Artificial Neural Network Based Wear and Tribological Analysis of Al 7010 Alloy Reinforced with Nanoparticles of SIC for Aerospace Application

[1]Rajendra Pujari, [2]Mageswari M, [3]Herald Anantha Rufus N, [4]Prabagaran S, [5]Mahendran G and [6]Saravanan R
[1]Bharati Vidyapeeth (Deemed to be University), Institute of Management and Rural Development Administration, Sangli, Maharashtra, India.
[2]Department of Civil Engineering, Panimalar Engineering College, Chennai, TamilNadu, India.
[3]Department of Electronics and Communications Engineering, Vel Tech Rangarajan Dr Sagunthala R & D Institute of Science and Technology, Chennai, Tamil Nadu, India.
[4]Department of Mechanical Engineering, Faculty of Engineering, Karpagam Academy of Higher Education, Coimbatore, Tamil Nadu, India
[5]Department of Mechanical Engineering, R.M.K Engineering College, Kavaraipettai, Chennai, Tamil Nadu, India
[6]Department of Robotics and Automation, Rajalakshmi Engineering College, Chennai, Tamil Nadu, India
[1]rajendraspujari@gmail.com, [2]civilhod@panimalar.ac.in, [3]drrufus@veltech.edu.in, [4]s.prabagaran.cbe@gmail.com; [5]gmn.tyna@gmail.com, [6]saravananr85@gmail.com

Correspondence should be addressed to Rajendra Pujari : rajendraspujari@gmail.com

Article Info
Journal of Machine and Comp uting (http://anapub.co.ke/journals/jmc/jmc.html)
Doi: https://doi.org/10.53759/7669/jmc202303036
Received 02 March 2023; Revised from 16 June 2023; Accepted 08 July 2023.
Available online 05 October 2023.

Abstract – The current study investigates the wear behavior of three distinct composite compositions designated as C1, C2, and C3, with direct implications for aerospace applications. Critical factors such as the Coefficient of Friction (Cf), Specific Rate of Wear (Sw), and Frictional Force (FF) were meticulously analyzed using a systematic experimental approach and the Taguchi L27 array design. Significant relationships between input factors and responses emerged after subjecting these responses to Taguchi signal-to-noise ratio analysis. The optimal parameter combination of a 5% composition, 14.5 N Applied Load (Ap), 150 rpm Rotational Speed (Rs), and 40.5 m Distance of Sliding (Ds) highlights the interplay of factors in improving wear resistance. An Artificial Neural Network (ANN) was used as a predictive tool to boost research efficiency, achieving an impressive 99.663% accuracy in response predictions. The result shows comparison of the ANN's efficacy with actual experimental results. These findings hold great promise for aerospace applications where wear-resistant materials are critical for long-term performance under harsh operating conditions. The incorporation of ANN predictions allows for rapid material optimization while adhering to the stringent requirements of aerospace environments. This research contributes to the evolution of tailored composite materials, poised to improve aerospace applications with increased reliability, efficiency, and durability by advancing wear analysis methodologies and predictive technologies.

Keywords – ANN, Wear Analysis, Reinforcement, Optimisation, Prediction, Frictional Force.

I. INTRODUCTION

In the pursuit of developing advanced materials that can meet the rigorous demands of modern applications, the study of wear behavior analysis has emerged as a crucial area of research [1,2]. This is particularly significant in industries such as aerospace, where materials must endure extreme conditions and mechanical stress [3,4]. Wear behavior, encompassing factors like friction, abrasion, and erosion, plays a pivotal role in determining the durability and reliability of materials in such environments [5,6]. Wear behavior analysis of composite materials has garnered substantial attention due to its direct relevance in various engineering applications. Researchers have diligently investigated the intricate interplay between material constituents, microstructural features, and processing techniques, all of which significantly influence the wear resistance of composites [7,8]. For instance, the incorporation of reinforcing nanoparticles or fibers into the matrix material has demonstrated a remarkable enhancement in wear resistance [9]. Notably, nanoparticles like silicon carbide (SiC) have been effectively introduced into aluminum matrix composites, where they form a protective layer on the surface, thereby mitigating wear-induced degradation [10,11].

The Taguchi experimental design technique has emerged as a rigorous and disciplined approach to wear analysis. Its features, such as applied weight, sliding speed, and sliding distance, must be altered carefully for it to be utilised efficiently. Researchers get a comprehensive understanding of wear behaviour by measuring the effect of many elements and their interactions on wear performance [12,13]. The integration of Taguchi's signal-to-noise ratio approach simplifies quantifying the contributions of each parameter to the overall wear characteristics of composite materials [14,15].

The advent of Artificial Neural Networks has revolutionized predictive modeling in materials research, offering an efficient alternative to exhaustive experimental campaigns. ANNs possess the remarkable ability to learn intricate patterns and relationships within datasets [16,17]. They excel at extrapolating these learned relationships to predict wear behavior based on input factors, providing invaluable insights without the need for extensive physical testing [18,19].

In the domain of wear analysis, feed-forward backpropagation ANNs have gained prominence. Researchers have adopted various training functions to optimize ANN performance, and one noteworthy example is the utilization of the Levenberg-Marquardt optimization algorithm. Transfer functions such as TANSIG introduce non-linearity, enabling the network to approximate complex relationships within wear data more effectively [20,21].

The aerospace industry stands as a prime example of an arena where wear analysis and advanced materials play a pivotal role. Aerospace applications subject materials to a gamut of challenging conditions encompassing high velocities, extreme temperatures, and mechanical loads [3,22]. Wear behavior becomes a paramount consideration in the selection of materials for components subjected to such environments. Composite materials, lauded for their high strength-to-weight ratio and customizable properties, have emerged as integral candidates in aerospace material development [23,24].

