INVESTIGATION OF MACHINABILITY OF BIOCOMPOSITES: MODELING AND ANN OPTIMIZATION

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***ABSTRACT**: The This work studies the drilling performance of bio composites reinforced with cellulosic fibres. The drilling was carried out at three spindle speeds and at three feed rates using three dissimilar drills namely: HSS-TITAN, HSS-CARBIDE, and HSS-SUPER. The drilling performance was evaluated in terms of the delamination factor which was determined using the free software image J. The results showed that the value of this factor decreased with increasing spindle speed and increased with increasing feed rate. On the other hand, the HSS-SUPER drill causes less delamination than the other two drills. To predict the delamination value, the artificial neural network (ANN) method was used. The best hole quality was obtained when using the HSS-SUPER drill, with a spindle speed of 2200 rpm and a feed rate of 40 mm/rev. The worst case was brought when using an HSS-carbide drill, with a spindle speed of 500 rpm and a feed rate of 120 mm/ rev.*

***KEYWORDS:** Bio composite; Drilling; Palm fiber; Delamination; ANN*

1 INTRODUCTION

Recently, composites have continued to develop towards products that are the least expensive and the most efficient. In this context, composites based on vegetable fibers such as kenaf, jute, hemp, sisal, coconut (Nayak and Satapathy 2021; Pujari, Ramakrishna, and Balaram Padal 2017; Wang et al. 2022; Archana, Jagannatha Reddy, and Paruti 2022; Norhasnan et al. 2021) are of great interest to researchers and manufacturers, especially in the automotive, aviation, steamship, and spacecraft industries, because they are ecological, recyclable, less expensive and light, and thanks to these features. It is necessary to study the techniques for their manufacture, and the most important of these techniques is drilling (Mohammed and Wolla 2022; Slamani et al. 2021; Sherwani et al. 2021; Benyettou, Amroune, Mohamed, et al. 2022).

In the manufacturing industry. Drilling is one of the most essential machining processes in the final assembly of parts, where this process is exposed to several problems, the most significant of which is delamination, and in order to reduce this problem. Several research works have focused on this phenomenon among which: (Yallew, Kumar, and Singh 2015) have studied the effect of drilling process parameters namely: the spindle speed of 900, 1800, 2800 rpm, the feed rate of 0.05, 0.12, 0.19 mm/rev and drill tip geometry (twist drill, Jo drill and parabolic CARBIDE drill at 118° angle and 8 mm diameter) on the drilling behavior of woven jute composites and reinforced with polypropylene fabrics. The results indicate in the case of drilling with the helical and Jo drills, an aggressive increase in the delamination factor with an increase in the feed rate, on the other hand the value of this factor increases slightly with the parabolic drill. (Rezghi Maleki et al. 2018) evaluated the effect of machining conditions on the scale of delamination of jute fiber reinforced polymer composites using a fully factorial experimental design technique. They stated that the type of drill has a significant influence on the delamination factor where the high speed steel (HSS) twist drill produces a smaller delamination size than Coro-Drill 854 and Coro-Drill 8563. Similar observations were reported by (Babu, Babu, and Gowd 2013). Reported that delamination is strongly influenced by cutting parameters. They indicated the need to use a low feed rate and high cutting speed to minimize delamination. An experimental study was conducted by (Saravana Kumar, Maivizhi Selvi, and Rajeshkumar 2017) on the effect of factors on delamination of drilled unidirectional sisal-banana fiber reinforced composites, where they found a decrease in delamination factor with an increase in speed spindle where optimum conditions were obtained at 1500 rpm, 50 mm/min and a drill diameter of 6mm.

