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STATISTICAL ANALYSIS OF DEBONDING FIBER- REINFORCED POLYMER PLATE AND SHEET

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Abstract: *The fracture mechanics are based on many theoretical models which are analyzed in order to evaluate debonding load in fiber-reinforced polymer composites and concrete. To show the influence of different geometrical and mechanical structural on its values, for this purpose we have developed a statistical model which is based multi linear regression (MLR) to predict the debonding load of FRP reinforced concrete surface. The parameters used in MLR model were FRP type (plate, sheet), FRP geometry, concrete compressive and specimen width, in this study we perform MLR model using experimental data, then we make comparison between prediction result and experimental result. Then we have showed the performance this model. Next, we perform an evaluation of the MLR validation steps by calculating the statistical parameters. The analysis were performed using the statistical program R version 3.1.0.*

Key words: *Analyses variance, correlation, debonding load, fiber reinforced polymer, multi linear regression.*

1. INTRODUCTION

Fiber-reinforced polymer(FRP) composites are the combination of fibers and matrices given by interface that guarantee a good performance [1], FRP plays an important role in maintaining and strengthening infrastructure, it is used also in development of many type of hybrid material and engineering structural systems , whether in aerospace structure or in civil structure [2,3] sheet or plates are useful model for the use of FRP material, they are bonded to the tension or the compression face of the beam [4]. In numerical analysis three-technique are used in reinforcement in reinforced concrete for finite element models are the discrete model, the embedded model and the smeared model [5].

Interfacial bond strength models through single-lap shear-bond tests have been made by many researchers. yingwu zhou et al [6] collected a total of 20 bond strength models and presented the analysis of a large data by artificial neural networks (ANN) using his models, ardalan and davood [7] determined the existing models of effective bond length using single-shear bond tests j.g. teng et al [8] presented a strength model based on a recent FRP-concrete bond strength model for ic debonding failures and the available limited test values of beams and slabs that failed in this mode, carlo et al [9] introduced certain common formulations for effective bond length by experimental programmer, khalifa et al [10] presented model algorithms for evaluating the impact of FRP on the shear capacity of rc bending members and Hong et al [11] band strength model solve non-linear interfacial stress transfer problems. We have remarked that all tests of FRP-concrete in research produce rupture.

Multiple linear regression approach is considered as one of most effective and admirable approach in analysis of research phenomenon, [12]. The aim of this approach is to give an effective formulation to develop competencies in formulating models according to the individual research problems, some of the main uses of this approach include to forecast information, analysis of variance and analysis of covariance [13], factors (proportions of

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variance and correlation and regression coefficients). It is a major tool for statistical hypothesis testing, estimation and power analysis.[14] was analyzed the optimization of five parameters on thermoforming process namely by statistical method., [15] an analysis of variance (ANOVA) was performed to determine the contribution rates of the control parameters affecting the two efficiencies (thermal and energy). [16] variance analysis (ANOVA) was employed to analyze the impacts and contributions of the cutting and vibration parameters on the variation of strain rates , [17] evaluating the value of the B-Basis strength parameters of the carbon composite material by ANOVA method, [18] correlation analysis is used to measure the changes in the Lamb wave signals between the damaged state and the undamaged state, Randall Marrett [19] Variation of spatial correlation with length scale.

In the application of band text on FRP-concrete, the concrete block is charged by a pushing force whereas the FRP reinforcement is put under tension force by a pull operation. According to the push–pull test results in terms of debonding loads [20].

We use R software for statistical computing [21].to calculate the proportions of statistical factors of variance and the correlation and regression coefficients and predicts the value of the debonding load that leads to the fracture.

The objective of our current work is divided into both parts. The first one aims at New analysis include information to determine the fracture in structure caused by the debonding laod, Otherwise to evaluate the relative influence of geometrical and mechanical parameters (FRP type (plate or sheet), FRP geometry, concrete compressive and specimen width) on FRP-concert surface using principal statistical analysis to predict FRP (sheet/plate) debonding load by developing MLR model and evaluate the quality of the model when we forecast , we detect observations that may exaggerate the results.