Materials like carbon-fiber-reinforced composites have been extensively investigated for aerospace applications. Wear analysis provides vital insights into how these composites interact with other materials, particularly metals in mechanical components. The integration of predictive modeling, particularly ANN-based predictions, offers aerospace engineers a tool to assess the wear performance of composite materials under varying conditions. This expedites the material development process, enabling the creation of high-performance materials tailored to the unique demands of aerospace applications [25,26].

This research delves into wear behavior analysis of composite materials, vital for applications like aerospace. Experimental methods, including Taguchi's systematic approach, investigate factors influencing wear resistance, revealing optimal combinations. Artificial Neural Networks (ANNs) introduce predictive modeling, enabling accurate wear response forecasts without extensive experiments. Aerospace, demanding robust materials, benefits from wear analysis to design components resilient to extreme conditions. The fusion of experimental insights and ANNs presents a comprehensive framework for advancing aerospace material development.

II. MATERIAL PREPARATION

The research focused on creating and characterising composite materials consisting of Al 7010 alloy and SiC nanoparticles. The Al 7010 alloy was given by RK Aluminium and Exports in Chennai, while SiC nanoparticles with an average size of 30 nm were obtained for the study. The mechanical and thermal properties of the Al 7010 alloy were expected to be improved by adding SiC nanoparticles via a stir casting process. During the first step of the experiment, the Al 7010 alloy was heated to 750 degrees Celsius. This was done inside a dedicated stir casting machine, as shown in **Fig 1**. The molten alloy was then combined with warmed SiC nanoparticles prepared to 200 degrees Celsius. To include the SiC nanoparticles, the liquid was constantly agitated for 30 minutes. This thorough whirling ensured that the nanoparticles were disseminated evenly throughout the alloy matrix.

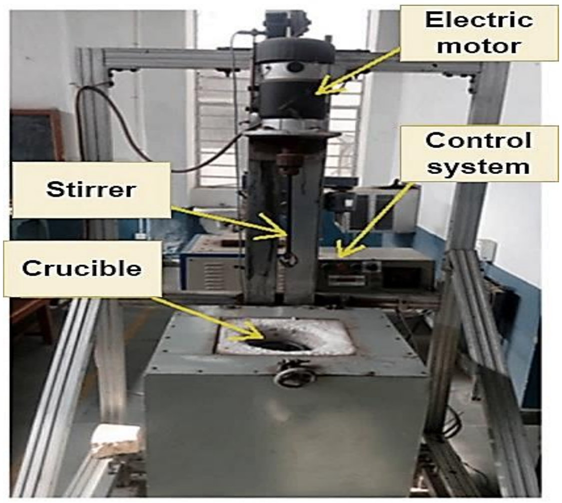

Fig 1. Equipment Used in this Research.

The study used three different material combinations to see how varying SiC nanoparticle concentrations affected the outcomes. 1% SiC nanoparticles were added to the first composition, C1. In the second component, C2, there were 3% SiC nanoparticles. The following batch, indicated by C3, had 5% more SiC nanoparticles. The properties of each material composition are listed in **Table 1.**

Table 1. Material Compositions

Composition	SiC Nanoparticle Concentration	Al 7010
C1	1%	99%
C2	3%	97%
C3	5%	95%

III. METHODOLOGY

Examining the wear characteristics of composite materials is crucial in materials science and engineering to comprehend its performance and wide variety of applications. With the help of an advanced pin-on-disc wear testing technique, the current study investigates the wear behaviour of three different composite materials. Table 1 includes all of the results. The experimental examination of these composites attempts to clarify the intricate interaction between the material's component parts and the frictional forces they experience, supplying crucial knowledge regarding their wear resistance and all-around durability. Pin-on-disc wear testing equipment is a frequently used tool for detecting friction and wear. This device simulates real-world conditions by exposing the pin-shaped composite material to the surface of a rotating disc. The rotating disc used in this research is made up of EN 24 alloy which is used in may research. The wear testing machine is shown in **Fig 2**.

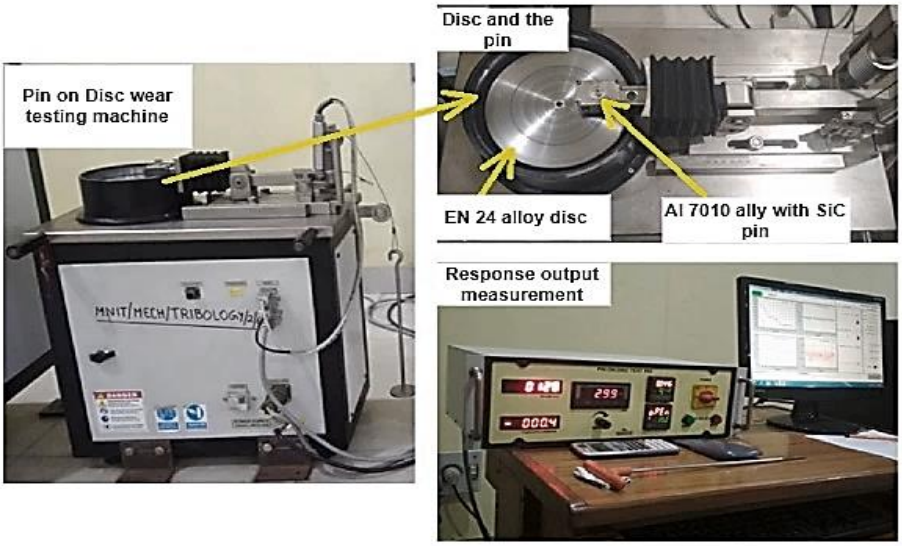

Fig 2. Experimental Setup

Coefficient of Friction (Cf): This response reflects the ratio of the Frictional Force (FF) resisting motion to the Applied Load (Ap). Mathematically, it can be expressed as: Cf = FF / Ap. Specific Rate of Wear (Sw): Offering insights into the rate of material removal from either the pin or disc, the Specific Rate of Wear is normalized by the Applied Load (Ap) and the Distance of Sliding (Ds). The equation is: Sw = Weight Loss / (Ap * Ds). Frictional Force (FF): Representing the force that counteracts the sliding motion, the Frictional Force (FF) can be calculated using: FF = Ap * Cf.

