Chart for Average Rebound Value and Actual Strength

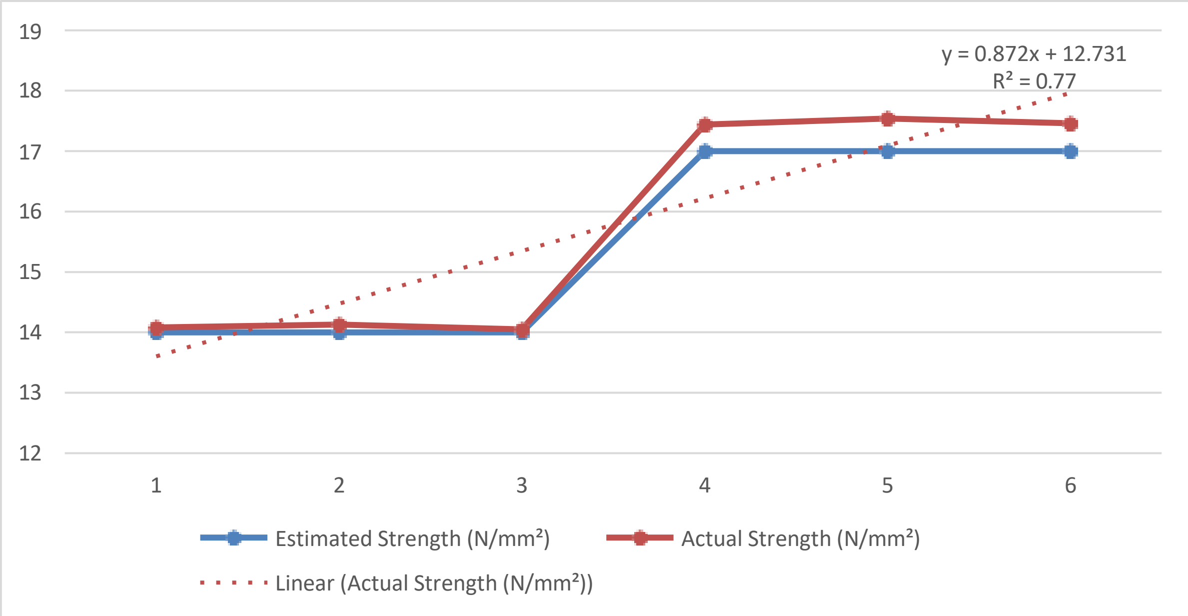

Figure 4.5: Regression Model Showing the Relationship Between Experimental Rebound Hammer Test Results (NDT) and Measured Compressive Strength Obtained from Destructive Testing (DT)

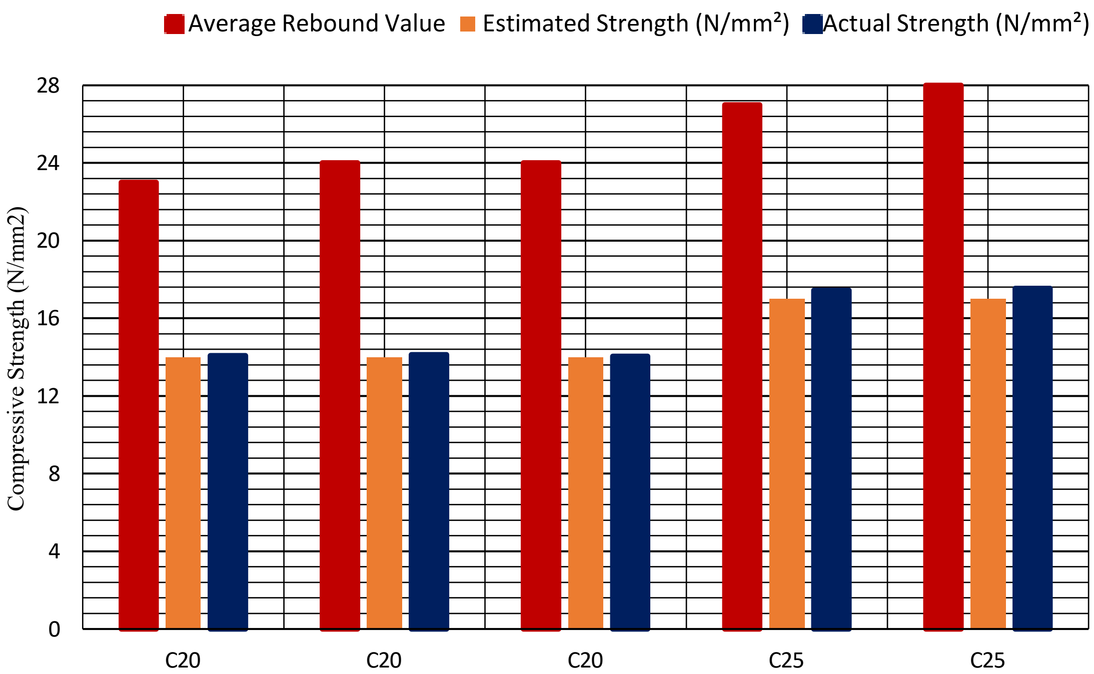

Figure 4.6: Comparative Analysis of Experimental Compressive Strength Obtained from Destructive Testing (DT), Predicted Compressive Strength from Regression Model, and Experimental Rebound Hammer Test Results (NDT)