The Artificial Neural Network (ANN) model has been applied in several studies among them the study of (SIM et al. 2022).They have implemented the feed-forward ANN prediction model to predict flank wear. They have studied the prediction of tool wear using a machine vision approach. The prediction model showed the best prediction performance where the prediction accuracy of flank wear using this model reached 93%. The ANN prediction model also demonstrates a very good relationship and fit with R^2 of 0.99 for flank wear. Another study by (Zhenjun 2017).in order to improve the automation error problem. The effect of feed rate, process stiffness, and machining times on the error of the processed parts was analysed by a neural network model to optimize the machining parameters. They indicated through their findings that the experimental and predictive results are in good statistical agreement

From the review of the literature, it can be said that few research studies have addressed the field of drilling natural fiber bio composites. In this context, the objective of this work is to study the evaluation of delamination drilling for bio composites reinforced with cellulosic date palm fibers (CDPF). This study aims to provide readers with more knowledge on the phenomenon of delamination in bio composites. And to test the feasibility of the artificial neural network (ANN) method that was developed to predict the delamination factor.

2 MATERIALS AND METHODS

2.1 Material preparation

The bio composite (palm fiber/polyester) was developed with a palm fiber reinforcement volume fraction of 40% by weight. The bio composite was produced by a vacuum molding technique in the form of two equal crossed plies of fibers, each ply 5mm thick. Three samples was constructed as rectangular pieces with dimensions of 85×60×10 mm^3 for each specimen (Figure 1a). The samples were placed in an oven at a temperature of 75° C. for 12 hours to ensure complete polymerization.

2.2 Experimental drilling procedure

Three different types of drill bits of Ø10mm and 118° Tip angle were chosen, namely, a high speed steel drill bit with a TITAN protection layer (T1:HSS-TITAN), a carbide drill bit (T2:HSS-CARBIDE), and a super high speed steel drill bit (T3:HSS-SUPER) as shown in Figure 2, in order to drill nine holes for each specimen in total (3×9= 27 holes) at three spindle speeds of 500,1100 and 2200 rpm, and at three feed rates of 40, 80 and 120 mm/min. Cutting conditions are listed in Table 1. The samples were drilled under dry cutting conditions with a Doosan DNM 650 II CNC universal milling machine equipped with a 9000 rpm spindle with a feed rate of 2.0 to 1600 mm/rev.

The drilling process was programmed under these operating conditions in a CNC machine with the help of the MasterCam software. It started by designing the two-dimensional parts into three-dimensional ones, with respect to accurate geometric dimensions. The center of the sample was defined as the reference principle for drilling (hole center 2: 2). The latter moves on the x-axis with a distance of 25 mm and is driven on the y-axis with a distance of 15 mm in both directions (positive/negative) for each drilling center (Figure 1b) of the order 1:1 at 3:3 (9 holes) for the first plate and of order 4:4 to 6:6 for the second plate and of order 7:7 to 9:9 for the third plate, and then after that. It was manufactured with distinct operating conditions for the spindle speed and feed rate for each hole, the same process was repeated with the three drills (27 operations of drilling). It was manufactured using several steps. The first step was the selection of the type of machine (milling by default) then the toolpath (drilling) was selected. After that, the working conditions were changed for each drilling operation. And finally. G-code programs based on the MasterCam were automatically generated by the G-code generation module based on basic information for machining features, such as basic dimensions and cutting information(Nguyen, Phung, and Bui 2020) (Figure 1c). The latter converts the geometry of the piece and its cutting parameters into preparatory functions G and auxiliary functions M (e.g. G90: absolute programming «absolute coordinates», G80: cancel drilling cycles, G83: Peck drilling cycle, M3: spindle rotation clockwise...etc.)(Liu, Liu, and Gao 2017) in order to apply the conditions of manufacturing by the CNC machine.

