Journal Homepage: - www.journalijar.com

INTERNATIONAL JOURNAL OF ADVANCED RESEARCH (IJAR)

Article DOI: 10.21474/IJAR01/21070
DOI URL: http://dx.doi.org/10.21474/IJAR01/21070

ISSN NO. 2320-5407

RESEARCH ARTICLE

EXPLORING THE RELATIONSHIP BETWEEN NDT AND DT TECHNIQUES IN CONCRETE: LINEAR, QUADRATIC, AND CUBIC CORRELATION MODELS

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Manuscript Info

Manuscript History
Received: 02 April 2025
Final Accepted: 05 May 2025
Published: June 2025

Key words:-
Non-Destructive Testing (NDT), Destructive Testing (DT), Concrete Strength, Linear Regression, Quadratic Regression, Cubic Regression, Rebound Hammer, Compressive Strength

Abstract

The present study involves the development of a correlation of Non-Destructive Testing (NDT) and Destructive Testing (DT) techniques for evaluation of concrete strength. The models selected are linear, quadratic, cubic for the present study. Concretes with grades M10 to M40 were used and compressive strength relationships developed between what was obtained from the destructive testing using a compression testing machine and surface hardness measurement gotten through non-destructive testing using a rebound hammer. The analysis showed good correlations, where the coefficients of determination (R^2) ranged from 91.6% to 97.9% for the different models. This can be used to prove that the NDT, when calibrated on DT data, allows for accurate estimation of concrete strength with very low intrusion and time investment. The study highlights how advanced mathematical models can facilitate more accurate predictions for concrete strength—which may decisively determine the safety and durability of larger engineering works.

Introduction:-

One of the most popular building materials is concrete. Large engineering constructions like railroads, bridges, dams, and nuclear power plants must consider the consequences of dynamic loads like earthquakes, impacts, and explosions in addition to static loads. The foundation for the design and optimisation of these engineering structures is provided by the mechanical characteristics of concrete and the dynamic failure mechanism. However, concrete's mechanical behavior and damage characteristics differ significantly from those of static conditions. The strain rate effect is responsible for the apparent strength increase that is typically seen under dynamic load. The mesoscopic heterogeneity of concrete, the modification of the concrete damage pattern, and the structural impact resulting from the transverse inertia force can all be attributable to this phenomenon [1]. Controlling the durability and life expectancy of structures requires an understanding of the fracture propagation characteristics of concrete. Therefore, for mission-critical facilities, strict discretization approaches for crack growth are crucial [2]. The impact of heterogeneity on concrete fracture characteristics and the explicit knowledge of this relationship made possible by the enormous advances in computational power and numerical methods is one of the major areas of research. Voids, coarse aggregates, micro cracks, dehydrated particles, and fibres are the causes of this heterogeneity.

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The rapid advancement of construction technology has led to the construction of numerous large-span concrete structures worldwide. However, as this long-span concrete structures age, deflection at their mid-span tends to increase due to factors such as concrete shrinkage and creep, pre-stress loss in pre-stressed tendons, and sustained loading effects. This will lead to increased deflection and further compromise the structure's serviceability for a long period, and in serious cases, may even cause early failure. Thus, the probability of the failing concrete structure under excessive deflection should be estimated, and adequate forecast of long-term deflection should be made to put forward proper targeted maintenance and reinforcement plans for such concrete structures [3]. X-CT technology was of great help in concrete material research conducted over the last few decades. It provides a nondestructive possibility to three-dimensionally visualize interior properties of material. There are, however, only a few studies that are dedicated to the issue of segmenting multiphase concretes on micro and meso levels, and to methods of visualization. Few studies have quantified variations in concrete pores and cracks due to erosion. These have all not involved loading and have only focused on virgin or environmentally degraded concrete [4].

Reliability of in-situ compression strength measurements is of great importance for assessment of the quality of concrete existing structures in the course of their service life. Strong data about in-situ compressive strength is necessary to make trustworthy structural evaluation and strengthening treatments when seismic capabilities of existing constructions are assessed. These constructions frequently follow antiquated seismic regulations with reduced safety factors or are solely intended to support gravity loads [5].

Core testing have more accurate destructive test methods than NDT. However, a number of drawbacks are listed as very expensive, invasive, sometimes infeasible, and time-consuming process. In combat, combining core testing with NDT will improve the concrete strength evaluation, yield more data, and reduce costs from fewer cores required. In spite of that, there is scant research on NDT methods in the evaluation of concrete strength in either dry or wet cycle environments both nationally and internationally. Besides, the assessment of deterioration in concrete strength under such conditions is also considerably different [6].

Testing the strength of concrete forms one of the cornerstones in the field of construction and thus serves for assurance of the safety, durability, and overall structural integrity of a building and infrastructure. The need for an accurate determination of concrete strength is critical in a number of ways, since it has to establish that the concrete is following the design specifications and has the capacity to bear or support applied loads and environmental stresses. Lack of reliable testing may result in failures at high risk, which may mean expensive repairs and safety risks, or even catastrophic collapses in some extreme cases [7].

Traditional techniques of concrete strength testing, such as the compressive strength test for concrete cylinders or cubes, have raised many problems. Much of the time, sample curing requires a very considerable amount of time; thus, these approaches delay the construction process. These tests can also become inaccurate due to a variety of factors, which include improper handling of samples, variability in testing conditions, and the intrinsic heterogeneity of concrete as a material. This can then further be a reason for incorrect estimation of the actual strength of concrete and may result in overdesign or, worse, underestimation of the concrete capacity [8].

Coupled with the challenges, disruptive and vital trends and developments are witnessed within concrete strength testing technologies in the construction industry. The more recent advancements include nondestructive testing techniques that allow for in situ concrete strength evaluation without causing structural damage, such as ultrasonic pulse velocity and rebound hammer tests. Digital imaging techniques, on the other hand, are now being coupled with machine learning algorithms in testing processes to help increase the accuracy of the strength prediction and offer real-time monitoring of concrete quality.

Other developing trends associated with the assessment of concrete quality are related to sustainability and durability. More attention is given to the long-term assessment of concrete performance, particularly resistance to environment-specific agents like freeze-thaw cycles, chemical exposure, and moisture infiltration [9]. Smart sensors embedded in concrete structure have become quite helpful in continuous data provision relevant to the condition and performance of this material over some time. These developments are making the construction industry one of more efficiency, reliability, and sustainability to ensure concrete studies for longevity while minimizing environmental impact.