The Taguchi method and an L27 array were used to carefully organise the wear experiment in this investigation. The Taguchi Method is a dependable optimisation technique that carefully investigates the influence of numerous elements on experiment results. The L27 array has the variables composition (C), applied load (Ap), rotation speed (Rs), and sliding distance (Ds) for each of the 27 experimental runs. This design makes it easier to fully understand the wear behaviour of composite materials by allowing for exact data across a wide range of parameter spaces. The key factors affecting wear performance are more easily recognised thanks to the Taguchi technique and L27 array.

IV. RESULT AND DISCUSSION

The Taguchi L27 array design was used for the experiment, and **Table 2** displays the outcomes for that setup. Over three levels, every element—including C, Ap, Rs, and Ds—was systematically altered. The information produced by this multifactorial experimental design lays the groundwork for additional research and offers vital insights into how various components and their interactions affect the experiment's objectives.

Table 2. Experimental Results

C (%)	Ap (N)	Rs (rpm)	Ds (m)	Cf	Sw (mm^3/Nm)	FF (N)
1	14.5	100	35.5	0.35	5.45	2.79
1	14.5	100	35.5	0.35	5.45	2.79
1	14.5	100	35.5	0.35	5.45	2.79
1	20.2	150	37.5	0.4	2.11	6.71
1	20.2	150	37.5	0.4	2.11	6.71
1	20.2	150	37.5	0.4	2.11	6.71
1	25.3	200	40.5	0.42	1.49	10.68
1	25.3	200	40.5	0.42	1.49	10.68
1	25.3	200	40.5	0.42	1.49	10.68
3	14.5	150	40.5	0.36	1.83	2.87
3	14.5	150	40.5	0.35	1.81	2.79
3	14.5	150	40.5	0.35	1.82	2.79
3	20.2	200	35.5	0.2	2.48	2.79
3	20.2	200	35.5	0.4	2.48	6.71
3	20.2	200	35.5	0.4	2.47	6.71
3	25.3	100	37.5	0.15	3.22	2.87
3	25.3	100	37.5	0.77	3.24	20.99
3	25.3	100	37.5	0.29	3.23	6.84
5	14.5	200	37.5	0.15	1.61	0.78
5	14.5	200	37.5	0.17	1.65	0.98
5	14.5	200	37.5	0.15	1.63	0.78
5	20.2	100	40.5	0.2	1.46	2.74
5	20.2	100	40.5	0.2	1.47	2.74
5	20.2	100	40.5	0.19	1.49	2.55
5	25.3	150	35.5	0.21	1.82	4.51
5	25.3	150	35.5	0.25	1.83	5.69
5	25.3	150	35.5	0.27	1.85	6.27

The Taguchi signal-to-noise ratio approach was used to analyse the test data completely in an effort to enhance the outcomes and attain "smaller is better" characteristics. This analytical strategy aimed to enhance performance by minimising replies. These results are represented visually in **Fig 3**, which also demonstrates how various combinations of variables affected the experiment's goals. With the help of this graphical representation, a clear pattern illustrating the varying response levels for various parameter values may be seen. Notably, the graphical representation showed which concoction of variables resulted in the best response reduction results. According to the research, the best parameter choices for reaching this goal are 5% composition, 14.5 N Ap, 150 rpm Rs, and 40.5 m Ds.

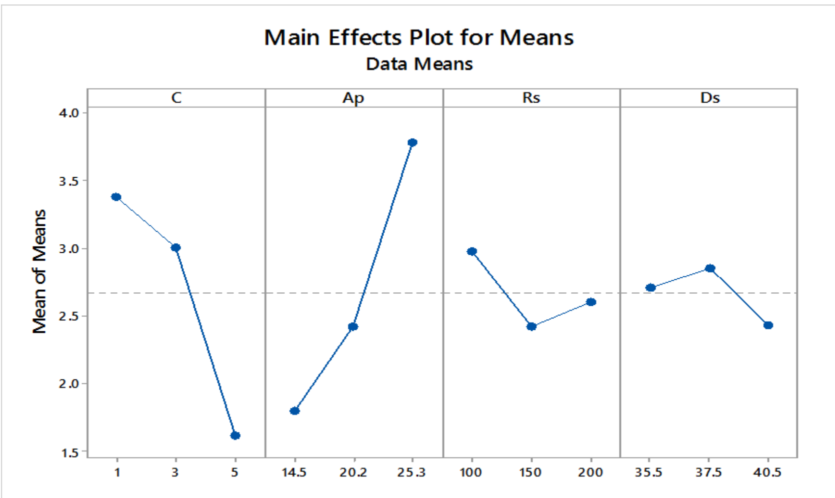

Fig 3. Optimal Combination for Minimising the Output Variables

Fig 4 depicts the variation in the Cf in response to changes in the input parameters. Notably, the graph demonstrates a clear trend demonstrating how changes in the input factors affect the Cf. Surprisingly, the C reaches its highest percentage when the Cf reaches its lowest value. This finding emphasises how the composition of composite materials has a significant impact on how they behave when in contact.

Changes in Rs and Ap have a significant impact on the Cf, as shown by the graphical representation. When these two parameters are increased, the Cf value changes noticeably, highlighting their critical importance in determining the frictional interaction between the pin and the disc. In contrast, the Ds has a much smaller effect on changes in the Cf. Changes in Ds have a relatively smaller impact on the frictional behaviour of the materials within the studied parameter range, according to this result.