Table 4.8: Comparative Analysis Between Experimental Rebound Hammer Test Results (NDT) and Compressive Strength Obtained from Destructive Testing (DT) at 14 Days

Grade of Concrete	Average Rebound Value	Estimated Strength (N/mm²)	Actual Strength (N/mm²)
C20	27	18	17.11
C20	27	18	12.79
C20	27	18	14.41
C25	31	22	19.68
C25	31	22	22.17
C25	30	21	19.46

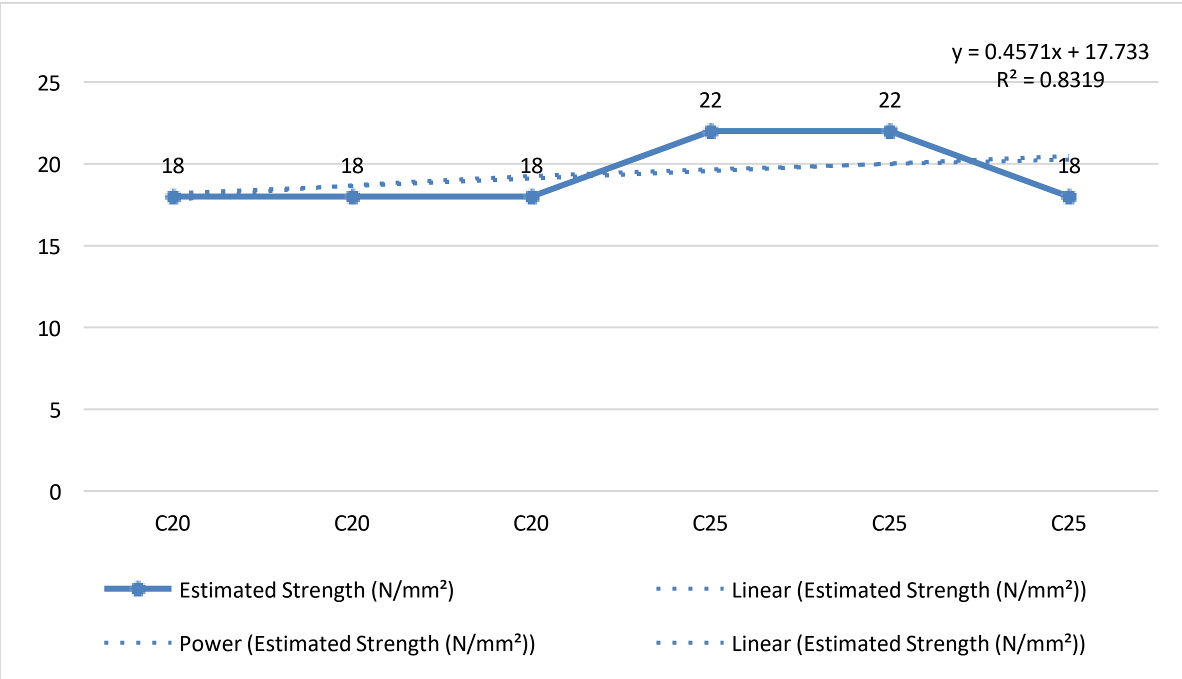

