Estimating Mechanical Tensile Strength of Single Fiber Composites by Adopting Multiple Linear Regression

Muhammad Nasrun Faris Mohd Zulkifli[1,2], Mohamad Faizul Yahya[1]*

[1]Textile Research Group, Faculty of Applied Sciences, Universiti Teknologi MARA, Shah Alam, 40450 Selangor, Malaysia.

[2]Midwest Composites Sdn Bhd, Bandari Sri Sendayan, Seremban, 71950 Negeri Sembilan, Malaysia.

***Corresponding Author**

DOI: https://dx.doi.org/10.47772/IJRISS.2024.8110232

Received: 05 November 2024; Accepted: 16 November 2024; Published: 21 December 2024

ABSTRACT

The determination of mechanical tensile strength in polymer fiber composites is crucial for classifying their fundamental strength performance. Beyond physical examination tests, statistical analysis can estimate potential tensile strength behavior based on previous experimental data. This study employed a multiple linear regression method to identify the most significant independent variables affecting tensile strength. The results indicated that there are two factors plays a major role; composite density and fiber volume fraction. A mathematical equation was derived to predict future tensile strength behavior, and validation findings demonstrated that the equation could calculate tensile strength with up to 99% accuracy.

Keyword: Single Carbon fiber, Single Glass Fiber, Composite, Tensile Strength, Multiple linear regression,

INTRODUCTION

Multiple Linear Regression (MLR) is a statistical method that utilises multiple explanatory variables to predict the outcomes of response variables. The primary objective of MLR is to establish a relationship between explanatory and response variables [1], [2]. In MLR calculations, the variables are categorised into one dependent variable (DV) and multiple independent variables (IV). The regression coefficients indicate how the response variable changes in relation to a one-unit change in the corresponding independent variable, when all other independent variables are held constant. The error term represents the discrepancy between the predicted and observed values. MLR can be employed for both basic and complex datasets to predict values and test hypotheses. Furthermore, MLR can assess the relationship between independent and dependent variables.

Numerous studies have employed MLR analysis to evaluate the performance of textile yarns, woven fabrics, and woven composites. In a previous study, a group of researchers [3] examined yarn strength performance extracted from plain, twill 2/2, and twill 3/1 weave structures. Nine independent variables were identified. The study revealed that the most significant variables influencing yarn tenacity performance are the number of load-bearing and transverse yarns. Additionally, another group of researchers [4] conducted a statistical analysis to determine the relationship between open-end yarn tenacity and various yarn properties. Four independent variables representing the yarn properties were utilised in this study. The researchers determined that the yarn count and fibre blend ratio were the most influential factors. Both findings successfully identified the yarn properties contributing to yarn tenacity behaviour.

In the meantime, a scientific study. [5] utilised MLR analysis to recognize the factors affecting the tensile strength degradation of thermal retardant fabrics. The computation findings determined that three of the eight factors were highly related to fabric tensile degradation. Furthermore, one of the literature [6]

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS |Volume VIII Issue XI November 2024

examined the fabric tensile strength degradation used as a firefighter cloth owing to radiant heat exposure. Researchers used three independent variables in the statistical analysis based on experimental work. Researchers have identified that fabric count and thickness properties are the most important elements. These results allowed the researchers to develop a statistical relationship between the physical attributes and the tensile strength of the woven fabric. Moreover, the statistical analysis output significantly helps researchers optimize the woven fabric properties for better tensile strength.

On the contrary, several scientific studies [7]–[9] reported a similar problem: MLR analysis was unable to establish a statistical regression relationship between certain independent and dependent variables. Livingstone [2] and Figueiredo [10] described the statistical error phenomenon as plausible. In these studies, researchers acknowledged that the population sample size and independent variable collinearity factors caused this issue. A small sample size may lead to errors in the entire linear regression computation. It is important to verify the collinearity issue for all independent variables. Collinearity occurs when an independent variable is statistically correlated with another independent variable.

Besides that, MLR analysis were also utilized to establish a prediction model on textile preforms. Numerous studies have reported that use of MLR analysis successfully computed the textile and composite strength prediction accuracy between 90 to 99 % [11]–[14]. It is agreed that prediction accuracy can be accomplished by providing a large group of data which represents the high and low performance of the intended output. It is important to achieve high accuracy of prediction model to make sure the model is reliable to be incorporated in the real-world application.