Literature Review:-

Coric, V. (2023) [10]Pre-stressed concrete bridges are vulnerable to degradation over time, which can significantly impact their structural capacity and overall performance. In recent decades, infrastructure owners have recognized the value of continuous monitoring as a crucial tool for managing these assets, as it aids in making informed decisions about necessary interventions. However, with the rapid advancement of data acquisition and measurement technologies, the sheer volume of data collected daily has become increasingly challenging to manage and analyze.The present study assesses the suitability of several machine learning techniques in terms of delivering estimates and interpretations of structural responses; further, it studies the feasibility of mapping independent variables. Thereafter, the aspects regarding metric performance, learning curves, and residual plots were investigated. A few machine learning algorithms were compared against each other regarding regression analysis, and they all yielded a value of more than 98% with regards to the R-squared value.
The data used in this study were collected from a continuously monitored prestressed concrete bridge located in Autio in northern Sweden over a period of more than three years.

B. Gunes et al., (2023) [11] examined thatnon-destructive in-situ testing of concrete strength by means of a drilling test method has been performed. In this context, the correlation between the drilling resistance factor and the concrete compressive strength for a few studies is discussed. Tests from RH and UPV have also been conducted; the results have produced multivariate regression models, which combined the DR with data from RH and UPV. There has also been an approach to machine learning using Support Vector Machines. The experimental results show that by integrating DR and UPV and/or RH, compressive strength may be consistently predicted. With fewer data, the support vector regression model outperformed nicely.

Anoni L. G. et al. (2024) [12] studiedultrasonic tomography is a technique of non-destructive testing without causing any destruction to the concrete, visualizing from the inside of concrete constructions. A common method for locating reinforcement within concrete and for the identification of various types of deterioration: voids, cracks, rebar corrosion, and debonding. Various methods of image reconstruction have been studied and developed in order to increase the precision and sharpness of the resulting concrete tomogram. On the other hand, with increasing data volume, landscape comprehension may become difficult and sometimes indicates areas that must be further improved. This review represents a deep systematic analysis of different image reconstruction techniques used in ultrasonic tomography and underlines the latest developments in this area. The provided analysis concerns all the standard methods of both transmission and reflection tomography and delineates their peculiarities.Additionally, enhancement techniques have been documented and discussed. This comprehensive review serves as a foundation for identifying future advancements in ultrasonic tomography for concrete structures.

Javed, M. F., and Khan, M. (2023) [13] Supplementary cementitious materials (SCMs) are often used in concrete mixtures to replace some of the clinker or some percentage of the cement content. This common approach has significant benefits for the construction industry since it usually produces concrete with lower manufacturing costs, less of an impact on the environment, improved long-term durability, and increased strength over time. Scholars and professionals in the industry are actively investigating methods to predict the efficiency of blended cement concrete (BCC) mixes, in order to avoid the expenses and time involved in testing numerous choices through experimentation. Because machine learning techniques have a reputation for handling large datasets and accurately identifying relationships within the data, they were used in this investigation.Three models—one ensemble model, two distinct models, and one model—were used to predict the properties of mixed cement concrete. The database for the model's creation was constructed using 1,287 points of data for the compressive strength, 361 for the carbonation process, and 323 for chloride resistivity, all of which were derived from experimental experiments. The performance of these models was assessed using a number of error metrics. The decision tree (DT) model's coefficient of correlation (R) value for both training and validation sets was 0.99, demonstrating its high degree of predictive accuracy for compressive strength. With an R-value of 0.98, the AdaBoost regressor (AR) model demonstrated strong prediction performance for the durability aspects of BCC. The AR model's average absolute error (MAE) and root mean square error (RMSE) for carbonation and chloride penetration, respectively, were less than 0.5 and 400. The application of the SHapley Additive exPlanation (SHAP) approach yielded further data, demonstrating that among the SCMs, calcined clay and silica fume significantly increase compressive strength. Nonetheless, the carbonation resistance of BCC is adversely affected by most SCMs. It was found that adding materials such as crushed granulated slag from blast furnaces, calcined clay, limestone powder, and silica fume in place of Portland cement increased the cement's resistance to cations by reducing the material's ability to penetrate cations.

It has been pointed out by Dabholkar, T. et al. 2023 [14] that a large portion of the architectural layout of the concrete made from RCC depends on the compressive strength of concrete. The methods used in evaluating this strength are also categorized mainly into three kinds: destructive, non-destructive, and partly destructive approaches. Although the approaches for non-destructive methods often require costly equipment as well as expertise, they do not tamper with the integrity of the structure. Materials and compositional characteristics are among many factors that have influenced the compressive strength of concrete. In recent years, soft computing methods such as AI and ML have shown considerable promise in attempting to figure out the intricate correlations between these many aspects for obtaining results with accuracy. The approaches characterized in the concrete strength are becoming quite sophisticated, assessing specific parts in materials or digital picture correlation inclusive of AI and ML in the area. This work comprehensively reviews the development attained in the use of AI and ML techniques for the forecast of the compressive strength of concrete. It provides a review of the literature by emphasizing the different approaches taken using machine learning, the datasets employed in such approaches, metrics selected to assess the various approaches, and how the different approaches succeeded. It's crucial to remember that this study does not address compressive strength predictions in situations when there is dynamic loading or high strain rate loading. The study also intends to point out possibilities for future research, especially in the use of soft computing approaches for compressive strength estimation, and to figure out gaps in the existing body of knowledge.

C. Lan et al., (2024) [15] experimentedin a controlled laboratory setting, 8 concrete specimens were constructed, and artificial fissures were created. The grouting method's basic principles were then followed to fix the cracks using two different types of agents: a paste of cement and cement mortar. Over the course of 28 days, impedance signals were recorded, and the quality of the repairs was assessed using three quantitative metrics: correlation coefficient deviation, mean absolute percentage deviation, and root mean square deviation. The outcomes showed that, in comparison to conventional SAs, SSAs offered improved sensitivity and stability. Normalized values of quantitative indicators have helped in distinguishing between different repair chemicals. A mathematical model using exponential function was presented that would help in evaluating and predicting the quantitative efficacy of repairs. The study also accounted for temperature, humidity, width, and depth of fracture while obtaining experimental results. Numerical models were used to validate the experimental results and ensure their reliability.

Rezaei et al., (2023) [16] had studied the properties of cement containing Colloidal Nano-Silica and both types of aggregates, namely recycled and organic coarse aggregates. So, in this paper, some mechanical properties of the concrete made with different percentages of substituting natural gravel by recycled coarse aggregate are studied. Thirteen different experimental groups were prepared, consisting of a total of 195 specimens by using different contents of nano-silica (0%, 1.5%, 3%, 4.5%, and 6%), as well as recycled coarse aggregate (0%, 25%, 50%, 75%, and 100%). Compressive strength, split tensile and flexural strength, modulus of elasticity, water absorption, and porosity, and UPV were some of the key parameters tested. These test results showed that the mechanical properties and durability of concrete decreased with the rise in the percentage of the recycled coarse aggregate. However, the addition of natural or recycled aggregates to nano-silica increased the mechanical properties and durability of the concrete. The response surface method was implemented to find the optimum ratios of the RCAs and NS for the optimization of concrete characteristics. It was noted that the optimum ratios were 26% recycled coarse aggregate and 4% nano-silica. In addition, GEP has been applied in predicting the compressive strength of cement incorporating nano-silica and RCA. The model developed a good fit with test results obtained from the experiment, hence the model could be reliably used to forecast the performance of concrete. The model was developed based on data from 168 concrete specimens collected from the literature.