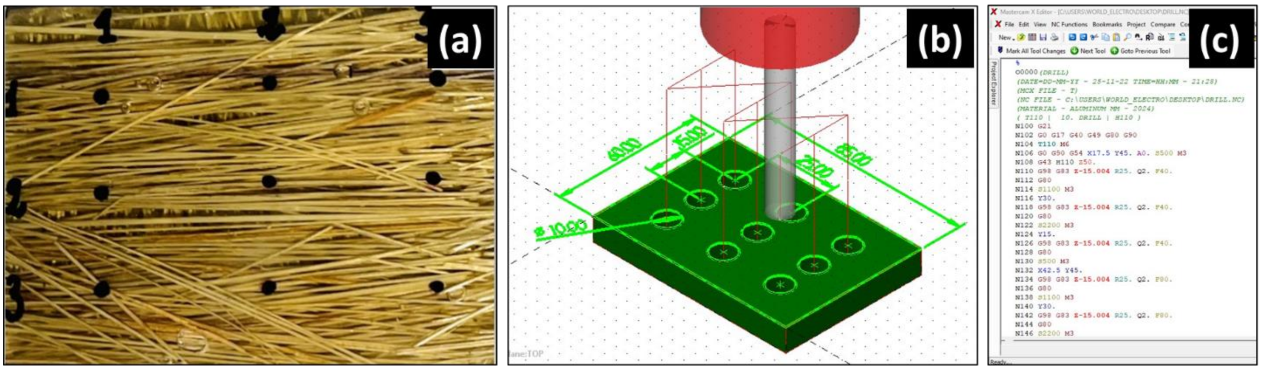

Fig. 1 a) the prepared bio composite, b) Drilling simulation of a bio-compound in MasterCam, c) The G-code program.

Table 1. Design of experiments

N°	Factors	Notation	Units	Levels		
				-1	0	+1
A	Spindle speed	N	Rpm	500	1100	2200
B	Feed rate	f	mm/min	40	80	120
C	Drill materials	~	~	T1 : T1:HSS-TITAN	T2 : T2:HSS-CARBIDE	T3 : T3:HSS-SUPER

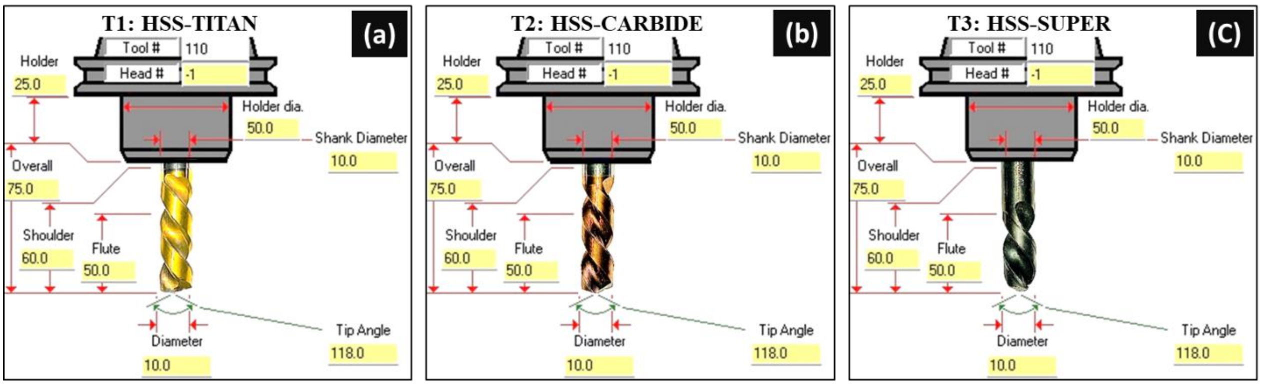

Fig. 2 Drilling tools used in the drilling of bio composites: a) T1: HSS-TITAN, b) T2: HSS-carbide, and c) T3: HSS-SUPER

2.3 Assessment of delamination

After the drilling tests, the samples were put under the microscope to observe the damage of the emptying of the holes using the free software Image J (Figure 3), the delamination factor value at the exit of the drilled holes was obtained by the following equation Eq1.

$$F_d = \frac{A_{max}}{A_{nom}} \quad (1)$$

Where A_{nom} is the surface related to the real hole and A_{max} is the maximum area of damage around the periphery of the hole (Lotfi et al. 2019).

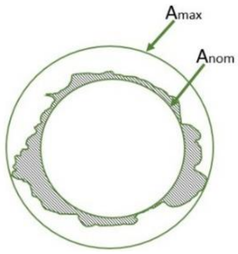

Fig. 3 Example of delamination measuring

2.4 Artificial Neural Network(ANN)

The scheme of the modeling of the artificial neural network (ANN) has been represented in figure 4. The input parameters (spindle speed, feed rate and the materials of the drills) and output (delamination factor) used during the training 70% (19 samples), validation 15% (4 samples), and testing phases 15% (4 samples). The Levenberg–Marquardt algorithm is used, the number of epochs (19) and number of training sets used (5). The development of the ANN model was performed using MATLAB tools.