MATERIAL AND METHOD

Material

8 layers single carbon fibre; carbon plain (CP), and single glass fibre; glass plain (GP), glass twill (GT), and glass satin (GS) was fabricated via hand lay-up approach. Epoxy resin was used as the composite matrix reinforcement where it was cured at room temperature for 6 hours. Two physical composite properties were performed; composite density and fiber volume fraction. The physical characterization was performed according to the established American Society of Testing Material (ASTM) standard, ASTM D792 and ISO 14127:2008(en) compliances. Meanwhile, the composite specimens were prepared for uniaxial tensile strength analysis, where the test will be conducted based on the ASTM D638.

Table 1 presented the single fiber physical characterization on density property indicated the GP composite samples produced the lightest density at 1.292 g.cm^{-3} whereas GT composite samples resulted with the heaviest density at 1.623 g.cm^{-3}. Meanwhile, the fiber volume fraction percentage analysis revealed that GP composites recorded the highest fiber at 57.83 % while the GT composites had the lowest fiber fraction at 53.10 %.

Table 1 Single fiber composites physical characteristics

Samples	CP	GP	GT	GS
Density (g.cm^{-3})	1.463	1.292	1.623	1.582
FVF (%)	53.45	57.83	53.1	54.36

Table 2 presented the experimental results recorded on the single fiber composites tensile strength based on warp and weft directions. Based on warp direction, CP composites generated the highest maximum tensile at 405.57 MPa, whereas GP composites had the minimum performance at 237.89 MPa. On the other hand, based on weft direction, CP composites yielded the highest maximum tensile at 425.26 MPa, while GP

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS |Volume VIII Issue XI November 2024

composites had the lowest tensile performance at 261.88 MPa.

Table 2 Woven composite tensile strength performance in warp and weft directions

Warp Direction			
Layer	**Sample**	**Max. Stress (MPa)**	**SD**
	CP	405.57	30.44
	GP	237.89	15.65
8	GT	254.45	25.85
	GS	306	23.76
Weft Direction			
Layer	**Sample**	**Max. Stress (MPa)**	**SD**
	CP	425.26	30.56
	GP	261.68	15.45
8	GT	285.95	25.67
	GS	300.17	29.45

Statistical Analysis

Multiple linear regression (MLR) analysis was conducted to evaluate the correlation between the physical characteristics of the woven composites, as well as the mechanical tensile strength performance. The total sample size, n, was 40 for each respective IV and DV item. The sample size was acquired based on the average ASTM standard compliance for experimental work. The sample size is sufficient as it represents the average population of the experimental output in this research work. IBM SPSS version 27, run on Windows 10, was used to conduct the MLR analysis with a 95 % confidence interval.

The statistical work required the independent variables (IV) data compiled to be validated based on the multicollinearity parameter. Multicollinearity is a parameter that determines whether each IV is directly related to the DV or whether a specific IV is interrelated with other IVs instead. Multicollinearity was measured using the variance inflation factor (VIF) value. Furthermore, it is proposed that the VIF value be below 10. An IV with a VIF value higher than 10 indicates that it is highly interrelated with other IVs instead of DV [1].

Equation 1 (Eq. 1) was used for the MLR analysis where the b_0 is the MLR coefficient regression value, $b_1 \ldots b_2$ as the IV coefficient value, whereas $x_1 \ldots x_2$ as the input value of the respective IV.

$$MLR = b_0 + b_1 x_1 + b_2 x_2 + \ldots\ldots b_5 x_5 \qquad \text{(Eq. 1)}$$

RESULTS AND DISCUSSIONS

Statistical Analysis

Table 3 and 4 presents the multiple linear regression output on eight-layer woven composite tensile strength performance. The coefficient represents the regression equation value to predict the dependent variable performance from the independent variable property. Besides that, the p-value reflects the statistical significance level of IV. It was found that only three IV items passed the multicollinearity test with a VIF value of less than 10. The qualified IVs were woven composite density, and fiber volume fraction properties.

