International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Journal Européen des Systèmes Automatisés
Vol. 58, No. 9, September, 2025, pp. 1839-1849
Journal homepage: http://iieta.org/journals/jesa

Prediction of Specific Wear Rate of Laser Powder Bed Fusion Manufactured Inconel 718 Material Using Different Supervised Machine Learning Algorithms

Tejan Chavan[1], Nitin Khedkar[1,2], Vijayshri Khedkar[3*]

[1] Department of Mechanical Engineering, Symbiosis Institute of Technology, Pune Symbiosis International (Deemed University), Pune 412115, India
[2] Dr. Vishwanath Karad MIT World Peace University, Pune 411038, India
[3] Department of Computer Science Engineering, Symbiosis Institute of Technology, Pune Symbiosis International (Deemed University), Pune 412115, India

Corresponding Author Email: vijayshri.khedkar@sitpune.edu.in

https://doi.org/10.18280/jesa.580907

Received: 1 August 2025
Revised: 3 September 2025
Accepted: 16 September 2025
Available online: 30 September 2025

Keywords:
specific wear rate, Inconel 718, Random Forest, Polynomial Regression, Gaussian Process Regression, Linear Regression, machine learning, laser powder bed fusion

ABSTRACT

The Inconel 718 superalloy materials are having properties such as high strength, and excellent wear resistance. These properties make it crucial material wherein wear resistance become decisive factor in structural and functional performance of components. This research paper investigates prediction of specific wear rate of Inconel 718 material manufactured by laser powder bed fusion process, using supervised machine learning models like Linear Regression, Random Forest, Polynomial Regression and Gaussian Process Regression. The data acquisition was done by performing experiment on pin-on-disk apparatus under dry friction condition for different loads, sliding distance and rotational speed of disk. Total of 100 data points were collected from experiments to study effect of load, sliding distance and volume loss on specific wear rate. The results shown that Polynomial Regression displayed best performance compared to other machine learning models thereby achieving a coefficient of determination (R^2) value of 0.9969 and 5-Fold Cross validation value of 0.9968 i.e. 99.68%. Further investigation is carried using Pearson correlation heatmap to determine the most influential parameter that can affect specific wear rate and conclusion drawn is that volume loss and normal load applied have strong influence on specific wear rate of Inconel 718 material.

1. INTRODUCTION

Inconel 718 is a specialized nickel-chromium alloy mainly because of aluminum, titanium, and niobium as alloying elements that forms precipitation of γ' Ni3(Al-Ti) phase and metastable γ" Ni3Nb phase [1]. Inconel 718 has been used in aerospace components, such as critical rotating parts like gas turbine blades and pressure vessels, thus making up for 30% extra of the total heaviness of a modern airplane engines [2]. This alloy is designed for high strength, creep resistance, and good fatigue life which can give good performance at elevated temperatures of up to 700°C and is known to have good weldability property [3]. The industry 4.0, fourth version of industrial revolution, which strive to substitute traditional manufacturing with a manufacturing process which exactly opposite to traditional manufacturing like additive manufacturing process that can produce nearly final product component or part as economically and capable for bulk quantity production [4]. An example of a revolutionary approach is Additive Manufacturing (AM), which can create products far more quickly and with better accuracy as compared to traditional techniques [5] Additive manufacturing (AM), generally called as tri-dimensional printing, in which parts are fabricated by adding material layers, thereby forming complex geometry. The AM processes include extrusion, binder jetting material jetting, sheet lamination, laser powder bed fusion directed energy deposition, and vat polymerization, all of which require the initial modelling of the object on a computer before converting it into machine instructions for construction [6]. Several studies consistently show that LPBF process parameters such as laser power, scan speed, hatch distance, and volumetric energy density critically affect the microstructure, including grain morphology, phase distribution, and porosity, which directly influence wear resistance and friction behavior. Optimization of these process parameters can enhance densification and reduce defects, leading to better mechanical and tribological performance and also variations in scanning strategies further impact microstructural texture and wear mechanisms [7-15]. The application of heat treatment improves the wear resistance of LPBF manufactured Inconel 718. The alloy that has undergone heat treatment displays a higher density and increased hardness of precipitates, specifically the γ' and γ″ phases, which collectively enhance hardness and diminish the wear rate when contrasted with the as-fabricated state [16]. Heat treatments like SR, HIP, ST are the most widely used heat treatments process in industries. The LPBF processes generate significant residual stresses due to high power of laser and given that its dynamic nature of manufacturing, which can degrade mechanical properties. The residual stresses can reduce through heat treatments called SR, performed at high temperatures with prolonged holding periods for microstructure control. HIP is used in reducing porosity of printed parts. Earlier studies have specified that porosity of Inconel 718 can be minimized through HIP because the defects like lack of fusion and gas pores formed during L-PBF process now during heat treatment are reduced to some extent and thereby reducing the porosity of printed parts, with equiaxed grain formation also observed. Thus, post-build heat treatments promote the precipitation of strengthening phases (γ', γ″), recrystallization, and residual stress relief. These changes yield important improvements in hardness, tensile strength and wear resistance, reducing wear rates and friction coefficients under various test. Heat-treated samples display more stable tribo-layers and lower wear rates compared to as-built counterparts [17-22]. The sliding wear test of Inconel 718, manufactured by laser powder bed fusion, was conducted for following temperatures viz 28°C, 400°C, 500°C, and 600°C. The result is giving indication that wear damage and friction coefficient increased with temperature. At 28°C, abrasion wear was predominant, while delamination and oxidation wear dominated at higher temperatures. The wear debris size increased with temperature [23]. The wear rate of heat-treated L-PBF Inconel 718 is significantly improved compared to the as-fabricated state. Specifically, heat-treated L-PBF Inconel 718 demonstrates nearly half that of the as-fabricated sample. This substantial reduction indicates that post-process heat treatment such as solution treatment and aging effectively enhances the alloy's hardness and wear resistance [24, 25]. The corrosive environment has been demonstrated to increase the wear rate by 29.24% and 49.5% for additive manufactured and wrought Inconel 718 before the beginning of corrosion [26]. Multiple insights from research paper shows, in particular about Inconel 718, show that use of tungsten carbide (WC) or titanium carbide (TiC) particles significantly increased the hardness, friction resistance, and wear performance. The composite acquired a significantly low coefficient of friction. The presence of a gradient interface plays important role in improving the wear performance of LPBF-processed WC/Inconel 718 and TiC/Inconel 718 composites [27]. Various ML algorithms are trained for LPBF manufactured Inconel718 material specimen, the Naïve Bayes and ANN show more than 85% accuracy for porosity prediction while RF algorithm shows the best fit for density prediction. This highlights that ML plays important role in LPBF process [28]. Machine learning algorithms are also used to predict mechanical properties [29]. Zhan and Li [30] used different ML models like SVM, RF and ANN, to predict the fatigue life of additively manufactured 316 L stainless steel, using a database developed by engineering mechanics method called continuum damage mechanics.

The Gaussian Process Regression Machine Learning model found to effective in prediction of wear rate with $R^2 > 0.96$ of L-PBF manufactured materials [31]. ANN and LSTM are effective for capturing nonlinear time evolution of wear when time-series sensors are available, but require more training data and careful regularization [32, 33]. But these are used for milling and composite wear studies.

While the laser powder bed fusion technique presents considerable benefits regarding geometric intricacy and material characteristics, the wear rate of Inconel 718 can be further refined through meticulous regulation of processing variables, including heat treatment, laser remelting, and energy density. Such optimizations are essential for contexts where wear resistance is paramount, particularly within the aerospace and automotive sectors.