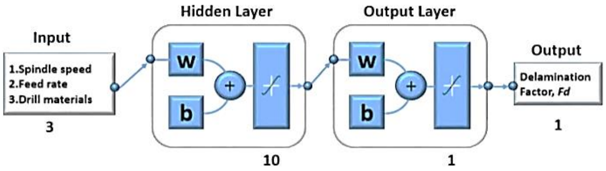

Fig. 4 Schematic representation of ANN modeling.

3 RESULTS AND DISCUSSION

3.1 Delamination

The The results of the delamination factor with different cutting conditions are summarized in Table 2. Table 2 confirmed that the value of the delamination factor at a feed of 40 mm/min was reduced by approximately 28% compared to a feed of 120 mm/min, and about 21% at a spindle speed of 2200 rpm compared to a spindle speed of 500 rpm, for the part drilled with the HSS-TITAN drill bit"

On the other hand, the study showed that the delamination factor value at a feed of 40 mm/min and at a spindle speed of 500 rpm for the part drilled with the HSS-SUPER drill was reduced by approximately 18% compared to the part which was drilled with the HSS-TITAN drill and approximately 37% compared to the part which was drilled with the HSS-CARBIDE drill".

The best hole quality was obtained with the HSS-SUPER drill, with a spindle speed of 2000 rpm and a feed rate of 40 mm/min (figure 5a-5b). While the most unfavorable hole quality was obtained with the HSS-CARBIDE drill, with a spindle speed of 500 rpm and a feed rate of 120 mm/min (figure 5c-5d).

The results obtained in this work are in clear agreement with previous studies such as the results of (Benyettou, Amroune, Slamani, et al. 2022) indicate that increasing the spindle speed reduces the delamination size of drilled holes, while increasing advance causes an increase in the delamination factor. The best hole quality was obtained with a spindle speed of 2240 rpm and a feed rate of 40 mm/rev. In a similar work conducted by (Bayraktar and Turgut 2020), they referred that uncoated drills caused less delamination than HSS drills coated with TiN and TiAlN. In addition, increasing the feed leads to a magnification of the delamination factor.

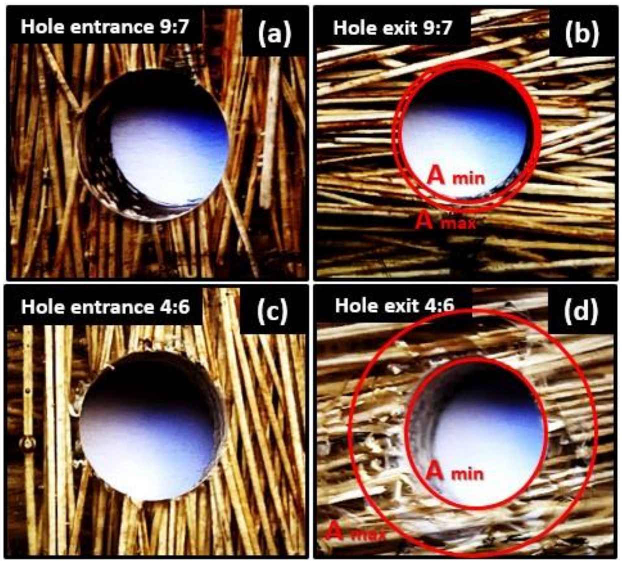

Fig. 5 (a), (b) The best hole quality and, (c), (d) The worst hole quality.

3.2 ANN

In this study, MSE (mean squared error) and regression analysis were used to assess the precision of fit. The accuracy of the ANN model in the prediction increases as the value of the MSE decreases, since the MSE is accepted when it is < 0.001(Aydoğmuş, Arslanoğlu, and Dağ 2021).

