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Utilizing Regression Analysis (RA) to Analyse Concrete Beams Confined with GFRP Laminates Using FEA Methodology

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Regression Analysis (RA) serves as a cornerstone statistical method for estimating relationships between a dependent variable and one or more independent variables. Through generating regression equations, RA unveils coefficients that depict the relationships between these variables. This paper delves into a detailed exploration of RA, focusing on its primary and secondary functions. The primary function involves RA's predictive capabilities, overlapping with the domain of machine learning (ML), while the secondary function delves into inferring relationships between dependent and independent variables. Utilizing Legendre's principle of least squared errors, this study extracts unknown coefficients using data from experiments or other sources. Specifically, regression equations are applied to predict ultimate load and deflection values in concrete beam testing, with subsequent comparison to experimental results. The study encompasses analysis of twelve beam sets, including control specimens with varying shear reinforcement spacing and specimens reinforced with Glass Fiber-Reinforced Polymer (GFRP) laminates of different configurations.

Keywords: Regression Analysis (RA), Regression Co-efficient, Yield load, Ultimate load, ANSYS.

1. Introduction

Regression Analysis (RA) stands as a fundamental statistical tool for discerning relationships between variables, crucial within various fields including structural engineering. This paper embarks on a comprehensive investigation into RA, elucidating its role in predicting and inferring relationships pertinent to concrete beam testing. By scrutinizing the predictive and inferential aspects of RA, this study seeks to enhance understanding and utilization within the realm of structural analysis. Regression analysis is a statistical tool utilized for examining relationships between variables. When applied to a single explanatory variable, it is termed simple regression, while multiple regression allows for the incorporation of additional factors into the analysis separately. This technique proves invaluable in quantifying the combined impact of various influences on a single dependent variable. By employing statistical principles, regression analysis establishes a procedure for linking known input variables to an output parameter. Typically, this involves assuming a specific relationship between input parameters and results, characterized by several unknown coefficients. These coefficients are then determined using available data, often obtained from experiments or alternative sources, employing Legendre's principle of least squared errors. The process of regression analysis is illustrated in detail in Figure 1.

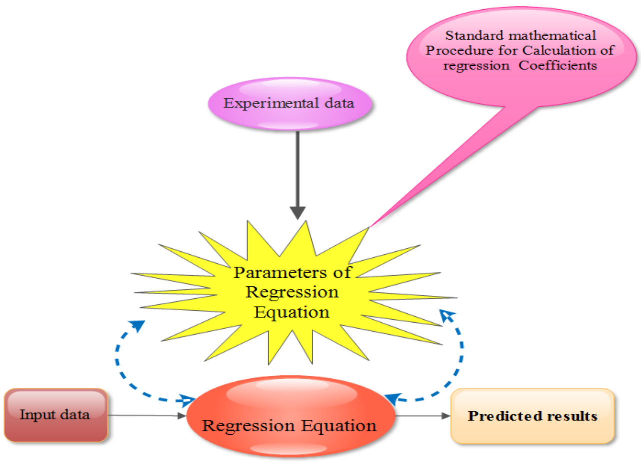

Fig. 1 Regression flow process

Legendre's principle of least squared errors serves as a versatile curve fitting technique crucial for determining the values of unknown coefficients, also known as regression coefficients. This principle operates on the premise of optimizing the agreement between predicted results and target results to the greatest possible extent [7,8]. Various terms associated with regression analysis are elucidated in the subsequent subsections. Notably, regression analysis encompasses diverse methodologies including Linear Regression, Logistic Regression, Ridge Regression, Lasso Regression, Polynomial Regression, and Bayesian Regression [9].

1.1 Regression

Regression analysis entails a mathematical technique for fitting curves, be they linear or non-linear, to a predetermined shape. Its primary objective is to assess the unknown coefficients within an equation. The equation's form is typically assumed a priori, chosen to best represent the anticipated relationship between the input and output variables [10].