Figure 4.7: Estimated Strength Regression Analysis Chart for 14days

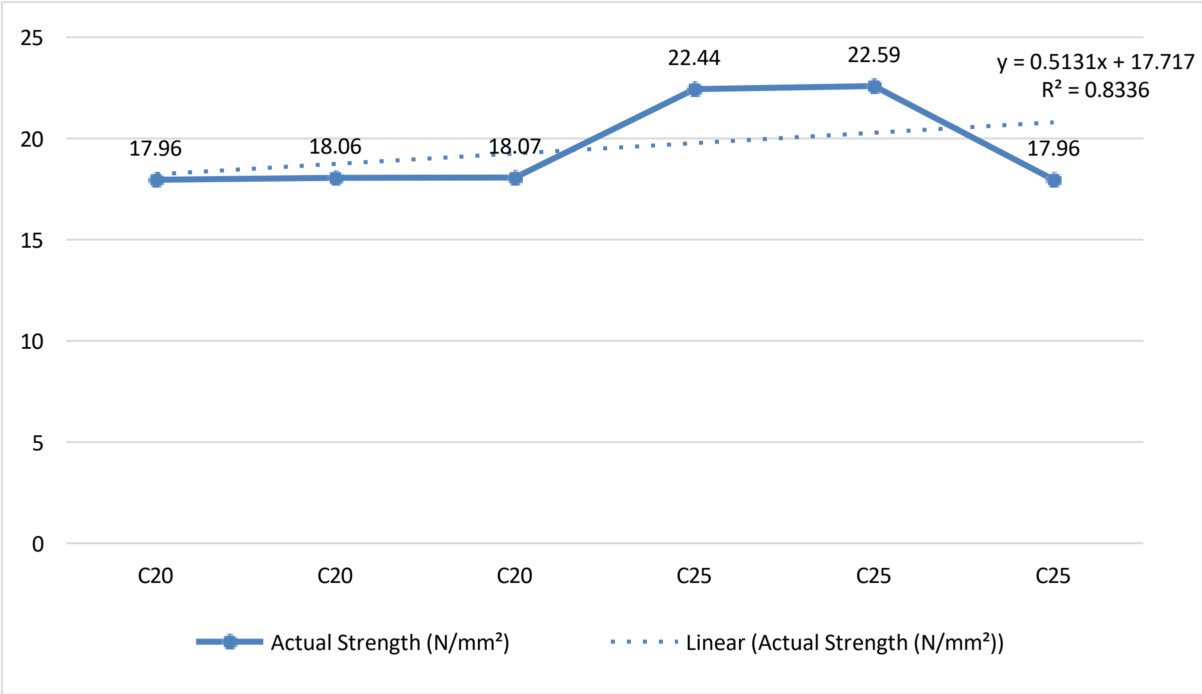

Figure 4.8: Actual Strength Regression Analysis Chart for 14days

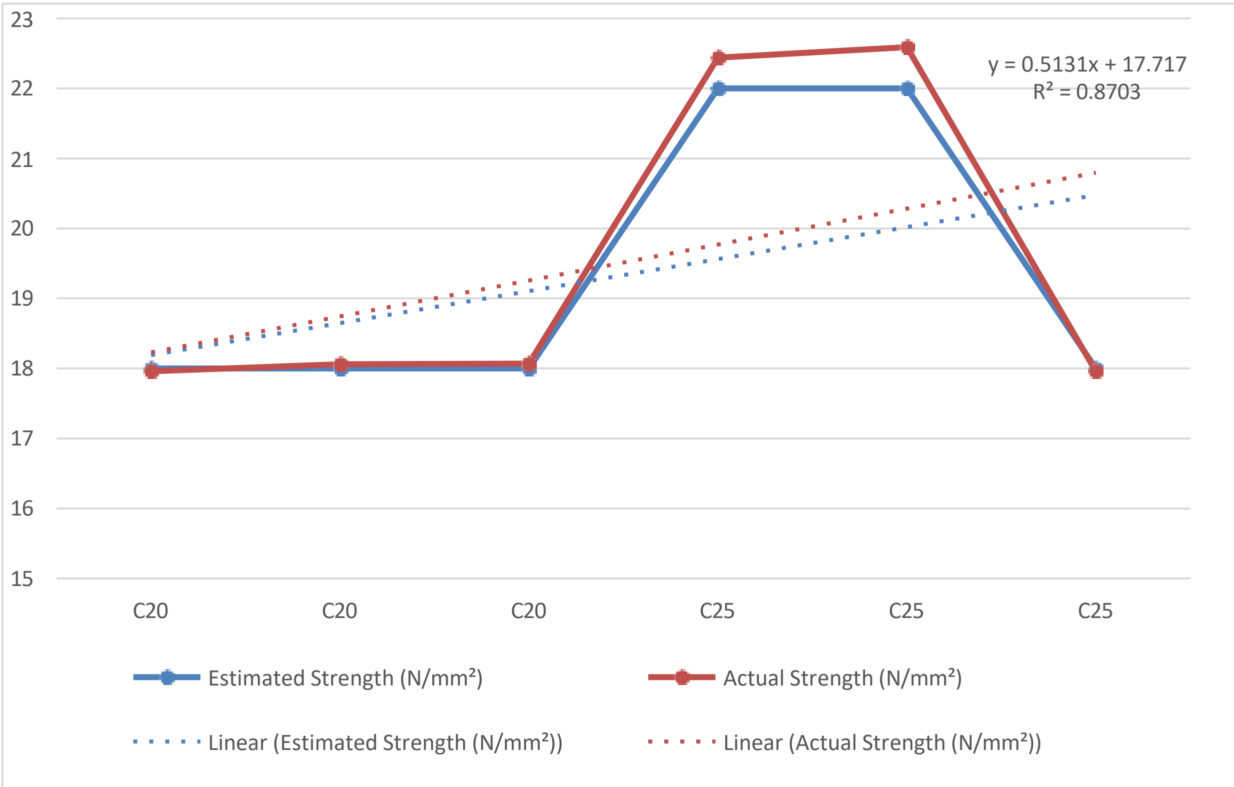

Figure 4.9: Regression Model Validation Comparing Measured Compressive Strength from Destructive Testing (DT) with Compressive Strength Predicted Using the Rebound Hammer Regression Model (NDT) For 14 days