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left|(Y_{p,i} - Y_{e,i})^2\right| \quad (2)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Y_{p,i}-Y_{e,i})^2}{\sum_{i=1}^{n}(Y_{p,i}-Y_{e})^2} \quad (3)$$

Where MSE is the root mean square error, R^2 is the coefficient of determination, $Y_{p,i}$ is the predicted corresponding data and $Y_{e,i}$ is the experimental data , Y_e is the mean value of the experimental data. (Adeniyi, Ighalo, and Marques 2021; Ighalo et al. 2021)

It can be seen from Figures 6a and 7 and Table 3 that the MSE has exculent values, of approximately 1.04×10^{-7} for training, 1.09×10^{-4} for validation and 2.51×10^{-4} for testing, and that the value of the correlation coefficient "R" for training, validation and testing are all greater than 0.98. While Figure 6b and Table 2 show the comparison between the experimental values and the expected values for ANN for the delamination factor, as well as the residual between them, and it becomes clear that these values are very close with a very small deviation error, the average value of which is estimated at 4.3×10^{-4}. And this absolutely corresponds to the results obtained in the work of (Tabet et al. 2021), who examined the effect of the drilling parameters used on the delamination damage in a biosandwich structure. Where they indicate that the ANN models developed for HSS drills TiN and BSD are used as an effective prediction tool for the delamination factor.

Table 2. Experimental and predictive results for delamination factor

N°	Drilling Condition			Delamination Factor, F_d		
	f (mm/min)	N (rpm)	Drill materials	EXP	ANN	ERR
1	500	40	HSS-TITAN	1.36	1.36	-0.006
2	1100	40		1.32	1.31	0.001
3	2200	40		1.06	1.07	-0.019
4	500	80		1.86	1.85	0.002
5	1100	80		1.56	1.51	0.047
6	2200	80		1.20	1.19	0.004
7	500	120		1.92	1.94	-0.022
8	1100	120		1.63	1.64	-0.014
9	2200	120		1.42	1.42	-0.005
10	500	40	HSS –CARBIDE	1.77	1.75	0.011
11	1100	40		1.52	1.51	0.001
12	2200	40		1.10	1.10	-0.003
13	500	80		1.91	1.92	-0.013
14	1100	80		1.68	1.68	-0.008
15	2200	80		1.23	1.22	0.008
16	500	120		1.97	1.91	0.051
17	1100	120		1.83	1.68	0.140
18	2200	120		1.55	1.54	0.006
19	500	40	HSS-SUPER	1.10	1.12	-0.027
20	1100	40		1.10	1.09	0.005
21	2200	40		1.01	1.02	-0.012
22	500	80		1.25	1.20	0.040
23	1100	80		1.15	1.12	0.020
24	2200	80		1.08	1.06	0.016
25	500	120		1.32	1.33	-0.015
26	1100	120		1.16	1.15	0.001
27	2200	120		1.15	1.19	-0.042