1.2 Regression Coefficient

A regression coefficient serves as an unknown parameter incorporated into an equation to adjust the input variable or a combination of input variables. When solving the regression problem through the principle of least squared errors, all regression coefficients are evaluated to optimize the agreement between predicted and target results.

1.3 Legendre's Principle of Least Squared Errors

Legendre's principle of least squared errors aims to address the regression problem by minimizing the square of the difference between the actual value and the value predicted by the equation. This minimization is achieved by calculating the derivative of the square of the error with respect to each of the unknown coefficients in the assumed equation. Each derivative yields one equation, and the total number of equations generated is equal to the total number of unknown regression coefficients to be evaluated.

1.4 Karl Pearson's Coefficient of Correlation

Karl Pearson's coefficient of correlation is a numerical measure, ranging from 0 to 1, indicating the strength of the relationship between input parameters and resulting values. A value closer to 1 suggests a stronger relationship between the inputs and outputs. Importantly, the coefficient of correlation remains unaffected by predictions from the regression equation; instead, it reflects the inherent relationship within the given set of inputs and outputs.

$$r = \frac{\sum (x-\overline{x})(y-\overline{y})}{\sqrt{\sum (x-\overline{x})^2 \sum (x-\overline{y})^2}} \quad (1)$$

1.5 Sum of Squared Errors (SSE)

Sum of squared errors is the summation of the squares of the difference between values predicted by the regression equation (or by any other system) and the actual results expected for the given input values. Larger value of SSE indicates higher deviation of the predicted values from the expected values.

$$SSE = \sum_{l}^{N} (x-\hat{x})^2 \quad (2)$$

1.6 Mean Squared Error (MSE)

Mean squared error is evaluated as the sum of squared errors divided by the number of values summed up The MSE is a better measure of error than SSE, since it signifies the squared error per data point.

$$MSE = \frac{\sum_{1}^{N} (x-\hat{x})^2}{N} \quad (3)$$

1.7 Root Mean Squared Error (RMSE)

The root mean squared error (RMSE) represents the square root of the Mean Squared Error and signifies the extent of deviation from the expected value, whether higher or lower. Consequently, RMSE serves as a superior measure of error compared to MSE due to its direct interpretation of the error magnitude in the same units as the original data.

$$RMSE = \frac{\sqrt{\sum_{1}^{N} (x-\hat{x})^2}}{N}$$

1.8 Root Mean Squared Percentage Error (RMSPE)

The root mean squared percentage error (RMSPE) is computed as the square root of the sum of squared percentage errors, divided by the number of error values summed up, and multiplied by one hundred. RMSPE serves as a normalized parameter, enabling understanding independent of the numerical values of the resulting data. In contrast to other error metrics like RMSE, MSE, or SSE, where a value of 10 might signify different scenarios depending on the mean value of the results, RMSPE offers a normalized comparison. Smaller RMSPE values indicate better fit conditions, irrespective of the scale of the data, as outlined by Carpenter and Barthelemy (1994).

$$RMSPE = \sqrt{\frac{\sum_{1}^{N} \left(\frac{x-\hat{x}}{\bar{x}}\right)^2}{N}} \times 100 \tag{4}$$

2. Multivariate Linear Regression

Multivariate linear regression facilitates the construction of first-order equations involving more than one independent variable. The basic formulation for multivariate linear regression can be expressed as follows,

$$\begin{Bmatrix} \frac{\partial}{\partial a_0} \\ \frac{\partial}{\partial a_1} \\ \frac{\partial}{\partial a_2} \\ \frac{\partial}{\partial a_3} \\ \vdots \\ \frac{\partial}{\partial a_n} \end{Bmatrix} \sum_{i=1}^{K} (P_i - (a_0 + a_1 x_{1i} + a_2 x_{2i} a_3 x_{3i} + \cdots + a_n x_{ni})) = \begin{Bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ \vdots \\ 0 \end{Bmatrix} \tag{5}$$

