Chaudhari and Bhangale
J Mater. Sci: Mater Eng. (2025) 20:22
https://doi.org/10.1186/s40712-025-00233-8

Journal of Materials Science: Materials in Engineering

ORIGINAL PAPER Open Access

Tribological behavior of unfilled PTFE under static loading in dry sliding condition: a Taguchi-ANN perspective

Kiran Ashokrao Chaudhari[1*] and Jayant Hemchandra Bhangale[1]

Abstract

This work explores the friction and wear characteristics of unfilled polytetrafluoroethylene (PTFE) operating in static unlubricated sliding conditions using Taguchi analysis. The research uses a design of experiment (DOE) technique, focused on sliding velocity, and applied pressure and sliding time as parameters. Systematic experimentation is facilitated with Taguchi's L9 orthogonal array, and Minitab 17 software is used to evaluate the findings. Signal-to-noise ratios (SNR) are used in the evaluation of individual parameter effects, the creation of regression models, and the establishment of ideal operating conditions. The analysis focuses on predicting wear (W), specific wear rate (Ws), and friction coefficient (f) through regression and ANN (artificial neural network) models, with ANN demonstrating better performance. The results advocate for optimal operating condition for PTFE under static load. This study adds important information for sectors where PTFE is employed as a primary material, such as rolling and sliding contact bearings.

Keywords Tribology, Static load, Taguchi analysis, ANN, PTFE

Introduction

Polytetrafluoroethylene (PTFE) is a polymer with low friction coefficient, excellent wear resistance, chemical resistance, and high thermal stability, making it excellent for applications such as seals, bearings, and sliding components. These properties make PTFE ideal for applications requiring low friction and durability under unlubricated sliding conditions. Its widespread use in industries such as aerospace, automotive, chemical processing, and manufacturing further supports its relevance for this study where the focus is on evaluating the material's performance in static and unlubricated environments. Additionally, PTFE's self-lubricating nature enhances its suitability for investigating friction and wear behavior without external lubrication. Also, PTFE polymer is comparatively cheaper and easily available material for the experimentation. While PTFE's dynamic tribological properties have been widely studied, its behavior under static loading in dry sliding conditions is less understood. This study examines the friction and wear performance under these circumstances, examining factors like wear (W), SWR (Ws), and friction coefficient (f). The goal is to enhance the understanding of PTFE's performance in static dry environments, which is crucial for optimizing its use in engineering applications. An insight is provided to researcher for comparison between Taguchi analysis and artificial neural network using MATLAB.

Research into the tribological behavior of polymers, especially unfilled polytetrafluoroethylene (PTFE) and its composites, has advanced significantly. A review outlines the evolution of tribological studies since the mid-twentieth century focusing on PTFE's characteristics and the development of tribometers for measuring friction and wear (Myshkin et al. 2005). Another assessment provides an overview of various polymers and their combinations

*Correspondence:
Kiran Ashokrao Chaudhari
ckaditya@gmail.com
[1] Matoshri College of Engineering and Research Centre, Eklahare, Nashik, Maharashtra State, Nashik 422105, India

in engineering applications, emphasizing design principles that reduce wear against smooth metallic surfaces (Friedrich 2018). Additional studies explore the tribological behaviors of diverse polymeric systems, revealing complexities in frictional interactions and opportunities for optimization (Rymuza 2007). Recent insights also discuss polymeric materials made from manufactured fibers, highlighting their tribological properties and potential uses (Aldousiri, et al. 2013). A review of PTFE emphasizes its versatility as a fluoropolymer used in coatings, insulation, and lubrication, alongside engineering approaches that incorporate nano and micro fillers to enhance its performance (Dhanumalayan and Joshi 2018). These studies collectively document the historical development of tribological research and set the stage for future innovations in polymer applications especially PTFE material across various industries.

The tribological behavior of unfilled PTFE and its composites has been extensively studied. Research focused on unfilled nylon, and PTFE revealed the impact of sliding speed, specific pressure, run time, and temperature on friction and wear patterns, suggesting limiting PV factors for continuous operation under the tested conditions (Shah and Basu 1984). Because of its low friction coefficient, PTFE has been recognized as a crucial engineering substance when sliding against hard surfaces, albeit with a high wear rate, prompting mechanistic and physical investigations into its frictional behavior (Biswas and Vijayan 1992). In another research the author investigated how sliding speed and temperature impacts, revealing two distinct friction regimes: high friction at elevated speeds or low temperatures and low friction with the development of a thin PTFE film at low speeds and moderate temperatures (Makinson and Tabor 1964). Further investigation into PTFE-based reciprocating seals demonstrated that friction coefficients varied with sliding speed and normal load, while wear rates and counterface damage were influenced by counterface hardness and surface finish. A predictive method for seal wear based on multiple factors was proposed (Lewis 1986). Finally, research on PTFE-based composites with various fillers indicated that the type of filler does not significantly affect friction, which remains comparable to that of unfilled PTFE. The study emphasized the role of filler material, shape, and size on wear behavior under constant load and varying sliding speeds (Tanaka and Kawakami 1982). These findings collectively enhance the understanding of PTFE's tribological properties and inform its applications in engineering contexts.

Numerous research have been undertaken to explore the wear and friction behavior of PTFE and its composites. In a study that investigated the effects of test speed and load on pure PTFE and various composites, the researchers discovered that the friction coefficient reduced as the load increased. The best wear performance was observed in PTFE reinforced with 17% glass fiber, recommended as an effective tribo-material (Unal et al. 2004). Another review discussed mechanistic theories of wear reduction through fillers and investigated the change from light to heavy wear in unfilled PTFE, providing guidelines for maintaining mild wear under varying operational conditions (Blanchet and Kennedy 1992). Further research explored the wear and friction behavior of PTFE, POM, and PEI against steel, supporting the selection of operational parameters for tribological studies (Unal and Mimaroglu 2003). A study on breakaway friction of PTFE-based materials highlighted the importance of lubrication conditions in understanding wear behavior (Golchin et al. 2012). The incorporation of wollastonite into PTFE composites showed improved performance in elastic composite cylindrical roller bearings, reducing rolling stress significantly under varying loads (Yu et al. 2015). Additional studies examined how different fillers affected the wear and friction of PTFE, revealing significant enhancements in wear resistance (Pansare, et al. 2021). Investigations into glass-filled PTFE highlighted wear behavior in both dry and water-lubricated conditions, assessing various glass forms (Klaas et al. 2005). The effects of rolling motion on PTFE wear were also studied, demonstrating that wear characteristics depend on the motion setup (Shibo, et al. 2017). Research on self-lubricating polymer composites indicated their effectiveness in naval and hydropower applications, emphasizing the significance of transfer layer formation during dry sliding (Rodiouchkina, et al. 2021). The studies on zinc-based composite coatings with PTFE particles underscored the importance of composition and distribution in enhancing tribological performance (Pazderova, et al. 2011). In another study, incorporating hexagonal boron nitride (0–5 wt %) into PAEK significantly enhanced its microhardness and thermal stability. Nanocomposites reduced wear rate by 22 times compared to pure PAEK, with only a modest and steady increase in coefficient of friction under static loading (pin on disk tribometer testing) (Joshi et al. 2016). Researchers also modified the pin on disk tribometer for tribological behavior of PTFE materials subjected to constant and variable loading conditions (Patil and Ahuja 2014). In another study, the force produced by the pressure of the friction pad in the railway brake disk is calculated by the researcher. The author came to the conclusion that uneven wear oriented along the friction force results from a lack of parallelism between the braking disks' and friction pads' surfaces (Bocîi 2021). Using several commercial PTFE membranes that are experimentally investigated under the influence of operating circumstances and membrane pore sizes, researchers investigated the energy aspects and cost analysis in direct contact membrane distillation (DCMD) (Ve et al. 2024). The researcher also studied the tribological outputs and effect of friction in dry sliding wear behavior of PA66/PTFE blend with glass-carbon fiber composites against sliding velocity and load as input parameters (Rudresh 2020). These findings contribute to a deeper understanding of PTFE's tribological properties and its applications in various engineering contexts.

Numerous researchers have employed various analytical techniques, including regression analysis, design of experiments (DOE), and Taguchi analysis, to evaluate experimental results in tribological studies. One investigation focused on the wear of polymers, utilizing an empirical wear equation to develop models for investigating the frictional characteristics of polymers and composites (Vishwanath and Bellow 1995). A different study employed a pin-on-disk wear apparatus to assess the tribological characteristics of glass epoxy polymer composites that include SiC and graphite particles during dry sliding. This research incorporated DOE and statistical analyses, including ANOVA and regression analysis, to derive linear equations for predicting the wear and friction of unfilled PTFE (Basavarajappa et al. 2009). These techniques improve our understanding of tribological performance and make it easier to optimize polymer composite materials for engineering applications.

The tribological performance of unfilled PTFE materials has been explored using artificial neural network (ANN) techniques, although research in this area remains limited. A study found that artificial neural networks can replicate difficult scientific and technical challenges, drawing inspiration from the organic nervous system. The interconnections between artificial neurons, which mirror natural biological systems, have a substantial impact on an ANN's performance. Training a neural network in polymer composites requires a specified amount of experimental data, allowing prediction of new data without substantial experimentation. The goal of using artificial neural networks is to optimize composite material design for specific applications through systematic parameter investigations. This paper examines neural network concepts for forecasting fatigue life, wear performance, combined loading response, and dynamic mechanical features. Furthermore, ANNs have been applied to optimize composite processing (Zhang and Friedrich 2003). In related research, the ANN method has been utilized to assess the effects of various parameters on vibrations through experimental data (Kanai et al. 2016). Another study utilized a supervised feed forward multilayered ANN architecture, trained with scaled conjugate gradient algorithms, to enhance predictions in material behavior (Bose and Liang 1996). The researcher created ANN model to predict the Nu value. The Nu value found by experimentation and regression correlation are compared with the predicted by ANN model and found that they are within 3% of one another in variance (Barhatte and Lele 2024). The authors describe the neural network-based principal component analysis facial recognition technique (Shukla et al. 2023). Several machine learning and deep learning models, including support vector machines (SVM), random forests, multilayer perceptrons (MLP), and gradient boosting and artificial neural networks (ANNs) are proposed in this research to investigate the topic (Arya and Anju 2024). These findings emphasize the significance of employing ANNs to anticipate and create tribological properties for polymers and composite materials.