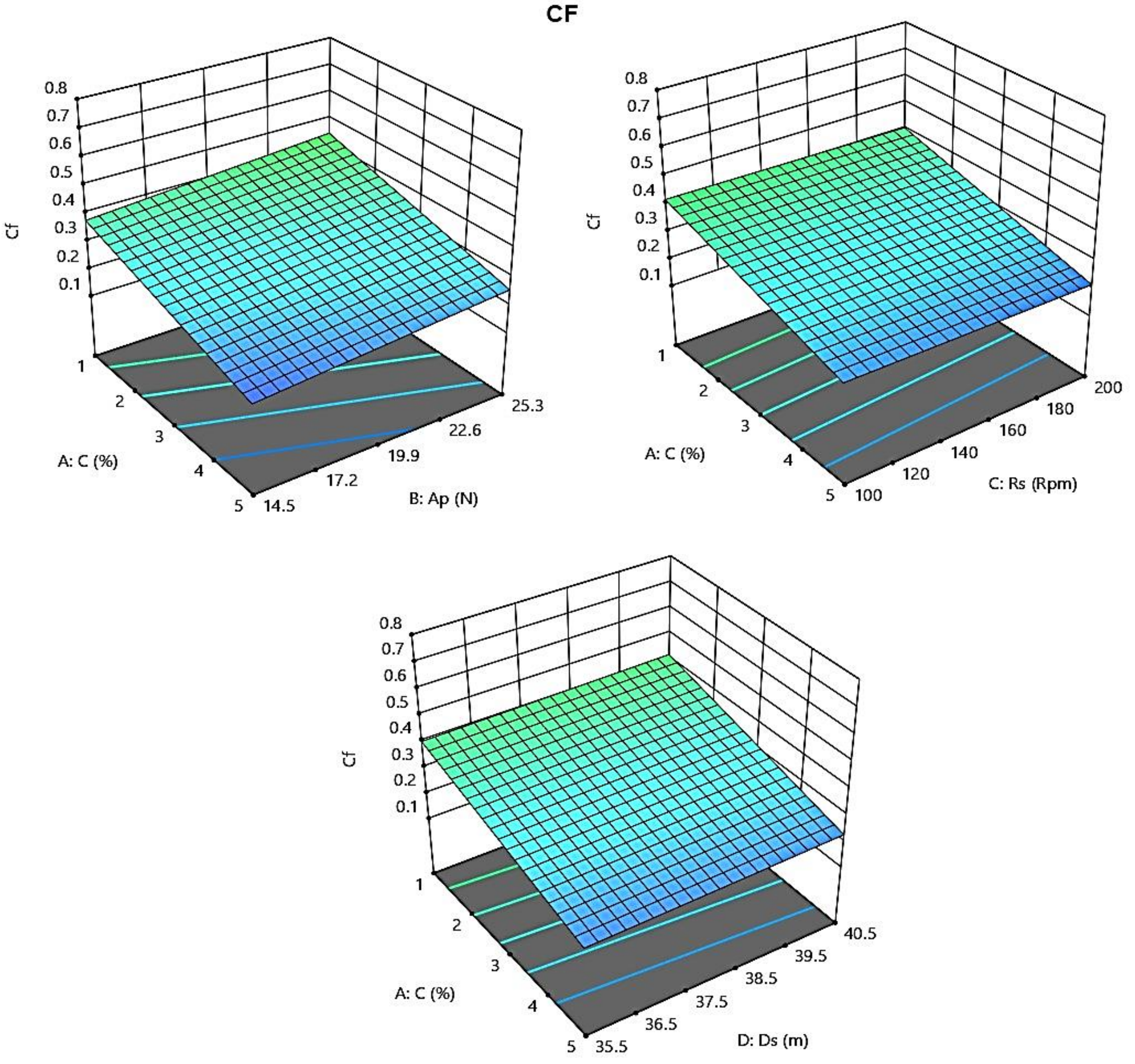

Fig 4. Variation of Cf on the change in input responses

Fig 5 depicts a comprehensive representation of the Sw variation in terms of input responses. This visual representation clearly shows the Sw value's relationship to changes in the input parameters. The graph shows an interesting trend in which rising Rs and rising Ap are correlated with rising Sw. This discovery highlights the significance of Rs and Ap in influencing wear behaviour by demonstrating their significant influence on the specific wear rate of composite materials. The graph also shows that the factors Rs and Ap are the primary causes of the increase in Sw responses. Their effects are especially strong, emphasising how important they are in determining the specific wear rate of the materials under consideration. It's especially interesting to see how the Sw reacts as the levels of C change. The analysis reveals that at the lowest C value, the Sw value is elevated, indicating a higher specific wear rate. In contrast, at the lowest level of C, the Sw value decreases, indicating a lower rate of specific wear. This finding leads to a compelling conclusion: increasing Rs and Ap at the same time as C content results in lower Sw values, indicating less wear and greater wear resistance.