In multivariate linear regression, the goal is to estimate the values of the regression coefficients β0,β1,β2,...,βn that minimize the difference between the predicted values and the actual values of the dependent variable.. On executing the partial derivative operators, equation 5.5 reduces to,

$$\sum_{i=1}^{N}\begin{bmatrix} 1 & x_{1i} & x_{2i} & x_{3i} & \cdots & x_{ni} \\ x_{1i} & x_{1i}^{3} & x_{1i}x_{3i} & x_{1i}x_{3i} & \cdots & x_{1i}x_{ni} \\ x_{2i} & x_{2i}x_{1i} & x_{2i}^{2} & x_{2i}x_{3i} & \cdots & x_{2i}x_{ni} \\ x_{3i} & x_{3i}x_{1i} & x_{3i}x_{2i} & x_{3i}^{2} & \cdots & x_{3u}x_{ni} \\ \vdots & \vdots & \vdots & \vdots & \cdots & \vdots \\ x_{ni} & x_{ni}x_{1i} & x_{ni}x_{2i} & x_{ni}x_{3i} & \cdots & x_{ni}x_{ni} \end{bmatrix} \begin{Bmatrix} a_0 \\ a_1 \\ a_2 \\ a_3 \\ \vdots \\ a_n \end{Bmatrix} = \sum_{i=1}^{K}\begin{Bmatrix} P_i \\ P_1P_i \\ P_2P_i \\ \vdots \\ P_nP_i \end{Bmatrix} \qquad (6)$$

The equation for multivariate linear regression cannot be directly solved by simply summing up the values of independent and dependent variables after carrying out required operations. Instead, the coefficients β0,β1,β2,...,βn are estimated using statistical methods, typically through techniques such as ordinary least squares (OLS) or gradient descent. These methods involve minimizing the difference between the predicted values and the actual values of the dependent variable by iteratively adjusting the coefficients until the best fit line is obtained. The process entails more complex mathematical operations and statistical computations rather than simple summation.

3. Regression Equation for Strength

The data used for the regression analysis is presented in Table 1 and the regression equations are presented in Table 2

Table 1 Data Used for the Regression Analysis

Beam Designation	First Crack load (kN)	Def. @ FCL (mm)	Yield Load (kN)	Def. @ Yeld Load (mm)	Ultimate Load (kN)	Def. @ UL (mm)	Width of Crack (mm)	No. of Cracks	Average Spacing of Cracks (mm)	Spacing of Stirrups	Tensile strength for FRP	E for FRP	Deflection ductility	Energy ductility
200 NS 0	10	0.95	25	2.6	50	9.24	0.4	8	140	100	0	0	3.55	6.74
200 CS 0	12.5	1.05	27.5	2.85	57.5	10.82	0.44	11	128	100	0	0	3.79	9.13
100 NS 0	15	1.12	30	3.2	60	12.1	0.5	13	124	200	0	0	3.78	6.37
100 CS 0	20	1.16	35.5	3.65	65	14.54	0.58	16	116	200	0	0	3.98	7.88
200 NS 3	22.5	1.28	42.5	3.98	90	16.6	0.64	18	108	100	446.9	13965	4.17	8.61
200 CS 3	25	1.34	50	4.18	100.5	18.76	0.72	21	96	100	446.9	13965	4.48	8.59
100 NS 3	27.5	1.48	54.5	4.33	110	20.34	0.8	23	94	200	446.9	13965	4.69	9.89
100 CS 3	30	1.64	60	4.62	120.5	22.5	0.88	25	90	200	446.9	13965	4.87	9.98
200 NS 5	30	1.86	64.5	5.16	130	24.8	0.98	27	88	100	451.5	17365	4.8	10.4
200 CS 5	32.5	2.1	68	5.82	135	26.2	1.2	28	84	100	451.5	17365	4.5	10.05
100 NS 5	32.5	2.46	70	6.28	142.5	28.1	1.34	30	76	200	451.5	17365	4.48	10.32
100 CS 5	35	3.1	72.5	6.85	145	30.4	1.52	33	68	200	451.5	17365	4.43	10.48