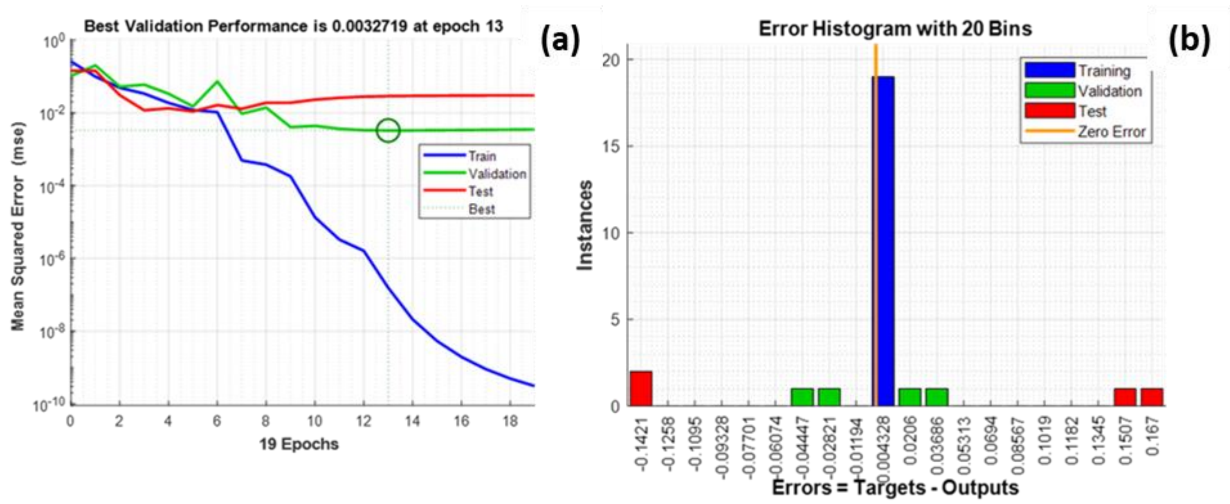

Fig. 6 a) MSE of network data with increasing, b) Graphic representation of ANN errors epoch.

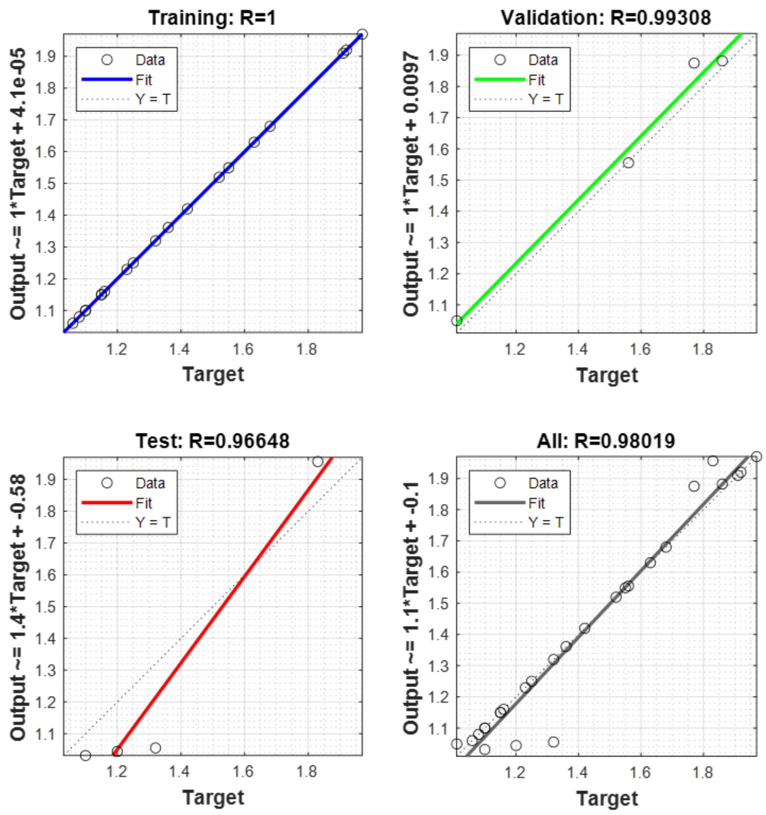

Fig. 7 ANN model regression analysis.

. Table 3. Performance of Artificial Neural Network Architecture

Materials	Data used	sample	*MSE*	R^2
CDPF	Training	19	1.04731×10^{-7}	0.999999
	Validation	41	1.09879×10^{-4}	0.996943
	Testing	20	2.51005×10^{-4}	0.987593

4 CONCLUSION

In The following conclusions are drawn:

- Increasing the value of the cutting speed resulted in a reduction in the delamination factor, while increasing the value of the feed rate increased this factor.
- Coated drills (“HSS-TITAN” and “HSS-CARBIDE”) caused plenty of delamination than uncoated drill (HSS -SUPER)
- The best hole quality was obtained with the HSS-SUPER drill, with a spindle speed of 2000 rpm and a feed rate of 40 mm/min.
- The lowest hole quality was obtained with the HSS-CARBURE drill, with a spindle speed of 500 rpm and a feed rate of 120 mm/min.
- The MSE has excellent values of about 1.04×10^{-7}, 1.09×10^{-4} and 2.51×10^{-4} for training, validation and testing, respectively.
- All values of the “R” correlation coefficient of the datasets are above 0.98.
- Moreover, the ANN models obtained, allowing to predict the cutting parameters in the drilling processes, are very well correlated with the experimental data where the average error value was estimated at 4.3×10^{-4}.

