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Investigation of Sliding Wear of SCF-PP Composites and Comparison with Wear Prediction by Machine Learning Methods

K. N. Arun Kumar[1*], V. G. Pradeep Kumar[2], R. Nikhil[3], C. S. Thamme Gowda[1] and B. Shivamurthy[4]

[1]Department of Mechanical Engineering, Vidyavardhaka College of Engineering, Mysuru - 570002, Karnataka, India; arunkn.10@vvce.ac.in

[2]Department of Mechanical Engineering, JSS Science and Technology University, SJCE, Mysuru - 570006, Karnataka, India

[3]Department of Mechatronics Engineering, School of Mechanical Engineering, REVA University, Bangalore - 560064, Karnataka, India

[4]Department of Mechanical and Industrial Engineering, Manipal Institute of Technology, Manipal Academy of Higher Education, Manipal - 576104, Karnataka, India

Abstract

In this study, the sliding wear loss of Short Carbon Fibre Reinforced Polypropylene (SCF-PP) composites were investigated. The samples containing various concentrations (3-12 wt.% in steps of 3 wt.%) of SCF-PP were prepared by the injection moulding process. Several experimental trials to estimate sliding wear loss were designed according to the L16 orthogonal array. Further, for all 16 trials of SCF-PP composites, dry-sliding wear loss was examined by experimenting using a pin-on-disc operated as per the American Society for Testing and Materials (ASTM) standard. The wear loss was predicted for the same sliding wear conditions and sample types, applying machine learning algorithms such as Linear Regression (LR), Random Forest, Artificial Neural Network (ANN), and K Nearest Neighbour (KNN) and compared with the experimental results. Using a scanning electron microscope, the worn surface morphology of the selected samples and the sliding wear behaviour of the SCF-PP composites were examined.

Major Findings: *The effect of SCF concentration on wear loss, Wear loss prediction with Machine Learning (ML), Experimental validation, Worn surface Morphology analysis and Comparative performance of ML models.*

Keywords: *Machine Learning, Pin-On-Disc, Polypropylene (PP), Scanning Electron Microscope (SEM), Short Carbon Fibre (SCF), Wear Loss*

1.0 Introduction

Using modern technology, several automobile component manufacturers are substituting fibre reinforced polymer composite materials for metals and engineering plastics due to their attractive structural and functional properties. In recent days, fuel efficiency, low noise and vibration, and fewer exhaust emissions are driving forces behind the shift to lighter composite structures used in automobiles.

Carbon fibres have a limited application in polymer composites in comparison to glass fibres because of cost. Even though glass fibres are used in most fibre-reinforced polymers, carbon fibres have become the preferred material for a wide range of applications owing to their

**Author for correspondence*

attractive properties. Carbon Fibre Reinforced Polymer (CFRP) matrix composites are extensively studied and recommended for automobile and aerospace applications owing to their high specific strength, high electrical and thermal conductivity, specific modulus, exceptional self-lubricating properties and low expansion coefficient. Carbon fibre improves the thermal stability, dimensional stability and resistance to abrasion of the composites. Substantial work has been published on carbon fibre reinforced polymers for diverse applications[1]. The fibre reinforced thermoplastic matrix composites have advantages in terms of durability and longevity. Their inherent recycling ability is now acknowledged as a potential factor in their applications as compared to a few fibre-reinforced thermoset composites. SFRPS were designed to close the performance gap between unreinforced polymers and the continuous-fibre laminates utilised for major components in the aerospace and aviation sectors[2]. Because of their exceptional mechanical qualities, low production cost, and ease of manufacture, SFRP composites are highly desirable. Although SFRP composites are frequently manufactured using traditional polymer manufacturing techniques, such as injection moulding and extrusion compounding, compression moulding is a comparatively easy and economical procedure for making short fibre composites.

Polypropylene composites with excellent mechanical properties are employed in a variety of applications. SCF-PP composites are effective for automobile applications[3]. Some studies show that the SCF-PP composite is an excellent candidate for substituting steel in automobile bonnets and can meet car bonnet specifications, and it is significantly lighter. It was reported that the addition of Carbon Nanotubes (CNT) enhanced tensile strength and modules of PP[4]. Tribology is the science of surface interactions. As a result, material loss due to wear can cause significant failures of the component. In this direction, investigating the tribological behaviour of SCF-PP is crucial. The addition of CNT, CF, and GF improved the wear resistance of PP[4-6] as reported. The experimental research on wear behaviour is well recognised as time-consuming and expensive. In recent years, the present computing capability has enabled the quick development of innovative methodologies in data-driven analysis that can yield unique insights.