2. INFORMATION THEORETICAL BOND STRENGTH MODEL

In the previous section we have talked about band strengths models which are introduced in several works. In our study we are interested in chen & teng [22] band strength model which is the base of debonding load and effective bond leigh of FRP composite, this model is presented in the expression below:

$$P=\alpha\beta_w\beta_l b_f \sqrt{k_f}\,\sqrt[4]{f_c} \tag{1}$$

$$\beta_w = \sqrt{\frac{2-{p_f}/{p_c}}{1+{p_f}/{p_c}}} \tag{2}$$

$$k_f = \sqrt{E_f t_f} \tag{3}$$

$$\beta_l = \sin\frac{\pi l_f}{2l_e} \quad \text{if} \quad l_f \text{ p } l_e \quad \text{or } \beta_l = 1 \tag{4}$$

$$l_e = \sqrt{\frac{E_f t_f}{\sqrt{f_c}}} \tag{5}$$

where f_c is the mean of compressive strength of concrete; k_f is FRP stiffness and equal to the multiplication of FRP elastic modulus (E_f) and the FRP thickness (t_f), α is given by chen & teng and equal 0.43 , β_w is a geometry factor depends on the bond length l_f and l_e, factor β_l, finally b_f and b_c defined respectively FRP width and the concrete substrate width.

3. MATERIAL AND METHODS

3.1 Data Base

The experimental values [20] used in this work were obtained by six parameter (k_f , β_w, β_l , b_f , f_c and P : FRP deboning load). These data express 34 single shear tests have been implemented in two types: FRP sheet – concrete structure and FRP plate- concert structure.

Fiber-reinforced polymer sheet include fiber with thickness 0.166 mm and unit weight 330 g/m^2 while fiber-reinforced polymer plate include fiber with thickness 1.44 mm and unit weight 113 g/m^2.

The specimen which was adopted for this study is illustrated in figure 1. It is composed of a concrete and fiber-reinforced polymer sheet or plate.

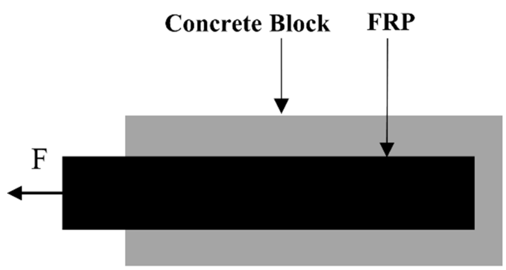


Fig. 1. FRP -concrete structure

Tables (01) and (02) are filled using the experimental data and previous theoretical equations (2-5)

Table 1

Data of FRP sheet-concrete structure.

Test N°	f_c (MPa)	k_f (GPa.mm)	β_w	β_l	b_f (mm)	P (KN)
01	23.8	38,18	0,89	1	100	21.4
02	23.8	38,18	0,89	1	100	21.8
03	23.8	38,18	0,89	1	100	21.2
04	23.8	38,18	0,89	1	100	21.6
05	23.8	38,18	0,89	1	100	20.7
06	23.8	38,18	0,89	1	100	22.1
07	21.4	38,18	0,89	1	100	19.3
08	21.4	38,18	0,89	1	100	20.3
09	21.4	38,18	0,89	1	100	22.5
10	21.4	38,18	0,89	0,01	100	16,8
11	21.4	38,18	0,89	0,01	100	21,2
12	21.4	38,18	0,89	0,01	100	19,0
13	26.0	40,006	0,89	1	100	24.0
14	26.0	40,006	0,89	1	100	24.9
15	26.0	40,006	0,89	1	100	23.6
16	26.0	40,006	0,89	1	100	21,8
17	26.0	40,006	0,89	1	100	21.4
18	26.0	40,006	0,89	1	100	21.9