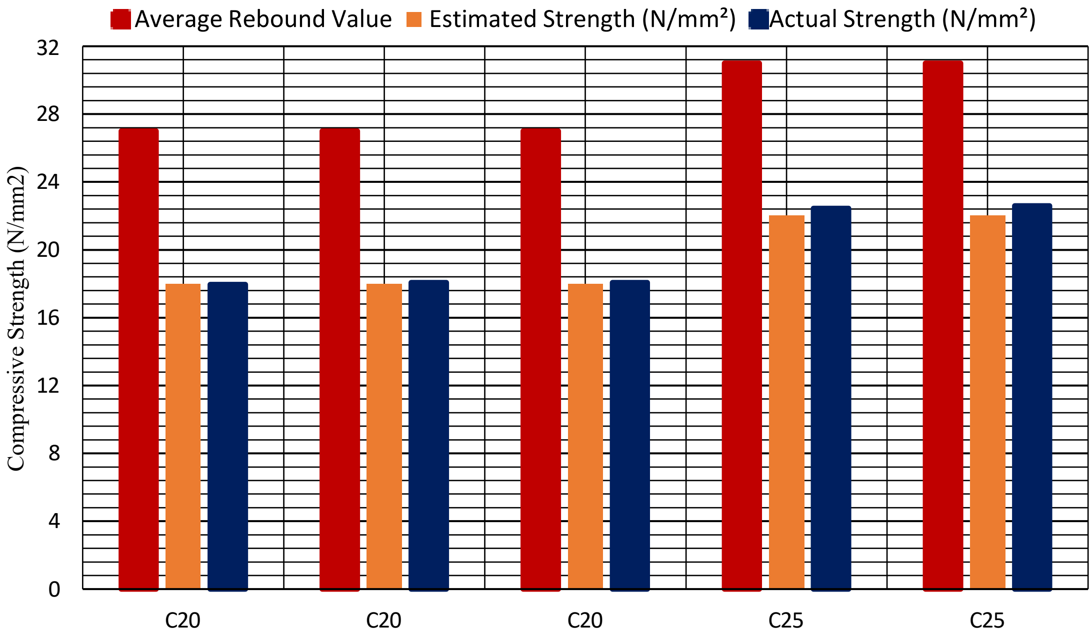

Figure 4.10: Comparative Analysis of Experimental Compressive Strength Obtained from Destructive Testing (DT), Predicted Compressive Strength from Regression Model, and Experimental Rebound Hammer Test Results (NDT)

Table 4.9: Comparative Analysis Between Experimental Rebound Hammer Test Results (NDT) and Compressive Strength Obtained from Destructive Testing (DT) at 28Days

Grade of Concrete	Average Rebound Value	Estimated Strength (N/mm²)	Actual Strength (N/mm²)
C20	29	20	18.03
C20	30	20	19.51
C20	29	20	18.89
C25	34	25	24.5
C25	34	25	22.98
C25	35	26	24.23