Table 2 Data Used for the Regression Analysis for Experimental vs Predictions

Specimen	Yield load(kN)		deflection at YL(mm)		Ultimate load(KN)		deflection at UL(mm)		Energy ductility		Deflection ductility		Crack width(mm)	
	Expt	Pred	Expt	Pred	Expt	Pred	Expt	Pred	Expt	Pred	Expt	Pred	Expt	Pred
200 NS 0	25	26.125	2.6	2.77	50	50	9.24	10.1975	6.74	7.75	3.55	3.77	0.4	0.365
200 CS 0	27.5	26.125	2.85	2.77	57.5	52.1875	10.82	10.1975	9.13	7.75	3.79	3.77	0.44	0.365
100 NS 0	30	33.4375	3.2	3.465	60	65.15625	12.1	13.63125	6.37	7.815	3.78	3.89	0.5	0.5775
100 CS 0	35.5	33.4375	3.65	3.465	65	65.15625	14.54	13.63125	7.88	7.815	3.98	3.89	0.58	0.5775
200 NS 3	42.5	48.09375	3.98	3.93	90	98.765625	16.6	17.833125	8.61	9.235	4.17	4.4925	0.64	0.65375
200 CS 3	50	48.09375	4.18	3.93	100.5	98.765625	18.76	17.833125	8.59	9.235	4.48	4.4925	0.72	0.65375
100 NS 3	54.5	55.40625	4.33	4.625	110	111.734375	20.34	21.266875	9.89	9.3	4.69	4.6125	0.8	0.86625
100 CS 3	60	55.40625	4.62	4.625	120.5	111.734375	22.5	21.266875	9.98	9.3	4.87	4.6125	0.88	0.86625
200 NS 5	64.5	65.09375	5.16	5.68	130	131.640625	24.8	25.658125	10.4	10.28	4.8	4.4925	0.98	1.15375
200 CS 5	68	65.09375	5.82	5.68	135	131.640625	26.2	25.658125	10.05	10.28	4.5	4.4925	1.2	1.15375
100 NS 5	70	72.40625	6.28	6.375	142.5	144.609375	28.1	29.091875	10.32	10.345	4.48	4.6125	1.34	1.36625
100 CS 5	72.5	72.40625	6.85	6.375	145	144.609375	30.4	29.091875	10.48	10.345	4.43	4.6125	1.52	1.36625

4. Observations on the Regression Equations

The regression equations were utilized to predict the ultimate load and ultimate deflection values. Evaluation of the fitness measures of regression indicates that multivariate linear regression demonstrates reasonable levels of accuracy in estimating various parameters for GFRP-strengthened RC beams, including yield load, yield deflection, ultimate load, ultimate deflection, deflection ductility, energy ductility, deflection ductility ratio, energy ductility ratio, number of cracks, maximum crack width, and total energy absorption [15]. The root mean square error values ranged from 0.17 to 13.76. However, it's important to note that linear regressions inherently possess limitations in modeling complex datasets comprehensively, as first-order regression parameters attempt to fit a linear relationship with monotonically varying curvature for the prediction parameter. The predictions derived from the regression equations were juxtaposed against experimental values and illustrated in Figures 2 to 4. Specifically, the comparison between regression and experimental values for yield load was depicted in Figure 2.