Table 2

Data of FRP plate-concrete structure

Test N°	f_c (MPa)	k_f (GPa.mm)	β_w	β_l	b_f (mm)	P (KN)
01	23,8	238	1,11	1	50	20,1
02	23,8	238	1,11	1	50	21,7
03	23,8	238	1,11	1	50	20,1
04	23,8	238	1,11	1	50	21,5
05	21,4	238	1,11	1	50	19,0
06	21,4	238	1,11	1	50	19,8
07	21,4	238	1,11	1	50	17,2
08	21,4	238	1,11	0,01	50	19,4
09	21,4	238	1,11	0,01	50	19,3
10	21,4	238	1,11	0,01	50	20,7
11	26	216	0,97	1	80	30,1
12	26	216	0,97	1	80	33,5
13	26	216	0,97	1	80	32,4
14	26	216	0,97	0,01	80	28,3
15	26	216	0,97	0,01	80	27,5
16	26	216	0,97	0,01	80	30,2

3.2 Data Modeling Techniques

Sample multiple linear regression allows a numeric variable to be explained by several other independent numeric variables. It models the relationship between the variable to be explained and the explanatory variables in the form of an equation of the type $Y = b_0 + b_1X_1 + b_2X_2 + ...$ where Y is the variable to be explained, X_n the independent variables, has a constant and bn has partial regression coefficients. So, if the regression model is satisfactory, we predict the values of the dependent variable as a function of the values of the explanatory variables [23]. In this context we propose nonlinear models to predict the FRP debonding loads. The mathematical formulation is given by the following equations:

$$P = \alpha\, \beta_w^{a_1} \beta_l^{a_2} b_f^{a_3} k_f^{a_4} f_c^{a_5} \tag{6}$$

These equations are put in linear form by using the natural logarithm as follows

$$\ln P = \ln(\alpha\, \beta_w^{a_1} \beta_l^{a_2} b_f^{a_3} k_f^{a_4} f_c^{a_5}) \tag{7}$$

$$\ln P = \ln\alpha + \ln\beta_w^{a_1} + \ln\beta_l^{a_2} + \ln b_f^{a_3} + \ln k_f^{a_4} + \ln f_c^{a_5} \tag{8}$$

$$\ln P = \ln\alpha + a_1\ln\beta_w + a_2\ln\beta_l + a_3\ln b_f + a_4\ln k_f + a_5\ln f_c \tag{9}$$

4. RESULTS AND DISCUSSION

4.1 Correlation analysis

The method of statistical analysis (correlation) used to study the relationship between FRP debonding load concrete and geometrical, mechanical structural parameters (k_f, β_w, β_l, b_f, f_c and α)

Table 3

Relationship value

	b_f	k_f	f_c	β_l	β_w	α
P_{PLATE}	0.952	-0.952	0.904	-0.098	-0.952	0
P_{SHEET}	0	0.5	0.571	0.621	0	0

1. The relationship level between the main geometrical, mechanical characteristic and debonding phenomenon in FRP sheet-concert and FRP plate-concert is illustrated in table (3) The relationship between three parameters FRP stiffness (k_f), concrete compressive strength (f_c), (β_l) and FRP debonding load (P_{SHEET}) estimated by 50%, 57% and 62% respectively, now we can say the relation is medium expulsion when k_f, f_c and β_l increases the P_{SHEET} increase.
2. FRP sheet width (b_f), geometry factor (β_w) and α do not affect to FRP debonding load (P_{SHEET}) Despite the affect of FRP width (b_f) and FRP stiffness (k_f) on FRP debonding load (P_{PLATE}) they were eliminated to get more accurate mathematical model.
3. The relationship between geometry factor (β_w) and FRP debonding load (P_{PLATE}) estimated by - 95% it gives strong reverse when the β_w increase, the P_{PLATE} decreases.
4. The relationship between concrete compressive strength (f_c) and FRP debonding load (P_{PLATE}) estimated by 90% it gives strong expulsion when the f_c increase the P_{PLATE} increases.
5. The relationship between length influence coefficient (β_l) and FRP debonding load (P_{PLATE}) estimated by - 9, 8% it gives weak reverse when the β_l increase the P_{PLATE} decreases.
6. α doesn't affect on P_{PLATE}.