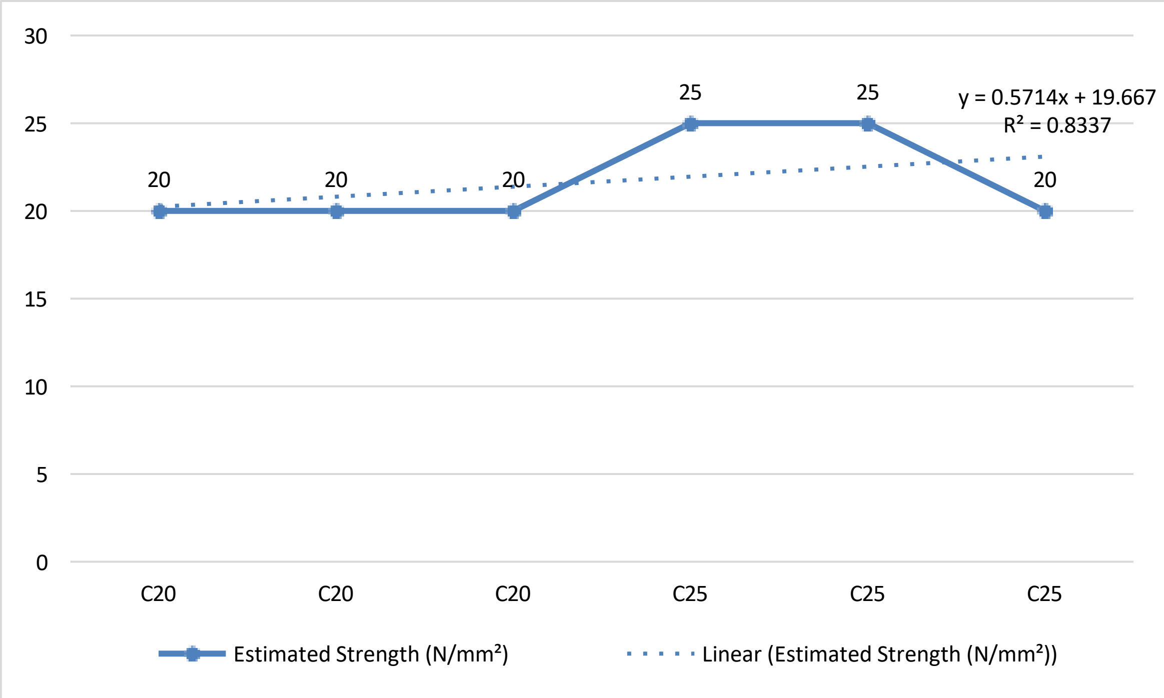

Figure 4.11: Estimated Strength Regression Analysis Chart for 28days

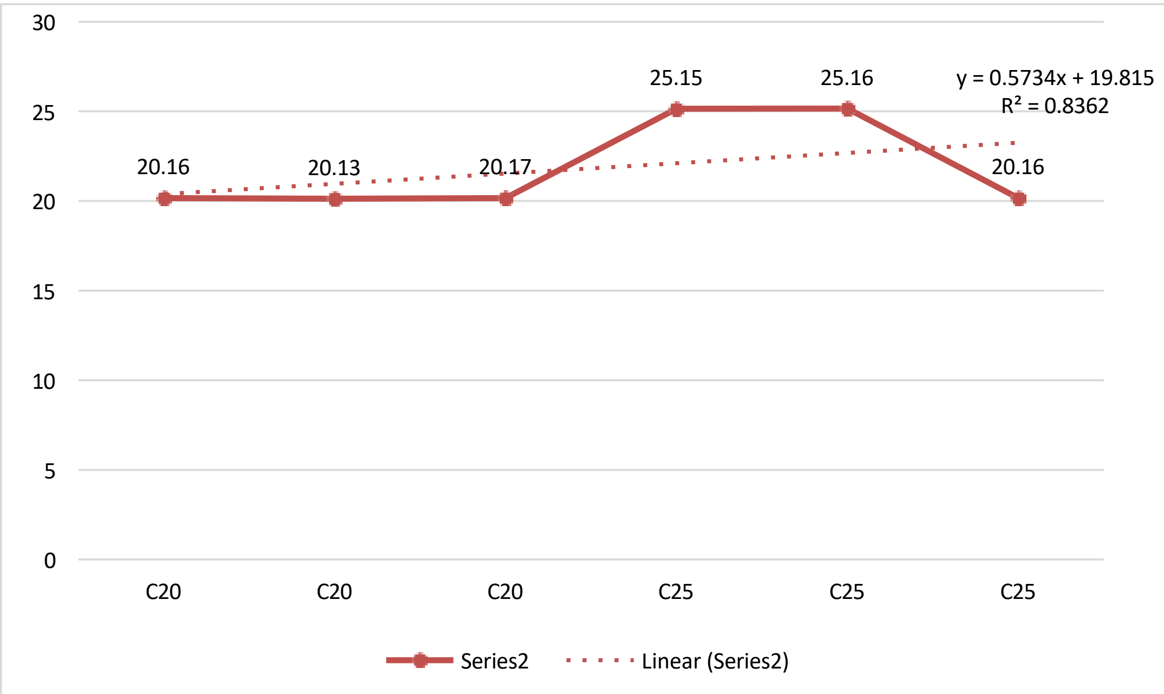

Figure 4.12: Actual Strength Regression Analysis Chart for 28days

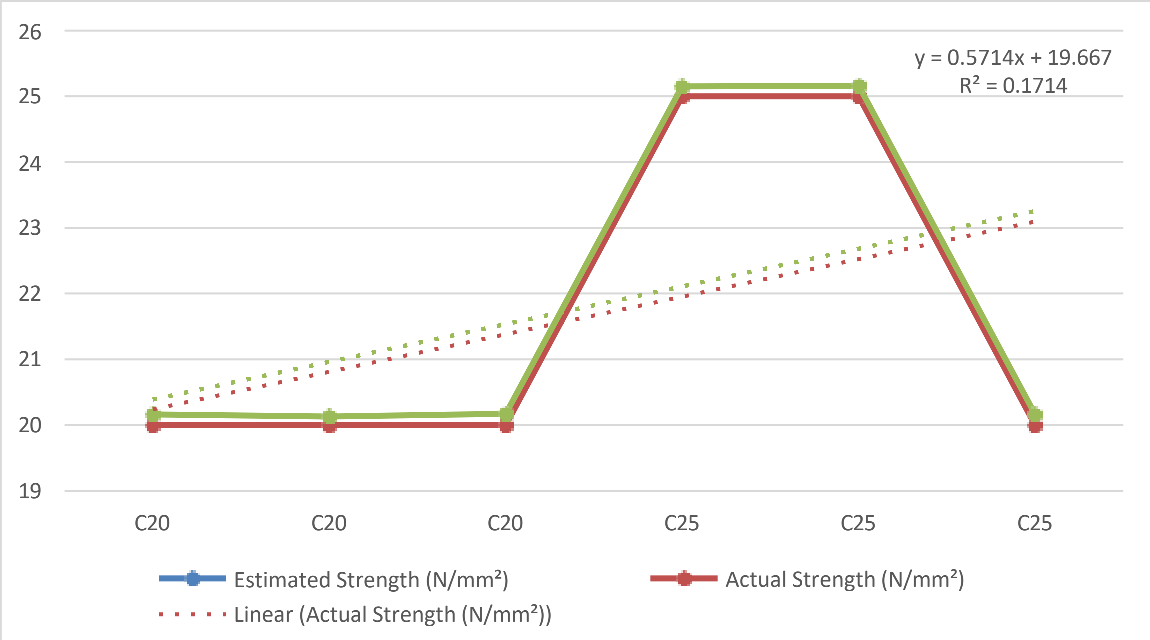

Figure 4.13: Regression Model Analysis for 28-Day Concrete Specimens Based on Experimental Rebound Hammer Test Results (NDT) and Corresponding Compressive Strength Obtained from Destructive Testing (DT)