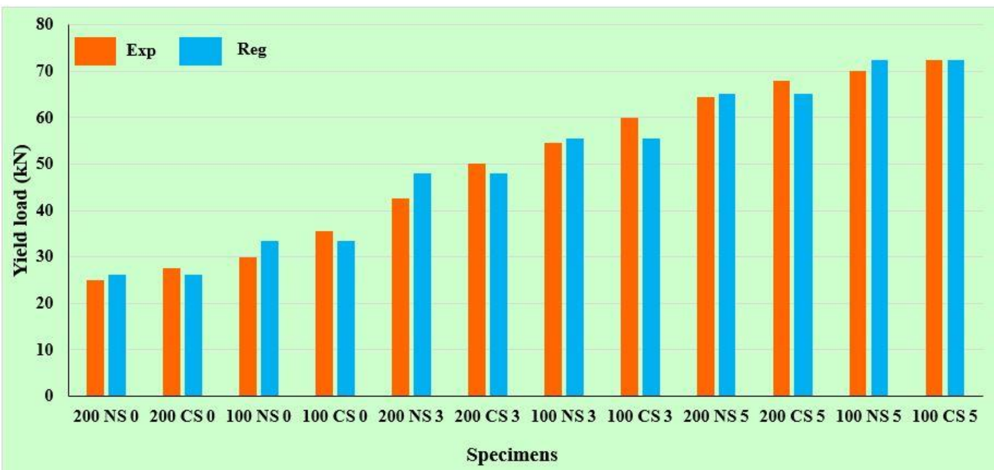

Fig. 2 Specimens Predictions for Yield Load (KN)

The ultimate load values and the experimental values were compared and shown in the fig 3

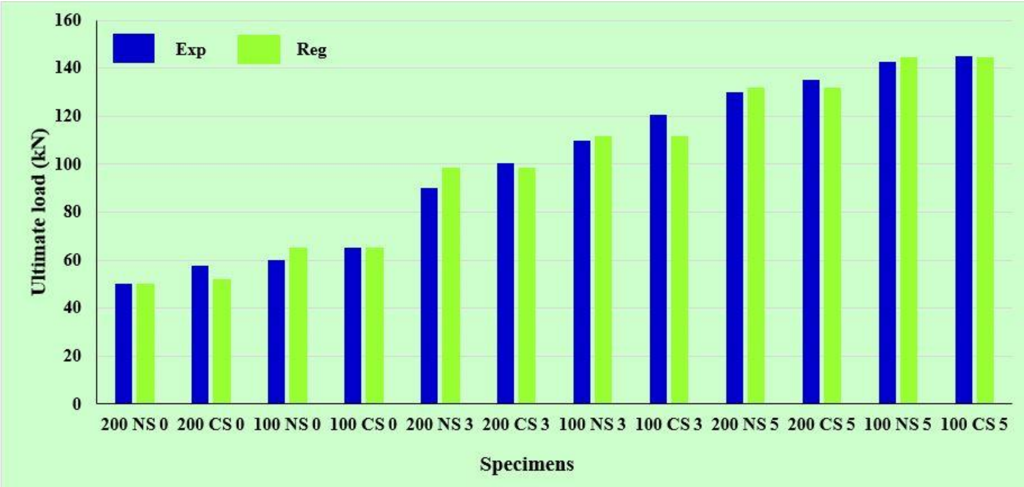

Fig. 3 Specimens Predictions for Ultimate Load (KN)

The values for the energy ductility were compared with predicted value and experimental value and shown in fig 4