Based on Table 3, for the warp direction, the woven composite density property had shown a strong

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS |Volume VIII Issue XI November 2024

correlation towards the DV with the coefficient at -413.99 and the *p*-value at 0.000, which does not exceed the 0.05 confidence level. Meanwhile, the woven composite fiber volume fraction properties led to a weak correlation as the *p*-values were 0.782, respectively. Hence, it can be assumed that the single fiber composite tensile strength in the warp direction was statistically affected by the woven composite density property. In addition, the coefficient result implies that by reducing the density of the single fiber composite, the tensile strength can be increased. Based on the MLR coefficient output, a new regression equation (Eq. 2) can be formulated to represent the single fiber composite tensile strength model prediction in the warp direction.

Table 3 Multiple linear regression summary on woven composite tensile at warp

DV	8 layers Woven Composite Tensile Warp		
	Coefficient	p	VIF
(Constant)	941.679	–	–
Co_Den8L	-413.99	0	3.21
Co_FVF8L	-0.87	0.782	3.812

Meanwhile, based on Table 4, for the weft direction, both woven composite density and fiber volume fraction traits indicated a strong correlation value towards DV with the p-value at 0.000 and 0.001, respectively. In the meantime, the coefficient value for woven composite density and fiber volume fraction are -327.066 and 20.538, respectively. Consequently, it can be remarked that the woven composite tensile strength in the weft direction was strongly influenced by the woven composite density and fiber volume fraction attributes. Furthermore, the coefficient finding implies that there is a statistically significant negative correlation between woven composite density and woven composite tensile strength. Meanwhile, the coefficient output suggests there is a statistically significant positive correlation between the woven composite fiber volume fraction and the woven composite tensile strength. Hence, the woven composite tensile strength performance in the weft direction can be enhanced by reducing the woven composite density and increasing fiber volume fraction. Based on the MLR coefficient output, a new regression equation (3) can be expressed to represent the woven composite tensile strength model prediction in the weft direction. The new regression equation is:

Table 4 Multiple linear regression summary on woven composite tensile at weft

DV	8 layers Woven Composite Tensile Weft		
	Coefficient	p	VIF
(Constant)	-289.181	–	–
Co_Den8L	-327.066	0	1.348
Co_FVF8L	20.538	0.001	3.21

Therefore, the new multiple linear equation can be written as $Y_{CoTsWarp}$ represents the estimation model for composites tensile at warp direction (Eq. 2). Meanwhile, $Y_{CoTsWeft}$ denotes the estimation model for composites tensile at weft direction (Eq. 3).

YCoTsWarp = 941.679 + 21.128*F_CF – 413.990*Co_Den8L – 0.87*Co_FVF8L. (Eq. 2)
YCoTsWeft = -289.181 – 52.202*F_CF – 327.066*Co_Den8L + 20.538*Co_FVF8L (Eq. 3)

INTERNATIONAL JOURNAL OF RESEARCH AND INNOVATION IN SOCIAL SCIENCE (IJRISS)
ISSN No. 2454-6186 | DOI: 10.47772/IJRISS |Volume VIII Issue XI November 2024

Model Validation

Table 5 and 6 below presents the prediction finding on single fiber composite tensile. Moreover, the woven composite tensile performance finding by using the coefficient regression equation clearly indicate that the adoption of woven composite density and fibre volume fraction properties are capable of predicting the woven composite tensile strength. Generally, the validation test on different types of woven composite, CP, GP, GT, and GS, have successfully achieved prediction findings with minimal error, less than 2 %. An in-depth examination of tensile strength shows that the coefficient model provided an accurate tensile strength in the warp and weft prediction with an average of 0.19 and 1.18 %, respectively.

Table 5 Coefficient regression model validation on single carbon fiber and single glass fiber composites tensile performance at warp direction

Woven Composite Tensile Strength (MPa)			
	Warp	**Model Warp**	**Error %**
CP	368.44	368.02	0.11
GP	233.75	234.24	0.21
GT	255.31	254.64	0.26
GS	304.37	305.04	0.21
Average	–	–	**0.19**

Table 6 Coefficient regression model validation on single carbon fiber and single glass fiber composites tensile performance at weft direction

Woven Composite Tensile Strength (MPa)			
	Weft	**Model Weft**	**Error %**
CP	441.27	442.64	0.31
GP	252.88	251.24	0.64
GT	269.65	275.2	2.03
GS	297.76	292.53	1.77
Average	–	–	**1.18**

In general, the model validation in the study results demonstrate a high accuracy of 99% in predicting the tensile strength of single fiber and woven composites, for various types of woven composites (CP, GP, GT, and GS). However, the applicability of this model to other composite types or manufacturing methods remains uncertain due to different material property, and composite fabrication procedure limitation.