From the literature review it is obvious that most of study has been aligned to optimization of process parameter for LPBF process and subsequent studying its effect on mechanical properties and also influence of post processing heat treatment. The high temperature wear rate of Inconel 718 has been studied extensively and it also known that it is difficult to machine Inconel 718 material at room temperature. There is lack of studies regarding combined approach of experimentation on pin on disk apparatus and subsequent prediction of specific wear rate using machine learning models but rather they are focused milling, tool wear and composites wear studies. The novelty of this paper that it will address this gap by prediction of specific wear rate of Inconel 718 at room temperature with application of machine learning technique to find out best suitable ML model that can predict the specific wear rate proximity to experimental values.

2. METHODOLOGY

A. Material description:

In718 alloy has nickel element with mass fraction more than 50 % alloyed with iron and chromium up to 21%, along with additional elements. The mechanical properties comprise of high strength; excellent corrosion resistance and an operating temperature ranges up to 650°C. The material is in powder form with particle size distribution around 38-53 μm, prepared using Vacuum Inert Gas Atomization (VIGA) technique. The exact chemical configuration of IN718 alloy powder is given in Table 1.

Table 1. Chemical configuration of Inconel 718 alloy powder

Elements	% Mass
Nickel	35-55%
Chromium	17-21%
Iron	Balanced
Niobium	4.75-5.5%
Tantalum	4.75-5.5%
Molybdenum	2.8-3.3%
Titanium	0.65-1.15%
Cobalt	≤ 1%
Aluminum	0.2-0.8 %
Manganese	≤ 0.35%
Silicon	≤ 0.35%
Copper	≤ 0.30%
Carbon	0.02-0.05%
Nitrogen	≤ 0.03%
Oxygen	≤ 0.03%
Phosphorous	≤ 0.015%
Calcium	≤ 0.01%
Magnesium	≤ 0.01%

B. Sample fabrication:

The samples were fabricated at facility of Amison Engineering Pvt Ltd. Pune, using laser powder bed fusion machine named RenAM500 series with size of build volume of 250mm×250mm×350mm using ytterbium fibre lasers and with laser focus diameter of 80 μm. The fabrication of samples was done in controlled environment of argon shielding gas. The argon used has purity of 99.998% ensuring the process is not affected by residual oxygen. The L-PBF which is one of the additive manufacturing processes, is used to manufacture a cylindrical pin specimen with geometric specifications of diameter 8 mm and length 30 mm as shown in Figure 1.

After printing, the samples underwent a solution heat treatment at 980°C ± 10°C for 1 hr. The following Process parameter used to fabricate samples given in Table 2.

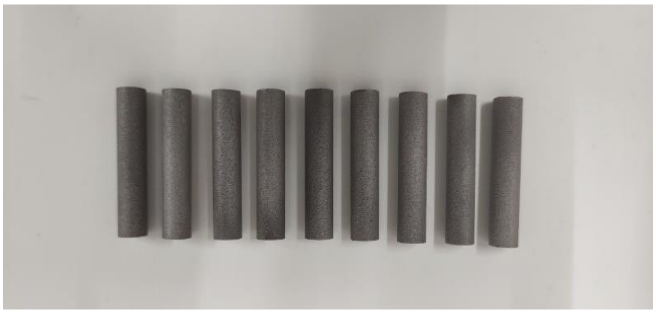

Figure 1. LPBF manufactured IN718 wear test samples as per ASTM G99 standards

Table 2. L-PBF process parameter values

Process Parameters Names	Units
Laser Power	380 W
Scanning Speed	1750 mm/s
Hatch Distance	95 µm
Layer Thickness	60 µm
Exposure Time	25 µs
Energy Density	44.44 J/mm^3
Scanning Strategy	Stripe

The methodology adopted in this research paper is represented as stepwise stages in Prediction of Specific wear rate of Inconel 718 flowchart as shown in Figure 2, from data acquisition to Pearson correlation heatmap.

2.1 Data acquisition

The pin-on-disk apparatus is a widely used tribological testing device designed to evaluate materials' wear rates, and lubrication properties under controlled conditions. This apparatus is involved in various fields, including aerospace, polymer science, corrosion studies, biotribology, and industrial applications. The pin-on-disk apparatus consists of an immobile pin pressed against a rotating disk. The wear and frictional forces are measured as the disk rotates, simulating sliding contact between two surfaces [34]. A personalized, low-cost pin-on-disk apparatus was designed for testing polymeric materials under dry-sliding conditions, demonstrating its utility in measuring friction coefficients and wear rates with high precision [35]. In biotribology, a multidirectional motion pin-on-disk apparatus was developed to study the wear behaviour of prosthetic joint materials, highlighting the influence of shear stress in multidirectional sliding [36]. The apparatus is also used in industrial settings to evaluate the effects of lubrication on wear parameters of metals, showing significant reductions in friction with the application of lubricants [37]. Figure 3 shows various components of the disk apparatus, which consists of a pin holder, a provision for adding weights, a linear variable differential transformer (LVDT) sensor to measure the linear displacement of the pin, and an adjustable track diameter for measuring wear volumes of specimens.