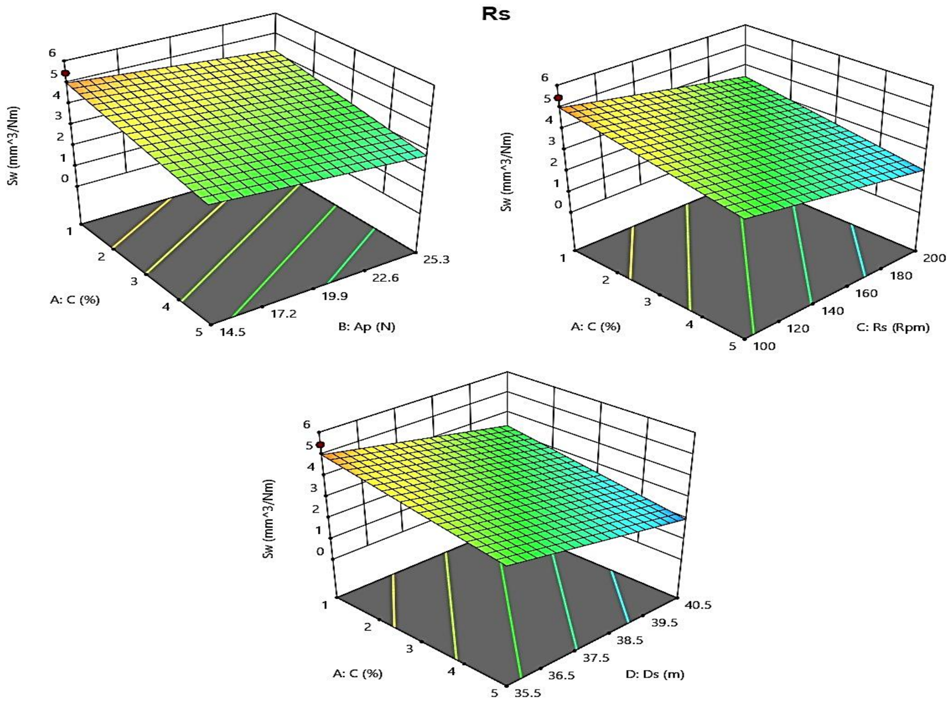

Fig 5. Variation of Sw on the change in input responses

A detailed illustration of the FF variation in response to altering input factors is shown in **Fig 6**. The dynamic relationship between the input parameters and the FF values is usefully depicted graphically. The graph, in particular, highlights the influence of various input factors on the FF response by exhibiting a clear trend. The observation in the graph emphasises how the FF increases as the Ap increases. According to this relationship, a higher applied load causes a greater amount of motion resistance, which is represented by a higher FF. In a similar vein, the graph demonstrates that raising Rs causes an increase in FF. This result confirms the intuitive hypothesis that frictional forces between interacting surfaces increase with rotational speed. The graph, however, displays a divergent pattern for the C levels. It is obvious that decreasing the FF by increasing the percentage of C in the composition. This finding is intriguing because it suggests that modifications to material composition may have a significant impact on frictional behaviour, which in turn may affect FF responses.

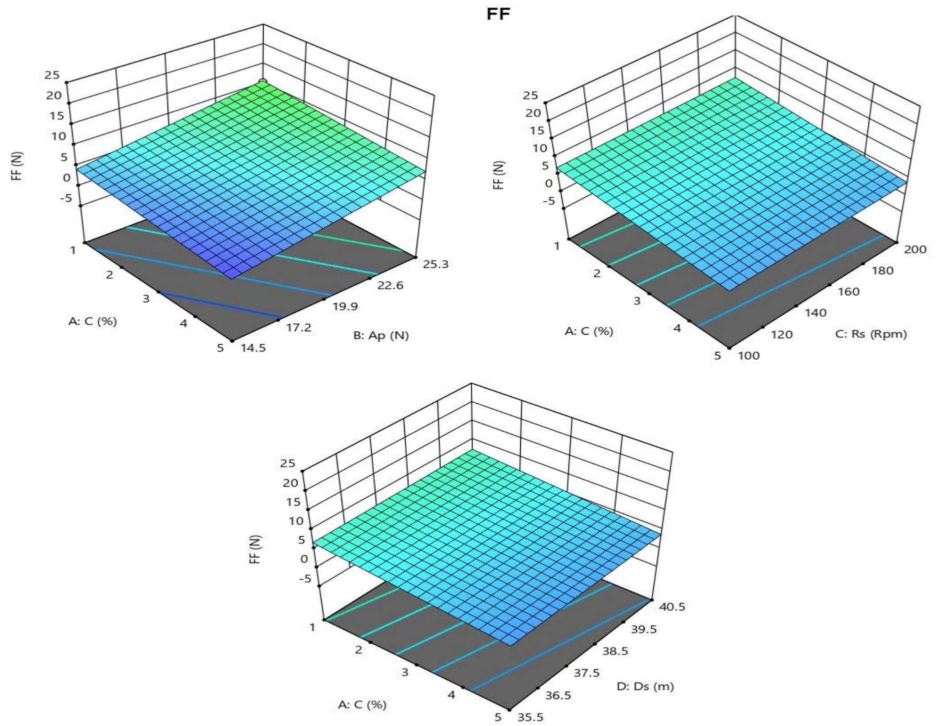

Fig 6. Variation of FF on the change in input responses

Additionally, to predict the results in this study, an Artificial Neural Network (ANN) methodology was used. In the field of experimental analysis, this novel approach has many advantages. Without the need for additional experiments, the responses to different combinations of input values can be predicted by using a trained ANN model. The ability of ANN to identify intricate patterns in datasets and extrapolate from the data it has been trained on is what motivates the use of ANN as a predictive tool.