Moreover, the unique behaviors and interactions introduced by different types of composites and manufacturing methods need to be accounted for. Factors such as fiber orientation [15]–[17], matrix composition [18], [19], and processing techniques [20], [21] significantly influence the mechanical properties of composites. By studying these variations, the model can be refined to better predict the performance of composites under diverse conditions. Comprehensive characterization will also allow for the identification of potential limitations and weaknesses in the existing model. This iterative process of validation and refinement is essential for developing a model that can generalize well across different applications. Understanding the boundaries within which the model can be reliably applied will increase its practical utility.

CONCLUSION

In conclusion, the multiple linear regression analysis of eight-layer single carbon fibre and single glass fibre composites tensile strength performance has revealed significant insights. The investigation determined that woven composite density exhibits a strong negative correlation with tensile strength in both warp and weft directions, suggesting that a reduction in density may enhance tensile strength. Furthermore, the fibre volume fraction demonstrated a strong positive correlation with tensile strength in the weft direction, indicating that an increase in fibre volume fraction may further improve tensile strength. The regression model exhibited high accuracy in predicting tensile strength, with minimal errors, thus validating its reliability.

For future studies, it is recommended to investigate the impact of additional potential independent variables on tensile strength, such as fibre orientation and matrix properties. Moreover, examining the long-term durability and performance of these composites under various environmental conditions could provide valuable insights for practical applications. Further research could also focus on optimising the balance between density and fibre volume fraction to achieve optimal tensile strength performance. These comprehensive studies will enable the prediction model to be utilised for more general composites mechanical strength performance.

ACKNOWLEDGEMENT

The authors would like to thanks Faculty of Applied Sciences, Universiti Teknologi MARA (UiTM) for providing facility and technical support to accomplish the experimental works.

REFERENCES

1. Abdullah, M.L.; Nasir, *Basic Statistic For Research*. Penerbit UMT, 2022.
2. J. Livingstone and D. W. Salt, “Judging the significance of multiple linear regression models,” *J. Med. Chem.*, vol. 48, no. 3, pp. 661–663, 2005, doi: 10.1021/jm049111p.
3. Mishra, A. Majumdar, and B. S. Butola, “Modeling of yarn strength utilization in cotton woven fabrics using multiple linear regression,” *J. Eng. Fiber. Fabr.*, vol. 9, no. 2, pp. 105–111, 2014, doi: 10.1177/ 1558925014 009 00213.
4. Erbil, O. Babaarslan, and İ. Ilhan, “A comparative prediction for tensile properties of ternary blended open-end rotor yarns using regression and neural network models,” *J. Text. Inst.*, vol. 109, no. 4, pp. 560–568, 2018, doi: 10.1080/00405000.2017.1361164.
5. Liu, M. Tian, Y. Wang, Y. Su, and J. Li, “Modeling to predict thermal aging for flame-retardant fabrics considering thermal stability under fire exposure,” *Text. Res. J.*, vol. 91, no. 21–22, pp. 2656–2668, 2021, doi: 10.1177/00405175211013835.
6. U. S. Mazumder, S. Mandal, R. J. Agnew, A. Petrova, L. M. Boorady, and G. Song, “Characterizing the Tensile Strength of the Fabrics Used in Firefighters’ Bunker Gear under Radiant Heat Exposure,” *Polymers (Basel).*, vol. 14, no. 2, 2022, doi: 10.3390/polym14020296.
7. Shanbeh, M. Safar Johari, M. Zarrebini, M. Barburski, and A. Komisarczyk, “Analysis of shear characteristics of woven fabrics and their interaction with fabric integrated structural factors,” *J. Eng. Fiber. Fabr.*, vol. 14, 2019, doi: 10.1177/1558925019867520.
8. V. M. Potočić Matković and Z. Skenderi, “Mechanical properties of polyurethane coated knitted fabrics,” *Fibres Text. East. Eur.*, vol. 100, no. 4, pp. 86–91, 2013.
9. Bañon, A. Sambruno, M. Batista, B. Simonet, and J. Salguero, “Study of the surface quality of carbon fiber–reinforced thermoplastic matrix composite (CFRTP) machined by abrasive water jet (AWJM),” *Int. J. Adv. Manuf. Technol.*, vol. 107, no. 7–8, pp. 3299–3313, 2020, doi: 10.1007/s00170-020-05215-