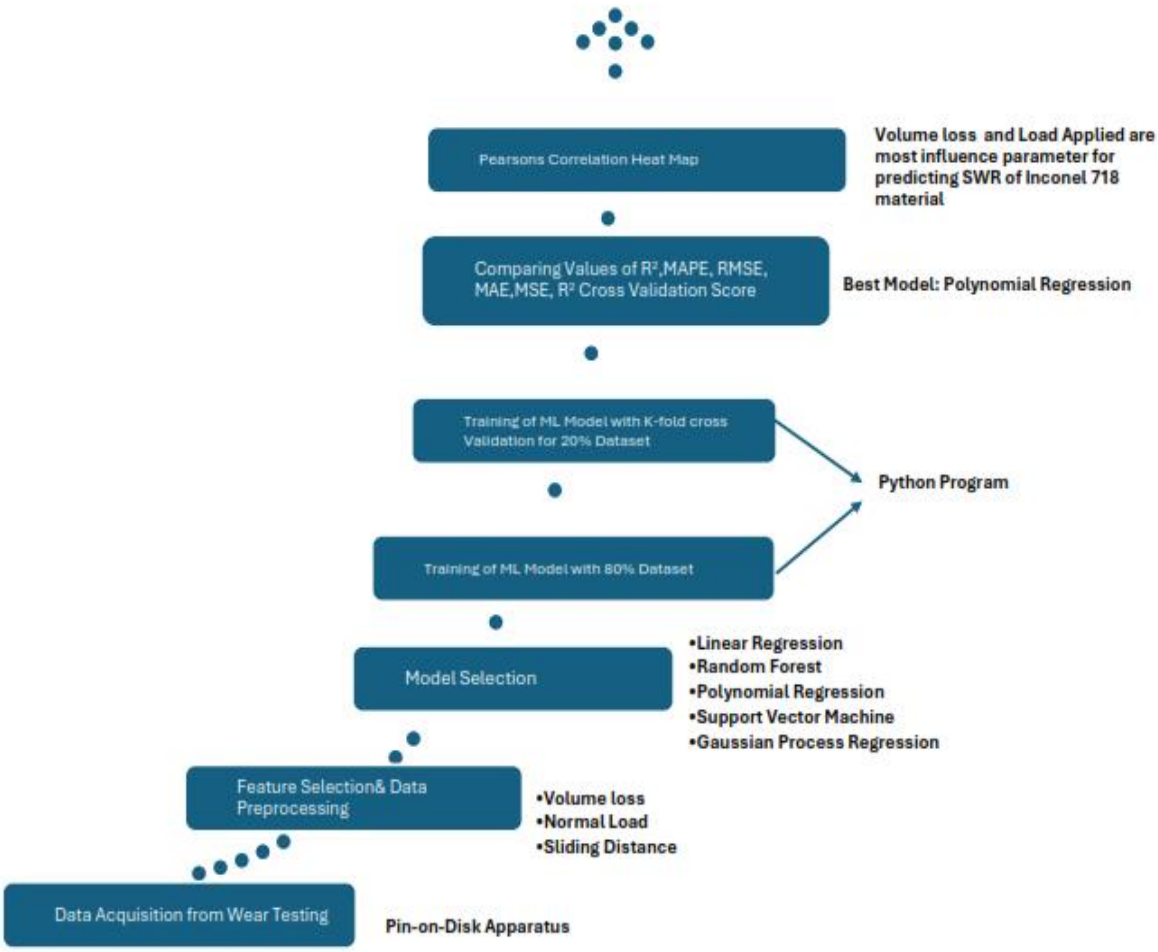

Figure 2. Proposed methodology for current study

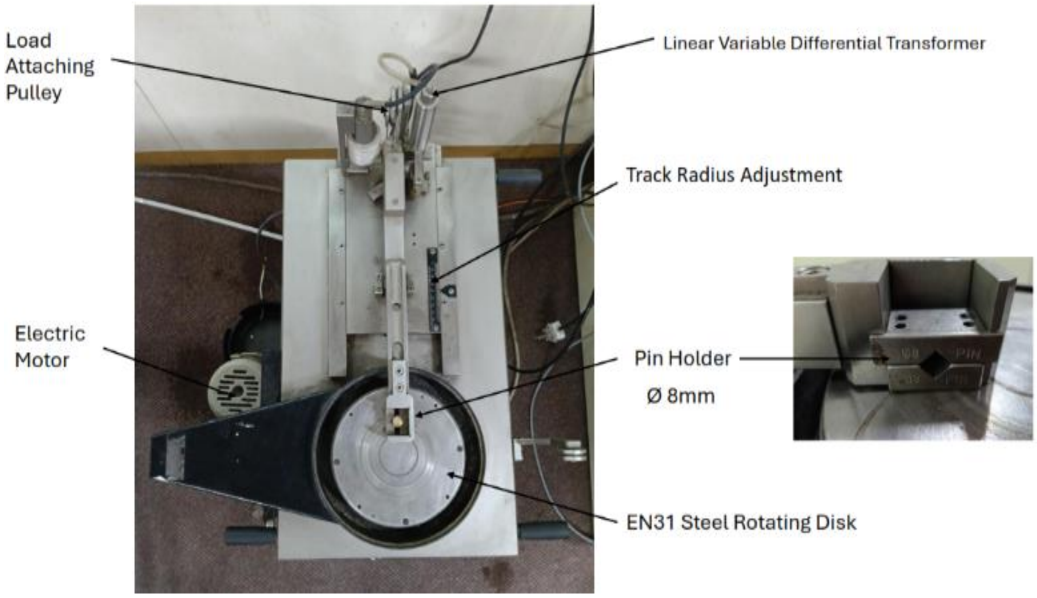

Figure 3. Pin-on disk apparatus experimental setup

The dry wear test experiment is carried out on a pin on disk apparatus per ASTM G99 standards. In this study, design of experiment was done using L27 orthogonal array. The pin material is Inconel 718 and the disk material is EN31. The total 100 set of data was obtained by performing a wear test by varying the parameters such as the speed of the rotating disk in rpm, the load applied in N, track diameter in mm were varied according to Table 3, the time for wear test in minutes kept constant at 20 min,

Table 3. Wear test parameters values

Parameters	Values
Speed (rpm)	400,600,800
Load (N)	1,2,3
Test Time (min)	20
Track Diameter (mm)	80,90,100

Isopropyl Alcohol and sandpaper were used to clean the disk after the test. The observations noted are the specimen's initial weight and the specimen's final weight after performing the wear test. The properties of disk and pin material are given in Table 4.

Table 4. Properties of pin & disk materials

Properties	Pin (Inconel 718)	Disk (EN31)
Elastic Modulus (GPa)	205	200
Poisons Coefficients	0.29	0.30
Diameter (mm)	8	165
Hardness (HRC)	36	45

Table 5. Descriptive statistics of experimental dataset

Variables	Mean	Mode	Median
Volume loss (mm^3)	6.24	5.29	3.2
Normal load Applied (N)	18	7.78	20
Sliding distance (m)	3338.53	935.33	3352.62
Specific wear rate (mm^3/Nm)	0.000087	0.000059	0.000063

The Table 5 shows statistics descriptive assessment of data was performed to provide clear and brief characteristics of data for making data driven decision simpler and more robust.

2.2 Feature selection and preprocessing

In the context of dry friction sliding wear testing for Inconel 718 LPBF, a high-performance nickel chromium superalloy, "feature selection" refers to identifying the most influential parameters and characteristics that govern its tribological behavior i.e., friction and wear. These features can be categorized into experimental parameters, and material properties, and the resulting wear mechanisms. These features can be experimental parameter like Normal load, sliding velocity, temperature, sliding distance, counter body material, cooling or lubricating conditions [38-42].

Formula of specific wear rate is given as [43],

Volume loss,

$$v = \frac{\Delta w}{\rho}\ (\mathrm{cm}^3) \tag{1}$$

where,
V = Volume loss in (cm^3)
Δw = Weight loss
ρ = Density of Inconel 718 material

Specific wear rate,

$$\text{Sliding distance} = S = 2\pi rNT \tag{2}$$

where,
r = radius of wear track m
N = rotational speed in rps
T = time in sec

$$\text{Specific wear rate} = SWR = \frac{v}{F \cdot S}\ (\mathrm{mm}^3/\mathrm{Nm}) \tag{3}$$

where,
V = Volume loss in (mm^3),
F = Normal Load Applied (N),
S = Sliding Distance (m)

In this research work, the feature selection is based on the experimental parameter and above derived formula for specific wear rate. So, that there is balance between experimental parameter i.e., input parameter and specific wear rate i.e. response parameter. The data preprocessing i.e. data cleaning was done to remove any outlier or anomaly data point, missing values to improve quality of experimental data further analysis for machine learning prediction.

2.3 Machine learning model selection

It can be defined as "A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P if its performance at tasks in T, as measured by P, improves with experience E" [44]. Basically, ML is programmed to classify things, find patterns, predict outcomes, and make informed decisions [45]. In this research paper ML has been employed for making prediction outcomes. specific wear rate of Inconel 718 material and also help to identifying influential parameters that are having effect on specific wear rate i.e. making informed decision about specific wear rate of Inconel 718 material. Machine learning has an immense contribution in the forecasting of wear rates, for the enhancement of material performance, and ensuring the reliability across various industrial applications. Machine learning can handle complex datasets and uncover patterns that are not easily visible through traditional methods, making it an invaluable tool in wear rate prediction. This capability is particularly helpful in materials science, tribology, and mechanical engineering, where accurate wear predictions can lead to better selection of material, improved manufacturing processes, and better maintenance strategies [46].

The supervised machine learning model like Linear Regression, Random Forest, Polynomial Regression, Gaussian Process Regression. The main benefits that supervised machine learning algorithms provides that is high prediction accuracy when trained with high quality data, contributes in data driven decision making with widely accepted machine learning models [47]. The above listed machine learning model were employed, and corresponding plots were generated using Python code.

a) Linear Regression model:

Linear Regression model is a popular machine learning algorithm; it is used the identify relationship between input and output parameter. Though, it is simple to implement and easy to interpret result. But this method can used as benchmark model and one can proceed with complex model for further analysis [48].

b) Random Forest model:

The Random Forest algorithm is beneficial in predicting wear rate because of its adaptable nature across a wide range of materials. It is known that machine learning algorithms such as RF can handle complex and multidimensional datasets with a high degree of accuracy, ensuring their robustness. The working principle of Random Forest is that it constructs multiple decision trees and then accumulates their outputs to give precise prediction outputs, thereby reducing the overfitting in the model. The nature of assembling makes it a popular choice of machine learning model for predicting wear rate in diverse applications ranging from brake pad materials to industrial tools and biomedical implants. Random Forest has been used to predict effectiveness by optimization using the Northern Goshawk Optimization algorithm, which highlighted its superiority in predicting the wear rate of the tool when compared with optimization techniques like Genetic Algorithm and Gray Wolf Optimization [49]. The Random Forest machine learning found its potential application in predicting wear rate wear rate of modified ZA-27 alloy under dry friction conditions, the results showed that the R^2 value tends closer to unity while minimizing mean absolute error [50]. The main benefit of Random Forest is ability to predict the importance of features, which is a crucial insight for understanding the wear mechanism [51]. Wear rates in brake pad materials. Although it was found to be less accurate than Extreme Gradient Boosting in this specific application, it gained importance by providing insights regarding the influence of sliding distance [52].