ML and Artificial Intelligence (AI) approaches are being used in big data research to identify innovative connections in data-driven areas that would be difficult to discover using the traditional approach[7]. Using data-driven methods, the field of tribology has expanded to include what is known as Tribo-informatics or intelligent tribology machine[8]. These techniques anticipate wear behaviours by utilising experimental data. To forecast the wear loss of materials, several machine learning algorithms such as Linear Regression (LR), K Nearest Neighbour (KNN), Random Forest (RF) and Artificial Neural Network (ANN) are utilised[9]. In this study, short carbon fibres of various concentrations were used to reinforce polypropylene (PP) and develop specimens using injection moulding. Further, the sliding wear loss of all SCF-PP composite samples was tested for different loads, sliding speed and sliding distance. The wear loss was also predicted for all the samples by machine learning algorithms such as LR, KNN, RF and ANN. Finally, the numerical results were compared with experimental results. Also, the wear behaviour of samples was studied using a scanning electron microscope.

2.0 Materials and Methods

Commercial impact polypropylene copolymer was used as the matrix material. It has a melt flow index of 6.8g per 10min at 230°C (PP MFI 60), tensile strength 34 MPa, Vicat softening temperature 145-150 °C and Rockwell hardness 95. It was received in pellet form. The SCF had a density of 1.5g.cm-3, length 8mm, and diameter 1.5mm used as reinforcement.

Initially, SCF-PP composite pellets were manufactured by a compound using a twin-screw extruder. Further wear test samples were developed by injection moulding. The number of wear test trials was designed by the design of the experiment. The sliding wear test was conducted using pin-on-disc wear apparatus. In each trial, the wear loss was measured using a three decimal place accuracy weighing machine. Further, the machine learning methods were applied to predict wear loss and compared with experimental results.

3.0 Experiments

3.1 Material Preparation

A twin-screw extruder with an intermeshing structure of screw length of 800 mm and diameter of 32 mm

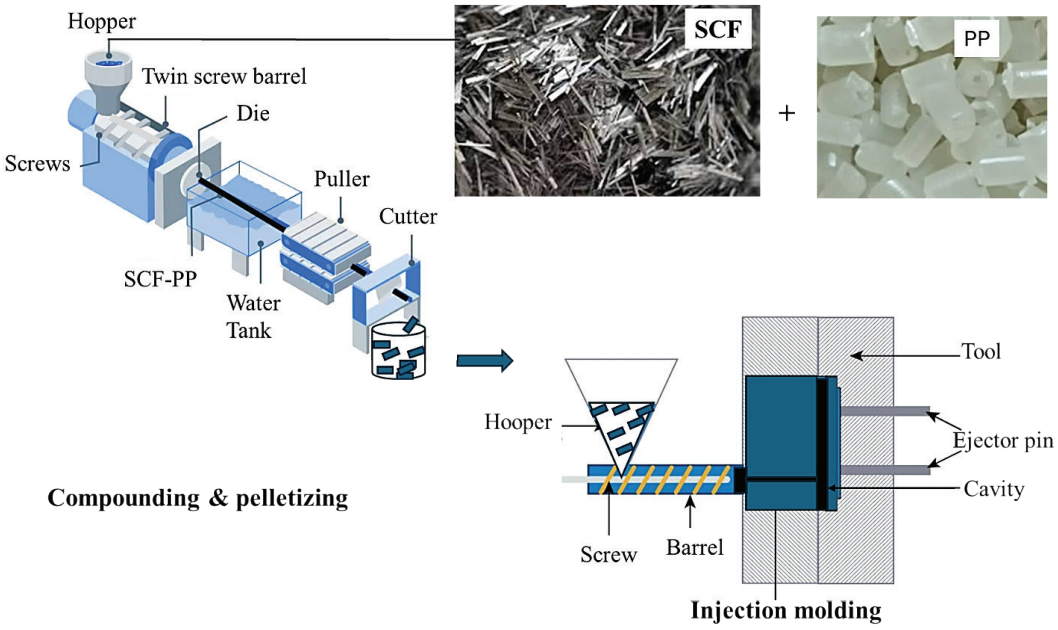


Figure 1. Specimen preparation process by compounding, pelletising and injection moulding.