Methodology:-

The 14-day concrete study was focused on the preparation of concrete cubes of 150mm × 150mm × 150mm dimensions. Concrete grade studies in the present investigation were M10, M15, M20, M25, M30, M35, and M40. Mixing of concrete and casting of cubes were done in a prescribed manner. The prepared cubes were left to set for 24 hours, after which the cubes were de-moulded. The cubes were then put in a curing tank to maintain consistent moisture levels until the 14-day testing period.

The testing for compressive strength of concrete cubes was done under destructive testing in a compressive testing machine as per procedures outlined in IS: 516. The determination of compressive strength at 14 days for each grade of concrete had to be made from 7 specimens. Results were recorded and analyzed to determine the strength characteristics for each concrete mix.

The rebound hammer was used to carry out NDT for measuring the surface hardness of concrete, which is directly related to its compressive strength. The test was used on the same concrete cubes used for DT to provide a measure of its strength by the surface response.

The detailed mix designs and quantities of materials used for each concrete grade were as follows:

Mix Proportions	**M10**	**M15**	**M20**	**M25**	**M30**	**M35**	**M40**
Water-Cement Ratio (w/c)	0.55	0.55	0.5	0.5	0.45	0.45	0.45
Cement Content	-	-	-	300 kg/m³	320 kg/m³	340 kg/m³	340 kg/m³
Mix Grade	1:3:6	1:2:4	1:1.5:3	1:1:2	1:0.75:1.5	1:0.5:1	1:0.25:0.5

Quantity of Materials:
For M10, M15, M20, and M25:

Material	**Cement**	**Fly Ash**	**Fine Aggregate**	**Coarse Aggregate**	**Water**	**Super Plasticizer**
Quantity (kg)	280	270	799	834	182	3.3

For M30:

Material	**Cement**	**Fly Ash**	**Fine Aggregate**	**Coarse Aggregate**	**Water**	**Super Plasticizer**
Quantity (kg)	290	270	836	858	166	4.48

For M35:

Material	**Coarse Aggregate**	**Water**	**Fly Ash**	**Super Plasticizer**	**Cement**	**Fine Aggregate**
Quantity (kg)	814	172	110	3.48	430	814

For M40:

Material	**Fine Aggregate**	**Water**	**Cement**	**Coarse Aggregate**	**Super Plasticizer**	**Fly Ash**
Quantity (kg)	814	172	430	814	3.48	110

Experimental Investigation
In this study, concrete samples of different grades were tested for compressive strength at 14 days of curing by using Destructive Testing and Non-Destructive Testing methods. Concrete grades M10, M15, M20, M25, M30, M35, and M40 were assessed. The concrete cubes cast in the laboratory as per IS 456 for normal weight concrete used in this study were of standard dimensions 150mm × 150mm × 150mm. Each grade was mixed and poured into cube molds by hand, de-moulded after 24 hours, and allowed to immerse in a curing tank for 14 days. A total of 126 concrete cubes were prepared, with 7 specimens for every grade and curing period.

Table 1:- Total Specimens Casted in the Study.

Grade of Concrete	**M10**	**M15**	**M20**	**M25**	**M30**	**M35**	**M40**
Size of Cube (150mm³)	18	18	18	18	18	18	18

Concrete Mix Design and Properties
Concrete mix designs adhered to IS 10262 specifications. The mix designs for different grades were as follows:

Mix Proportions (Cement: Fine Aggregate: Coarse Aggregate)	**1:1.5:3**	**1:0.5:1**	**1:3:6**	**1:0.75:1.5**	**1:2:4**	**1:1:2**	**1:0.25:0.5**
Water-Cement Ratio (w/c)	0.5	0.45	0.55	0.45	0.55	0.5	0.45
Concrete Grade	M20	M35	M10	M30	M15	M25	M40

Testing Procedures

Compressive strength was determined for DT using a Compression Testing Machine as per IS: 516; at the end of curing for 14 days, 7 specimens are tested for each grade of concrete. Compressive Strength values were obtained arithmetically by the equation:

$$\text{Compressive Strength} = \frac{Failure\ \ Load\ (kN)}{Area\ of\ Specimen\ \ (mm^2)}$$

For NDT, using the rebound hammer (Schmidt Hammer) test results, the surface hardness result of the concrete was obtained. Tests were performed using the same cubes that were done in the DT test, and for every grade of concrete, 18 readings were taken. The rebound number, which gives a representation of the surface hardness, varied between 11.5 to 60.3 corresponding to the compressive strength of 10.0 MPa and 45 MPa.

Table 2:- Mix Design Proportions and Water-Cement Ratios.

Mix Proportions	**1:3:6**	**1:2:4**	**1:1.5:3**	**1:1:2**	**1:0.75:1.5**	**1:0.5:1**	**1:0.25:0.5**
Water-Cement Ratio (w/c)	0.55	0.55	0.5	0.5	0.45	0.45	0.45
Cement Content	-	-	-	300 kg	320 kg	340 kg	340 kg
Mix Grade	M10	M15	M20	M25	M30	M35	M40

Table 3:- Quantity of Materials for Different Concrete Grades.

Grade	**M10, M15, M20, M25**	**M30**	**M35**	**M40**
Cement (kg)	280	290	430	430
Fly Ash (kg)	270	270	110	110
Fine Aggregate (kg)	799	836	814	814
Coarse Aggregate (kg)	834	858	814	814
Water (kg)	182	166	172	172
Super Plasticizer (kg)	3.3	4.48	3.48	3.48

Testing and Analysis

In order to determine the correlation between rebound number (NDT) and compressive strength (DT), tests on the specimens of concrete were conducted 14 days after they had cured. Regression analysis was used to model the found link between compressive strength and rebound number. 91.6–97.9% R2 values showed a perfect linear correlation in the results. This suggests that the anticipated compressive strengths derived from the rebound hammer readings have an extremely high degree of accuracy. The outcomes provide insightful information on the efficacy of DT and NDT techniques for assessing the quality of concrete.

This methodology can be used to get full information about the characteristics of concrete strength and relate these to non-destructive rebound testing, very essential for practical applications in construction and structural assessment.