4.2 Multiple linear Regression Modeling

We construct statistical models of FRP (sheet/plate) debonding load with multi linear regression (MLR) using the results and analysis from section (4.1) and mathematical formulas below

Let's consider a multiple linear regression model with m independent variables predictor $X_1 \ldots\ldots X_m$ And one response variable Y .In our case, we have n (number of tests) observations on the 4 variable

$$Y_i = b_0 + b_1X_{1i} + b_2X_{2i} + b_3X_{mi} + \varepsilon_i \qquad i = 1,\ldots\ldots\ldots,n \tag{10}$$

Our purpose in least squares regression is to adapt a hyperplane in a 4-dimensional space that the sum of squared residuals minimizes.

$$\sum_{i=1}^{n}\varepsilon_i^2 = \sum_{i=1}^{n}\left(Y_i - b - \sum_{j=1}^{m}X_{ij}\right)^2 \qquad m = 1,\ldots\ldots\ldots,3 \tag{11}$$

Where

$$Y_i = \begin{bmatrix} y_1 \\ y_2 \\ . \\ . \\ y_n \end{bmatrix} \quad X_i = \begin{bmatrix} 1 & x_{11} & x_{12} & x_{13} \\ 1 & x_{21} & x_{22} & x_{23} \\ . & . & . & . \\ . & . & . & . \\ 1 & x_{n1} & x_{n2} & x_{n3} \end{bmatrix} \quad b = \begin{bmatrix} b_0 \\ b_1 \\ b_2 \\ b_3 \end{bmatrix} \quad \varepsilon = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ . \\ . \\ \varepsilon_n \end{bmatrix}$$

With this way of notation, the linear regression model can be represented as follow.

$$Y_i = X_i b_m + \varepsilon_i \tag{12}$$

$$\begin{bmatrix} y_1 \\ y_2 \\ . \\ . \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & x_{11} & x_{12} & x_{13} \\ 1 & x_{21} & x_{22} & x_{23} \\ . & . & . & . \\ . & . & . & . \\ 1 & x_{n1} & x_{n2} & x_{n3} \end{bmatrix} \begin{bmatrix} b_0 \\ b_1 \\ b_2 \\ b_3 \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ . \\ . \\ \varepsilon_n \end{bmatrix} \qquad (13)$$

In the context of linear algebra, the least-squares parameter estimates b are the vectors that minimize.

$$\sum_{i=1}^{n} \varepsilon_i^2 = \varepsilon\ \varepsilon^{\perp} = \left(Y_i - X_i b_m\right)^{\perp}\left(Y_i - X_i b_m\right) \qquad (14)$$

$(Y_i - X_i b_m)^{\perp}$: transpose of matrix $(Y_i - X_i b_m)$

$\varepsilon^{\perp}$: transpose of matrix ε

We want to find the "best" b in the case where the sum of squares of the residuals is minimized. The lowest sum of squares that can be is zero. If all squares were zero, then

$$\hat{Y}_i = X_i\ \hat{b}_m \qquad (15)$$

Suppose further that $\hat{b}$ satisfies the equation above. Then the residuals $Y - \hat{Y}$ are orthogonal to the columns of X (by the Orthogonal Decomposition Theorem) and thus

$$X^{\perp}\left(Y - X\hat{b}\right) = 0 \qquad (16)$$

$$X^{\perp}Y - X^{\perp}X\hat{b} = 0 \qquad (17)$$

$$X^{\perp}X\hat{b} = X^{\perp}Y \qquad (18)$$

To solve the normal equations (i.e., to find the parameter estimates $\hat{b}$), multiply both sides with the inverse of $X^{\perp}X$. Thus, the least-squares estimator of b is (in vector form)

$$\hat{b} = \left(X^{\perp}X\right)^{-1} X^{\perp}Y \qquad (19)$$

To obtain the values of the parameters of this linear regression model in R, means to formulate the matrix X and the vector y and to use the equations of the previous one to calculate $\hat{b}$
Thus,