is employed. The extruder has 6 heating zones and maintains temperatures ranging from 230-240°C to facilitate melt-blending of carbon fibres and PP matrix under shear and elongational deformation. After extrusion, the composite filaments are cooled in a water bath to solidify and stabilise their shape. The continuous extruded filaments were cut into pellets by a cutter. An injection moulding is employed to prepare a rectangular sheet of thickness 3mm. The schematic Figure 1 depicts the process steps followed by manufacturing SCF-PP samples. Four types of samples were prepared with SCF concentration varying from 3 wt.% to 12 wt.% in steps of 3 wt.%.

3.2 Experimental Investigation of Sliding Wear

Taguchi technique is used to design the number of experiments considering four factors and four levels as illustrated in Table 1. The factors selected are concentration of SCF (wt.%), Load applied (N), sliding velocity (m.s-1), and sliding distance (m). A conventional L16 orthogonal array with sixteen rows and four columns was selected.

A Pin-on-disc wear test experimental setup, shown in Figure 2, is used to estimate the sliding wear loss of all the SCF-PP samples. The pin-on-disc test rig consists of a 180mm diameter rotating disc, made of EN31 hardened steel, composed of 0.95-1.20% carbon with a hardness of 62 High Rupturing Capacity (HRC). The test samples of all the composites have been made into pins with a cross-section of 10mm x 10mm in size. In each experiment, a track diameter of 100mm was maintained. The experiments were conducted at a normal load varying from 20N to 80N in steps of 20N, sliding velocities of 3, 4, 5 and 6 m.s-1, and sliding distances of 1000, 2000, 3000, and 4000 meters. Wear loss was measured with a tolerance of 0.001g using an electronic weighing and tabulated in Table 2.

Table 1. Factors and levels considered for the Taguchi experimental design

	Level 1	Level 2	Level 3	Level 4
SCF (wt.%) concentration in composites	3	6	9	12
Load (N)	20	40	60	80
Sliding Speed ($m.S^{-1}$)	3	4	5	6
Sliding distance (m)	1000	2000	3000	4000

3.3 Wear Prediction Using Different Machine Learning Models

In this study 85% of the data was used for training, while 15% was used for testing. Wear loss was calculated

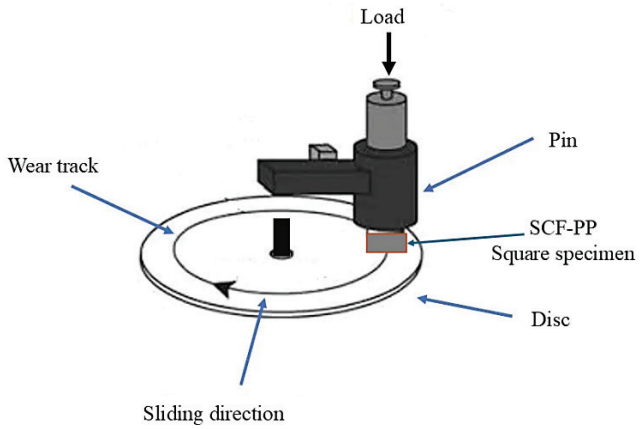


Figure 2. Pin-on-disc wear test experimental setup.

as a function of four input feature variables: weight percentage of SCF in the composites, load applied, sliding speed, and sliding distance. Table 2 shows a comparison of experimented results and predicted results obtained with different models for test data sets. Table 3 shows the performance metrics of ML models for predicting the wear loss of carbon fibre reinforced polypropylene composite.

Performance metrics give a quantitative assessment of how well Machine learning models fit with real data. The R2 value is the most significant performance indicator for supervised learning regression problems. The R2 value represents the proportion of data variation that the model can explain. This value is between 0 and 1. R2 = 0 denotes a lack of correlation and the model's inability to account for data variation. R2=0.5 denotes a weak correlation, and the ML model is viewed as being unable to accurately predict the output. An R2 value of 0.70 to 0.9 denotes acceptable performance, whereas a value over 0.9 denotes extremely acceptable model execution. When R2 = 1, which is improbable for experimental data, the model can precisely and error-free explain the data variation[10-12]. This shows perfect fitting.