Results and Discussions:-

This experimental investigation aims to assess the compressive strength of concrete in different concrete grades (M10, M15, M20, M25, M30, M35, and M40) utilizing both destructive and non-destructive testing methods. The goal of the study is to investigate the correlation between destructive and non-destructive test findings for concrete samples that were evaluated at two distinct ages, 14 and 28 days. In this investigation, a Schmidt hammer was used to perform non-destructive testing on typical concrete cubes. The same cubes were then subjected to destructive testing utilizing a compression testing apparatus. To produce concrete cubes with crushing strengths that vary from 10 to 40 MPa, various mix proportions were used in their preparation.

A comparison of the results of destructive and non-destructive testing procedures is one of the study's findings. Through data analysis, the study aims to evaluate the degree of correlation between non-destructive methods and destructive testing-determined compressive strength, as well as to develop a connection between these approaches for varying concrete ages and grades.

Compressive Strength Analysis of M10, M15, M20, M25, M30, M35, and M40 Concrete Grades Using Destructive and Non-Destructive Testing Methods at 14 Days

Table 4:- Comparative Analysis of 14-Day M10 Grade Concrete Destructive and Non-Destructive Testing.

Type	**Test of Compression Machine (D. T.)**	**The NDT Schmidt Hammer Test**
10	9.250	9.4000
10	9.600	9.8000
10	8.980	8.5000
10	9.140	9.7000
10	9.640	10.5000
10	9.870	9.6000
10	9.350	9.8000
10	9.320	9.1000
10	9.010	8.9000
10	9.160	9.7000
10	9.280	8.8000
10	8.880	7.9000
10	8.900	9.1000
10	9.450	9.4000
10	9.400	9.6000
10	9.710	10.6000
10	9.650	10.1000
10	9.260	9.5000

Evaluation of M15 Grade Concrete's Compressive Strength Over 14 Days Using Destructive and Non-Destructive Testing Techniques

Table 5:- A 14-day assessment using both destructive and non-destructive testing techniques of M15 grade concrete.

Type	**Test of Compression Machine (D. T.)**	**The NDT Schmidt Hammer Test**
15	13.600	13.7000
15	13.710	12.9000
15	13.430	13.5000
15	13.980	15.2000
15	14.060	13.9000
15	13.180	12.6000
15	12.910	13.4000
15	13.560	13.8000
15	14.200	14.3000
15	13.230	15.0000
15	12.890	11.8000
15	13.530	13.9000
15	14.250	14.2000
15	13.380	12.9000
15	13.480	13.9058
15	13.150	13.7000
15	12.930	14.6000
15	13.910	14.5000

14-Day Evaluation of M20 Grade Concrete's Compressive Strength Using Destructive and Non-Destructive Experimental Techniques

Table 6:- Examining M20 Grade Concrete for 14 Days with Both Destructive and Non-Destructive Experimental Techniques.

Type	Test of Compression Machine (D. T.)	The NDT Schmidt Hammer Test
20	18.600	18.9000
20	19.140	19.6000
20	17.690	18.1000
20	18.200	18.5000
20	18.620	18.3000
20	18.420	16.1000
20	17.540	20.0000
20	19.210	19.4000
20	18.150	18.6000
20	18.290	21.0000
20	18.390	18.6000
20	17.110	17.9000
20	17.780	16.5000
20	19.120	19.3000
20	18.840	18.4000
20	18.970	19.5000
20	18.640	19.0000
20	18.230	18.6000

Evaluation of M25 Grade Concrete's Compressive Strength Over 14 Days Using Destructive and Non-Destructive Experimental Techniques

Table 7:- A 14-day assessment using both destructive and non-destructive methods for testing of M25 grade concrete.

Type	Test of Compression Machine (D. T.)	The NDT Schmidt Hammer Test
25	22.780	23.4000
25	22.560	22.7000
25	21.900	22.2000
25	23.020	24.9000
25	22.180	24.8000
25	22.480	22.6000
25	23.140	21.9000
25	21.800	22.0000
25	22.720	22.8000
25	22.140	22.3000
25	22.840	23.0000
25	22.640	22.9000
25	22.580	20.0000
25	22.600	24.6000
25	22.740	21.8000
25	23.150	23.4000
25	21.900	22.0000
25	22.600	22.8000

14-Day Evaluation of M30 Grade Concrete's Compressive Strength Using Destructive and Non-Destructive Experimental Techniques

Table 8:- Examining M30 Grade Concrete for 14 Days with Both Destructive and Non-Destructive Examining Techniques.

Type	Test of Compression Machine (D. T.)	The NDT Schmidt Hammer Test
30	28.480	29.7000
30	27.150	30.5000
30	26.840	27.1000
30	27.320	27.4000
30	26.970	27.0000
30	27.250	27.8000
30	27.470	24.6000
30	27.390	24.8000
30	26.680	27.6000
30	27.960	28.6000
30	27.380	25.2000
30	26.620	30.1000
30	25.870	26.0000
30	25.930	26.2000
30	26.820	26.6000
30	27.540	30.4000
30	27.790	29.1000
30	27.140	27.5000

14-Day Evaluation of M35 Grade Concrete's Compressive Strength Using Destructive and Non-Destructive Experimental Techniques

Table 9:- A 14-day assessment using both destructive and non-destructive methods for testing of M35 grade concrete.

Type	Test of Compression Machine (D. T.)	The NDT Schmidt Hammer Test
35	31.920	32.4000
35	32.540	32.8000
35	31.600	30.6000
35	30.800	31.0000
35	32.100	32.1000
35	33.700	32.9000
35	30.140	28.4000
35	31.910	34.6000
35	31.650	33.9000
35	32.180	29.4000
35	31.600	31.8000
35	31.750	31.6000
35	30.260	28.4000
35	31.046	34.6000
35	31.280	32.4000
35	31.850	33.0000
35	31.590	32.7000
35	31.800	32.5000