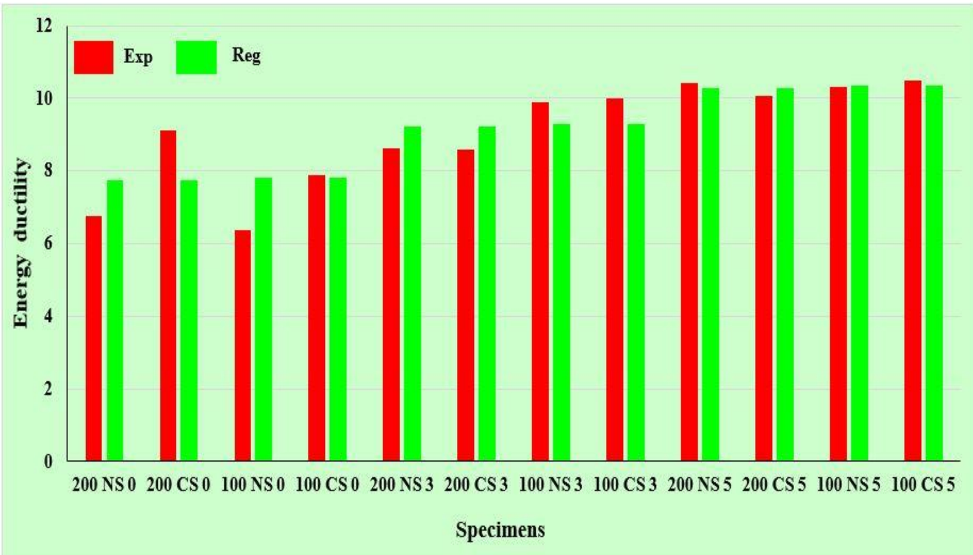

Fig. 4 Specimens Predictions for Energy Ductility

5. Observations from Ansys (FEA)

Three samples were utilized to verify the accuracy of the numerical model through a comparison of empirical findings. Additionally, various models were established to examine the effects of concrete FRP sheet type and size, reinforcement ratio, and compression strength on the bending performance of the beam. To leverage the symmetrical characteristics of the tested beam samples and align with boundary, loading, and geometry conditions, only a quarter of the sample was constructed and examined in ANSYS 15.0, utilizing two regular planes across and along every beam sample. Within the FRP sheet, a bond-slip stress was calculated to predict the deboning of the FRP sheet from the adjoining concrete surface. While this model accurately exemplifies the bond-slip mechanism between FRP and concrete interfaces, it is primarily utilized as an indicator to anticipate deboning failure mode. Failure is presumed to occur in the established FE models if:

- Stress in the FRP sheet reaches its maximum local bond stress.
- Strain of FRP laminates attains its maximum fracture strain.
- Concrete strain at the top compression fibers reaches 0.004.

It should be noted that for an under-reinforced concrete beam failure mode, the control beam samples adhere to a typical performance, wherein the bending steel bars yield supported by concrete crushing between the two loading points. Conversely, regarding the reinforcement of side-bonded FRP sheets and RC beam samples, all have experienced failure due to FRP debonding supported by concrete crushing.

5.1 YIELD LOAD Vs DEFLECTION

Yield strength denotes the maximum stress or load that a solid material can endure when it undergoes deformation within its elastic limit. When an external load is applied to a solid material, it experiences deformation, leading to stress development within the material to resist this deformation. The ability of a material to withstand deformation serves as a measure of its strength. From Table 3, the GFRP laminate strengthened beams 200NS3 and 200CS3 exhibit yield loads of 42.5 kN and 50 kN, respectively. The deflection at the first crack load level observed in the beam experimentally was 3.98 mm and 4.18 mm, while through non-linear FEA, it was 3.535 mm and 4.159 mm, respectively. Figure 8 illustrates the variation in deflection between the experimental and FEA results, which amounted to 11.18% and 0.50%, respectively. The yield load deflection of different types of beams under various loading conditions is depicted.

Table 3 Yield load and deflection of different beams

Beam ID	Load	Exp	Analysis	Variations
200NS0	26	2.6	2.348	9.6923077
200CS0	25	2.85	2.587	9.2280702
100NS0	31	3.2	2.825	11.71875
100CS0	31	3.65	3.345	8.3561644
200NS3	42	3.98	3.535	11.180905
200CS3	49	4.18	4.159	0.5023923
100NS3	54.5	4.33	4.491	3.5849477
100CS3	60	4.62	4.942	6.5155807
200NS5	64.5	5.16	5.113	0.9108527
200CS5	68	5.82	5.39	7.3883162
100NS5	70	6.28	5.498	12.452229
100CS5	72.5	6.85	5.688	16.963504