Three more crucial measures are used to assess the effectiveness of models: Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Square Error (RMSE). The MAE displays the absolute difference between the actual and anticipated values as an average. MSE is the average of the squared variations between the

Table 2. Comparison of experimental results and predicted results obtained with different models for test data sets

Trial No.	SCF (Wt.%)	P (N)	V ($m.s^{-1}$)	L (m)	W (mg)	Predicted Wear Loss			
						Linear Regression	KNN	Random Forest	ANN
1	3	20	3	1000	1.8	1.77	1.25	1.82	2.13
2	3	40	4	2000	2.2	1.95	2.00	1.97	1.75
3	3	60	5	3000	1.7	2.12	1.40	1.76	1.86
4	3	80	6	4000	2.5	2.29	1.90	2.15	2.61
5	6	20	4	3000	1.5	1.43	1.30	1.51	1.34
6	6	40	3	4000	1.3	1.65	1.25	1.52	1.48
7	6	60	6	1000	1.8	1.78	1.70	1.75	1.78
8	6	80	5	2000	2.1	2.00	1.95	1.93	1.83
9	9	20	5	4000	1.2	1.08	1.25	1.31	1.14
10	9	40	6	3000	1.1	1.26	1.30	1.25	1.11
11	9	60	3	2000	1.8	1.53	1.95	1.58	1.33
12	9	80	4	1000	1.6	1.71	1.70	1.58	1.76
13	12	20	6	2000	0.9	0.75	1.55	0.95	0.91
14	12	40	5	1000	0.7	0.97	1.25	0.91	0.81
15	12	60	4	4000	1.3	1.18	1.30	1.26	1.13
16	12	80	3	3000	1.4	1.41	1.55	1.42	1.66