For P_{SHEET}

$$\begin{bmatrix} b_0 \\ b_1 \\ b_2 \\ b_3 \end{bmatrix} = \begin{bmatrix} -0,729 \\ 0.740 \\ 0,347 \\ 0,021 \end{bmatrix}$$

With this, the estimated multiple regression equation becomes:

$$Y = \ln P,\ \ x_1 = \ln k_f,\ \ x_2 = \ln f_c,\ \ x_3 = \ln \beta_l$$

$$\ln P = -0,729 + 0.74\ \ln k_f + 0,347\ \ln f_c + 0,021\ \ln \beta_l \qquad (20)$$

And,
For P_{PLATE}

$$\begin{bmatrix} b_0 \\ b_1 \\ b_2 \\ b_3 \end{bmatrix} = \begin{bmatrix} 1,209 \\ 0.663 \\ -2,452 \\ 0,006 \end{bmatrix}$$

With this, the estimated multiple regression equation becomes:

$$Y = \ln P,\ \ x_1 = \ln f_c,\ \ x_2 = \ln \beta_w,\ \ x_3 = \ln \beta_l$$

$$\ln P = 1,209 + 0.663\ \ln f_c - 2,452\ \ln \beta_w + 0,006\ \ln \beta_l \qquad (21)$$

By the equation (20) we can predict a value FRP sheet debonding load whereas with the equation (21) we can find FRP plate debonding load.

4.3 Experimental and Predicted Values during Text

For test phase table (4) gives a numerical comparison between the experimental and the predicted FRP sheet debonding loads values on one hand, comparison between experimental and predicted FRP plate debonding loads on the other hand.

Table 4(a)

Numerical comparison between experimental and predicted model of FRP sheet -concrete structure

FRP sheet model			
Text N°	***P* (KN) Exp**	***P* (KN) Pred**	**Error %**
01	21.41	21,51	-0,48
02	21.81	21,43	1,73
03	21.24	21,55	-1,44
04	21.69	21,46	1,08
05	20.74	21,65	-4,39
06	22.11	21,37	3,33
07	19.37	21,45	-10,72
08	20.37	20,91	-2,67
09	22.58	19,86	12,03
10	16,85	20,09	-19,20
11	21,2	17,91	15,53
12	19,03	18,90	0,68
13	24.00	22,73	5,28
14	24.96	22,55	9,64
15	23.65	22,80	3,60
16	21,84	23,16	-6,07
17	21.49	23,24	-8,14
18	21.91	23,15	-5,66

Table 4(b)

Numerical comparison between experimental and predicted model of FRP plate -concrete structure

FRP plate model			
Text N°	***P* (KN) Exp**	***P* (KN) Pred**	**Error %**
01	20,10	21,15	-5,25
02	21,78	20,60	5,44
03	20,17	21,13	-4,76
04	21,55	20,67	4,09
05	19,02	19,65	-3,29
06	19,86	19,37	2,47
07	17,24	20,29	-17,69
08	19,46	18,84	3,17
09	19,30	18,89	2,10
10	20,74	18,45	11,02
11	30,14	30,93	-2,62
12	33,56	29,83	11,13
13	32,47	30,16	7,11
14	28,33	30,48	-7,59
15	27,58	30,76	-11,52
16	30,29	29,80	1,62

In this table (4) a and b we remark that the highest value for FRP sheet debonding load of percentage relative error for experimental versus predict is -19.86 (test10), and for FRP plate debonding load we observe that maximum error percentage relative error is determined to be -17.96 (test 7), for experimental versus predict conversely lowest value of error which is -0,48 (test1) for experimental versus predict in the case of FRP sheet debonding load and in other case the minimum error is determined 1.66 (test 16).

Now, we say that we can have two value close zero :test (1) and test (12) in the case of FRP sheet debonding load the value doesn't converge to zero at the last, the mean of percentage relative error was -0,32 % for the first case and - 0,26 % for the other case.

Figure 2 illustrates the absolute error percentage between the values of resultant FRP sheet debonding load from the regression model and the experiments, as well as between the regression model of FRP plate debonding load and the experiments.