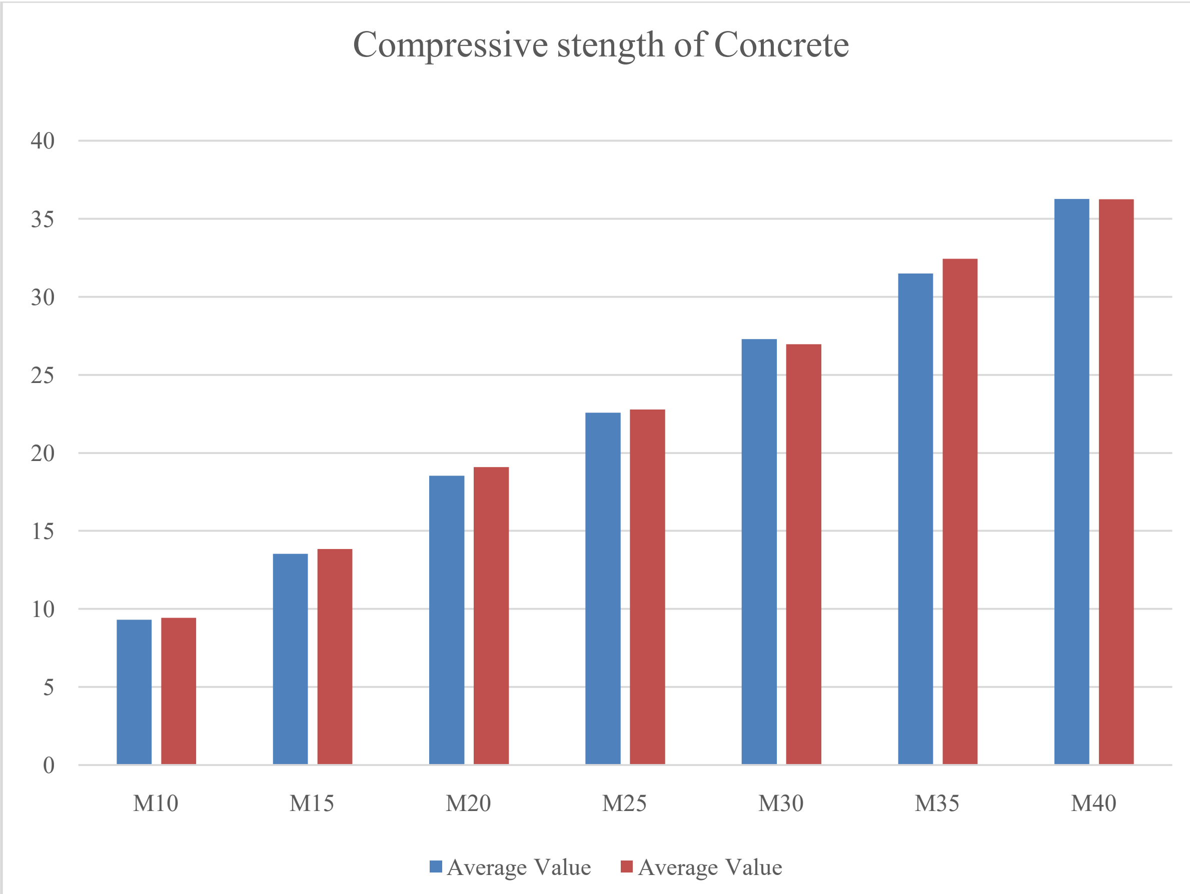

Fig. 1:- Concrete's compressive strength after 14 days.

14-Day Evaluation of M40 Grade Concrete's Compressive Strength Using Destructive and Non-Destructive Experimental Techniques

Table 10:-A 14-day assessment using both destructive and non-destructive methods for testing of M40 grade concrete.

TYPE	Test of Compression Machine (D. T.)	The NDT Schmidt Hammer Test
40	37.210	40.2000
40	36.200	36.6000
40	36.140	36.4000
40	36.580	33.1000
40	36.500	38.6000
40	36.140	32.5000
40	35.470	35.8000
40	35.010	33.5000
40	36.870	38.4000
40	34.560	35.0000
40	36.470	36.5000
40	36.080	36.2000
40	36.970	40.6870
40	35.470	29.4000
40	35.320	35.6000
40	36.450	35.8000
40	37.850	38.0000
40	38.450	41.6000

Average Value of concrete grade M10, M15, M20, M25, M30, M35 and M40 for 14 Days

Table 11:- Average Value for 14 Days.

Concrete Grade	Average Value	
	Destructive	Non-Destructive
M10	9.302	9.4278
M15	13.524	13.8448
M20	18.5344	19.0889
M25	22.5778	22.7722
M30	27.29	26.9556
M35	31.4968	32.4278
M40	36.2706	36.241

The Correlation Regression Equation was used to determine the correlation between destructive and non-destructive tests on various grades of concrete, such as M10, M15, M20, M25, M30, M35, and M40, at ages of 14 days.

Correlation and Regression Evaluation of M10 Grade Concrete at 14-Day Destructive and Non-Destructive Evaluations

Table 12:- 14-Day Correlation between M10 Grade Concrete Destructive and Non-Destructive Evaluation.

Type	Test of Compression Machine (D. T.)	The NDT Schmidt Hammer Test	Associated Values NDT + 7.564 DT = 0.1864	Errors
10	9.250	9.4000	9.3167	-0.06671
10	9.600	9.8000	9.3913	0.20871
10	8.980	8.5000	9.1489	-0.16892
10	9.140	9.7000	9.3726	-0.23265
10	9.640	10.5000	9.5218	0.11820
10	9.870	9.6000	9.3540	0.51600
10	9.350	9.8000	9.3913	-0.04129
10	9.320	9.1000	9.2608	0.05922
10	9.010	8.9000	9.2235	-0.21349
10	9.160	9.7000	9.3726	-0.21265
10	9.280	8.8000	9.2048	0.07515
10	8.880	7.9000	9.0370	-0.15705
10	8.900	9.1000	9.2608	-0.36078
10	9.450	9.4000	9.3167	0.13329
10	9.400	9.6000	9.3540	0.04600
10	9.710	10.6000	9.5404	0.16956
10	9.650	10.1000	9.4472	0.20278
10	9.260	9.5000	9.3354	-0.07536

Correlation and Regression Analysis of M15 Grade Concrete at 14-Day Destructive and Non-Destructive testing results.

Table 13:- 14-Day Correlation Between M15 Grade Concrete Destructive and Non-Destructive Assessment.

Type	Compression Machine Test (D. T)	NDT Schmidt Hammer Test (N.D.T)	Correlated Values DT= 10.954 + 0.1864 NDT	Errors
15	13.600	13.7000	13.5086	0.09138
15	13.710	12.9000	13.3595	0.35053
15	13.430	13.5000	13.4713	-0.04133
15	13.980	15.2000	13.7883	0.19171
15	14.060	13.9000	13.5459	0.51409
15	13.180	12.6000	13.3035	-0.12353
15	12.910	13.4000	13.4527	-0.54269

15	13.560	13.8000	13.5273	0.03273
15	14.200	14.3000	13.6205	0.57951
15	13.230	15.0000	13.7510	-0.52100
15	12.890	11.8000	13.1544	-0.26438
15	13.530	13.9000	13.5459	-0.01591
15	14.250	14.2000	13.6018	0.64816
15	13.380	12.9000	13.3595	0.02053
15	13.480	13.9058	13.5470	-0.06699
15	13.150	13.7000	13.5086	-0.35862
15	12.930	14.6000	13.6764	-0.74642
15	13.910	14.5000	13.6578	0.25222

14-Day Correlation Regression Analysis-Based Correlation Between Destructive and Non-Destructive Tests for M20 Grade Concrete

Table 14:- Relationship between M20 Grade Concrete Destructive and Non-Destructive Tests After 14 Days.