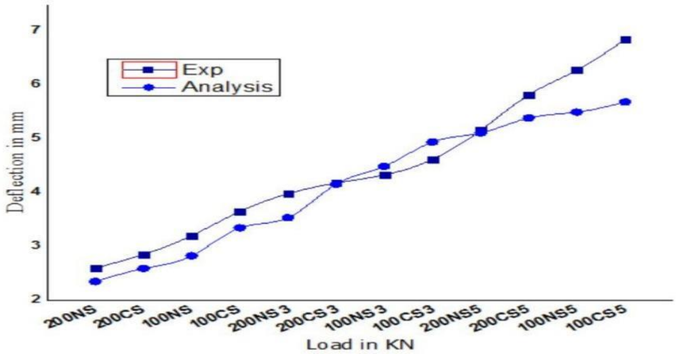

Figure 8. Yield Load Vs Deflection graph

5.2 ULTIMATE LOAD Vs DEFLECTION

Ultimate strength refers to the maximum stress or load-bearing capacity of a material when it undergoes plastic deformation. It represents the maximum stress or load that a material can endure before complete fracture under external loading conditions. Given that deformation induces stress within the material, its ability to withstand elastic and plastic stresses is delineated separately. Ultimate tensile strength assumes significance in the design of components or structures crafted from brittle materials. Moreover, it serves as a crucial parameter in metal forming processes.

Table 4. Ultimate load and deflection of different beams

Beam ID	Load	Exp	Analysis	Variations
200NS0	50	9.24	10.114	8.641487
200CS0	57.5	10.82	11.654	7.156341
100NS0	60	12.1	12.168	0.558843
100CS0	65	14.54	13.197	9.236589
200NS3	90	16.6	15.284	7.927711
200CS3	100.5	18.76	17.154	8.560768
100NS3	110	20.34	18.505	9.021632
100CS3	120.5	22.5	20.346	9.573333
200NS5	130	24.8	20.762	16.28226
200CS5	135	26.2	21.56	17.70992
100NS5	142.5	28.1	22.547	19.76157
100CS5	145	30.4	22.925	24.58882

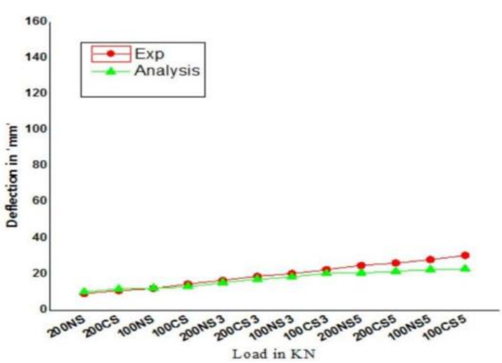

Figure 9. Ultimate Load Vs Deflection graph

6. Conclusions

Regression analysis, a fitness value of 0.801 was obtained, indicating the validity of the proposed regression equation for estimating performance parameters under both static and cyclic loading conditions. This research aimed to elucidate the general analysis of Regression Analysis, and various regression equations were explored to assess their performance. It was found that multivariate linear regression can reasonably estimate prediction values for parameters like yield load, yield deflection, ultimate load, ultimate deflection, and deflection ductility. Reinforced concrete beams were modeled and analyzed using ANSYS 15.0 software, yielding accurate results. Notably, the initial load-carrying capacity of the 100CS5 beam was observed to be 35 kN with deflections of 3.1 mm and 1.856 mm for experimental and analytical results, respectively, surpassing other specimens. The yield load of the 100CS5 beam was notably high at 72.5 kN compared to other specimens.

The maximum ultimate load recorded for 100CS5 was 145 KN with deflections of 30.4 mm and 22.925 mm for experimental and analytical results, respectively. The beam reinforced with 5mm thick GFRP and 100 mm c/c spacing exhibited a 24% increase in load-carrying capacity compared to other beams. The ratio of steel reinforcement significantly impacts the performance of beams reinforced with side-bonded CFRP sheets. As the ratio of steel reinforcement increases, the bending strength ratio of beams reinforced with side-bonded samples decreases. Additionally, the characteristics and type of FRP have a notable impact on the behavior of reinforced RC beams. Particularly, beams reinforced with GFRP and HFRP sheets demonstrated an increase in bending strength.

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