This research aims to delve into the tribological behavior of unfilled PTFE under static loading in dry sliding conditions, utilizing a Taguchi-ANN perspective. The presented study advances our understanding of how sliding velocity, pressure, and sliding time affect the tribological behavior of an unfilled PTFE material which is widely used in rolling and sliding contact bearings. The comparison of both regression and ANN models has been presented for unfilled PTFE material. Research in this topic aims to provide more efficient working conditions for unfilled PTFE, resulting in less wear.

Experimental work

Test method

The experiments were carried out using unfilled PTFE in the pin on disk configuration in accordance with the ASTM standard G99 (Designation 2000). This study utilized unfilled polytetrafluoroethylene (PTFE) having material properties as density of 2.2 g/cm^3, a failure strain of 350%, tensile yield strength 11 MPa, and an ultimate strength of 30 MPa. The PTFE wear samples were machined into cylindrical pins (Φ 10 × 35 mm) from billets supplied by Invento Sales, New Delhi, India. The counter surface consisted of an EN 31 steel disk (Φ 165 × 8 mm) with a surface hardness of RC 60–65, and surface roughness (Ra) was achieved through grinding. The wear and friction conditions in this study were designed to simulate real-world scenarios for unfilled PTFE under static unlubricated sliding. Key conditions included varying load to assess contact pressure's effect on wear, sliding speed to evaluate performance at different velocities, and duration to examine long-term wear behavior. The surface roughness of the counterface material was kept constant. A Taguchi L9 orthogonal array (OA) was employed to systematically investigate three parameters at three levels: sliding velocity (V) at 0.1, 0.3, and 0.5 m/s; pressure (P) at 0.125, 0.562, and 1 MPa;

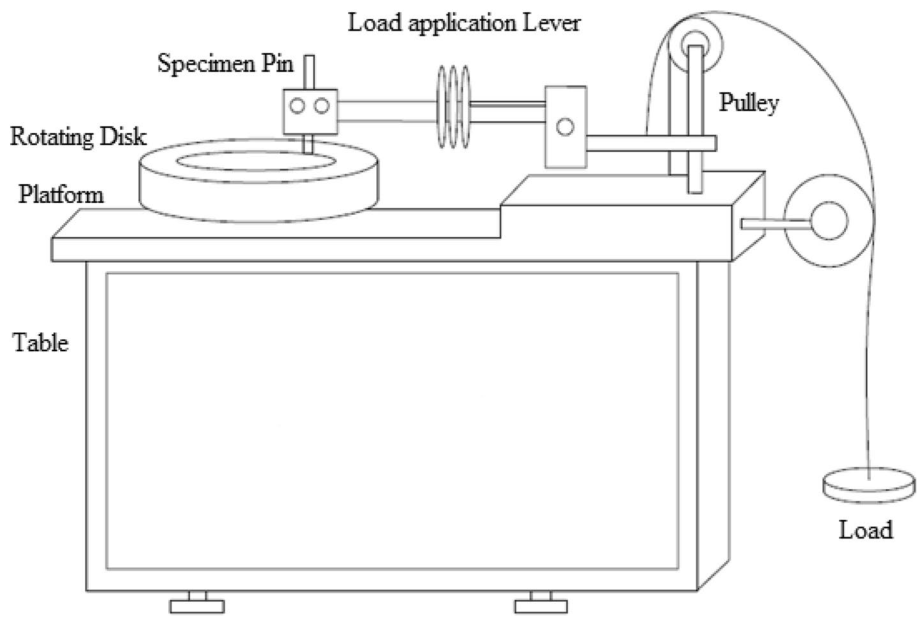


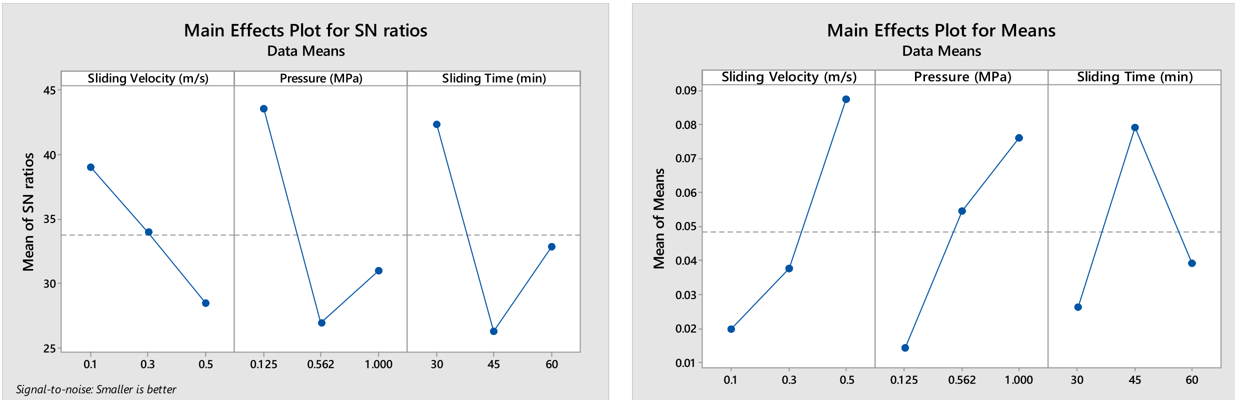
Fig. 1 Schematic diagram of experimental setup

and sliding time (t) at 30, 45, and 60 min. These conditions aimed to provide relevant insights for industrial applications. The study's goals were to create a linear regression model for significant wear features, assess the effects of individual parameters using analysis of variance (ANOVA), and identify the best operating parameters using signal-to-noise ratio (SNR) analysis. Friction and wear testing were done using a pin on disk tribometer. The tribometer used is a basic model (TR-20LE) supplied by DUCOM Instruments Bangalore, ensuring robust and reliable results. A schematic diagram of the experimental setup is shown in Fig. 1.

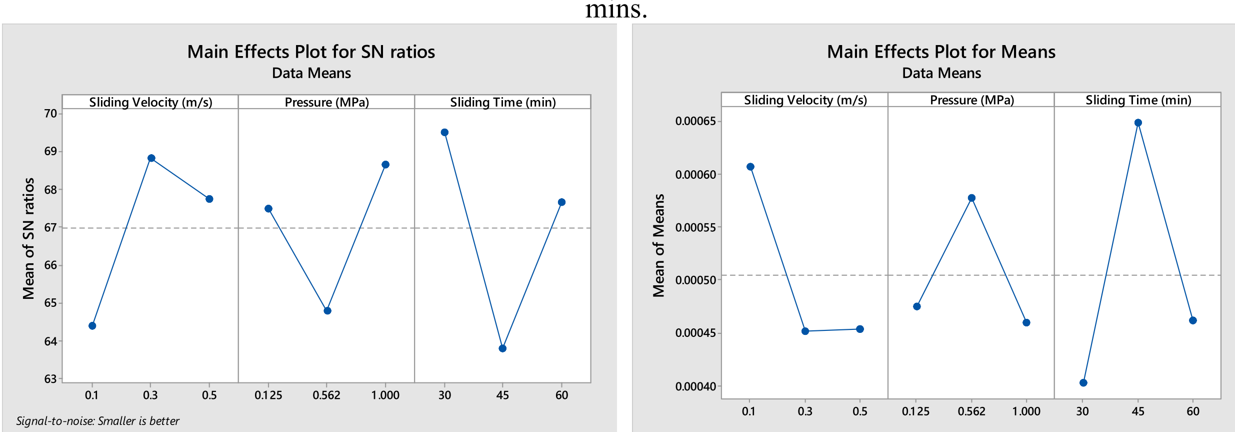
Taguchi method and design of experiments (DOE)

The design of experiments (DOE) constitutes a structured approach for examining the influence of one or more independent variables on a dependent variable. This methodology involves the careful definition and exploration of all relevant scenarios within a multifactorial framework. Key elements of DOE include meticulous planning to ensure the collection of appropriate data for subsequent analysis, the establishment of optimal conditions, and the evaluation of the influence of individual factors. The DOE framework and statistical analysis both are crucial for successfully solving experimental difficulties (Figs. 2 and 3).