c) Polynomial Regression model:

Polynomial regression is a statistical technique used in Machine Learning to predict the specific wear rate. The study conducted to examine wear properties of steel material utilizes a Polynomial Regression model to predict the wear rate by considering the influence of contact pressure, sliding speed, and surface hardness as parameters. The Polynomial Regression Model's output is confirmed by comparing it with actual experimental values. One of the advantages of Polynomial Regression is its capacity to handle multifaceted non-linear relationships, which are common in wear processes [53]. In this study, the second-degree polynomial is selected because of its simplicity and captures nonlinear relationship without introducing more complexity, which can reduce overfit the data as supported by K-Fold validation results.

d) Gaussian Process Regression model:

Gaussian Process Regression machine learning model is versatile and has high predictive accuracy and it also can evaluate uncertainty. This model can be used where there is need for predicting complex relationships due to its flexibility; however, it is sensitive to kernel options [54].

3. RESULTS AND DISCUSSION

3.1 Result of supervised machine learning models

This study aims to identify best suitable supervised machine learning model which can predict the specific wear rate values of Inconel 718 material as close to experimental values. The following supervised machine learning algorithms are under consideration, Linear Regression, Random Forest, Polynomial Regression and Gaussian Process Regression models to predict the wear rate by using three input parameters: volume loss, sliding distance, and applied load. To ensure the accuracy of machine learning models, 100 data points collected in the laboratory were segregated into 80% for the training set and 20% for the testing set. The four assessment standards were calculated: coefficient of determination (R^2) which is measure of model accurateness whose values should be closer to unity, MSE, MAE, RMSE, these metrics highlights significance of magnitude of error and its interpretation with dataset to estimate the behavior of machine learning models [55]. R_{cv}^2 is known as cross fold validation which can be interpreted as model can be generalized i.e. model can gives prediction of unknown data.

The equation to calculate the results are given below,

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{4}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (5)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (6)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (7)$$

$$R_{cv}^2 = \frac{1}{k}\sum_{i=1}^{k}(1 - \frac{\Sigma(y_i - \hat{y}_i)^2}{\Sigma(y_i - \bar{y})^2} \quad (8)$$

where, n is the number of trials, y_i represents the true experimental output value, $\hat{y}_i$ signifies the predicting experimental output values and $\bar{y}$ is designated as average of the actual experimental values [56]. The obtained net results are displayed in Table 6.

3.2 Comparison of supervised machine learning models

The criteria for selection of best suitable supervised machine learning can set as the model which has highest R^2 value and lowest value of RMSE, MSE and MAE respectively. This is because higher R^2 value i.e. closer to unity signifies that model is approaching closer to actual prediction values and lower values of RMSE, MSE, MAE represents that there are less errors in prediction of model.

From Figure 4, the Polynomial Regression model satisfies this criterion by having higher R^2 value of 0.9929 and lowest value of RMSE (3×10^{-6}), MSE (1.174139×10^{-11}) and MAE (2×10^{-6}).

The interpretation of Figure 5 can be done using inclined doted lines which represents line of prefect prediction i.e. reference line. The points of models which are closer to this reference line are considered to perform well in prediction of specific wear rates.

Points closer to this reference line, undermines that there are high correlations between actual and prediction values and whereas if there is high deviation from reference then that model is said to be poor in terms of performance for prediction task. Therefore, Polynomial Regression is good ML model because it shows less deviation from reference lines indicating accurate prediction of specific wear rates across different operating conditions while compared to other ML models.

The residual plot plays crucial part in statistically analyzing the ML Models. It reveals ML models critical insights about if models meet fundamental statistical assumptions, reveal problems about performance metrics, expose data problems. Overall, it is like quality control task for ML models. The Figure 6 illustrates residual plots indicates that Polynomial Regression model shows minimal and randomly distributed residual plot suggesting it captures the non-linear relationships between volume loss, normal load, sliding distance, and resulting wear rates from experimental conditions.

Table 6. Net result of supervised machine learning models

ML Model	R^2	RMSE	MSE	MAE	5-Fold Cross Validation R^2 Scores
Linear Regression	0.977287	9×10^{-6}	8.616979×10^{-11}	7×10^{-6}	0.9746
Random Forest	0.992139	5×10^{-6}	2.982480×10^{-11}	4×10^{-6}	0.9953
Polynomial Regression	0.996905	3×10^{-6}	1.174139×10^{-11}	2×10^{-6}	0.9968
Gaussian Process Regression	0.989683	6×10^{-6}	3.914370×10^{-11}	5×10^{-6}	0.9930