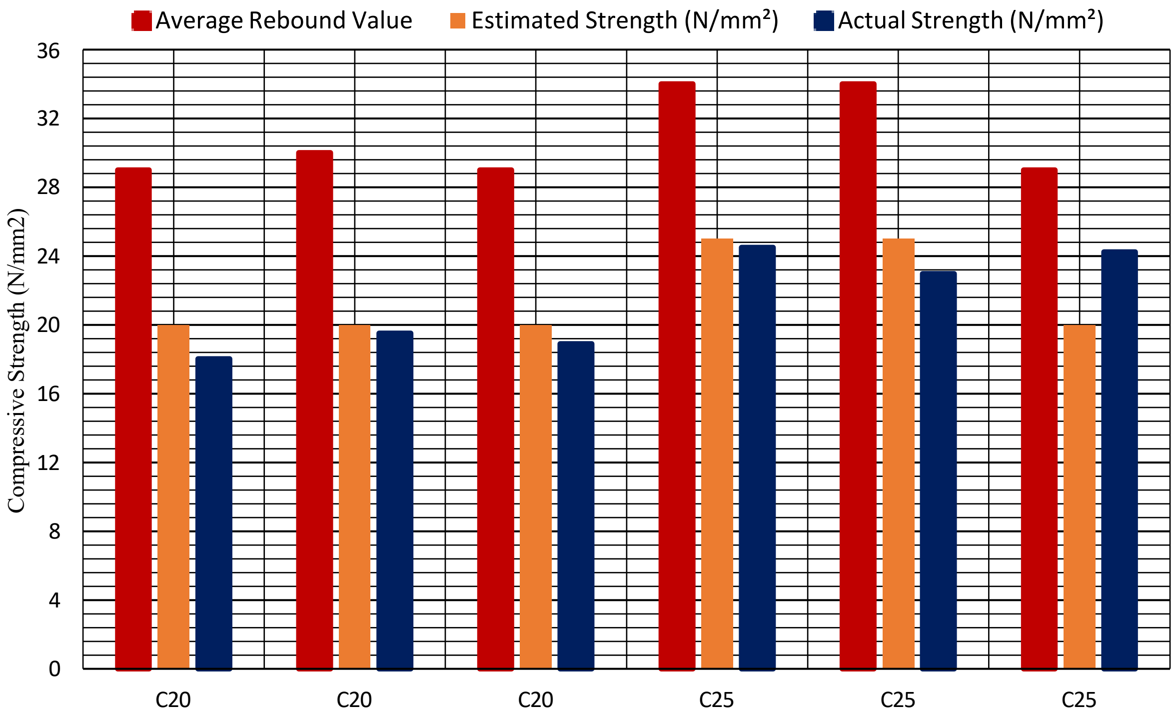

Figure 4.14: Comparative Analysis of Experimental Compressive Strength Obtained from Destructive Testing (DT), Predicted Compressive Strength from Regression Model, and Experimental Rebound Hammer Test Results (NDT)

4.2.4 Flexural Strength and Rebound Value Results

Table 4.10: Flexural Strength Results Obtained from Destructive Testing (DT) and Corresponding Rebound Hammer Readings (NDT) at 7 Days