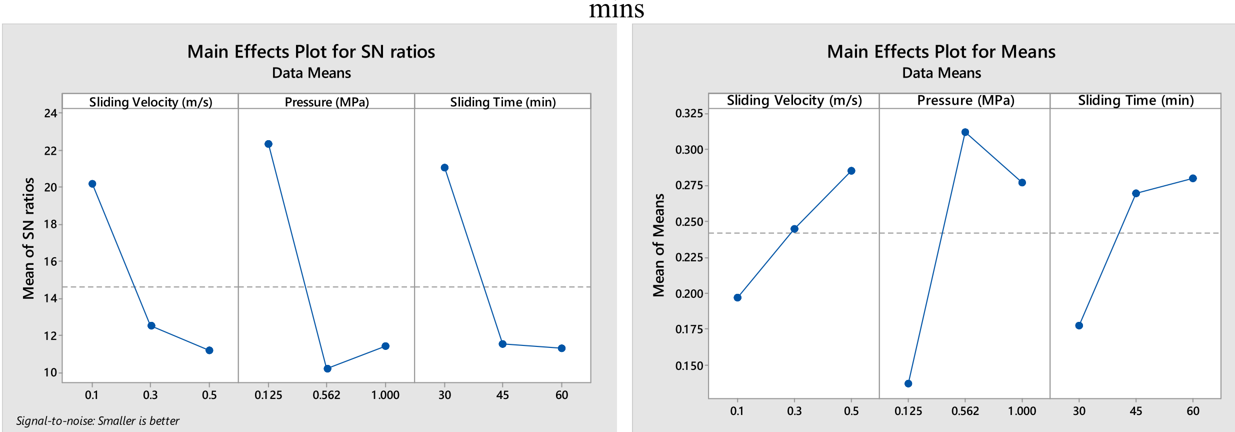
In this research, the L9 orthogonal array developed by Taguchi was utilized, incorporating three parameters, with each parameter assigned at three different levels. In each experimental iteration, three quality characteristics were assessed. The L9 orthogonal array was chosen over the L27 array due to its suitability for the study's experimental design, involving fewer factors and levels. The L9 array requiring only 9 trials offers a more efficient and cost-effective approach reducing complexity while still providing reliable data. It allows for the identification of key factors affecting PTFE's friction and wear properties without the need for the larger number of trials required by the L27 array, making it an optimal choice for the study's objectives. The gathered data underwent comprehensive examination to determine the ideal operating parameters via signal-to-noise ratio (SNR) evaluation. At the same time, the influence of each parameter was examined using statistical techniques, such as ANOVA and linear regression analysis. These methods offered important perspectives on the key factors influencing the experimental system. ANOVA is used in this study to determine the statistically significant factors influencing the friction and wear properties of unfilled PTFE under static unlubricated sliding conditions. It allows for the identification of key variables (e.g., pressure (load), sliding speed, and sliding time) that affects the material performance, assesses interactions between these factors, and quantifies the variability in the data. This statistical approach enables the optimization of experimental conditions providing a reliable basis for improving the design and performance of PTFE in relevant applications. The results from this research enhance our overall comprehension of how the system operates and aid in making



(a) Optimum value A3B2C2 sliding vel 0.5m/s, pressure 0.562MPa means load 4.5 kg, sliding time 45 mins.



(b) Optimum value A1B2C2 sliding vel 0.1m/s, pressure 0.562MPa means load 4.5 kg, sliding time 45 mins



(c) Optimum value A3B2C3 sliding vel 0.5m/s, pressure 0.562MPa means load 4.5 kg, sliding time 60 mins

Fig. 2 Main effect plots for SN ratios and means for (**a**) wear by weight loss (W), (**b**) SWR (Ws), and (**c**) friction coefficient (f)

decisions that target performance optimization or control maintenance under different circumstances.

Experiments using the orthogonal array yielded results for many parameter combinations. The findings were analyzed using Minitab 17, a well-known commercial program for DOE applications.

The experimental results were converted into signal-to-noise ratios (SNR) in order to assess the parameters under consideration. This transformation allowed for a

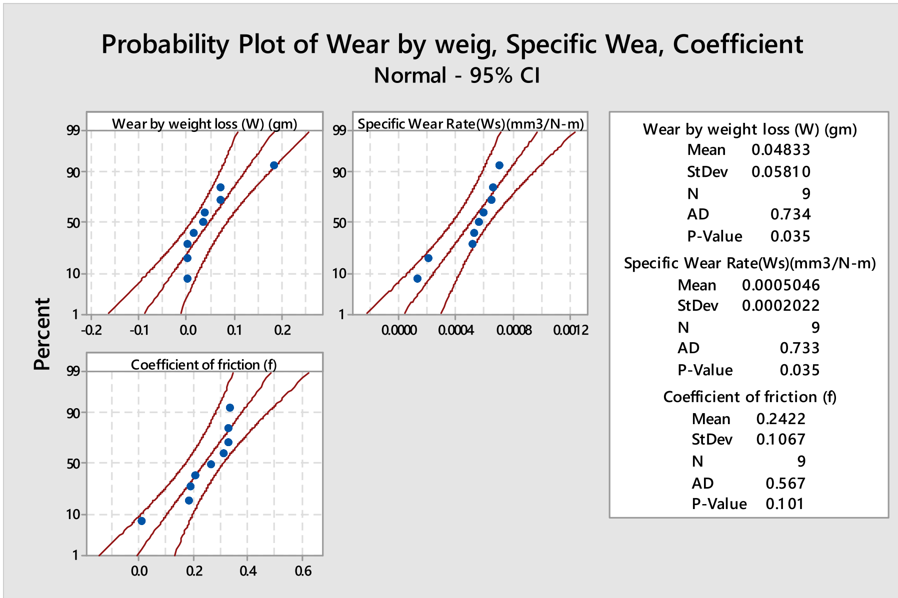


Fig. 3 Probability plot for wear by weight loss (W), SWR (Ws), and friction coefficient (f)

full investigation of the influence of variables like velocity of sliding (V), load applied (P), and sliding time (t) on wear parameters, notably wear by weight loss (W), SWR (Ws), and friction coefficient (f). The SNR responses allowed for a detailed investigation of how control parameters affect wear results.

This analysis' response tables prioritized the process parameters based on SNR calculated from wear by weight loss data, specific wear rate, and COF. This ranking allowed for the identification of essential elements and their relative importance within the experimental design. To improve analysis, logarithmic transformations were used to translate experimental data into SNR. This made the loss function more comprehensible and instructive. This method not only increased the findings' accuracy but also contributed to a more nuanced interpretation of the experimental data, strengthening the validity of the study's conclusions (Table 1).

$$\text{Smaller is better}: \ \mathrm{S/N} = -10 \times log\frac{1}{n}(\sum (y^2)/n) \tag{1}$$

Process parameters levels

Values of the selected influencing input parameters and the coding for levels are tabulated as below (Table 2).

Full factorial design is considered for experimentation with three parameters at three levels, i.e., nine experiments were conducted. The experimental conditions with actual values of parameters and results obtained are presented in Table 3.

The results obtained from experiment set have been analyzed so as to determine the most influencing factors and to establish the relationship among response variable and the influencing variable. The data analysis was carried out for assessing the influence of the velocity of sliding (V, m/s), pressure applied (P, MPa) and sliding time (t, min) on wear by weight loss (W, g), SWR (Ws, mm^3/N-m), and friction coefficient (f). The experimental results were analyzed using following techniques:

Table 1 Material properties

Specimen material and dimensions (mm)	**Pure PTFE cylindrical pins (φ 10×35)**
Counter surface	Circular disk (EN 31 steel) featuring a surface hardness of RC 60–65
Surface roughness	0.2-μm constant

Table 2 Input factors and levels for wear test

Sr. no	**Input parameters**	**Levels**		
1	**Sliding velocity (V) (m/s)**	**0.1**	**0.3**	**0.5**
2	Pressure (P) (MPa)	0.125	0.562	1
3	Sliding time (t) (min)	30	45	60

Table 3 Taguchi L9 (3 3) orthogonal array

Experiment no	Input parameters and levels			Measured responses		
	Sliding velocity (V) (m/s)	Pressure (P) (MPa)	Sliding time (t) (min)	Wear by weight loss (W) (g)	Specific wear rate (Ws) (mm^3/N-m)	Coefficient of friction (COF) (f)
1	0.1	0.125	30	0.002	0.000514832	0.011
2	0.1	0.562	45	0.017	0.000648307	0.266
3	0.1	1	60	0.041	0.000659629	0.314
4	0.3	0.125	30	0.037	0.000705511	0.211
5	0.3	0.562	45	0.073	0.000521983	0.336
6	0.3	1	60	0.003	0.000128708	0.187
7	0.5	0.125	30	0.004	0.000205933	0.19
8	0.5	0.562	45	0.074	0.000564409	0.334
9	0.5	1	60	0.184	0.000592057	0.331

SNR and ANOVA

In this study, we evaluated wear characteristics through metrics such as weight loss (W), SWR (Ws), and friction coefficient (COF) while simultaneously calculating the S/N ratio. The wear metrics serve as the response variables, whereas the process parameters include sliding velocity, applied pressure, and sliding time. In accordance with the principles of the Taguchi approach, we adopt a "smaller is better" criterion for assessing the S/N ratio. The primary aim is to optimize tribological conditions by minimizing these parameters. This approach allows for a systematic enhancement of performance by focusing on reducing wear and frictional losses, ultimately leading to improved durability and efficiency in practical applications. The mathematical formulation for this assessment is outlined below.

$$\text{Smaller is better}: \ S/N = -10log\frac{1}{n}\left(\sum\nolimits_{i=0}^{n} y_i^2\right) \quad (2)$$

The study on signal-to-noise (S/N) ratios has provided significant insights into the tribological performance of PTFE materials. Notably, the delta values indicate that sliding velocity has the greatest impact on wear, while sliding time is most influential for specific wear rate and applied pressure (load) significantly affects friction coefficient (f). The implementation of rank analysis further elucidates the hierarchical effects of these parameters on frictional performance of unfilled PTFE.