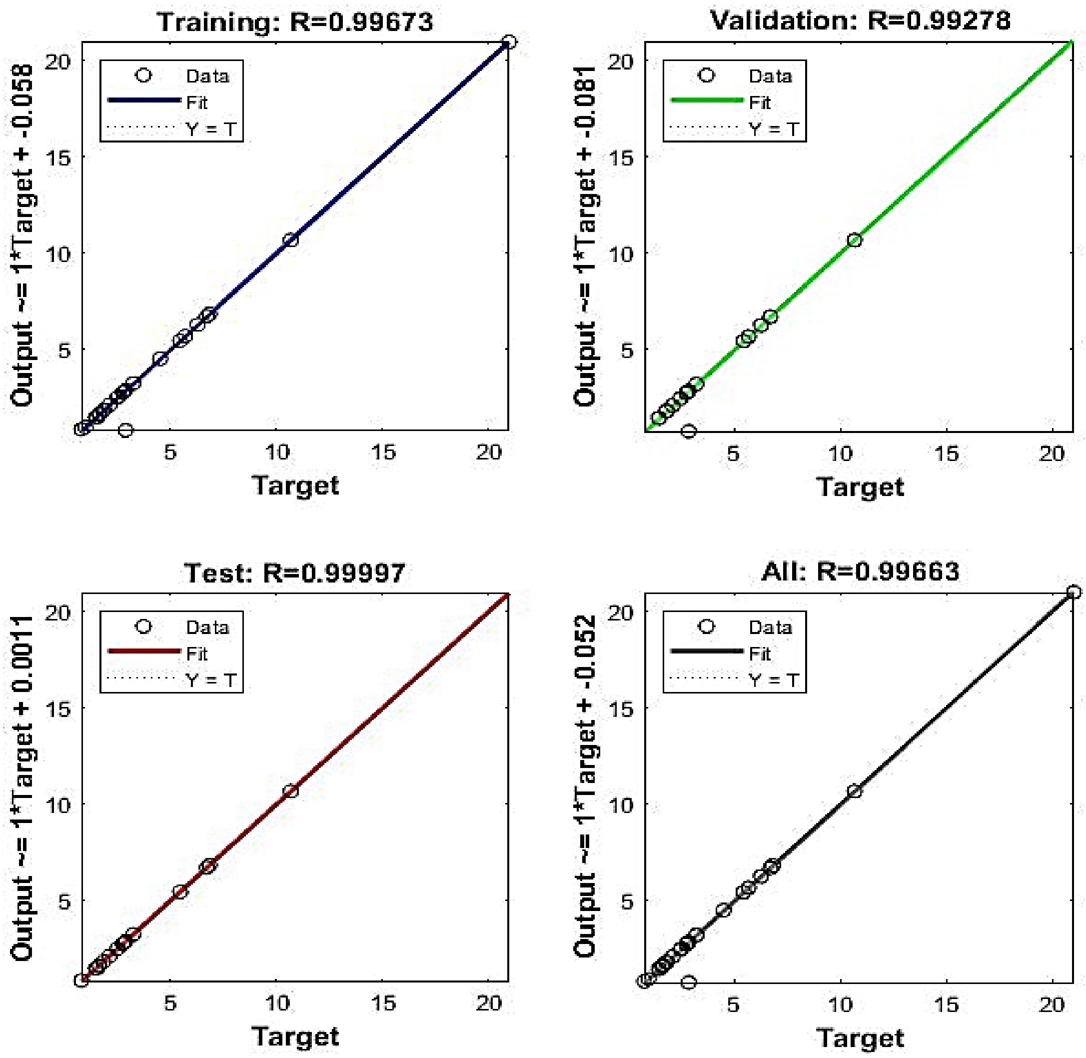

Fig 7. Predicted result from the ANN

The inherent benefit of using ANN is its capacity to streamline and accelerate the research process. The ANN model avoids this time-consuming process, which is required for traditional experimentation to explore a wide range of parameter combinations. Instead, the trained network uses the data from the initial experimental dataset that it has internalised to make precise predictions for new scenarios.

The use of an Artificial Neural Network (ANN) in this study's context adds a potent predictive dimension and improves the research methodology. The ANN architecture that was selected uses a feed-forward backpropagation algorithm, which is well known for its skill at modelling intricate relationships in datasets. The TRAINLM function controls the training process and makes use of the Levenberg-Marquardt optimisation algorithm (LEARNGDM) to adjust the weights and biases of the network. The goal of this optimisation strategy is to reduce the Mean Squared Error (MSE), a performance metric used to assess the predictive power of a model.

Two layers with ten neurons each make up the ANN configuration. This structure has been specifically designed to capture the dataset's complex patterns and correlations. The research uses the hyperbolic tangent sigmoid (TANSIG) transfer function, which introduces non-linearity and improves the network's ability to approximate complex functions. The created Artificial Neural Network (ANN) predicts responses with a 99.663% accuracy rate. Table 3 demonstrates this level of accuracy by comparing the ANN's predicted values to the actual experimental results.

Table 3. Experimental and the Predicted Result

C (%)	Ap (N)	Rs (rpm)	Ds (m)	Cf	Experimental result		Predicted result	
					Sw (mm^3/Nm)	FF (N)	Sw (mm^3/Nm)	FF (N)
1	14.5	100	35.5	0.35	5.45	2.79	5.44	2.78
1	14.5	100	35.5	0.35	5.45	2.79	5.44	2.78
1	14.5	100	35.5	0.35	5.45	2.79	5.44	2.78
1	20.2	150	37.5	0.4	2.11	6.71	2.10	6.70
1	20.2	150	37.5	0.4	2.11	6.71	2.10	6.70
1	20.2	150	37.5	0.4	2.11	6.71	2.10	6.70
1	25.3	200	40.5	0.42	1.49	10.68	1.46	10.68
1	25.3	200	40.5	0.42	1.49	10.68	1.46	10.68
1	25.3	200	40.5	0.42	1.49	10.68	1.46	10.68
3	14.5	150	40.5	0.36	1.83	2.87	1.82	2.87
3	14.5	150	40.5	0.35	1.81	2.79	1.81	2.78
3	14.5	150	40.5	0.35	1.82	2.79	1.81	2.78
3	20.2	200	35.5	0.2	2.48	2.79	2.48	2.78
3	20.2	200	35.5	0.4	2.48	6.71	2.47	6.70
3	20.2	200	35.5	0.4	2.47	6.71	2.47	6.70
3	25.3	100	37.5	0.15	3.22	2.87	3.22	0.78
3	25.3	100	37.5	0.77	3.24	20.99	3.23	20.98
3	25.3	100	37.5	0.29	3.23	6.84	3.23	6.83
5	14.5	200	37.5	0.15	1.61	0.78	1.59	0.83
5	14.5	200	37.5	0.17	1.65	0.98	1.67	0.95
5	14.5	200	37.5	0.15	1.63	0.78	1.59	0.83
5	20.2	100	40.5	0.2	1.46	2.74	1.47	2.73
5	20.2	100	40.5	0.2	1.47	2.74	1.47	2.73
5	20.2	100	40.5	0.19	1.49	2.55	1.47	2.54
5	25.3	150	35.5	0.21	1.82	4.51	1.81	4.51
5	25.3	150	35.5	0.25	1.83	5.69	1.83	5.68
5	25.3	150	35.5	0.27	1.85	6.27	1.85	6.27