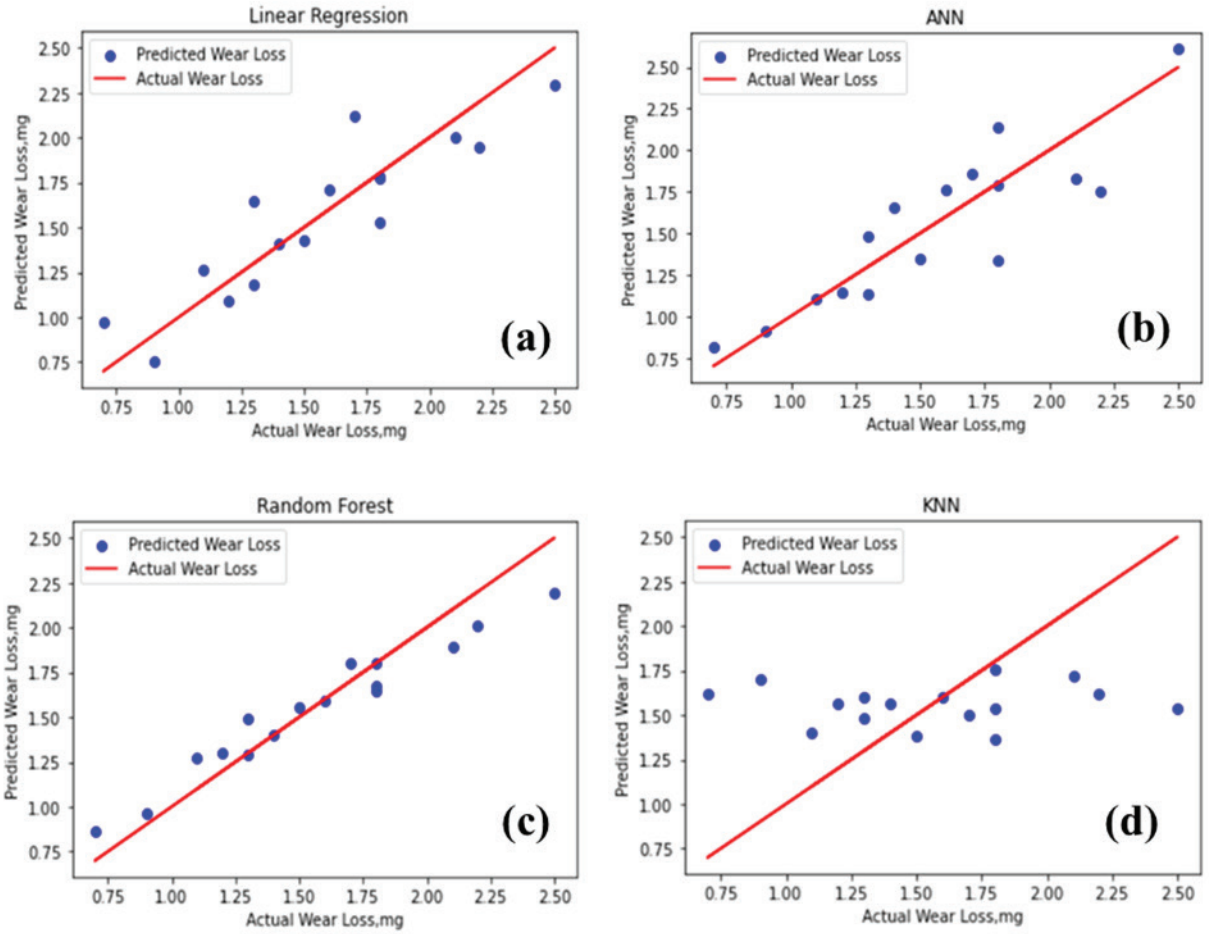


Figure 3 (a-d). Comparison of experimental wear loss and predicted wear loss by various machine learning methods **(a)** Linear regression, **(b)** ANN, **(c)** Random Forest, and **(d)** KNN.

data points' actual and predicted values, while RMSE is the square root of MSE. The performance of the model is crucially revealed by these error words. The small values of these error components specify the ML models' excellent prediction performance[13].

This value shows how the training results of the models compare to the results of the actual tests. The x-axis shows the actual wear loss by experiment, and the y-axis shows the predicted wear loss. The data points must be close to the vertical line for the model to work[14,15]. It was clear that the values indicated by the LR, RF and ANN models were close to what was seen in the experiments. But the value that the KNN model did not match up well with experimental results.

Table 3 shows the wear prediction performance of various machine learning methods for all SCF-PP composites. It is found that the test set R^2 values ranged from 0.511 to 0.923. The MAE ranged from 0.098 to 0.250, the MSE from 0.041 to 0.105 and the RMSE ranged from 0.128 to 0.325, all of which are

Table 3. Performance of the machine learning methods for the wear loss of 3%,6%,9% and 12% SCF-PP samples.

Algorithms	R^2	MAE	RMSE	MSE
Linear Regression	0.8112	0.165	0.202	0.041
KNN	0.5114	0.250	0.325	0.105
Random forest	0.9235	0.098	0.128	0.017
ANN	0.7590	0.182	0.228	0.052

noticeably low values. The proposed machine learning models can satisfactorily forecast the wear loss from the material, according to the values of various statistical performance measures. In comparison to the other machine learning models, Random Forest produced the highest R^2 value, which was 0.9235. This shows that the model can estimate the wear loss of SCF-PP composite with an accuracy of 92.35% using the material and tribological factors. Furthermore, this model's MSE, RMSE, and MAE values were noticeably low (0.0172, 0.1285, and 0.0985)[16,17].

Figure 4(a-d) shows the experimental and predicted wear loss values by LR, RF and ANN. The accuracy of the prediction values of the RF method was greater than that of other methods. It could be seen that the LR and ANN methods competed with the RF method. KNN generated lower prediction values than alternative models. Plot 4(a-d) demonstrates that the wear loss of SCF-PP composite had inherent variability that the RF model could handle and predict with satisfactory accuracy. These procedures are suggestive for use in wear studies to save time and cost.

3.4 Morphology Study of the Worn-Out Surface of SCF-PP Composite

Figure 5 shows worn surface images of fibre reinforced composites. Shallow craters and smooth regions were seen for the worn surface 3% CF with PP. Because of wear, shearing deformation and dislocation continuously accumulated beneath the surface, resulting in the formation of fractures or positive holes[18-21]. When the crackles were moulded to a given depth, the positive stress parallel to the surface inhibited the crackles from developing deeper, causing the crackles to extend parallel to the surface[22,23]. The composite between the crackles and the surface was peeled as wear debris once the crackles extended to the critical length. As shown, the worn surface of the 6% CF/PP composite had broader and shallower grooves than that of PP.CF appears to have slowed matrix deformation, indicating a reduction in mass loss for 9% CF with PP. As the CF content increased, the CF/PP counterpart's surface was smooth. There was no conglutinated material, and the wear course was steady.