This ranking not only highlights the most critical factors influencing performance but also aids in prioritizing adjustments for optimal tribological outcomes. The data summarized in Tables 4, 5, and 6 presents the response variables in relation to their mean predicted values, offering a thorough overview of the relative significance of each parameter. This thorough analysis enhances our understanding of the interactions and contributions of

Table 4 Response table for means for wear

Level	Sliding velocity (m/s)	Applied pressure (MPa)	Sliding time (min)
1	0.02000	0.01433	0.02633
2	0.03767	0.05467	0.07933
3	0.08733	0.07600	0.03933
Delta	0.06733	0.06167	0.05300
Rank	1	2	3

Most influential factor is sliding velocity, then pressure, i.e., load, and sliding time

Table 5 Response table for means for specific wear rate

Level	Sliding velocity (m/s)	Applied pressure (MPa)	Sliding time (min)
1	0.000608	0.000475	0.000403
2	0.000452	0.000578	0.000649
3	0.000454	0.000460	0.000463
Delta	0.000156	0.000118	0.000246
Rank	3	2	1

Most influential factor is sliding time, then sliding velocity, and pressure, i.e., load

Table 6 Response table for means for COF

Level	Sliding velocity (m/s)	Applied pressure (MPa)	Sliding time (min)
1	0.1970	0.1373	0.1773
2	0.2447	0.3120	0.2693
3	0.2850	0.2773	0.2800
Delta	0.0880	0.1747	0.1027
Rank	3	1	2

Most influential factor is pressure, i.e., load, then sliding time, and sliding velocity various factors in the tribological assessment of unfilled PTFE, paving the way for improved material performance in practical applications.

Results and discussion

The tribological parameters were studied using L9 (3^2) orthogonal arrays, as shown in Table 1. It provides a structured framework for the analysis. This study focuses on key factors including sliding velocity, applied pressure, and sliding time. The response variables examined are wear measured by weight loss (W), SWR (Ws), and friction coefficient (f) for unfilled PTFE. The experimental design aims to uncover key factors and interactions that impact wear, SWR, and COF. The tests were systematically structured using the orthogonal array methodology, which allows for efficient exploration of multiple factors simultaneously. This analysis aims to establish a coherent relationship between the identified parameters sliding velocity, applied pressure, and sliding time and their effects on wear, SWR, and COF. Ultimately, the goal is to pinpoint optimal operating conditions that minimize these response parameters, thereby enhancing the performance and longevity of unfilled PTFE in tribological applications. It is anticipated that the study's conclusions will provide insightful information about how to maximize material performance under various operating conditions.

Influence on wear by weight loss

Table 7 shows that sliding velocity, applied pressure, and sliding time have significant effect on wear by weight loss at the 95% of confidence interval. Also, it is revealed that sliding velocity, applied pressure, and sliding time have contribution of 53.35%, 44.64%, and 2.01%, respectively, for wear. The % contribution by each factor is the ratio of F-ratio of individual factor to the sum of F-ratio of all factors considered. Tables 7, 8, and 9 display the results of an variance analysis to assess the relative relevance of each controlling parameter for wear by weight loss (W), SWR (Ws), and friction coefficient (f).

Influence on SWR (Ws) specific wear rate

The investigation demonstrates that velocity of sliding has the most significant influence on the SWR (Ws) as demonstrated by a confidence interval of 95%. The calculated percentage contribution indicates that sliding velocity accounts for 86.11% of the overall influence on specific wear rate, underscoring its dominance among the evaluated parameters. This finding highlights the critical role of sliding velocity in determining wear characteristics, suggesting that optimizing this factor could lead to substantial improvements in the tribological performance of unfilled PTFE. The percentage contribution of applied pressure and sliding time is found to be nearly equal as 1.39% and 12.5%, respectively. The 1.39% percentage contribution of applied pressure for specific wear rate is found comparatively less than 44.64% percentage contribution for wear.

Influence on friction coefficient (f)

Applied pressure showing highest 51.69% contribution affects mostly the friction coefficient (f), and the percentage contribution of sliding time is seen as 27.83%. Sliding velocity is less contributory factor with 20.48% to coefficient of friction. As the applied pressure increases, the contact area between the sliding surfaces increases resulting in higher friction due to increased asperity contact. This enhanced contact leads to greater frictional resistance. Also, the applied pressure causes elastic and plastic deformation of the material increasing the real contact area subsequently leading to increase in friction coefficient values.

Higher applied pressure leads to increased wear due to enhanced contact and shear forces between surfaces. This results in greater material deformation, micro-wear, and wear debris formation accelerating wear and reducing wear resistance. The increase in applied pressure affects the long-term wear resistance of unfilled PTFE material.

Table 7 Variance analysis for wear (W)

Input factors	DF	SS	MS	F	P	% Contribution
Regression	3	0.012757	0.004252	1.49	0.324	
Sliding velocity (V)	1	0.006801	0.006801	2.39	0.183	53.35
Applied pressure (P)	1	0.005703	0.005703	0.005703	0.216	44.64
Sliding time (t)	1	0.000253	0.000253	0.09	0.777	2.01
Error	5	0.014247	0.002849			
Total	8	0.027004				

S 0.0827507, *R-sq* 62.39%, *R-sq (adj)* 39.82%

Table 8 Variance analysis for SWR (Ws)

Input factors	DF	SS	MS	F	P	% contribution
Regression	3	0.000000	0.000000	0.24	0.866	
Sliding velocity (V) (m/s)	1	0.000000	0.000000	0.62	0.468	86.11
Applied pressure (P) (MPa)	1	0.000000	0.000000	0.01	0.940	1.39
Sliding time [t], (min)	1	0.000000	0.000000	0.09	0.772	12.5
Error	5	0.000000	0.000000			
Total	8	0.000000				

S 0.0002392, *R-sq* 12.55%, *R-sq* (adj) 0.00%

Table 9 Variance analysis for friction coefficient (f)

Input factors	DF	SS	MS	F	P	% contribution
Regression	3	0.05679	0.018931	2.76	0.151	
Sliding velocity (V) (m/s)	1	0.01162	0.0111616	1.70	0.250	20.48
Applied pressure (P) (MPa)	1	0.02927	0.029367	4.29	0.093	51.69
Sliding time [t], (min)	1	0.01581	0.015811	2.31	0.189	27.83
Error	5	0.03424	0.006848			
Total	8	0.09103				

S 0.0827507, *R-sq* 62.39%, *R-sq (adj)* 39.82%

ANOVA for signal-to-noise ratio

ANOVA is a vital statistical method that allows for the assessment of the differences in variances among the means of various groups in experimental data. This approach helps in making well-informed choices by assessing the importance of different factors that impact the outcomes. In this study, the evaluated factors consist of sliding velocity, applied pressure, and sliding time, while the response variable is the SN as illustrated in Fig. 4.

The probability plot for wear by weight loss (W), SWR (Ws), and friction coefficient (f) indicates that the data dispersion aligns with a normal distribution (Fig. 3). Tables 7, 8, and 9 present a summary of the findings derived from ANOVA and provide insight into how each element contributes to the variability observed in the SNR.

The main effect plots for SNR and mean values visually represent the distinct impacts of sliding velocity, applied pressure, and sliding time on the tribological performance of unfilled PTFE. These graphical representations successfully illustrate the impact of each parameter, providing a comprehensive understanding of their effects on key metrics like wear (W), SWR (Ws), and friction coefficient (f).

This concise yet comprehensive portrayal is crucial for comprehending the main factors that impact the results of the Taguchi analysis aimed at minimizing response parameters for PTFE materials used in bearings. The Taguchi analysis was thoroughly performed to assess wear based on weight loss (W), SWR (Ws), and friction coefficient (f) with Fig. 2a, b, and c showcasing the results. Notably, Fig. 2a indicates that sliding velocity emerges as the most influential factor in minimizing wear.

It is observed that for wear to be minimum, the optimum values of sliding velocity, applied pressure, and sliding time to be used are 0.5 m/s, 0.562 MPa, and 45 min, respectively. Similarly, from Fig. 2b, sliding time is the most influential factor for minimum SWR (Ws). It is observed that for SWR (Ws) to be minimum, the optimum values of sliding velocity, applied pressure, and sliding time are 0.1 m/s, 0.562 MPa, and 45 min, respectively. Figure 2c indicates applied pressure is the most influential factor for minimum friction coefficient (f). It is found that for minimum friction coefficient (f), the optimum values of sliding velocity, applied pressure, and sliding time to be used are 0.5 m/s, 0.562 MPa, and 60 min, respectively. Thus, the main effects plot for SN ratios and means is a crucial element of the Taguchi analysis which offers useful insights into the elements that greatly affect the overall tribological performance of unfilled PTFE material. This tool effectively highlights the relative importance of each parameter, enabling a deeper understanding of their contributions to performance outcomes. By visually representing these relationships, the