V. CONCLUSION

Finally, extensive experimental research into the wear behaviour of three distinct composite compositions, denoted as C1, C2, and C3, has yielded valuable insights that can significantly impact material design for aerospace applications. The Coefficient of Friction (Cf), Specific Rate of Wear (Sw), and Frictional Force (FF) were thoroughly analysed using the Taguchi L27 array design. Following that, the obtained results were subjected to the Taguchi signal-to-noise ratio analysis, which revealed intriguing patterns in the relationships between input factors and responses. Notably, the optimal combination for minimising responses was identified as having a composition of 5%, an applied load (Ap) of 14.5 N, a rotational speed (Rs) of 150 rpm, and a sliding distance (Ds) of 40.5 m. This combination demonstrates the synergistic effect of various factors in increasing wear resistance.

Furthermore, the use of an Artificial Neural Network (ANN) as a predictive tool represented a significant step forward in the research. The ANN, which used a feed-forward backpropagation algorithm, performed exceptionally well, predicting responses with a precision of 99.663%. Table 3 shows how well the predictions matched the actual experimental results. This incorporation of ANN technology not only speeds up the research process, but it also opens up the possibility of optimising material properties in aerospace applications. To withstand the rigours of flight and operation, the aerospace industry requires materials with superior wear resistance. This study's findings, combined with ANN's predictive capabilities, have the potential to inform the development of composite materials tailored for enhanced performance, durability, and reliability in aerospace environments, thereby contributing to safer and more efficient aerospace applications.

Data Availability
The Data used to support the findings of this study will be shared upon request.

Conflicts of Interests
The author(s) declare(s) that they have no conflicts of interest.

Funding
No funding was received to assist with the preparation of this manuscript.

Ethics Approval and Consent to Participate
The research has consent for Ethical Approval and Consent to participate.

Competing Interests
There are no competing interests.