Type	Compression Machine Test (D. T)	NDT Schmidt Hammer Test (N.D.T)	Correlated Values DT= 14.902 + 0.1864 NDT	Errors
20	18.600	18.9000	18.4260	0.17405
20	19.140	19.6000	18.5565	0.58354
20	17.690	18.1000	18.2768	-0.58680
20	18.200	18.5000	18.3514	-0.15137
20	18.620	18.3000	18.3141	0.30591
20	18.420	16.1000	17.9039	0.51609
20	17.540	20.0000	18.6310	-1.09104
20	19.210	19.4000	18.5192	0.69083
20	18.150	18.6000	18.3700	-0.22002
20	18.290	21.0000	18.8175	-0.52748
20	18.390	18.6000	18.3700	0.01998
20	17.110	17.9000	18.2395	-1.12951
20	17.780	16.5000	17.9785	-0.19849
20	19.120	19.3000	18.5005	0.61947
20	18.840	18.4000	18.3327	0.50727
20	18.970	19.5000	18.5378	0.43218
20	18.640	19.0000	18.4446	0.19540
20	18.230	18.6000	18.3700	-0.14002

Relationship between Destructive and Non-Destructive Testing for M25 Grade Concrete after 14 Days Using Correlation Regression

Table 15:- Results of the Relationship between Destructive and Non-Destructive Tests for M20 Grade Concrete after 14 Days.

Type	Compression Machine Test (D. T)	NDT Schmidt Hammer Test (N.D.T)	Correlated Values DT = 18.295 + 0.1864 NDT	Errors
25	22.780	23.4000	22.6578	0.12225
25	22.560	22.7000	22.5272	0.03276
25	21.900	22.2000	22.4340	-0.53402
25	23.020	24.9000	22.9374	0.08259
25	22.180	24.8000	22.9188	-0.73877
25	22.480	22.6000	22.5086	-0.02860
25	23.140	21.9000	22.3781	0.76191
25	21.800	22.0000	22.3967	-0.59673
25	22.720	22.8000	22.5459	0.17411
25	22.140	22.3000	22.4527	-0.31266

25	22.840	23.0000	22.5832	0.25683
25	22.640	22.9000	22.5645	0.07547
25	22.580	20.0000	22.0238	0.55615
25	22.600	24.6000	22.8815	-0.28148
25	22.740	21.8000	22.3594	0.38056
25	23.150	23.4000	22.6578	0.49225
25	21.900	22.0000	22.3967	-0.49673
25	22.600	22.8000	22.5459	0.05411

Results of the Relationship between Destructive and Non-Destructive Tests for M30 Grade Concrete After 14 Days Based on Correlation Regression Equation

Table 16:- Results of the Relationship between Destructive and Non-Destructive Tests for M25 Grade Concrete after 14 Days.

Type	**Compression Machine Test (D. T)**	**NDT Schmidt Hammer Test (N.D.T)**	**Correlated Values DT= 22.005 + 0.1864 NDT**	**Errors**
30	28.480	29.7000	27.5422	0.93781
30	27.150	30.5000	27.6913	-0.54134
30	26.840	27.1000	27.0574	-0.21744
30	27.320	27.4000	27.1134	0.20663
30	26.970	27.0000	27.0388	-0.06879
30	27.250	27.8000	27.1879	0.06205
30	27.470	24.6000	26.5913	0.87867
30	27.390	24.8000	26.6286	0.76138
30	26.680	27.6000	27.1507	-0.47066
30	27.960	28.6000	27.3371	0.62290
30	27.380	25.2000	26.7032	0.67680
30	26.620	30.1000	27.6168	-0.99677
30	25.870	26.0000	26.8524	-0.98235
30	25.930	26.2000	26.8896	-0.95964
30	26.820	26.6000	26.9642	-0.14422
30	27.540	30.4000	27.6727	-0.13270
30	27.790	29.1000	27.4303	0.35968
30	27.140	27.5000	27.1320	0.00799

Results of the Relationship between Destructive and Non-Destructive Tests for M35 Grade Concrete after 14 Days

Table 17:- Results of the Relationship between Destructive and Non-Destructive Tests for M30 Grade Concrete after 14 Days.

Type	**Compression Machine Test (D. T)**	**NDT Schmidt Hammer Test (N.D.T)**	**Correlated Values DT = 25.694 + 0.1864 NDT**	**Errors**
35	31.920	32.4000	31.7348	0.18521
35	32.540	32.8000	31.8094	0.73063
35	31.600	30.6000	31.3992	0.20081
35	30.800	31.0000	31.4738	-0.67377
35	32.100	32.1000	31.6789	0.42114
35	33.700	32.9000	31.8280	1.87199
35	30.140	28.4000	30.9890	-0.84902
35	31.910	34.6000	32.1450	-0.23496
35	31.650	33.9000	32.0145	-0.36445
35	32.180	29.4000	31.1755	1.00454
35	31.600	31.8000	31.6229	-0.02292
35	31.750	31.6000	31.5856	0.16437

35	30.260	28.4000	30.9890	-0.72902
35	31.046	34.6000	32.1450	-1.09896
35	31.280	32.4000	31.7348	-0.45479
35	31.850	33.0000	31.8467	0.00335
35	31.590	32.7000	31.7907	-0.20072
35	31.800	32.5000	31.7534	0.04657

Results of the Relationship between Destructive and Non-Destructive Tests for M40 Grade Concrete after 14 Days

Table 18:- Results of the Relationship between Destructive and Non-Destructive Tests for M25 Grade Concrete after 14 Days.

TYPE	Compression Machine Test (D. T)	NDT Schmidt Hammer Test (N.D.T)	Correlated Values DT = 29.55 + 0.1864 NDT	Errors
40	37.210	40.2000	37.0410	0.16903
40	36.200	36.6000	36.3698	-0.16978
40	36.140	36.4000	36.3325	-0.19249
40	36.580	33.1000	35.7172	0.86277
40	36.500	38.6000	36.7427	-0.24266
40	36.140	32.5000	35.6054	0.53464
40	35.470	35.8000	36.2206	-0.75062
40	35.010	33.5000	35.7918	-0.78180
40	36.870	38.4000	36.7054	0.16463
40	34.560	35.0000	36.0715	-1.51147
40	36.470	36.5000	36.3511	0.11887
40	36.080	36.2000	36.2952	-0.21520
40	36.970	40.6870	37.1318	-0.16177
40	35.470	29.4000	35.0274	0.44261
40	35.320	35.6000	36.1833	-0.86333
40	36.450	35.8000	36.2206	0.22938
40	37.850	38.0000	36.6308	1.21920
40	38.450	41.6000	37.3020	1.14801

Regression Equation and Coefficient evaluation using Minitab for Grade of Concrete as M10 M15 M20 M25 M30 M35 and M40 for Age 14 Days.