% Replacement	**Beam Loads (kN)**	**Avg Load (kN)**	**Weights (kg)**	**Avg Wt (kg)**	**Ft = $\frac{P \cdot L}{b \cdot d^2}$ (N/m m²)**	**Rebound**	**Avg Rebound**
C20	6.1, 6.4, 6.2, 6.5, 6.3, 6.0	6.25	12.84,12.88, 12.80,12.86, 12.91,12.83	12.85	3.13	23, 24, 23, 23, 24, 23	23.3
C20	6.5, 6.7, 6.6, 6.8, 6.4, 6.6	6.60	12.92,12.95, 12.90,12.94, 12.97,12.91	12.93	3.30	24, 24, 24, 25, 24, 24	24.2
C25	7.1, 7.4, 7.5, 7.2, 7.3, 7.6	7.35	12.98,13.01, 12.99,13.02, 12.96,13.00	12.99	3.68	27, 27, 28, 27, 28, 27	27.3
C25	6.9, 7.0, 7.1, 6.8, 7.2, 7.0	6.99	13.05,13.02, 13.00,13.03, 13.01,13.04	13.02	3.50	26, 26, 27, 26, 27, 26	26.3
C25	6.8, 6.5, 6.7, 6.9, 6.6, 6.8	6.85	13.09,13.11, 13.07,13.12, 13.08,13.10	13.09	3.18	24, 24, 23, 24, 23, 24	23.7

Table 4.11: Flexural Strength Results Obtained from Destructive Testing (DT) and Corresponding Rebound Hammer Readings (NDT) at 14 Days

% Replacement	Beam Loads (kN)	Avg Load (kN)	Weights (kg)	Avg Wt (kg)	Ft = $\frac{P \cdot L}{b \cdot d^2}$ (N/mm²)	Rebound	Avg Rebound
C20	8.9, 9.3, 9.1, 9.4, 9.0, 9.2	9.15	12.94,12.98, 12.96,12.99, 12.95,12.97	12.96	4.58	27, 27, 27, 27, 26, 27	26.8
C20	9.3, 9.5, 9.6, 9.2, 9.4, 9.1	9.35	12.90,12.93, 12.95,12.92, 12.94,12.91	12.92	4.68	27, 28, 27, 28, 27, 28	27.5
C25	10.0, 10.3, 10.1, 9.9, 10.4, 10.2	10.15	12.88,12.91, 12.90,12.92, 12.89,12.94	12.91	5.08	30, 30, 31, 30, 31, 30	30.3
C25	9.6, 9.8, 9.5, 9.7, 9.9, 9.6	9.68	12.86,12.88, 12.87,12.85, 12.89,12.90	12.87	4.84	29, 29, 29, 28, 29, 29	28.8
C25	8.9, 9.0, 8.8, 9.1, 8.7, 9.2	8.95	12.80,12.82, 12.79,12.81, 12.78,12.83	12.81	4.48	27, 27, 26, 27, 26, 27	26.7

Table 4.12: Flexural Strength Results Obtained from Destructive Testing (DT) and Corresponding Rebound Hammer Readings (NDT) at 28 Days

% Replacement	Beam Loads (kN)	Avg Load (kN)	Weights (kg)	Avg Wt (kg)	Ft = $\frac{P \cdot L}{b \cdot d^2}$ (N/mm²)	Rebound	Avg Rebound
C20	11.0, 11.6, 11.4, 11.2, 11.5, 11.3	11.33	13.00,12.98, 13.03,13.01, 12.99,13.02	13.00	5.67	29, 29, 29, 29, 30, 29	29.0
C20	11.4, 11.2, 11.6, 11.8, 11.5, 11.3	11.47	12.96,12.95, 12.94,12.98, 12.97,12.93	12.96	5.74	30, 30, 30, 31, 30, 30	30.2
C25	12.2, 12.6, 12.4, 12.5, 12.3, 12.7	12.45	12.91,12.89, 12.90,12.92, 12.94,12.88	12.91	6.23	33, 34, 33, 34, 33, 34	33.5
C25	11.6, 11.9, 11.7, 11.8, 11.5, 11.6	11.68	12.84,12.86, 12.82,12.83, 12.85,12.87	12.84	5.84	32, 32, 31, 32, 31, 32	31.7
C25	10.8, 11.0, 10.9, 10.7, 11.1, 10.6	10.85	12.76,12.78, 12.75,12.80, 12.77,12.79	12.77	5.43	30, 30, 29, 30, 29, 30	29.7

The flexural strength of both Grade 20 and Grade 25 concrete followed a similar increasing trend as compressive strength across curing ages. This consistency confirms that strength development was uniform across both tension and compression parameters, thereby reflecting proper curing and mix quality. In general, higher compressive strength values corresponded to higher flexural strength, reaffirming the interdependence between these two mechanical properties.