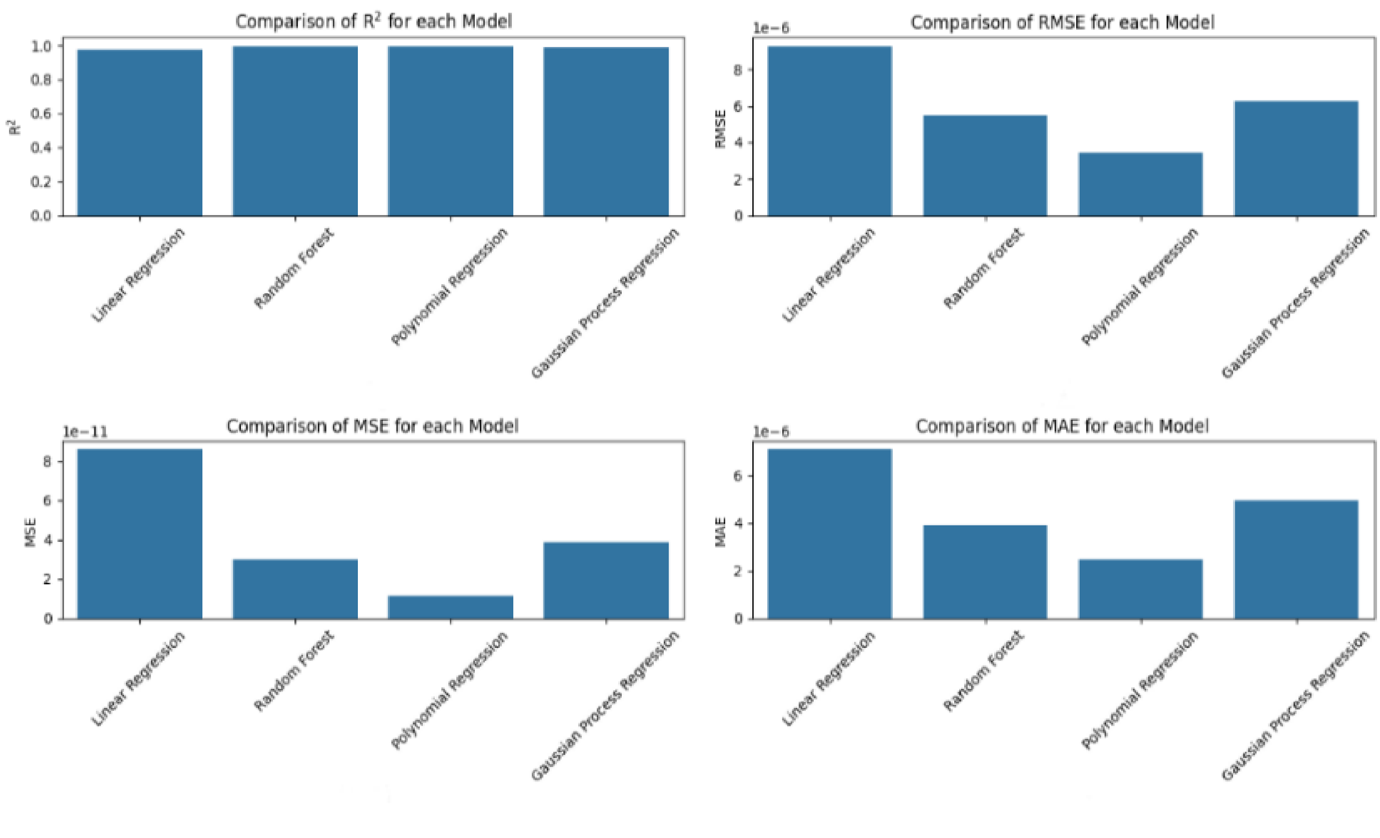

Figure 4. Comparison of results of supervised machine learning models

While, Linear Regression model captures linear relationships adequately but shows systematic limitations in predicting extreme wear rates (i.e., residual error increases as specific wear rate increases), Random Forest model shows randomly distribution of residual points which indicates no systematic pattern but it has higher magnitude of residual error than Polynomial Regression model. which provides an advantage to Polynomial Regression over random forest model. The Gaussian Process Regression shows dense cluster regions and some sparse regions with fewer data points showing wider residual spread. This indicates that it is not showing consistent performance as Polynomial Regression model across the entire wear rate prediction space. Each plot includes a Durbin-Watson statistics which quantify degree of autocorrelation and these values must be close to 2 because then and only then the model said be independent, unbiased. Therefore, these residual plots and Durbin-Watson statistics together confirms all four models are supporting the robustness of wear rate predictions for Inconel718 material.

3.3 Pearson correlation heat map

A Pearson correlation heat map is a pictorial visualization tool that displays the linear correlation between multiple variables as a color-coded matrix. It combines statistical analysis with visual representation to help researchers quickly identify relationships between variables in complex datasets [57]. The Pearson correlation coefficient gives information about value and direction of relationships between two variables of interest. The coefficient ranges from -1 to +1. Where +1 represent perfect positive correlation, coefficient value more than 0.7 represents solid correlation, 0.3 to 0.7 indicates moderate correlation, less than 0.3 indicates weak correlation, 0 indicates no linear correlation, -1 indicates perfect negative correlation. The heat map represents correlation coefficients through a color-coded matrix where each cell shows the relationship between two variables. Darker colours typically indicate stronger correlations, while lighter colours represent weaker relationships. Generally, Warm colors (red, orange) usually represent positive correlations, Cool colors (blue, green) typically represent negative correlations and unbiassed colors (white, gray) indicate weak or no correlation.

From Figure 7, it inferred that Volume Loss (mm^3) has nearly perfect positive correlation with specific wear rate i.e. Pearson coefficient value of 0.987, the normal load applied (N) has strong correlation with specific wear rate with coefficient value of 0.866 and sliding distance on the other hand has weak correlation with specific wear rate, highlighting that sliding distance has minimum influence on specific wear rate.

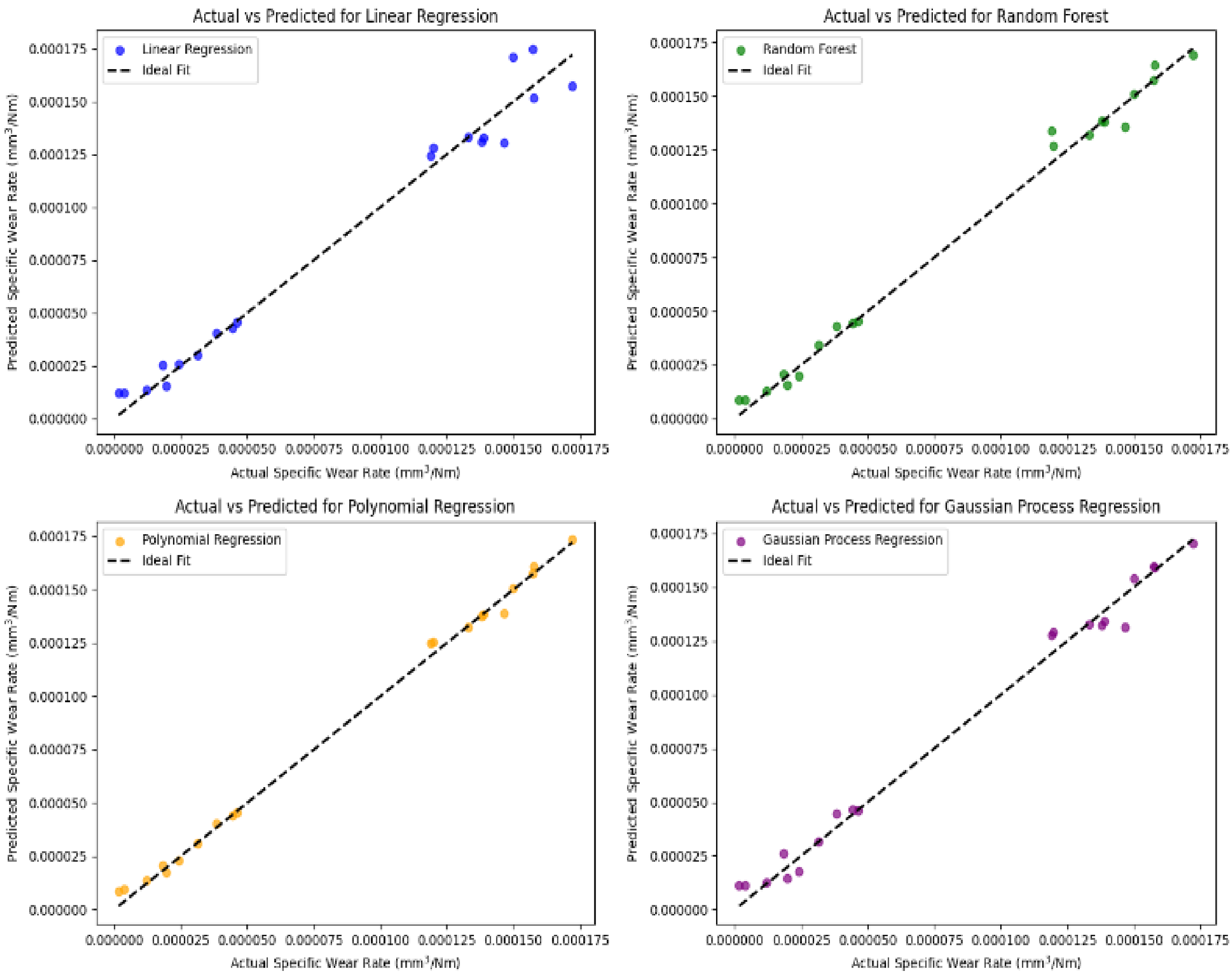

Figure 5. Plots of actual vs predicted specific wear rate by supervised ml models