Table 19:- Regression Equation for 14 Days.

Type	Equation
M10	DT = 7.693 + 0.1688 NDT
M15	DT = 11.155 + 0.1688 NDT
M20	DT = 15.194 + 0.1688 NDT
M25	DT = 18.743 + 0.1688 NDT
M30	DT = 22.471 + 0.1688 NDT
M35	DT = 26.34 + 0.1688 NDT
M40	DT = 30.36 + 0.1688 NDT

Table 20:- Coefficient Value for Constant and NDT.

Term	Coeff	SE Coeff	T-Value	P-Value	VIF
Constant	7.693	0.360	21.40	0.000	
NDT	0.1688	0.0337	5.01	0.000	28.05

Table 21:- Coefficient Value for Different Concrete Grade.

Term	Coeff	SE Coeff	T-Value	P-Value	VIF
15	3.461	0.267	12.96	0.000	2.54
20	7.500	0.396	18.95	0.000	5.22
25	11.050	0.504	21.91	0.000	8.47
30	14.777	0.640	23.08	0.000	12.69
35	18.650	0.784	23.79	0.000	21.89
40	22.663	0.937	24.17	0.000	35.17

Table 22:- Analysis of Variance for Regression.

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	7	7599.67	1085.67	3491.60	0.000
NDT	1	7.79	7.79	25.05	0.000
Type	6	190.36	31.73	102.04	0.000
Error	80	24.87	0.31		
Lack of Fit	71	23.87	0.33	2.51	0.068
Pure Error	9	1.20	0.13		
Total	87	7624.55			

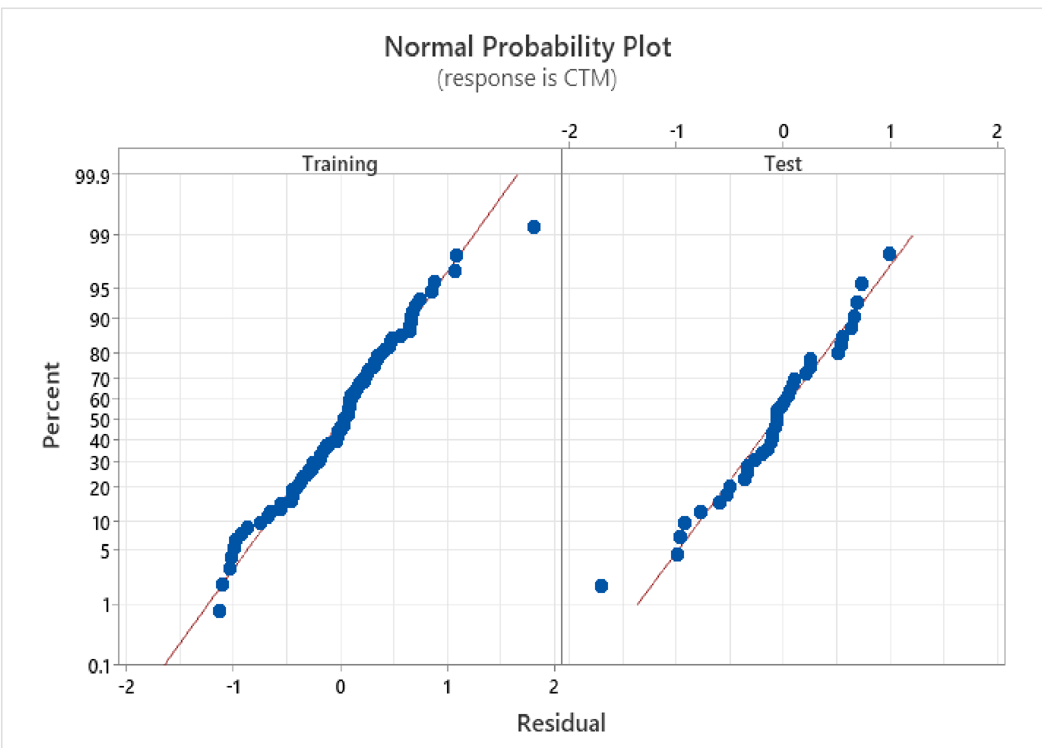

Fig. 2:- Normal Probability Plot for Residuals of linear, quadratic and cubic correlation models.

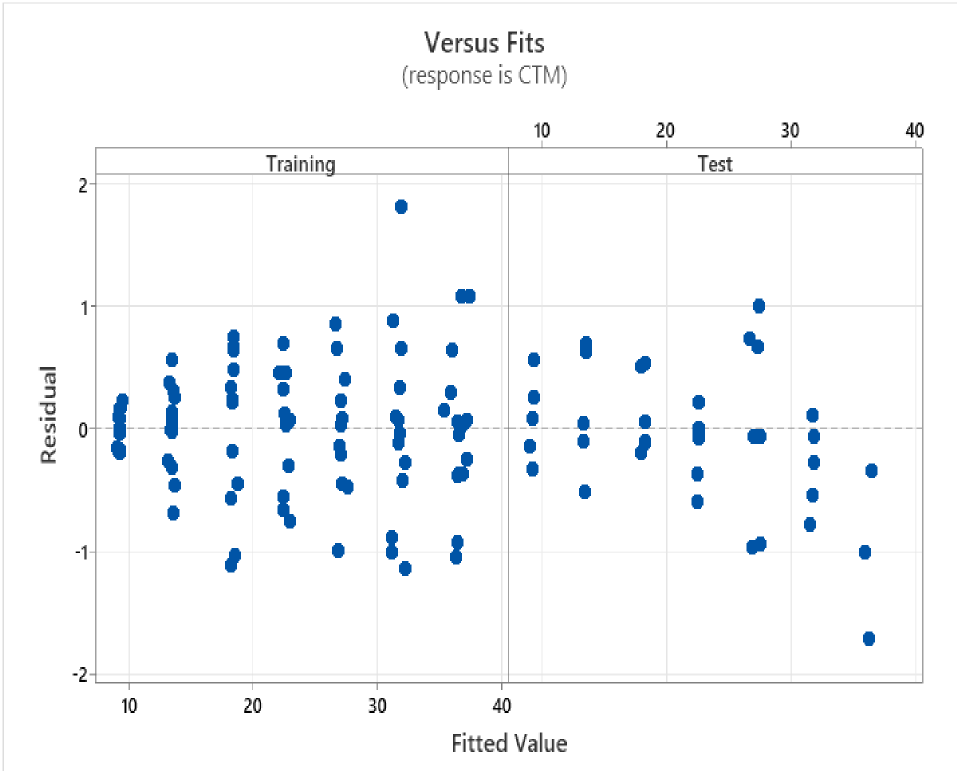

Fig. 3:- Residuals vs fitted values for linear, quadratic and cubic models.