ANN models represent an important industrial interest for mechanical manufacturing companies, which contributes to significant savings in time and material.

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6 REFERENCES

Adeniyi, Adewale George, Joshua O. Ighalo, and Gonçalo Marques. (2021). Utilisation of machine learning algorithms for the prediction of syngas composition from biomass bio-oil steam reforming. *International Journal of Sustainable Energy* 40 (4):310-25. doi: 10.1080/14786451.2020.1803862.

Archana, D. P., H. N. Jagannatha Reddy, and Basavaraju Paruti. (2022). Mechanical Characterization of Biocomposites Reinforced with Untreated and 4% NaOH-Treated Sisal and Jute Fibres. *Advances in Materials Science and Engineering* 2022:7777904. doi: 10.1155/2022/7777904.

Aydoğmuş, Ercan, Hasan Arslanoğlu, and Mustafa Dağ. (2021). Production of waste polyethylene terephthalate reinforced biocomposite with RSM design and evaluation of thermophysical properties by ANN. *Journal of Building Engineering* 44:103337. doi: https://doi.org/10.1016/j.jobe.2021.103337.

Babu, G Dilli, K Sivaji Babu, and B Uma Maheswar Gowd. (2013). Effect of machining parameters on milled natural fiber-reinforced plastic composites. *Journal of Advanced Mechanical Engineering* 1 (1):1-12. doi: 10.7726/jame.2013.1001

Bayraktar, Şenol, and Yakup Turgut. (2020). Determination of delamination in drilling of carbon fiber reinforced carbon matrix composites/Al 6013-T651 stacks. *Measurement* 154:107493. doi: https://doi.org/10.1016/j.measurement.2020.107493

Benyettou, Riyadh, Salah Amroune, Slamani Mohamed, Yasemin Seki, and Alain Dufresne. (2022). Experimental Investigation of the Absorption Behavior of Date Palm Fiber Reinforced Iso-Polyester Composites: Artificial Neuron Network (ANN) Modeling. *Journal of Natural Fibers*:1-17.

Benyettou, Riyadh, Salah Amroune, Mohamed Slamani, Yasemin Seki, Alain Dufresne, Mohammad Jawaid, and Salman Alamery. (2022). Assessment of induced delamination drilling of natural fiber reinforced composites: a statistical analysis. *Journal of Materials Research and Technology* 21:131-52. doi: https://doi.org/10.1016/j.jmrt.2022.08.161.

Ighalo, Joshua O., Chinenye Adaobi Igwegbe, Adewale George Adeniyi, and Sulyman A. Abdulkareem. (2021). Artificial Neural Network Modeling of the Water Absorption Behavior of Plantain Peel and Bamboo Fibers Reinforced Polystyrene Composites. *Journal of Macromolecular Science, Part B* 60 (7):472-84. doi: 10.1080/00222348.2020.1866282.

Liu, C., J. Liu, and W. Gao. 2017. Principle and application of mirror function in CNC system based on PMAC. Paper presented at the 2017 IEEE 2nd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC), 25-26 March 2017.

Lotfi, Amirhossein, Huaizhong Li, Dzung Viet Dao, and Gangadhara Prusty. (2019). Natural fiber–reinforced composites: A review on material, manufacturing, and machinability. *Journal of Thermoplastic Composite Materials* 34 (2):238-84. doi: 10.1177/0892705719844546.

Mohammed, Nurhusien Hassen, and Desalegn Wogaso Wolla. (2022). Optimization of machining parameters in drilling hybrid sisal-cotton fiber reinforced polyester composites. *AIMS Materials Science* 9 (1):119-34. doi: 10.3934/matersci.2022008.