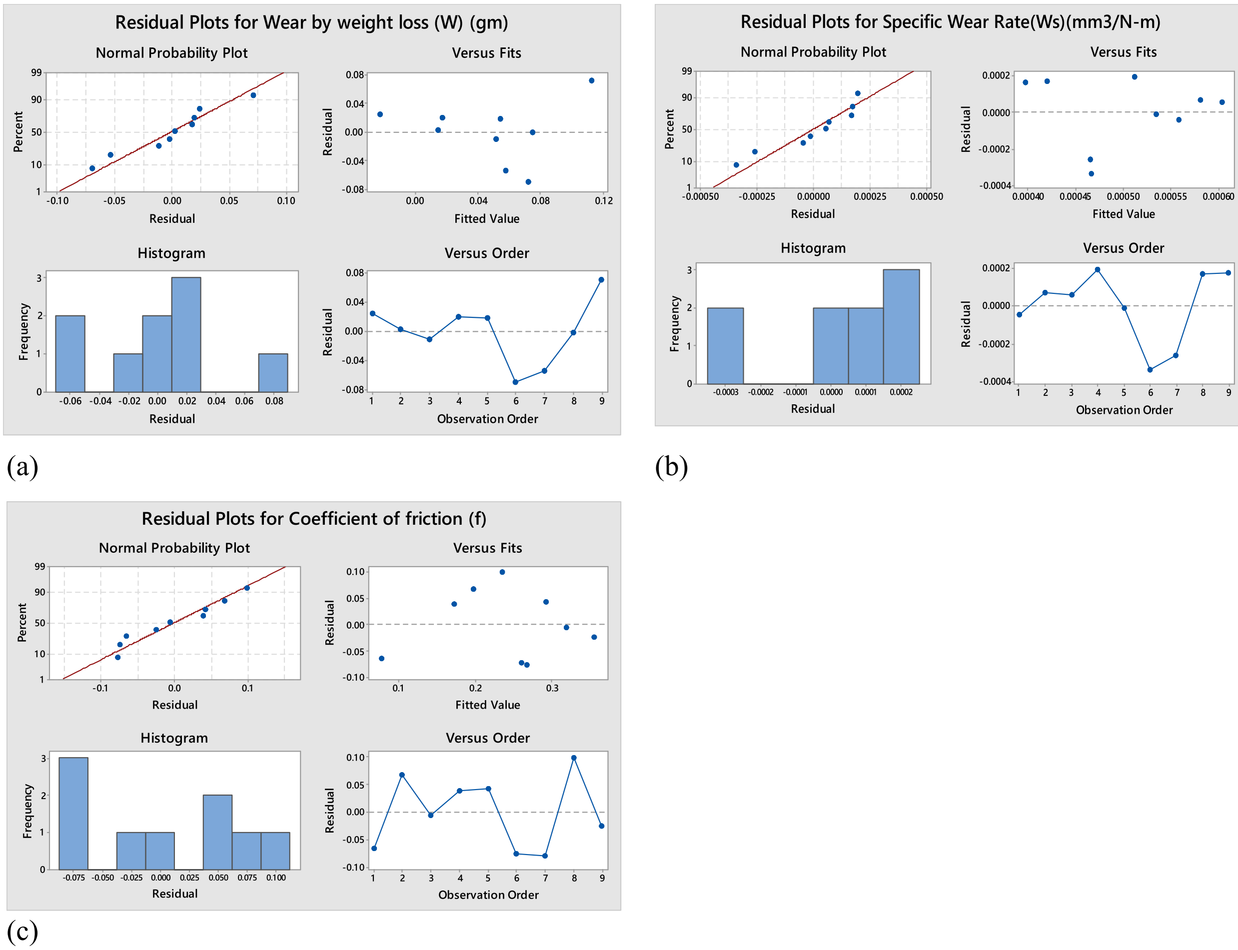


Fig. 4 **a**, **b**, **c** Residual plot (means) for wear (W), SWR (Ws), and friction coefficient (f)

plot aids in identifying optimal conditions for minimizing wear and enhancing the durability of PTFE in tribological applications.

Regression model for wear by weight loss (W), SWR (Ws), and friction coefficient (f) due to sliding velocity, applied pressure, and sliding time

The regression model (Eq. 3) developed for wear, as measured by weight loss, in relation to sliding velocity, applied pressure, and sliding time provides a quantitative framework for predicting the tribological behavior of unfilled PTFE material. This model elucidates the intricate relationships between the operating parameters and response variables, thereby facilitating precise optimization of tribological properties. One notable result of the Taguchi analysis is that the model provides a structured method for improving the performance of PTFE in bearing applications. By clearly delineating the influence of each variable, it supports informed decision-making aimed at achieving superior surface tribological characteristics.

The evaluation of the residual plots presented in Fig. 4a, b, and c offers valuable insights into the appropriateness of the linear model for the dataset. A consistent vertical spread of the data points around the horizontal line at zero reflects the model's fit. When the residuals demonstrate a random and uniform distribution about this central line, it suggests that the linear model adequately captures the underlying relationship in the data. Importantly, the absence of significant deviations between the residual line and the fitted line reinforces the notion of a linear association between the predictor variables and the dependent variable.

The visual representations offer a detailed insight into how the predictors relate to the response variable, which helps assess whether the linear model is suitable for the dataset. Regression analysis was used to identify the relationships between the response variable and the input factors, reinforcing the validity of the established model in predicting tribological performance. Hence, summarized results for all responses according to the regression analysis (Tables 7, 8, and 9) are processed leading to the formulation of the generalized equations for all the three responses.

Equation (3) delineates the association between wear by weight loss and the parameters sliding velocity, applied pressure, and sliding time used in the process.

$$\text{Wear by weight loss (W) (g)} = -0.0613 + 0.168\text{V} + 0.0705\text{P} + 0.00043\text{t} \tag{3}$$

Equation (4) establishes the connection between the SWR (Ws) and the factors of sliding velocity, applied pressure, and sliding time utilized in the process.

$$\text{SWS (Ws) (mm}^3/\text{N} - \text{m}) = 0.000540 - 0.000018\text{P} + 0.000002\text{t} \tag{4}$$

Equation (5) gives the association between friction coefficient (f) and the parameters sliding velocity, applied pressure, and sliding time used in the process.

$$\text{Friction coefficient (f)} = -0.068 + 0.220\text{V} + 0.1599\text{P} + 0.00342\text{t} \tag{5}$$

Table 10 shows optimum parametric combination for the individual response desirability with single objective optimization.

Contour plots of wear (W), SWR (Ws), and friction coefficient (f) for sliding velocity and applied pressure

Contour plots serve as useful instruments for illustrating how a response variable interacts with two control variables, providing a visual depiction of predicted response values across discrete contours. In Fig. 5, the graphs demonstrate how process parameters are connected to wear as shown by weight loss.

A closer examination of Fig. 5a reveals that higher wear by weight loss occurs at elevated sliding speeds and applied pressures. Conversely, the data indicates that lower levels of wear can be achieved at reduced sliding speeds and pressures. Notably, minimal wear is observed at high sliding speeds coupled with pressures up to 0.3 MPa, reinforcing the linear correlation between pressure and wear; specifically, increased pressure tends to lead to greater wear. Figure 5b illustrates how sliding velocity and pressure influence the SWR. The SWR reaches its peak at low pressure and moderate sliding speed. Conversely, the minimum SWR occurs at higher pressure levels with moderate sliding speeds, indicating an inverse relationship with pressure. This suggests that to achieve the lowest specific wear rate, it is beneficial to maintain higher pressure combined with moderate sliding speed, as illustrated in the contour plot. Figure 5c further explores the effect of sliding velocity and pressure on the friction coefficient (f). The plot demonstrates a linear relationship, indicating that as sliding velocity and pressure increase, the COF also rises. Therefore, to minimize COF, it is advisable to keep both sliding velocity and pressure at lower levels, as shown in the contour plot. These findings underscore the importance of carefully selecting operating parameters to optimize tribological performance in practical applications.

Worn surface morphology

Scanning electron microscope (Field Electron and Ion Company Model Quanta 200 ESEM) was used to obtain the micrographs of the worn surfaces of the test specimen tested on pin on disk setup for sample number 2 subjected to 0.1 m/s sliding velocity, 0.562-MPa sliding pressure, and 45-min sliding time), sample number 8 (0.5 m/s sliding velocity, 0.562-MPa sliding pressure, 45-min sliding time), and sample number 9 (0.5 m/s sliding velocity,1-MPa sliding pressure, 60-min sliding time).

PTFE is likely to leave the contacting area during the friction process and generate large flakes (Wang and Yan 2006). The wear mechanism of an unfilled PTFE can be described by different modes such as adhesive wear, wear debris formation, and contact plateau formation. Some of researchers also mention the wear mechanisms for PTFE material (Khedkar et al. 2002). Figure 6a shows the sample before wear. Figure 6b shows wear occurs due to adhesive wear, contact plateau, and wear debris

Table 10 Optimum parametric combination

Response	Optimal actual values			Optimal response value
	Sliding velocity (V) (m/s)	Pressure (P) (MPa)	Sliding time (T) (min)	
Wear W (gm)				0.074
	0.5	0.562	45	
Specific wear rate Ws (mm^3/Nm)				0.000648307
	0.1	0.562	45	
Friction coefficient (f)	0.5	0.562	60	0.332