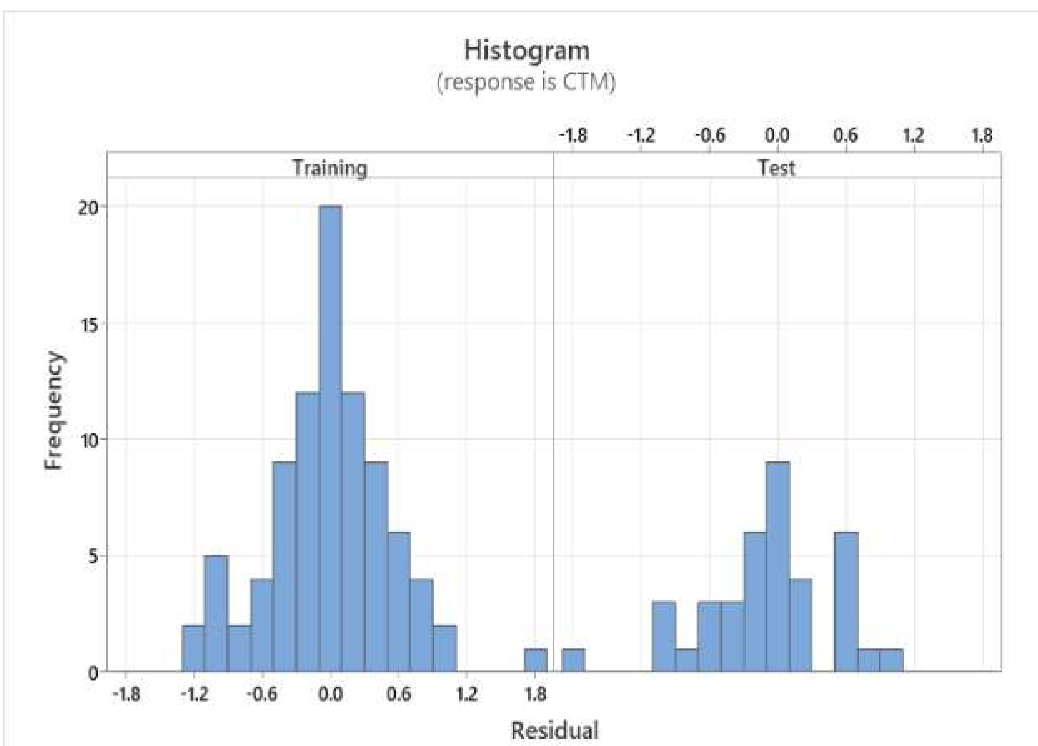

Fig. 4:- Histogram of Residuals for linear, quadratic and cubic models.

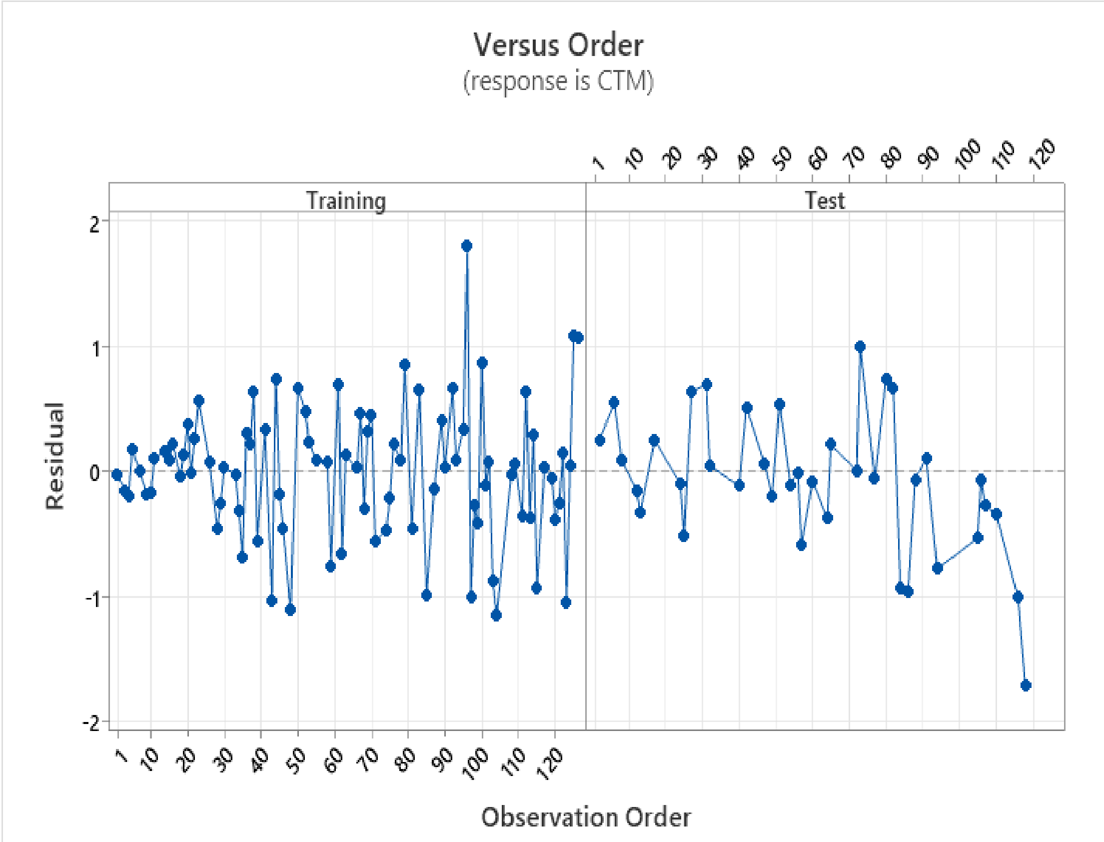

Fig. 5:- Residuals vs Observation Order for linear, quadratic and cubic models.

Conclusion:-

It confirms great correlation between the NDT and DT methods for the assessment of concrete strength, with very high coefficients of correlation obtained using linear, quadratic, and cubic regression models. This high correlation coefficient showed that the NDT methods—for instance, the rebound hammer test—can be reliably used in predicting compressive strength, especially if calibrated with DT data. This has huge implications for the construction industry, where NDT can offer less-intrusive, faster, and more cost-effective solutions compared with conventional DT methods. These relationships further provide a basis for more efficient and accurate concrete strength evaluation. This is not only useful in new constructions but also in continued controls on already existing structures to ascertain their safety progressive over time. The paper calls for increased use of NDT methods in routine structural assessments, especially in cases where damage to the structure needs to be kept at a minimum.

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