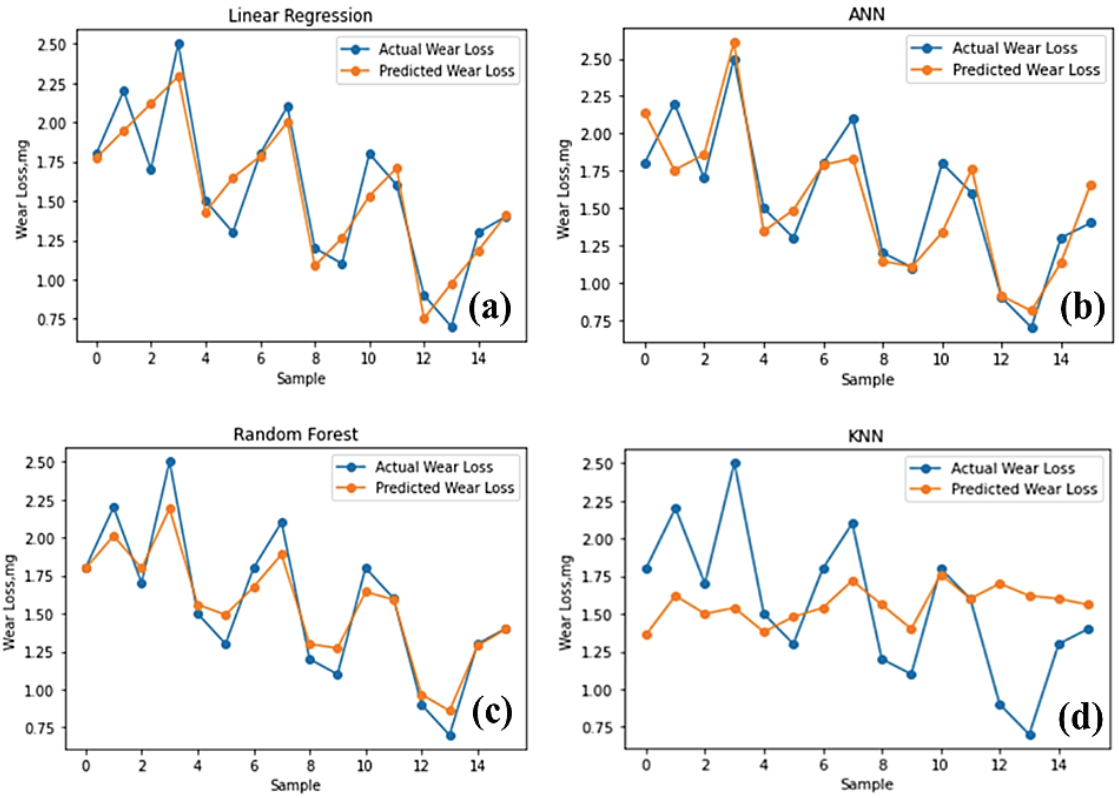


Figure 4(a-d). Comparison of experimental wear loss and predicted wear loss by various machine learning methods of all SEF-PP samples **(a)** Linear regression, **(b)** ANN, **(c)** Random Forest, and **(d)** KNN.