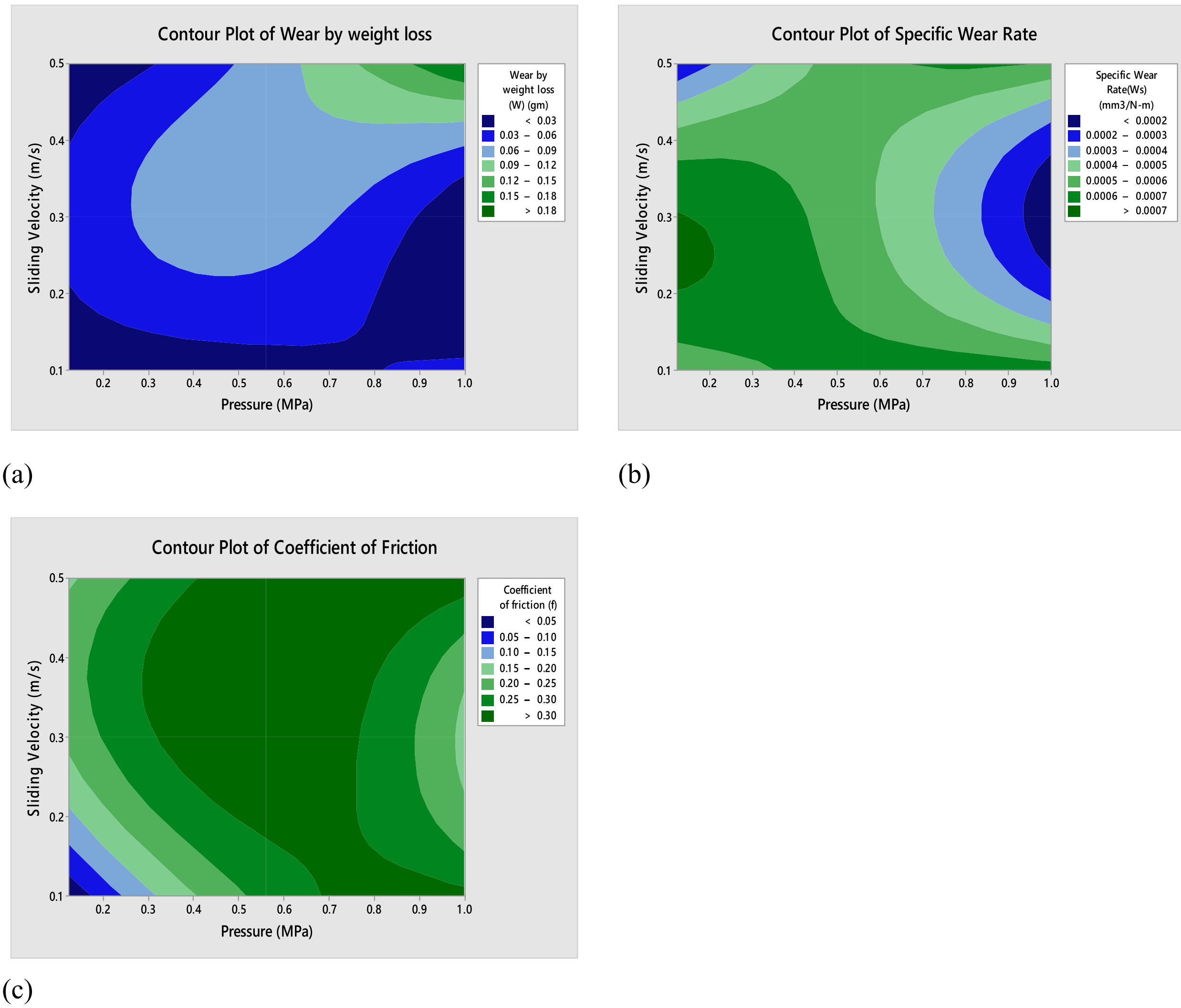


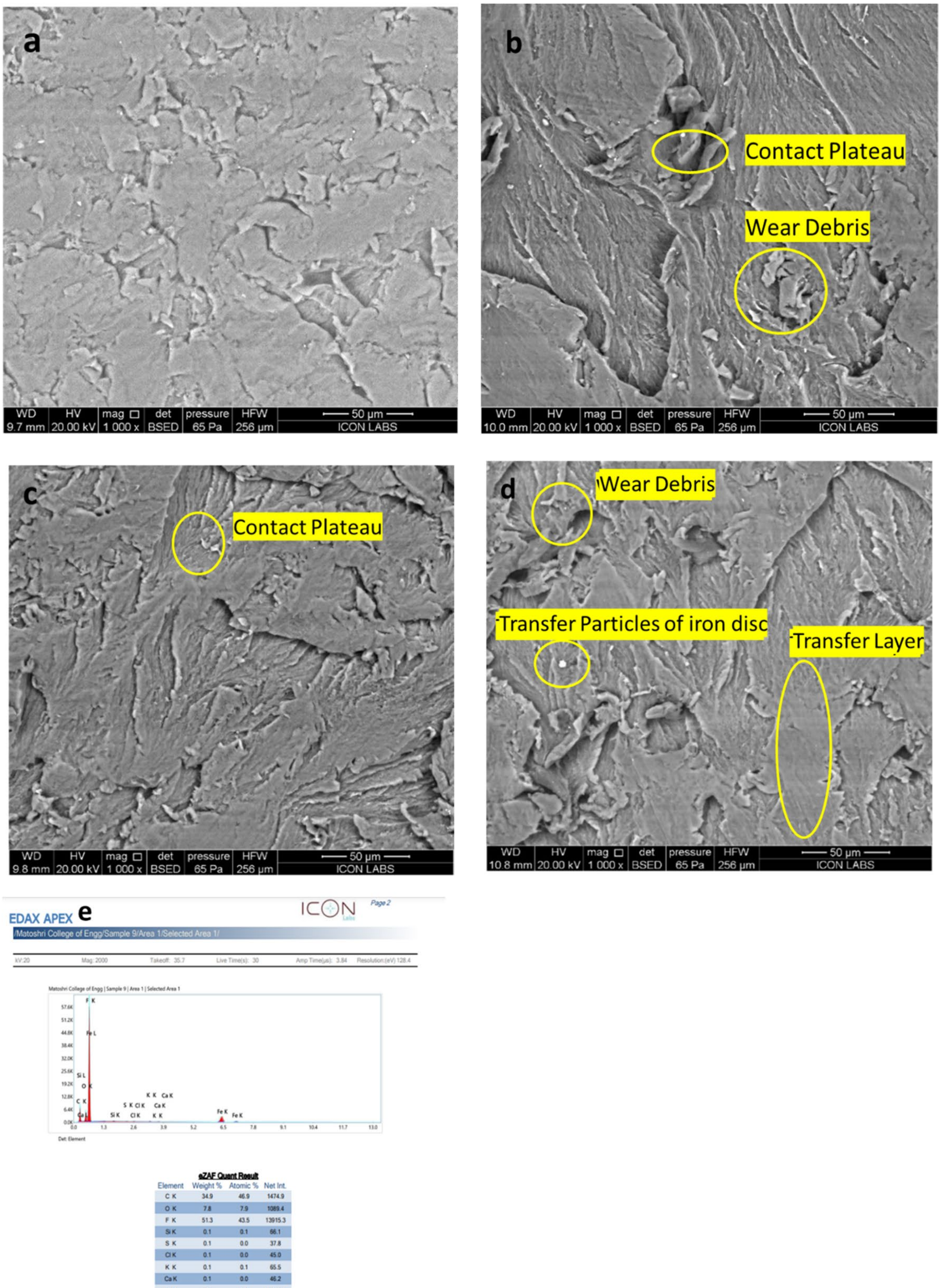
Fig. 5 Contour plots of (**a**) wear for sliding velocity and applied pressure, (**b**) specific wear rate for sliding velocity and applied pressure, and (**c**) coefficient of friction for sliding velocity and pressure

formation. Sample number 2 is subjected to 0.1 m/s sliding velocity, 0.562-MPa sliding pressure, and 45-min sliding time. The wear by weight loss and COF is lesser as compared to sample numbers 8 and 9 which are subjected to higher sliding speed (Tanaka and Kawakami 1986). But the SWR is higher as compared to other samples. Similarly, sample 8 as shown in Fig. 6c shows wear due to adhesive wear and multiple contact plateau. Sample 9 as shown in Fig. 6d shows wear due to multiple contact plateaus, transfer particles of rotating iron disc, transfer layer, and wear debris. This occurs due to higher sliding velocity, sliding pressure, and sliding time as compared to sample numbers 2 and 8 (Tanaka and Kawakami 1986). Figure 6e shows the EDAX report of sample 9 showing main constituents as fluorine, chlorine, iron particles, and also dust particles like silica and calcium.

Multilayer ANN structure

Artificial neural networks (ANNs) are computational tools designed to develop mathematical models that mimic the functioning of the human brain (Zhang and Friedrich 2003). Inspired by the human nervous system, ANNs consist of interconnected neurons that communicate information among themselves. They are widely utilized for tasks involving pattern recognition, data classification, and prediction (Kanai et al. 2016).

In the current study, an input–output mapping was established using ANNs, which utilized a network of interlinked nodes (neurons). The input data were introduced to the network through input units, subsequently passed to a hidden layer, and ultimately processed to generate predictions through the output layer located on the far right. The architecture employed was a supervised



Element	Weight %	Atomic %	Net Int.
C K	34.9	46.9	1474.9
O K	7.8	7.9	1089.4
F K	51.3	43.5	13915.3
Si K	0.1	0.1	66.1
S K	0.1	0.0	37.8
Cl K	0.1	0.0	45.0
K K	0.1	0.1	65.5
Ca K	0.1	0.0	46.2
Fe K	5.5	1.6	1325.0

Fig. 6 **a** SEM image of PTFE sample before wear. **b** SEM image of PTFE sample number 2 after wear. **c** SEM image of PTFE sample number 8 after wear. **d** SEM image of PTFE sample number 9 after wear. **e** EDAX report of sample number 9

feed forward multilayered ANN, trained using scaled conjugate gradient algorithms (Bose and Liang 1996).

The input layer consisted of three design variables: sliding velocity, applied pressure, and sliding time. The outputs of interest included the tribological performances characterized by wear, SWR, and friction coefficient (f). A hidden layer was positioned between the input and output layers, as illustrated in Fig. 7. This structured approach allows for effective modeling of the complex relationships among the input variables and the response outputs, enhancing the predictive capabilities of the network.

Every dataset for training, validation, and testing, combined with a comprehensive trend analysis, offers important insights into how input parameters affect the wear, SWR, and friction coefficient of PTFE material. The graphs generated through MATLAB for wear, specific wear, and COF serve as essential tools for optimizing tribological parameters. The trends observed in these graphs facilitate the identification of optimal conditions for sliding velocity, applied pressure, and sliding time, enabling researchers and practitioners to achieve a balance that minimizes wear, specific wear rate, and COF. By contrasting the expected values with real results, these graphs enhance trust in the predictive model. A strong correspondence between the anticipated and real value underline the model's precision and its usefulness in determining ideal operating conditions for PTFE materials.

In conclusion, the graphs illustrating wear, SWR, and friction coefficient, generated from the MATLAB artificial neural network analysis and shown in Fig. 8, act as effective visual tools that enhance comprehension, verification, and optimization of design variables. Their role in improving the predictive accuracy of models and supporting advancements in practical operating conditions is vital for refining the selection of design variables. Additionally, the *R*-values from the regression analysis assess the relationship between outputs and targets, where an *R*-value of 1 represents a strong correlation, while an *R*-value of 0 indicates randomness. The average squared deviations between expected outputs and actual targets are measured by the mean-squared error (MSE) where a value of zero denotes perfect accuracy, and lower MSE values imply better model performance.