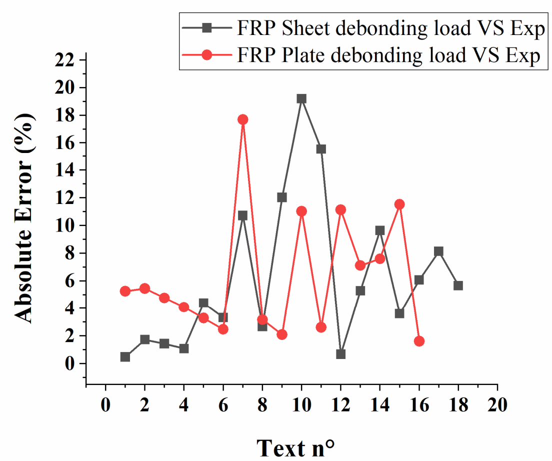


Fig. 2. Absolute error comparison

The figure (2) indicates that the two lines are reversing in the direction of several points (test n° 5 and from 13 to 16). In the point 8, the error value is equal, at point 8, the error value is approximately the same, while for the rest of the points the error values are different.

4.4 Analysis of Variance for MLR

Table (05) gives the analysis of variance by considering all tests are performed on FRP plates debonding load (16) and FRP sheets debonding load (18) as follows. The coefficient of determination 56, 1 % and93.1% respectively FRP sheet-concert and FRP sheet-concert by considering all tests.

Table 5

Analysis of variance for regression models (all test)

source		sum of squares	freedom degree	mean square	ration
FRP plate	model	0,686	3	0,229	59.87
	residual	0,051	12	0,004	
FRP sheet	model	0.077	3	0.026	5.96
	residual	0.06	14	0.004	

The analysis of variance for multiple linear regression modeling we eliminate the tests n° 9, 10, and 11 for FRP sheet debonding load model and exclude tests n° 7,10, 11 and 15 for FRP plates debonding load model result of analyses variance as it is illustrated in table (06).

Table 6

Analysis of variance for regression models

source		sum of squares	freedom degree	mean square	ration
FRP plate	model	0,581	3	0,194	93.78
	residual	0,019	9	0,002	
FRP sheet	model	0,052	3	0,017	8,383
	residual	0,023	11	0,002	

In addition, r is equal to 69.6 % and 96.9% respectively for FRP sheet-concert and FRP plate-concert that ensure the best performance with a high linear regression coefficient r.

4.5 Analysis Statically From Box Plot of Values MLR Modeling

Box plot determine patterns that may be hidden in a collection of values which is used to summary and visually compare FRP (sheet/plate) model value with experimental values.

Figure (3) and (4) illustrates a comparison between experimental value and FRP sheet debonding load model value respectively experimental value and FRP Plate debonding load by plot box.