References
[1]. D. S. E. J. Dhas, C. Velmurugan, and K. L. D. Wins, "Investigations on the Effect of Tungsten Carbide and Graphite Reinforcements during Spark Erosion Machining of Aluminium Alloy (AA 5052) Hybrid Composite," Silicon, vol. 10, no. 6, pp. 2769–2781, Apr. 2018, doi: 10.1007/s12633-018-9817-0.
[2]. C. Fenghong, C. Chang, W. Zhenyu, T. Muthuramalingam, and G. Anbuchezhiyan, "Effects of Silicon Carbide and Tungsten Carbide in Aluminium Metal Matrix Composites," Silicon, vol. 11, no. 6, pp. 2625–2632, Jan. 2019, doi: 10.1007/s12633-018-0051-6.
[3]. S. Dhanesh, K. S. Kumar, N. K. M. Fayiz, L. Yohannan, and R. Sujith, "Recent developments in hybrid aluminium metal matrix composites: A review," Materials Today: Proceedings, vol. 45, pp. 1376–1381, 2021, doi: 10.1016/j.matpr.2020.06.325.
[4]. Nagaraj and S. Gopalakrishnan, "A Study on Mechanical and Tribological Properties of Aluminium 1100 Alloys 6% of RHAp, BAp, CSAp, ZnOp and Egg Shellp Composites by ANN," Silicon, vol. 13, no. 10, pp. 3367–3376, Oct. 2020, doi: 10.1007/s12633-020-00731-8.
[5]. G. Saravanan and G. B. Bhaskar, "Influence of Silicon Carbide Reinforcements on Mechanical and Wear Behaviour AA7075/15% wt. Glass fiber Hybrid Composites," Silicon, vol. 15, no. 3, pp. 1451–1464, Sep. 2022, doi: 10.1007/s12633-022-02117-4.
[6]. S. Chakravarty, P. Haldar, T. Nandi, and G. Sutradhar, "Fabrication and machinability studies on cupola slag reinforced aluminium metal matrix composites using Taguchi method," Materials Today: Proceedings, Feb. 2023, doi: 10.1016/j.matpr.2023.02.080.
[7]. T. Banerjee, S. Dey, A. P. Sekhar, S. Datta, and D. Das, "Design of Alumina Reinforced Aluminium Alloy Composites with Improved Tribo-Mechanical Properties: A Machine Learning Approach," Transactions of the Indian Institute of Metals, vol. 73, no. 12, pp. 3059–3069, Oct. 2020, doi: 10.1007/s12666-020-02108-2.
[8]. P.P. Ikubanni, M. Oki, A.A. Adeleke, and O.O. Agboola, "Optimization of the tribological properties of hybrid reinforced aluminium matrix composites using Taguchi and Grey's relational analysis," Scientific African, Vol. 12, pp. e00839, 2021, doi: 10.1016/j.sciaf.2021.e00839.
[9]. S. Pradeep Devaneyan, R. Ganesh, and T. Senthilvelan, "On the Mechanical Properties of Hybrid Aluminium 7075 Matrix Composite Material Reinforced with SiC and TiC Produced by Powder Metallurgy Method," Indian Journal of Materials Science, vol. 2017, pp. 1–6, Jan. 2017, doi: 10.1155/2017/3067257.
[10]. Y. Sesharao ., "Optimization on Operation Parameters in Reinforced Metal Matrix of AA6066 Composite with HSS and Cu," Advances in Materials Science and Engineering, vol. 2021, pp. 1–12, Jul. 2021, doi: 10.1155/2021/1609769.
[11]. T. K. Kandavel and T. Panneerselvam, "Experimental investigations on tribological behaviour and cutting tool performance of sinter-forged Cu, Mo and Ti added plain carbon steel," International Journal of Machining and Machinability of Materials, vol. 18, no. 3, p. 201, 2016, doi: 10.1504/ijmmm.2016.076280.
[12]. M. Ramesh, D. Kumar, and A. Kumar, "Investigation of the effect of age hardening on the mechanical properties of aluminium metal matrix composites reinforced with graphite particulate," Materials Today: Proceedings, Feb. 2023, doi: 10.1016/j.matpr.2023.02.163.
[13]. T. Panneerselvam, T. K. Kandavel, and P. Kishore, "Experimental Investigation on Cutting Tool Performance of Newly Synthesized P/M Alloy Steel Under Turning Operation," Arabian Journal for Science and Engineering, vol. 44, no. 6, pp. 5801–5809, Feb. 2019, doi: 10.1007/s13369-019-03763-4.
[14]. B. M. S, V. M, A. varthanan P, V. P. G, and S. P, "Multi-objective optimization of process parameters in dry sliding wear characteristics of Al/sic composites using Taguchi grey relation analysis," Materials Today: Proceedings, vol. 45, pp. 1882–1886, 2021, doi: 10.1016/j.matpr.2020.09.133.
[15]. S. K. Choudhary, R. S. Jadoun, and P. Singh, "Optimization of EDM process parameters for TWR on machining of Inconel 600 superalloy using Taguchi approach," Materials Today: Proceedings, vol. 57, pp. 2281–2288, 2022, doi: 10.1016/j.matpr.2022.01.059.
[16]. Canakci, S. Ozsahin, and T. Varol, "Prediction of Effect of Reinforcement Size and Volume Fraction on the Abrasive Wear Behavior of AA2014/B4Cp MMCs Using Artificial Neural Network," Arabian Journal for Science and Engineering, vol. 39, no. 8, pp. 6351–6361, May 2014, doi: 10.1007/s13369-014-1157-9.
[17]. E. N. Osegi and E. F. Jumbo, "Comparative analysis of credit card fraud detection in Simulated Annealing trained Artificial Neural Network and Hierarchical Temporal Memory," Machine Learning with Applications, vol. 6, p. 100080, Dec. 2021, doi: 10.1016/j.mlwa.2021.100080.
[18]. T. Varol, A. Canakci, and S. Ozsahin, "Modeling of the Prediction of Densification Behavior of Powder Metallurgy Al–Cu–Mg/B4C Composites Using Artificial Neural Networks," Acta Metallurgica Sinica (English Letters), vol. 28, no. 2, pp. 182–195, Dec. 2014, doi: 10.1007/s40195-014-0184-6.
[19]. Canakci, T. Varol, and S. Ozsahin, "Artificial neural network to predict the effect of heat treatment, reinforcement size, and volume fraction on AlCuMg alloy matrix composite properties fabricated by stir casting method," The International Journal of Advanced Manufacturing Technology, vol. 78, no. 1–4, pp. 305–317, Dec. 2014, doi: 10.1007/s00170-014-6646-1.
[20]. R. Hesse, F. Krull, and S. Antonyuk, "Prediction of random packing density and flowability for non-spherical particles by deep convolutional neural networks and Discrete Element Method simulations," Powder Technology, vol. 393, pp. 559–581, Nov. 2021, doi: 10.1016/j.powtec.2021.07.056.
[21]. U. Maheshwera Reddy Paturi, H. Devarasetti, and S. Kumar Reddy Narala, "Application Of Regression And Artificial Neural Network Analysis In Modelling Of Surface Roughness In Hard Turning Of AISI 52100 Steel," Materials Today: Proceedings, vol. 5, no. 2, pp. 4766–4777, 2018, doi: 10.1016/j.matpr.2017.12.050.

[22]. B. Vishnu Vardhana Naidu, M. Natarajan, G. M. Surendranatha, and K. C. Varaprasad, “Fabrication of aluminium hybrid metal matrix composites and development multiple regression models for wire electrical discharge machining,” International Journal on Interactive Design and Manufacturing (IJIDeM), Jun. 2022, doi: 10.1007/s12008-022-00920-2.
[23]. H. Pulikkalparambil, A. Babu, A. Thilak, N. P. Vighnesh, S. Mavinkere Rangappa, and S. Siengchin, “A review on sliding wear properties of sustainable biocomposites: Classifications, fabrication and discussions,” Heliyon, vol. 9, no. 3, p. e14381, Mar. 2023, doi: 10.1016/j.heliyon.2023.e14381.
[24]. M. P. Sudeshkumar, R. Ramadoss, V. Jayaseelan, and S. Vijayananth, “Preparation and Characterization of Amino-Silanized Opuntia Cladode Fibre and Fumed Silica Toughened Epoxy Composite,” Silicon, vol. 15, no. 6, pp. 2963–2972, Nov. 2022, doi: 10.1007/s12633-022-02228-y.
[25]. T. Gao et al., “Fiber-reinforced composites in milling and grinding: machining bottlenecks and advanced strategies,” Frontiers of Mechanical Engineering, vol. 17, no. 2, Jun. 2022, doi: 10.1007/s11465-022-0680-8.
[26]. N. Sunitha and K. G. Manjunatha, “Evaluation of Corrosion Studies of as Casted and Heat Treated Aluminum 6065 Metal Matrix Composite by Weight Loss Method,” Materials Today: Proceedings, vol. 5, no. 10, pp. 22727–22733, 2018, doi: 10.1016/j.matpr.2018.06.651.