Model comparison

In this section, there is a comparative analysis of the prediction outcomes from the modified regression model and the ANN aimed at enhancing the tribological performance of unfilled PTFE material. The two models' capacity for prediction were evaluated in the context of wear performance under static loading conditions for rolling and sliding bearings. The study utilized the tribological behavior of unfilled PTFE with input parameters sliding velocity, applied pressure, and sliding time and output parameters including wear, SWR and Friction Coefficient (f). The ANN was trained utilizing the Levenberg Marquardt (LM) learning algorithm in conjunction with a tangent sigmoid activation function (Zhang and Friedrich 2003). A detailed dataset consisting of nine sets was used, with 50% designated for training, 25% for validation, and the final 25% for testing (Zhang and Friedrich 2003). This dataset provided diversity and strength in the modeling process.

The results demonstrated remarkable accuracy, achieving an overall R2 value of 92.78% (as shown in Table 11). In evaluating the predictive accuracy of the modified regression model against that of the ANN, the latter exhibited superior results, achieving over 85% accuracy based on R^2 values for the training dataset. Both models demonstrated robust predictive performance; however, the analysis clearly indicates the potential of ANN structures to significantly improve predictions regarding the tribological behavior of unfilled PTFE under static loading conditions.

This comparison highlights the superior capability of the ANN in forecasting wear, specific wear rate, and friction coefficient when compared to the regression model's predictions of the signal-to-noise ratio (SNR) of unfilled PTFE. Overall, the findings underscore the efficacy of ANN models in optimizing tribological analyses and guiding the selection of optimal operating conditions for PTFE materials.

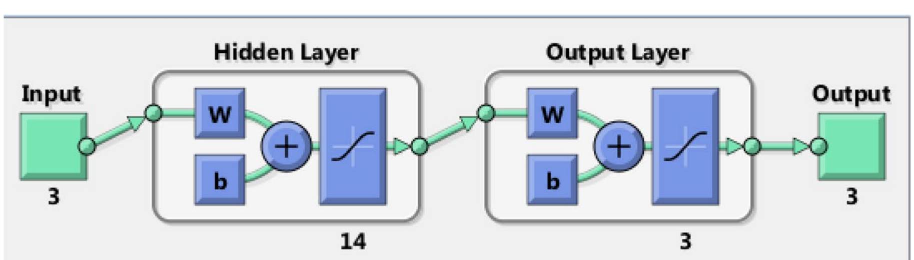


Fig. 7 Schematic illustration of ANN structure

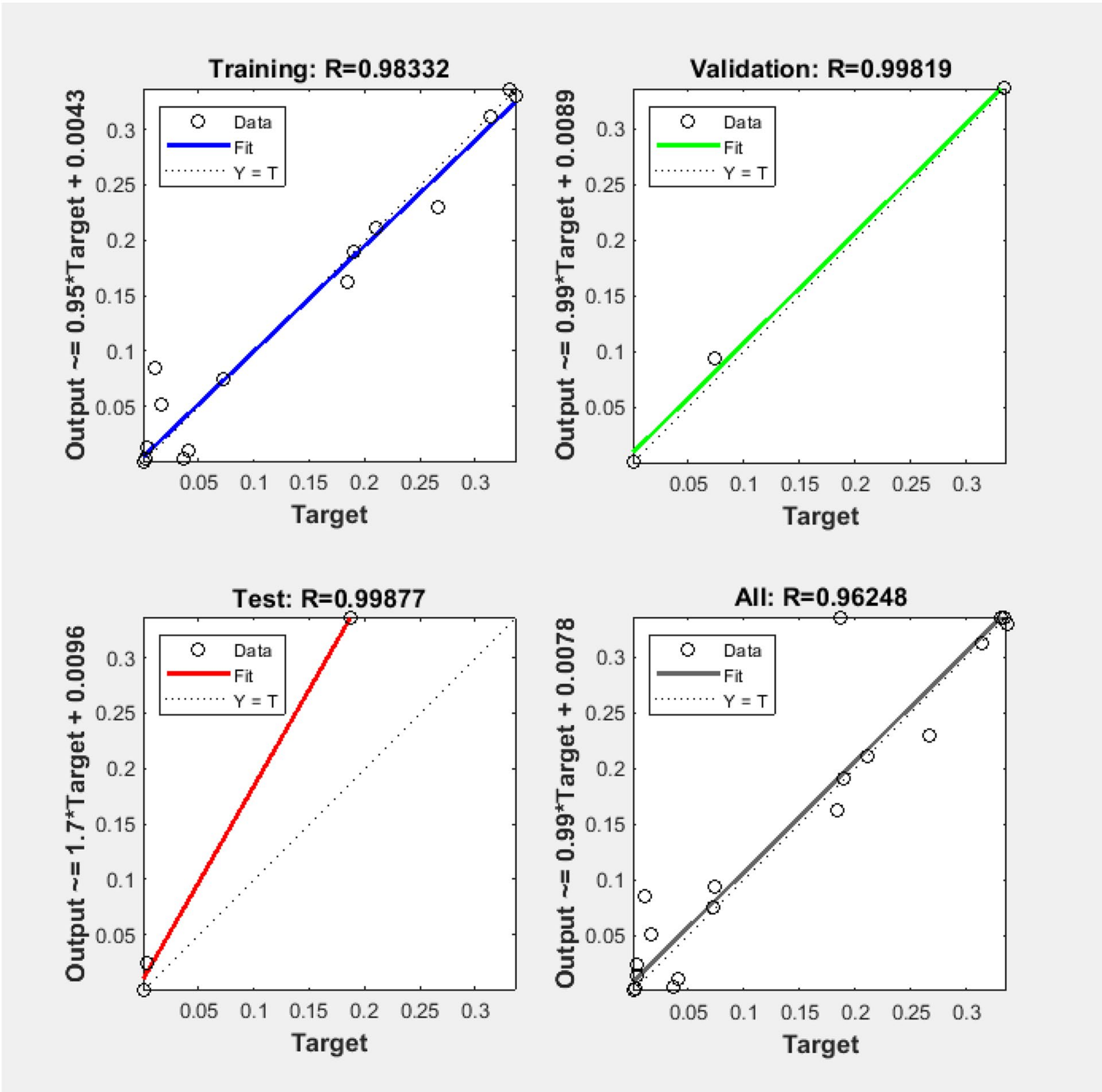


Fig. 8 ANN regression graphs for the training, validation, test, and total datasets

Table 11 Comparison between the regression models and artificial neural networks (ANNs)

Model	Statistical method	Factors considered	Response variable	Performance metric	Accuracy (%)
Regression models	Ordinary least squares (OLS)	Sliding velocity, pressure, sliding time	Signal-to-noise ratio (SNR)	R-squared (R^2)	62.39
Artificial neural networks (ANNs)	Levenberg–Marquardt algorithm (Zhang and Friedrich 2003)	Sliding velocity, pressure, sliding time	Wear (W), SWR (Ws), and friction coefficient (f)	R-squared (R^2)	96.25

Conclusion

- The primary objective of this study was to investigate the effects of sliding velocity, applied pressure, and sliding time on the tribological behavior of unfilled PTFE material used in rolling and sliding contact bearings. The research specifically aimed to optimize these operating parameters concerning wear (W), SWR (Ws), and friction coefficient (f) through the Taguchi analysis.
- The findings from the research offer important perspectives on enhancing optimization of operational parameters for bearing applications. It was found that sliding velocity is the most influential factor affecting wear by weight loss, while sliding time significantly impacts SWR and applied pressure is critical for COF. The interplay among these factors has an important role in determining the tribological properties of unfilled PTFE.
- To improve predictive accuracy, the research implemented both regression and artificial neural network models, aimed at understanding the intricate relationships between operating parameters and tribological responses. While both models exhibited different levels of effectiveness, a thorough evaluation of the estimated outcomes and error metrics was performed to determine the most appropriate model for precise wear estimation. This careful methodology guarantees the identification of a dependable model for forecasting wear (W), SWR (Ws), and friction coefficient (f) for unfilled PTFE material. Considering the growing importance of advanced machine learning models for accurate prediction and optimization in engineering applications, this study aligns with recent research trends exploring deep learning-based solutions in complex systems. Leveraging concepts from digital twin technology can further enhance predictive insights and real-time process optimization for wear and frictional behavior analysis (Khamkar and Patil 2024).
- The study suggests employing an ANNs as a predictive instrument to assess and improve existing regression models. By utilizing a combination of operating and response variables, the ANN was trained and evaluated resulting in exceptionally high R^2 values of 99.98%, which signify an outstanding fit and strong correlation. A comparative assessment demonstrated that ANN models surpassed conventional regression models as shown by their higher R^2 values. This approach reflects the broader utility of artificial intelligence techniques in tribological research, similar to their successful application in industrial automation contexts, such as collision avoidance tasks in robotic systems. The integration of reinforcement learning could be further explored to optimize predictive models for wear dynamics (Kadam and Patil 2024).
- To assess the performance of the created ANNs models, separate data sets were employed confirming their accuracy in predicting process wear (W), SWR (Ws), and friction coefficient (f). The modified regression model produced predictions wear (W), SWR (Ws), and friction coefficient (f) up to 62%, while the ANN demonstrated even higher accuracy, surpassing 96% based on R^2 values. This underscores the ANN's superiority as a predictive tool for monitoring wear by weight loss, specific wear rate, and COF for unfilled PTFE.
- Overall, the findings highlight the potential for real-time control of tribological properties, ensuring optimal wear, specific wear rate, and COF for bearing applications. This study offers an in-depth examination using regression and ANN models to forecast wear by weight loss, specific wear rate, and COF for unfilled PTFE which were used in sliding and rolling contact bearings. The suggested ANN tool exhibits enhanced predictive abilities when compared to conventional regression models, thereby providing significant contributions to the selection and application of unfilled PTFE materials in tribological contexts.
- The results of this investigation contribute to the advancement of PTFE by providing critical insights into its friction and wear behavior under static unlubricated conditions. This contributes to improved material performance such as wear resistance, improved mechanical properties, and lowered friction in PTFE as a reinforcement in acetate composites. The development of PTFE composites supports the design of more durable PTFE components. It enhances product longevity and offers potential for cost-effective solutions by minimizing wear and reducing dependency on lubrication. Ultimately, these developments can lead to more efficient and reliable PTFE-based products in aerospace, automobile, medical devices, industrial manufacturing such as heavy machinery, and other sectors. Given the success of machine learning-based solutions in agricultural disease detection tasks, the implementation of CNN techniques could also serve as a valuable tool for automated monitoring of tribological properties and defect detection in PTFE components during manufacturing processes (Upadhye et al. 2023).