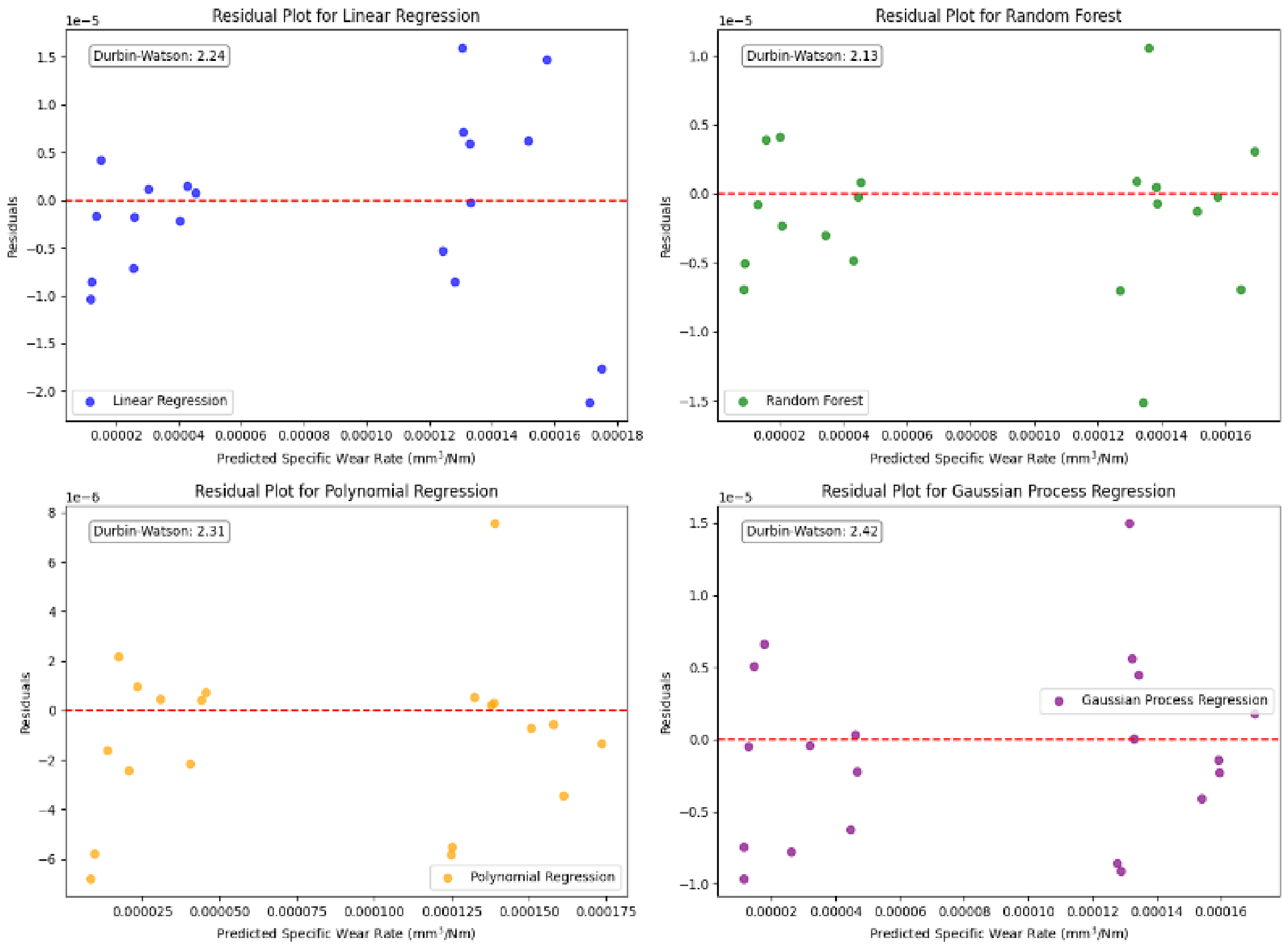

Figure 6. Residual plots for supervised machine learning models

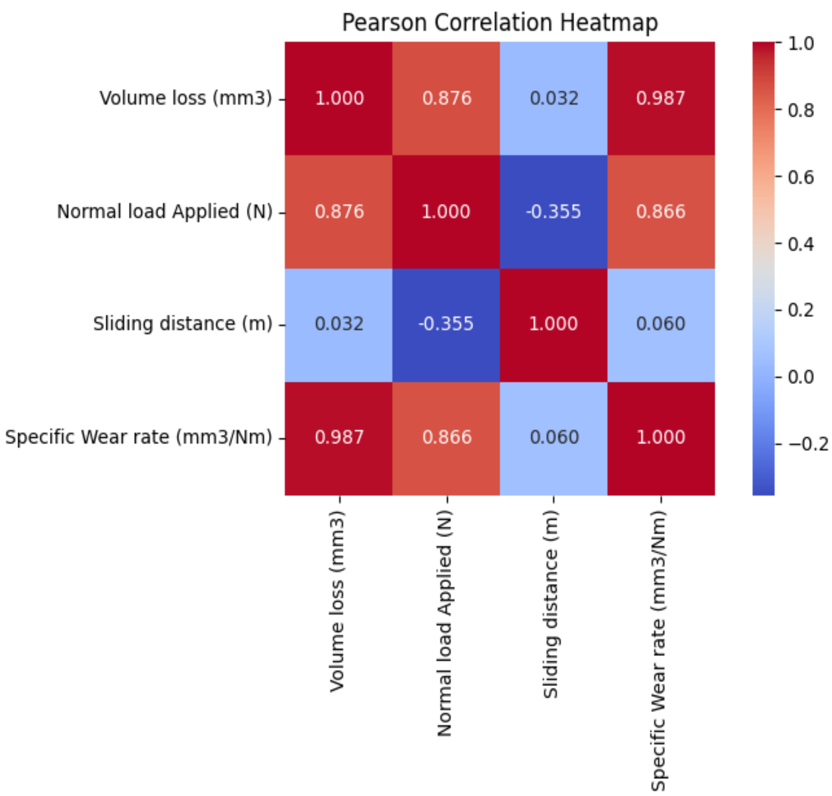

Figure 7. Pearson correlation heatmap for specific wear rate

4. CONCLUSIONS

The Supervised Machine Learning Models like Linear Regression, Random Forest, Polynomial Regression and Gaussian Process Regression were employed to predict specific wear rate of LPBF manufactured Inconel 718 material using Python code and corresponding result showed that Polynomial Regression Model performed better than other Machine learning model with coefficient of determination value of 0.9969 and cross validation score of 0.9968 i.e., 99.68% generalization can be obtained through this model. The influence of various input parameter was investigated against response parameter of specific wear rate using Pearson correlation heatmap, the heat map revealed that volume loss and normal load applied showed positive strong correlation with value of Pearson coefficient above 0.7 and thus highlighting their importance as decision making factor in specific wear rate. Overall, the present study presents a robust and dependable approach for prediction of specific wear rate of Inconel 718 material. The insights derived from machine learning analysis have the potential to be applied in the assessment of Nickel-based superalloy materials for specific tribological contexts.

ACKNOWLEDGMENT

The authors express their gratitude to the Management of Symbiosis International Deemed University Pune for providing the essential funding for the publication of this work.

DECLARATION OF COMPETING INTEREST

All Authors confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

REFERENCES

[1] Adamczyk-Cieślak, B., Pieja, T., Sieniawski, J., Mizera, J., Maj, P., Slesik, M., Mizera, J., Pieja, T., Sieniawski, J., Gancarczyk, T., Dudek, S. (2017). The precipitation processes and mechanical properties of aged Inconel 718 alloy after annealing. Archives of Metallurgy and Materials.

[2] Qi, H., Azer, M., Ritter, A. (2009). Studies of standard heat treatment effects on microstructure and mechanical properties of laser net shape manufactured Inconel 718. Metallurgical and Materials Transactions A, 40(10): 2410-2422. https://doi.org/10.1007/s11661-009-9949-3

[3] Davis, J.R. (Ed.). (2000). Nickel, Cobalt, and Their Alloys. ASM International.