Nayak, Sandip Kumar, and Alok Satapathy. (2021). Mechanical and Dry Sliding Wear Characterization of Marble Dust and Short Kenaf Fiber Reinforced Hybrid Polyester Composites. *Journal of Natural Fibers*:1-13. doi: 10.1080/15440478.2021.1982815.

Nguyen, Trung Kien, Lan Xuan Phung, and Ngoc-Tam Bui. (2020). Novel integration of capp in a g-code generation module using macro programming for CNC application. *Machines* 8 (4):61.

Norhasnan, Nurul H., Mohamad Z. Hassan, Ariff F. Nor, S. A. Zaki, Rozzeta Dolah, Khairur R. Jamaludin, and Sa'ardin A. Aziz. (2021). Physicomechanical Properties of Rice Husk/Coco Peat Reinforced Acrylonitrile Butadiene Styrene Blend Composites. *Polymers* 13 (7). doi: 10.3390/polym13071171.

Pujari, Satish, A. Ramakrishna, and K. T. Balaram Padal. (2017). Prediction of Swelling Behaviour of Jute and Banana Fiber Composites by using ANN and Regression Analysis. *Materials Today: Proceedings* 4 (8):8548-57. doi: https://doi.org/10.1016/j.matpr.2017.07.201.

Rezghi Maleki, Hadi, Mohsen Hamedi, Masatoshi Kubouchi, and Yoshihiko Arao. (2018). Experimental study on drilling of jute fiber reinforced polymer composites. *Journal of Composite Materials* 53 (3):283-95. doi: 10.1177/0021998318782376.

Saravana Kumar, A, P Maivizhi Selvi, and L Rajeshkumar. 2017. Delamination in drilling of sisal/banana reinforced composites produced by hand lay-up process. Paper presented at the Applied Mechanics and Materials.

Sherwani, S. F. K., S. M. Sapuan, Z. Leman, E. S. Zainudin, and A. Khalina. (2021). Physical, Mechanical and Morphological Properties of Sugar Palm Fiber Reinforced Polylactic Acid Composites. *Fibers and Polymers* 22 (11):3095-105. doi: 10.1007/s12221-021-0407-1.

SIM, Pei Chin, Woon Kiow LEE, Haslina ABDULLAH, Norfazillah TALIB, Pauline ONG, Aslinda SALEH, Said AHMAD, and Aun Naa SUNG. (2022). PREDICTION OF TOOL WEAR USING MACHINE VISION APPROACH. *Academic Journal of Manufacturing Engineering* 20 (1).

Slamani, Mohamed, Nouha Karabibene, Jean-François Chatelain, Xavier Rimpault, and Yves Beauchamp. (2021). Statistical analysis of surface roughness during high speed edge trimming of flax-fiber composite based on the Split-Split plot randomized complete block design. *Measurement* 184:109921. doi: https://doi.org/10.1016/j.measurement.2021.109921

Tabet, Zohir, Ahmed Belaadi, Messaouda Boumaaza, and Mostefa Bourchak. (2021). Drilling of a bidirectional jute fibre and cork-reinforced polymer biosandwich structure: ANN and RSM approaches for modelling and optimization. *The International Journal of Advanced Manufacturing Technology* 117 (11):3819-39. doi: 10.1007/s00170-021-07679-y.

Wang, Jinfeng, Jianhong Bai, Harvey Hua, Bin Tang, Wenli Bai, and Xungai Wang. (2022). Characterization and Scalable Production of Industrial Hemp Fiber Filled PLA bio-composites. *Journal of Natural Fibers*:1-12. doi: 10.1080/15440478.2022.2095549.

Yallew, Temesgen Berhanu, Pradeep Kumar, and Inderdeep Singh. (2015). A study about hole making in woven jute fabric-reinforced polymer composites. *Proceedings of the Institution of Mechanical Engineers, Part L: Journal of Materials: Design and Applications* 230 (4):888-98. doi: 10.1177/1464420715587750.

Zhenjun, LI. (2017). APPLICATION OF NEURAL NETWORK TECHNOLOGY IN MACHINING ERROR RECOVERY. *Academic Journal of Manufacturing Engineering* 15 (3)..