Authors' contributions
Kiran Ashokrao Chaudhari : Writing - Original draft, Project Administration, Methodology, Investigation, Formal Analysis, Data curation, Conceptualization, Visualization, Validation.Jayant Hemchandra Bhangale : Writing - Review & editing, Writing - Original draft, Supervision, Project Administration, Methodology ,Resources, Formal Analysis, Conceptualization.

Funding
This work is not supported fully or partially by any funding organization or agency.

Declarations

Competing interests
The authors declare that they have no competing interests.

Received: 10 November 2024 Accepted: 6 February 2025
Published online: 17 February 2025

References
Aldousiri B et al (2013) Review on tribological behaviour of polymeric composites and future reinforcements. J Adv Mat Sci Eng. 2013(1):645923. https://doi.org/10.1155/2013/645923
Arya S, Anju, Ramli NA (2024) Predicting the stress level of students using supervised machine learning and artificial neural network (ANN). Ind J Eng 21:e9ije1684. https://doi.org/10.54905/disssi.v21i55.e9ije1684
ASTM Designation: G-99 – 95a (Reapproved 2000)ε1 Standard test method for wear testing with a pin-on-disk apparatus1
Barhatte S, Lele M (2024) Investigations on microchannel heat exchanger using numerical, experimental, and ANN techniques. Ind J Eng 21:e7ije1682. https://doi.org/10.54905/disssi.v21i55.e7ije1682
Basavarajappa S, Arun KV, Davim JP (2009) Effect of filler materials on dry sliding wear behavior of polymer matrix composites – a Taguchi approach. J Min Mat Charact Eng 8(5):379–391. https://doi.org/10.4236/jmmce.2009.85034
Biswas SK, Vijayan K (1992) Friction and wear of PTFE – a review. Wear 158(1-2):193–211. https://doi.org/10.1016/0043-1648(92)90039-B
Blanchet TA, Kennedy FE (1992) Sliding wear mechanism of poly tetra fluoro ethylene (PTFE) and PTFE composites. Wear 153(1):229–243. https://doi.org/10.1016/0043-1648(92)90271-9
Bocîi LS (2021) Theoretical and experimental determination of the force generated by the pressure of the friction pad in the brake disc of railway vehicles. Ind J Eng 18(50):446–452. ISSN 2319–7757 EISSN 2319–7765 I OPEN ACCESS
Bose NK, Liang P (1996) Neural network fundamentals with graphs, algorithms, and applications. McGraw-Hill, Inc.
Dhanumalayan E, Joshi GM (2018) Performance properties and applications of polytetrafluoroethylene (PTFE) - a review. J Adv Composites Hybrid Mat. https://doi.org/10.1007/s42114-018-0023-8
Friedrich K (2018) Polymer composites for tribological applications. Journal of Advanced Industrial and Engineering Polymer Research 1:3–39. https://doi.org/10.1016/j.aiepr.2018.05.001
Golchin A, Simmons GF, Glavatskih SB (2012) Break-away friction of PTFE materials in lubricated conditions. Tribol Int 48:54–62. https://doi.org/10.1016/j.triboint.2011.03.025
Joshi MD, Goyal A, Patil SM, Goyal RK (2016) Tribological and thermal properties of hexagonal boron nitride filled high-performance polymer nanocomposites. J Appl Polymer Sci Wiley Periodicals. https://doi.org/10.1002/app.44409
Kanai RA, Desavale1 RG, Chavan SP (2016) Experimental based faults diagnosis of rolling bearings using artificial neural network. J Tribol. https://doi.org/10.1115/1.4032525
Khamkar AD, Patil SM (2024) Digital Twin in fluid power: review- technology trends. Int Res J Multidisciplinary Scope (IRJMS) 5(2):596–610. https://doi.org/10.47857/irjms.2024.v05i02.0586
Khedkar J, Negulescu I, Meletis EI (2002) Sliding wear behavior of PTFE composites. J Wear 252:361–369. https://doi.org/10.1016/S0043-1648(01)00859-6
Klaas NV et al (2005) The tribological behaviour of glass filled polytetrafluoroethylene. J Tribol Int 38:824–833. https://doi.org/10.1016/j.triboint.2005.02.010
Lewis MWJ (1986) Friction and wear of PTFE-based reciprocating seals. Lubrication Eng. 42(3):152–158
Makinson KR, Tabor D (1964) The friction and transfer of polytetrafluoroethylene. Proc R Soc London, Series A: Mathematical and Physical Sciences. 1964;281:49–61. https://doi.org/10.1098/rspa.1964.0168
Myshkin NK, Petrokovets MI, Kovalev AV (2005) Tribology of polymers; adhesion, friction, wear, and mass transfer. Tribol Int. 38(11-12):910–921. https://doi.org/10.1016/j.triboint.2005.07.016
Pansare PD, Bajaj DS, Aher VS (2021) Tribological behaviour of PTFE composite material for journal bearing. Int J Innov Eng Res Technol. pp 1-5. https://repo.ijiert.org/index.php/ijiert/article/view/730
Patil SM, Ahuja BB (2014) Tribological behavior of PTFE under variable loading dry sliding condition. J Inst Eng India Ser C 95(2):179–185. https://doi.org/10.1007/s40032-014-0106-4
Pazderova M et al (2011) Tribological behavior of composite coatings. J Eng Procedia 10:472–477
Rodiouchkina M et al (2021) Tribological behaviour and transfer layer development of self-lubricating polymer composite bearing materials under long duration dry sliding against stainless steel. J Wear https://doi.org/10.1016/j.wear.2021.204027
Rudresh B, Ravikumar BN, Madhu D (2020) Dry sliding friction and wear behavior of hybrid glass carbon fiber reinforced PA66/PTFE composites. Tribol Finnish J Tribol 37(1–2):15–25. https://doi.org/10.30678/fjt.88615
Rymuza Z (2007) Tribology of Polymers. Arch Civil Mechan Eng, Warsaw University of Technology, Poland. 7(4). https://doi.org/10.1016/S1644-9665(12)60235-0
Shah NCF, Basu SK (1984) On tribological aspects of unfilled plastics. Mechan Eng Bull. 15:9–14. https://www.researchgate.net/publication/291755959_On_tribological_aspects_of_unfilled_plastics
Shibo W et al (2017) Tribological behavior of polytetrafluoroethylene:effect of sliding motion. J Tribol 139. https://doi.org/10.1115/1.4033130
Shukla AK, Shukla A, Singh R (2023) Neural networks based face recognition system for biometric security. Ind J Eng 20:e16ije1640 https://doi.org/10.54905/disssi/v20i53/e16ije1640
Tanaka K, Kawakami S (1982) Effect of various fillers on the friction and wear of PTFE-based composites. Wear 79:221–234
Tanaka K, Kawakami S (1986) Chapter 5 Effects of various fillers on the friction and wear of PTFE-based composites. Composite Mat Ser, Elsevier 1:137–174 ISSN 0927–0108, ISBN 9780444425249. https://doi.org/10.1016/B978-0-444-42524-9.50009-0
Unal H, Mimaroglu A (2003) Influence of test conditions on the tribological properties of polymers. Ind Lubrication Tribol, 55(4):178–183. https://doi.org/10.1108/00368790310480362
Unal H, Mimaroglu A, Kadioglu U, Ekiz H (2004) Sliding friction and wear behavior of PTFE and its composites under dry conditions. Mater des 25:239–245. https://doi.org/10.1016/j.matdes.2003.10.009
Ve QL, Do MC, Nguyen TC, Nguyen QH, Nguyen QL (2024) Energy aspects and cost analysis in direct contact membrane distillation using commercial PTFE membranes. Ind J Eng 21:e8ije1683. https://doi.org/10.54905/disssi.v21i55.e8ije1683
Vishwanath N, Bellow DG (1995) Development of an equation for the wear of polymers. Wear 181–183(1):42–49
Wang Y, Yan F (2006) Tribological properties of transfer films of PTFE-based composites. J Wear 261:1359–1366. https://doi.org/10.1016/j.wear.2006.03.050
Yu JH et al (2015) Study on the performance of wollastonite modified PTFE composite material. J Adv Mat Res 1089:28–32. https://doi.org/10.4028/www.scientific.net/AMR.1089.28
Zhang Z, Friedrich K (2003) Artificial neural networks applied to polymer composites: a review. J Composites Sci Technol 63:2029–2044. https://doi.org/10.1016/S0266-3538(03)00106-4
Kadam AC, Patil SM (2024) Reinforcement learning-based collision avoidance of Kinova Gen3 robot for ball balancing task. Int Res J Multidisciplinary Scope (IRJMS) 5(1):336–354. https://doi.org/10.47857/irjms.2024.v05i01.0213
Upadhye SA, Dhanvijay MR, Patil SM (2023) Sugarcane disease detection using CNN-deep learning method: an Indian perspective. Univ J Agri Res 11(1):80–97. https://doi.org/10.13189/ujar.2023.110108

Publisher's Note