[4] ElMaraghy, H., Monostori, L., Schuh, G., ElMaraghy, W. (2021). Evolution and future of manufacturing systems. CIRP Annals, 70(2): 635-658. https://doi.org/10.1016/j.cirp.2021.05.008

[5] Krishna, R., Manjaiah, M., Mohan, C.B. (2021). Developments in additive manufacturing. In: Additive Manufacturing. Woodhead Publishing, pp. 37-62. https://doi.org/10.1016/B978-0-12-822056-6.00002-3

[6] Roschli, A.C., Borish, M.C., Barnes, A.K., Feldhausen, T.A., Wang, P., MacDonald, E. (2023). Motion and Path Planning for Additive Manufacturing. Elsevier. https://doi.org/10.1016/C2022-0-01328-3

[7] Strößner, J., Terock, M., Glatzel, U. (2015). Mechanical and microstructural investigation of nickel-based superalloy IN718 manufactured by selective laser melting (SLM). Advanced Engineering Materials, 17(8): 1099-1105. https://doi.org/10.1002/adem.201500158

[8] Deng, D., Peng, R.L., Brodin, H., Moverare, J. (2018). Microstructure and mechanical properties of Inconel 718 produced by selective laser melting: Sample orientation dependence and effects of post heat treatments. Materials Science and Engineering: A, 713: 294-306. https://doi.org/10.1016/j.msea.2017.12.043

[9] Bai, S., Perevoshchikova, N., Sha, Y., Wu, X. (2019). The effects of selective laser melting process parameters on relative density of the AlSi10Mg parts and suitable procedures of the archimedes method. Applied Sciences, 9(3): 583. https://doi.org/10.3390/app9030583

[10] Wang, X., Gong, X., Chou, K. (2017). Review on powder-bed laser additive manufacturing of Inconel 718 parts. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 231(11): 1890-1903.

[11] Steyn, C., Biénie, D.C., Naeevis, M.T. (2024). Effect of selected laser–powder bed fusion parameters on the as-built properties of Inconel 718. MATEC web of Conferences, 406: 07013-07013. https://doi.org/10.1051/matecconf/202440607013

[12] Xu, Y., Gong, Y., Li, Y.P., Yang, G., Xi, Q.J. (2020). The effect of laser power on the microstructure and wear performance of In718 superalloy fabricated by laser additive manufacturing. The International Journal of Advanced Manufacturing Technology, 109(5-8): 2245-2254. https://doi.org/10.1007/s00170-020-05712-6

[13] Kumar, P., Farah, J., Akram, J., Teng, C., Ginn, J., Misra, M. (2019). Influence of laser processing parameters on porosity in Inconel 718 during additive manufacturing. The International Journal of Advanced Manufacturing Technology, 103(1): 1497-1507. https://doi.org/10.1007/s00170-019-03655-9

[14] Liu, F., Gao, J., Liu, F., Xu, Y., You, Q., Huang, C., Hu, X., Zheng, H., Lin, X. (2023). The anisotropic wear and friction property of Inconel 718 superalloy fabricated by laser directed energy deposition. Tribology International, 188: 108835. https://doi.org/10.1016/j.triboint.2023.108835

[15] Paramasivam, P., Natesan, S., Sebastian, R.B.A., Vijayakumar, S. (2024). Tribological effects of varying volumetric energy density in additive manufacturing of Inconel 718. Engineering Research Express, 6(4): 045417. https://doi.org/10.1088/2631-8695/ad8f14

[16] Sathisha, C.H., Ka, H., Arivu, Y., Pramod, S., Sridhar, M.R., Buravalla, V., Kesavan, D. (2024). Influence of heat treatment on fretting wear behavior of laser powder bed fusion Inconel 718 alloy. Journal of Tribology, 146(11): 114202. https://doi.org/10.1115/1.4066122

[17] Jiang, R., Mostafaei, A., Wu, Z., Choi, A., Guan, P.W., Chmielus, M., Rollett, A.D. (2020). Effect of heat treatment on microstructural evolution and hardness homogeneity in laser powder bed fusion of alloy 718. Additive Manufacturing, 35: 101282. https://doi.org/10.1016/j.addma.2020.101282

[18] Tillmann, W., Schaak, C., Nellesen, J., Schaper, M., Aydinöz, M.U., Hoyer, K.P. (2017). Hot isostatic

pressing of IN718 components manufactured by selective laser melting. Additive Manufacturing, 13: 93-102. https://doi.org/10.1016/j.addma.2016.11.006
[19] Başçı, Ü.G., Avcu, E., Kıraç, M., Sever, A., et al. (2024). Microstructural, mechanical, and tribological properties of selective laser melted Inconel 718 alloy: The influences of heat treatment. Crystals, 15(1): 18. https://doi.org/10.3390/cryst15010018
[20] Li, N., Wang, C., Li, C. (2024). Microstructures and high-temperature mechanical properties of Inconel 718 superalloy fabricated via laser powder bed fusion. Materials, 17(15): 3735. https://doi.org/10.3390/ma17153735
[21] Zhao, Z., Qu, H., Bai, P., Li, J., Wu, L., Huo, P. (2018). Friction and wear behaviour of Inconel 718 alloy fabricated by selective laser melting after heat treatments. Philosophical Magazine Letters, 98(12): 547-555. https://doi.org/10.1080/09500839.2019.1597991
[22] Anandakrishnan, V., Sathish, S., Dillibabu, V., Balamuralikrishnan, N. (2020). Dry sliding wear behavior of Inconel 718 additively manufactured by DMLS technique. Industrial Lubrication and Tribology, 72(4): 491-496. https://doi.org/10.1108/ILT-08-2019-0322
[23] Samuel, C.S., Arivarasu, M., Prabhu, T.R. (2020). High temperature dry sliding wear behaviour of laser powder bed fused Inconel 718. Additive Manufacturing, 34: 101279. https://doi.org/10.1016/J.ADDMA.2020.101279
[24] Sathisha, C.H., Kesavan, D., Sridhar, M.R., Arivu, Y., Pramod, S. (2024). Large area contact fretting wear mechanisms of heat-treated In718 produced via laser powder bed fusion under elevated temperature. Wear, 550-551: 205425. https://doi.org/10.1016/j.wear.2024.205425
[25] Naskar, S., Suryakumar, S., Panigrahi, B.B. (2024). Heat treatments-induced wear resistance of Inconel 718 superalloy fabricated via laser based powder bed fusion. Materials Today Communications, 41: 110789. https://doi.org/10.1016/j.mtcomm.2024.110789
[26] Siddaiah, A., Kasar, A., Kumar, P., Akram, J., Misra, M., Menezes, P.L. (2021). Tribocorrosion behavior of Inconel 718 fabricated by laser powder bed fusion-based additive manufacturing. Coatings, 11(2): 195. https://doi.org/10.3390/coatings11020195
[27] Rong, T., Gu, D., Shi, Q., Cao, S., Xia, M. (2016). Effects of tailored gradient interface on wear properties of WC/Inconel 718 composites using selective laser melting. Surface & Coating Technology, 307: 418-427. https://doi.org/10.1016/j.surfcoat.2016.09.011
[28] Sah, A.K., Agilan, M., Dineshraj, S., Rahul, M.R., Govind, B. (2022). Machine learning-enabled prediction of density and defects in additively manufactured Inconel 718 alloy. Materials Today Communications, 30: 103193. https://doi.org/10.1016/j.mtcomm.2022.103193
[29] Nasiri, S., Khosravani, M.R. (2021). Machine learning in predicting mechanical behavior of additively manufactured parts. Journal of Materials Research and Technology, 14: 1137-1153. https://doi.org/10.1016/j.jmrt.2021.07.004
[30] Zhan, Z., Li, H. (2021). Machine learning based fatigue life prediction with effects of additive manufacturing process parameters for printed SS 316L. International Journal of Fatigue, 142: 105941. https://doi.org/10.1016/j.ijfatigue.2020.105941
[31] Barrionuevo, G.O., Walczak, M., Ramos-Grez, J., Sánchez-Sánchez, X. (2023). Microhardness and wear resistance in materials manufactured by laser powder bed fusion: Machine learning approach for property prediction. CIRP Journal of Manufacturing Science and Technology, 43: 106-114. https://doi.org/10.1016/j.cirpj.2023.03.002
[32] Lu, X., Zeng, F., Xv, K., Zhang, Y., Liang, S.Y. (2024). Prediction of tool wear during micro-milling Inconel 718 based on long short-term memory network. Precision Engineering, 86: 195-202. https://doi.org/10.1016/j.precisioneng.2023.11.003
[33] Fusaro, R.L., Jones, S.P., Jansen, R. (1996). Neural network models of simple mechanical systems illustrating the feasibility of accelerated life testing. In Annual Meeting (No. NAS 1.15: 107108).
[34] Bruckner, R.J., Manco, R.A. (2018). High speed bearing wear rate measurements for spacecraft active thermal control fluid pumps with a novel pin on disk apparatus. In Aerospace Mechanisms Symposium (No. GRC-E-DAA-TN53046).
[35] Ølholm Larsen, T., Løgstrup Andersen, T., Thorning, B., Vigild, M.E. (2009). Pin-on-disk apparatus for tribological studies of polymeric materials. Industrial Lubrication and Tribology, 61(4): 203-208. https://doi.org/10.1108/00368790910960039
[36] Hua, Z., Zhang, J. (2010). Axiomatic design of a multi-directional motion pin on disk apparatus for biotribology study. In International Joint Tribology Conference, pp. 37-39. https://doi.org/10.1115/IJTC2010-41039
[37] Onyeanusi, C.F., Nwigbo, S.C., Anosike, N.B., Nwajude, C.A. (2019). Effects of lubrication on the wear parameters of metals using pin-on-disk test rig. Advances in Research, 18(5): 1-12. https://doi.org/10.9734/air/2019/v18i530103
[38] Xu, Z., Lu, Z., Zhang, J., Li, D., Liu, J., Lin, C. (2021). The friction and wear behaviours of Inconel 718 superalloys at elevated temperature. Frontiers in Materials, 8: 794701. https://doi.org/10.3389/fmats.2021.794701
[39] Jeyaprakash, N., Yang, C.H., Prabu, G., Balamurugan, K.G. (2021). Surface alloying of FeCoCrNiMn particles on Inconel-718 using plasma-transferred arc technique: Microstructure and wear characteristics. RSC Advances, 11(45): 28271-28285. https://doi.org/10.1039/D1RA03778A
[40] Thirugnanasambantham, K.G., Raju, R., Sankaramoorthy, T., Velmurugan, P., et al. (2018). Degradation mechanism for high-temperature sliding wear in surface-modified In718 superalloy. Cogent Engineering, 5(1): 1501864. https://doi.org/10.1080/23311916.2018.1501864
[41] Siddique, M.Z., Faraz, M.I., Butt, S.I., Khan, R., Petru, J., Jaffery, S.H.I., Khan, M.A., Tahir, A.M. (2023). Parametric analysis of tool wear, surface roughness and energy consumption during turning of Inconel 718 under dry, wet and MQL conditions. Machines, 11(11): 1008. https://doi.org/10.3390/machines11111008
[42] Silva, F.J., Sebbe, N.P., Costa, R.D., Pedroso, A.F., Sales-Contini, R.C., Barbosa, M.L., Martinho, R.P. (2024). Investigations on the surface integrity and wear mechanisms of TiAlYN-coated tools in Inconel 718 milling operations. Materials, 17(2): 443.