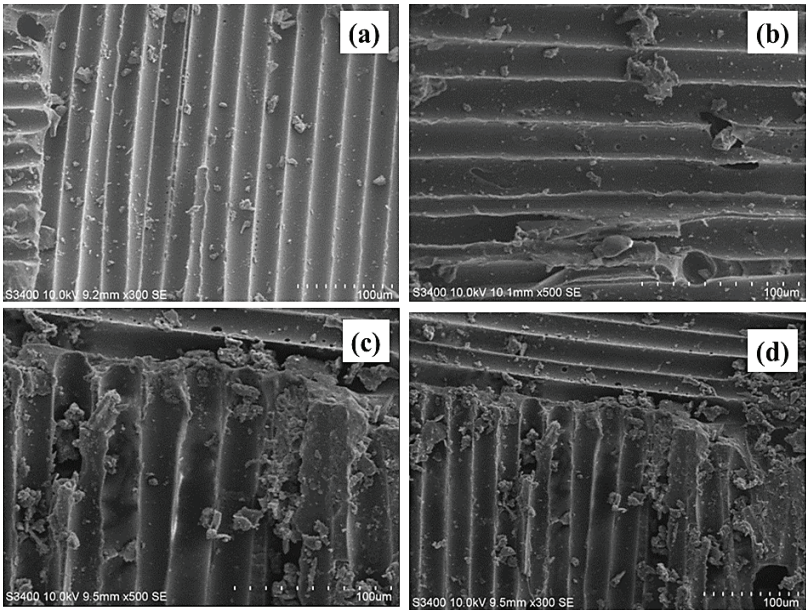


Figure 5 (a-d). Worn-out surface SEM images of SCF-PP composites; **(a)** 3 wt.% SCF-PP **(b)** 6 wt.% SCF-PP **(c)** 9 wt.% SCF-PP **(d)** 12 wt.% SCF-PP composite samples.

4.0 Conclusion

Polypropylene composites with different weight percentages of carbon fibres were produced by injection moulding. The samples were analysed in terms of their microstructure and wear behaviour. To predict volume loss, linear regression, ANN, RF and KNN methods were utilised. The subsequent conclusions were drawn:

The Polypropylene composites with 12% carbon fibre exhibited improved wear performance over Polypropylene composites with 3% carbon fibre. Abrasive wear was predominant at a load of 20N at a sliding of 6mm/s, while delamination occurred at a load of 80N. Under a load of 80N, the severely delaminated, cratered, and cracked surfaces on the worn surfaces for increased sliding speed (6 mm/s) were visible. The R^2 values of LR, KNN, RF and ANN were 0.811, 0.511, 0.923, and 0.759, respectively. The RF technique offers the best volume loss prediction performance. As a result, RF can anticipate findings with high accuracy, saving testing time, cost, and the number of test trials.

5.0 Acknowledgement

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6.0 Credit Author Statement

Dr. Arun Kumar K N: Conceptualization, supervision, resource gathering, and reviewing. **Dr. Pradeep Kumar V G**: Literature survey, analysis, and drafting of the manuscript. **Dr. Nikhil R:** Literature survey, interpretation, analysis. **Mr. Thamme Gowda C S:** Literature survey, Experimentation, and drafting of the manuscript. **Dr. Basavanna Shivamurthy**: Literature survey, Experimentation, and drafting of the manuscript. All authors have read and approved the final version of the manuscript.

7.0 Data Availability Statement

The data that support the findings of this study are available from the corresponding author, Basavanna Shivamurthy, upon reasonable request.

8.0 References

1. Shubhra QT, Alam A, Quaiyyum M. Mechanical properties of polypropylene composites: A review. J Thermoplast Compos Mater. 2013; 26(3):362-391. https://doi.org/10.1177/0892705711428659
2. Li J, Cai CL. Friction and wear properties of carbon fibre reinforced polypropylene composites. Adv Mater Res.