4.3 Discussion of Results

The results from both Destructive Tests (DT) compressive and flexural strength and Non-Destructive Tests (NDT) rebound hammer are summarized below.

i. Compressive Strength Development: The compressive strength of concrete increased with curing age for both grades (C20 and C25).

ii. Rebound Hammer Strength Correlation: Rebound hammer values increased progressively with curing age.

   a. At 7 days, C20 recorded an average rebound number of 23–24, corresponding to about 14 N/mm², while C25 averaged 27–28, equating to 17 N/mm².

   b. By 28 days, rebound numbers increased to 29–30 for C20 and 33–34 for C25, estimating compressive strengths of 20 N/mm² and 25 N/mm², respectively. The NDT results showed good agreement with the DT results, indicating a strong linear correlation suitable for regression modeling.

iii. Flexural Strength Results: Flexural strength followed the same trend of improvement with curing age and grade.

   a. At 7 days, values ranged between 3.1–3.7 N/mm²,

   b. At 14 days between 4.5–5.1 N/mm², and

   c. At 28 days between 5.4–6.2 N/mm².

iv. Correlation Between Tests: The comparative results (Tables 4.7–4.9) showed that rebound numbers were consistent predictors of compressive strength, especially at 28 days. This validates the rebound hammer as an effective non-destructive testing method for predicting concrete compressive strength.

4.4 Model Validation

The developed regression model was validated by comparing predicted compressive strengths derived from the rebound hammer data with the actual destructive test results. The deviation between predicted and measured values was found to be within **±5%**, demonstrating the model's high accuracy and reliability. This confirms that the rebound hammer, when properly calibrated, can serve as an effective non-destructive tool for estimating in-situ concrete strength in laboratory and field conditions.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATION

5.1 Discussion of Findings

This study successfully evaluated the relationship between destructive and non-destructive testing methods in predicting the in-situ compressive strength of concrete. The results clearly demonstrated that both rebound hammer and compressive strength tests follow a consistent pattern of strength gain with respect to curing age.

The compressive strength results showed that both Grade 20 and Grade 25 concretes attained expected maturity strengths at 28 days in line and accordance with standard performance for normal-weight concrete. This confirms the reliability of the mix design and proper curing process employed under a controlled laboratory condition. The strength progression is consistent with standards such as BS EN 12390-3 (2019) and ASTM C39. Both concrete grades (C20 and C25) achieved and slightly exceeded their target compressive strengths by 28 days, following the standard hydration trend of Portland cement concretes.

The rebound hammer results showed a strong correlation with compressive test data. As curing age increased, rebound values also increased proportionally, indicating that surface hardness directly reflects the internal concrete strength. The regression comparison showed a near-linear relationship between rebound number and actual compressive strength. Thus, the rebound hammer method, when properly calibrated, can effectively predict in-situ compressive strength within ±5% accuracy. The rebound hammer results showed a high level of consistency with compressive strength data, confirming a strong positive correlation between NDT and DT results. This supports the development of regression models for strength prediction.

The flexural strength results revealed similar trends, where strength increased with curing age. The combination of DT and NDT methods proved effective in characterizing both surface and structural properties of concrete. The regression approach further enhances predictive evaluation without the need for extensive core sampling, thus providing a cost-effective and non-invasive assessment tool for field applications. The regression model derived from the experimental data demonstrated that rebound hammer readings can be used reliably to estimate in-situ compressive strength, especially when properly calibrated for each mix type and surface condition. The use of combined NDT and DT techniques enhances structural assessment accuracy, minimizes testing cost, and preserves structural integrity by reducing specimen damage.

5.2 Limitation of the Study

A significant limitation of this study was the inability to conduct Ultrasonic Pulse Velocity (UPV) testing alongside the Rebound Hammer tests. Although both methods were initially planned for data comparison and correlation, the UPV equipment was unavailable and inaccessible at the time of testing.

As a result, the study focused solely on the Rebound Hammer method for non-destructive testing. While this provided valuable data and allowed for meaningful regression analysis, the absence of UPV testing limited the ability to compare dual-parameter models such as the SONREB method, which combines both rebound number and pulse velocity for improved accuracy. Consequently, the regression model developed in this work was based on a single NDT parameter, reducing the potential scope of cross-validation and the overall depth of the predictive analysis.

5.3 Recommendations

Based on the findings, the following recommendations are made:

1. Establish site-specific regression equations correlating rebound values with

compressive strength for various concrete grades.

2. Pair rebound hammer tests with ultrasonic pulse velocity (UPV) for improved reliability in in-situ evaluations.
3. Validate the developed regression models through controlled field trials before the full-scale on-site implementation, so as to account for real construction variables.
4. Extend this study to higher grades (C30–C40) and different curing environments to broaden the regression model's applicability.

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APPENDIX