y.
10. B. Figueiredo Filho *et al.*, “When is statistical significance not significant?,” *Brazilian Polit. Sci. Rev.*, vol. 7, no. 1, pp. 31–55, 2013, doi: 10.1590/s1981-38212013000100002.
11. Lu and W. Yu, “Predicting the tensile strength of single wool fibers using artificial neural network and multiple linear regression models based on acoustic emission,” *Text. Res. J.*, vol. 91, no. 5–6, pp. 533–542, 2021, doi: 10.1177/0040517520948200.
12. Noryani, S. M. Sapuan, M. T. Mastura, M. Y. M. Zuhri, and E. S. Zainudin, “A Statistical Framework for Selecting Natural Fibre Reinforced Polymer Composites Based on Regression Model,” *Fibers Polym.*, vol. 19, no. 5, pp. 1039–1049, 2018, doi: 10.1007/s12221-018-8113-3.
13. S. Ö. Hacioğullari and O. Babaarslan, “An investigation on the properties of polyester textured yarns produced with different fiber cross-sectional shapes,” *Ind. Textila*, vol. 69, no. 4, pp. 270–276, 2018, doi: 10.35530/ it.069.04.1281.
14. Schmidt, F. Berchtold, R. Griesbaum, J. T. Sehrt, and F. Finsterwalder, “Predicting tensile strength of material extrusion parts during the pre-process using neural networks,” *Int. J. Adv. Manuf. Technol.*, vol. 128, no. 11–12, pp. 5129–5138, 2023, doi: 10.1007/s00170-023-12256-6.
15. Abdulghaffar, “Study on the Arrangement of Fabric Materials for Multi-Layer Soft Body Armor Based on their Mechanical Properties,” *J. Fash. Technol. Text. Eng.*, vol. 03, no. 03, 2015, doi: 10.4172/2329-9568.1000126.
16. Dalfi, K. B. Katnam, and P. Potluri, “Intra-laminar toughening mechanisms to enhance impact damage tolerance of 2D woven composite laminates via yarn-level fiber hybridization and fiber architecture,” *Polym. Compos.*, vol. 40, no. 12, pp. 4573–4587, 2019, doi: 10.1002/pc.25325.
17. A. Ramírez-Herrera, I. Cruz-Cruz, I. H. Jiménez-Cedeño, O. Martínez-Romero, and A. Elías-Zúñiga, “Influence of the Epoxy Resin Process Parameters on the Mechanical Properties of Produced Bidirectional [±45 •] Carbon/Epoxy Woven Composites,” 2021, doi: 10.3390/polym.
18. Rajpurohit, S. Joannès, V. Singery, P. Sanial, and L. Laiarinandrasana, “Hybrid effect in in-plane loading of carbon/glass fibre based inter-and intraply hybrid composites,” *J. Compos. Sci.*, vol. 4, no. 1, pp. 1–20, 2020, doi: 10.3390/jcs4010006.
19. C. Nagaraja, S. Rajanna, G. S. Prakash, P. G. Koppad, and M. Alipour, “Studying the effect of different carbon and glass fabric stacking sequence on mechanical properties of epoxy hybrid composite laminates,” *Compos. Commun.*, vol. 21, no. July, p. 100425, 2020, doi: 10.1016/j.coco.2020.100425.
20. A. Talabari, M. H. Alaei, and H. R. Shalian, “Experimental investigation of tensile properties in a glass/epoxy sample manufactured by vacuum infusion, vacuum bag and hand layup process,” *Rev. des Compos. des Mater. Av.*, vol. 29, no. 3, pp. 179–182, 2019, doi: 10.18280/rcma.290308.
21. Abdurohman, T. Satrio, N. L. Muzayadah, and Teten, “A comparison process between hand lay-up, vacuum infusion and vacuum bagging method toward e-glass EW 185/lycal composites,” *J. Phys. Conf. Ser.*, vol. 1130, no. 1, 2018, doi: 10.1088/1742-6596/1130/1/012018.