2011; 284-286:2380-2833. https://doi.org/10.4028/www.scientific.net/AMR.284-286.2380
3. Yunus RB, Zahari NH, Salleh MAM, Ibrahim NA. Mechanical properties of carbon fibre-reinforced polypropylene composites. Key Eng Mater. 2011; 471-472:652-657. https://doi.org/10.4028/www.scientific.net/KEM.471-472.652
4. Mertens A, Johnney, Senthilvelan S. Mechanical and tribological properties of carbon nanotube reinforced polypropylene composites. Proc Inst Mech Eng L J Mater Des Appl. 2016; 232(8):669-680. https://doi.org/10.1177/1464420716642620
5. Yang H, Gong J, Wen X, Xue J, Chen Q, Jiang Z, et al. Effect of carbon black on improving thermal stability, flame retardancy, and electrical conductivity of polypropylene/carbon fibre composites. Compos Sci Technol. 2015; 113:31-37. https://doi.org/10.1016/j.compscitech.2015.03.013
6. Zhao ZK, Du SS, Li F, Xiao HM, Li YQ, Zhang WG, *et al*. Mechanical and tribological properties of short glass fibre and short carbon fibre reinforced polyethersulfone composites: A comparative study. Compos Commun. 2018; 8:1-6. https://doi.org/10.1016/j.coco.2018.02.001
7. Hasan MS, Kordijazi A, Rohatgi PK, Nosonovsky M. Triboinformatic modelling of dry friction and wear of aluminium base alloys using machine learning algorithms. Tribol Int. 2021; 161:107065. https://doi.org/10.1016/j.triboint.2021.107065
8. Aydın F, Durgut R. Estimation of wear performance of AZ91 alloy under dry sliding conditions using machine learning methods. Trans Nonferrous Met Soc China. 2021; 31(1):125-137. https://doi.org/10.1016/S1003-6326(20)65482-6
9. Formisano A, D'Addona DM, Durante M, *et al*. Evaluation and neural network prediction of the wear behaviour of SiC microparticle-filled epoxy resins. J Braz Soc Mech Sci Eng. 2021; 43:272. https://doi.org/10.1007/s40430-021-02987-6
10. Babič M, Pršić D, Jurković Z, Lajos B, Ipšić-Martinčić S, Lhotska L, *et al*. A novel method for statistical pattern recognition using the network theory and a new hybrid system of machine learning. Mater Technol. 2019; 53(1):95-100. https://doi.org/10.17222/mit.2018.116
11. Ul Haq MI, Anand A. Friction and wear behavior of AA 7075-Si_3N_4 composites under dry conditions: Effect of sliding speed. Silicon. 2018; 11(2):1047-1053. https://doi.org/10.1007/s12633-018-9967-0
12. Suresha B, Ravi Kumar BN, Venkataramareddy M, Jayaraju T. Role of micro/nano fillers on mechanical and tribological properties of polyamide66/polypropylene composites. Mater Des. 2010; 31(4):1993-2000. https://doi.org/10.1016/j.matdes.2009.10.031
13. Zhou S, Zhang Q, Wu C, Huang J. Effect of carbon fiber reinforcement on the mechanical and tribological properties of polyamide6/ polyphenylene sulfide composites. Mater Des. 2013; 44:493-499. https://doi.org/10.1016/j.matdes.2012.08.029
14. Li J, Xia YC. The reinforcement effect of carbon fiber on the friction and wear properties of carbon fiber reinforced PA6 composites. Fibres Polym. 2009; 10(4):519-525. https://doi.org/10.1007/s12221-009-0519-5
15. Li J, Xia YC. Evaluation of tribological properties of carbon fiber-reinforced PA6 composites. Polym Compos. 2010; 31(3):536-542. https://doi.org/10.1002/pc.20836
16. Zhang Z, Breidt C, Chang L, Friedrich K. Wear of PEEK composites related to their mechanical performances. Tribol Int. 2004; 37(3):271-277. https://doi.org/10.1016/j.triboint.2003.10.001
17. Friedrich K, Lu Z, Hager AM. Recent advances in polymer composites' tribology. Wear. 1995; 190(2):139-144. https://doi.org/10.1016/0043-1648(96)80012-3
18. Kukureka SN, Hooke CJ, Rao M, Liao P, Chen YK. The effect of fiber reinforcement on the friction and wear of polyamide 66 under dry rolling-sliding contact. Tribol Int. 1999; 32(2):107-116. https://doi.org/10.1016/S0301-679X(99)00017-1
19. Lingesh BV, Ravikumar BN, Rudresh BM. Combined effect of micro fillers on the mechanical and fracture behaviour of polyamide 66 and polypropylene (PA66/PP) blend. Trans Indian Inst Met. 2017; 70(7):1743-1753. https://doi.org/10.1007/s12666-016-0971-z
20. Zhang Z, Breidt C, Chang L, Friedrich K. Wear of PEEK composites related to their mechanical performances. Tribol Int. 2004; 37(3):271-277. https://doi.org/10.1016/j.triboint.2003.10.001
21. Friedrich K, Lu Z, Hager AM. Recent advances in polymer composites' tribology. Wear. 1995; 190(2):139-144. https://doi.org/10.1016/0043-1648(96)80012-3
22. Kukureka SN, Hooke CJ, Rao M, Liao P, Chen YK. The effect of fiber reinforcement on the friction and wear of polyamide 66 under dry rolling-sliding contact. Tribol Int. 1999; 32(2):107-116. https://doi.org/10.1016/S0301-679X(99)00017-1
23. Unal H, Mimaroglu A, Arda T, Gumus S. Friction and wear characteristics of PTFE and its composites under dry sliding conditions. Mater Des. 2004; 25(3):239-245. https://doi.org/10.1016/j.matdes.2003.10.009