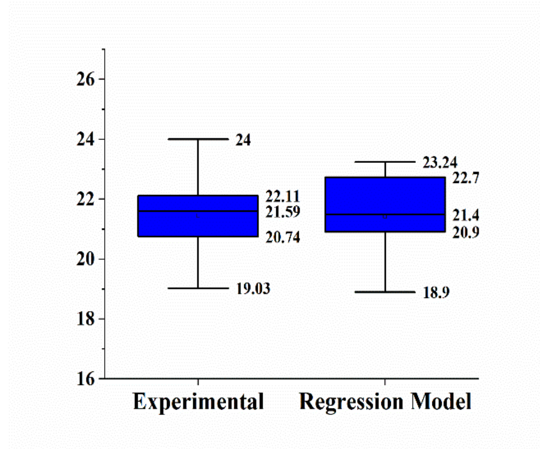


Fig. 4a. Comparison between experimental and FRP sheet model by plot box

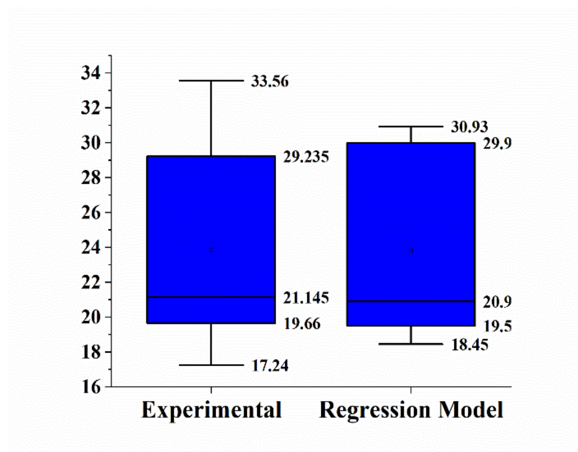


Fig. 4b. Comparison between experimental and FRP plate model by plot box

A graphical representation based on its quartiles, as well as its smallest and largest values. It attempts to provide a visual shape of the data distribution for experimental and predicted FRP sheet respectively plate.

4.6 Validation of MLR Model

We evaluate validation steps by calculating the following statistical parameters: correlation coefficient (R), mean bias error (MBE), mean absolute error (MAE) and root mean squared error (RMSE), then we obtain the following result introduce in the table (07).

Table 7

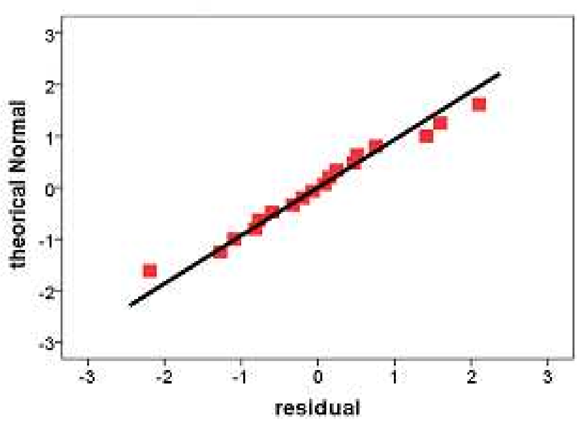
Calculates statistical parameters

	R	MBE	MAE	MSE	R Square
FRP sheet model	74.9%	-0,029	1,306	1,658	56.1%
FRP plate model	96.5%	-0,036	1,513	1,850	93.1%

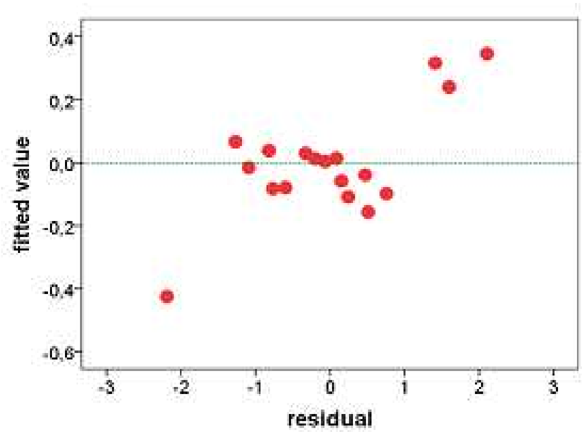
MBE is used to estimate the average bias in the model, MAE and RMSE is the standard deviation of the residuals (prediction errors). R square give a real result for model probability r provides the variability measure of the data reproduced in the model.

The discussion of linear regression concepts should not neglect the residue analysis step. Specifically, the residuals graph which is considered as one of the points that must be looked at after development of a linear model, to verify the correct fit and accuracy of the model

The figures (a1, a2, b1, b2) indicate: (quantile-quantile) plot and variance text of residual firstly we observe in the two figures (a1,a2) that the most of the points are attached in a straight line, which makes the residues distributed normally, secondly we notice in the figures (b1.b2) that the points are scattered and equal on the side of the reference line, which shows that the variance of the residuals is constant.

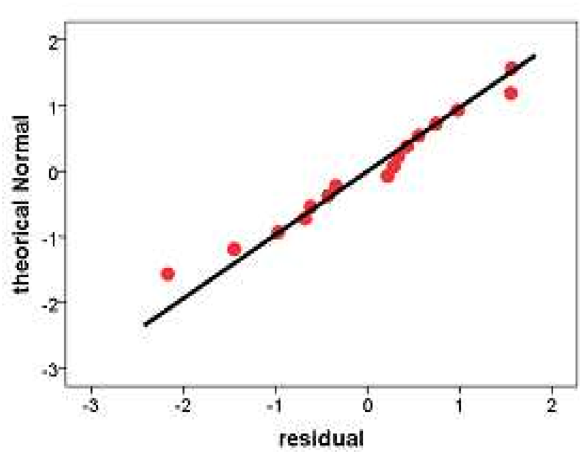


(a1) (quantile-quantile) plot

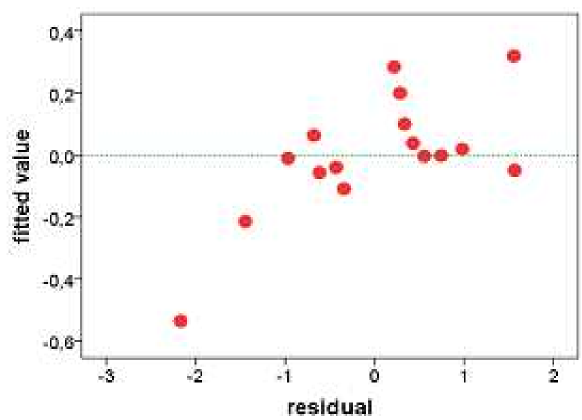


(b1) variance text of residual

Fig.5. (a1, b1) residual analysis of FRP sheet model



(a2) (quantile-quantile) plot



(b2) variance text of residual

Fig. 6. (a2, b2) residual analysis of FRP plate model

The result of table 07 and the analysis of graphs show that the model has a better accuracy.

5. CONCLUSION

In this research work, statistical analysis was performed using R software. For Fiber-Reinforced Polymer Composites and Concrete structure we have developed two models depending FRP type (sheet and plate) using multiple regression linear to predict FRP debonding load in two cases and we show new analysis employ correlation and analysis variance, the conclusions can be stated as follows:

- The model developed is a simple and use easy formulation to forecast.
- The input in the FRP sheet model is mean compressive strength of concrete; FRP stiffness and factor β_l.
- The input in the FRP plate model is mean compressive strength of concrete; factor β_l and geometry factor.
- An over view of the (mathematical) fundamentals of MLR is discussed.
- Highlights of the work include a discussion of key aspects of the practice of MLR
- Evaluate the quality of the model when we forecast by: correlation coefficient (R), mean bias error (MBE), mean absolute error (MAE) and root mean squared error (RMSE).
- ANOVA was carried out to determine the contribution rates of different geometrical and mechanical structures parameters affecting both debonding load and fracture
- Correlation analysis clarify how input parameters can influence on output parameters whereas the analyses of residual gives a more accurate formulation for both FRP sheet model and FRP plate model.

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ANALIZA STATISTICĂ A PLACII ȘI A FOLIEI DE POLIMER ARMATE CU FIBRE

Rezumat: Mecanica fracturii se bazează pe multe modele teoretice care sunt analizate pentru a evalua sarcina de dezlipire în compozite polimerice și beton armat cu fibre. Pentru a arăta influența diferitelor structuri geometrice și mecanice asupra valorilor sale, în acest scop am dezvoltat un model statistic care se bazează pe regresia multi liniară (MLR) pentru a prezice sarcina de dezlipire a suprafețelor din beton armat cu FRP. Parametrii utilizați în modelul MLR au fost tipul de FRP (placă, foaie), geometria FRP, compresiunea betonului și lățimea epruvetei, în acest studiu realizăm modelul MLR folosind date experimentale, apoi facem o comparație între rezultatul predicției și rezultatul experimental. Apoi am arătat performanța acestui model. În continuare, realizăm o evaluare a etapelor de validare a MLR prin calcularea parametrilor statistici. Analizele au fost efectuate cu ajutorul programului statistic R versiunea 3.1.0.

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