https://doi.org/10.3390/ma17020443
[43] Atta, M., Megahed, M., Saber, D. (2022). Using ANN and OA techniques to determine the specific wear rate effectors of A356 Al-Si/Al_2O_3 MMC. Neural Computing and Applications, 34(17): 14373-14386. https://doi.org/10.1007/s00521-022-07215-3
[44] Mitchell, T. (1997). Machine Learning. McGraw-Hill, New York.
[45] Niketh, M.S., Radhika, N., Adediran, A.A., Jen, T.C. (2024). Enhancing high-entropy alloy performance: Predictive modelling of wear rates with machine learning. Results in Engineering, 23: 102387. https://doi.org/10.1016/j.rineng.2024.102387
[46] França, R.P., Monteiro, A.C.B., Arthur, R., Iano, Y. (2021). An overview of deep learning in big data, image, and signal processing in the modern digital age. Trends in Deep Learning Methodologies, 63-87. https://doi.org/10.1016/B978-0-12-822226-3.00003-9
[47] Khurana, S., Balakumar, P., Sable, N.P., Sinha, S.K., Pandey, M., Saravanan, V.M. (2023). Analyzing the use of machine learning models for enhancing big data retrieval performance. In 2023 IEEE International Conference on Paradigm Shift in Information Technologies with Innovative Applications in Global Scenario (ICPSITIAGS), Indore, India, pp. 48-52. https://doi.org/10.1109/ICPSITIAGS59213.2023.10527534
[48] Gogulamudi, B., Bandlamudi, R.K., Bhanavathu, B., Guttula, V.S.K. (2023). A prediction model for additive manufacturing of AlSi10Mg alloy. Transactions of the Indian Institute of Metals, 76(2): 571-579. https://doi.org/10.1007/s12666-022-02676-5
[49] Sellami, A., Rekik, M., Njima, C.B., Elleuch, R. (2024). Towards an explainable multi-target regression, for wear and friction prediction for brake pad materials. Acta Polytechnica Hungarica, 21(11): 155-174.
[50] Cheng, Y., Zhou, S., Xue, J., Lu, M., Gai, X., Guan, R. (2024). Research on tool wear prediction based on the random forest optimized by NGO algorithm. Machining Science and Technology, 28(4): 523-546. https://doi.org/10.1080/10910344.2024.2359928
[51] Algur, V., Hulipalled, P., Lokesha, V., Nagaral, M., Auradi, V. (2022). Machine learning algorithms to predict wear behavior of modified ZA-27 alloy under varying operating parameters. Journal of Bio-and Tribo-Corrosion, 8(1): 7. https://doi.org/10.1007/s40735-021-00610-8
[52] Kappes, B., Moorthy, S., Drake, D., Geerlings, H., Stebner, A. (2018). Machine learning to optimize additive manufacturing parameters for laser powder bed fusion of Inconel 718. In: Ott, E., et al. Proceedings of the 9th International Symposium on Superalloy 718 & Derivatives: Energy, Aerospace, and Industrial Applications. The Minerals, Metals & Materials Series. Springer, Cham. https://doi.org/10.1007/978-3-319-89480-5_39
[53] Yan, Y.T., Sun, Z.L., Zhu, T. (2010). Wear rate predication for steel based on regression analysis. Advanced Materials Research, 126: 965-969. https://doi.org/10.4028/www.scientific.net/AMR.126-128.965
[54] Kizhakkinan, U., Duong, P.L.T., Laskowski, R., Vastola, G., Rosen, D.W., Raghavan, N. (2023). Development of a surrogate model for high-fidelity laser powder-bed fusion using tensor train and gaussian process regression. Journal of Intelligent Manufacturing, 34(1): 369-385. https://doi.org/10.1007/s10845-022-02038-4
[55] Zhu, C., Jin, L., Li, W., Han, S., Yan, J. (2024). The prediction of wear depth based on machine learning algorithms. Lubricants, 12(2): 34. https://doi.org/10.3390/lubricants12020034
[56] Breiman, L. (2001). Random forests. Machine Learning, 45(1): 5-32. https://doi.org/10.1023/A:1010933404324
[57] Deshpande, A.R., Kulkarni, A.P., Wasatkar, N., Gajalkar, V., Abdullah, M. (2024). Prediction of wear rate of glass-filled PTFE composites based on machine learning approaches. Polymers, 16(18): 2666. https://doi.org/10.3390/polym16182666

NOMENCLATURE

AM	Additive Manufacturing
LPBF	Laser Powder Bed Fusion
SR	Stress Relief
HIP	Hot Isostatic Pressing
ST	Solution Treatment
IN718	Inconel 718
ANN	Artificial Neural Network
RF	Random Forest
SVM	Support Vector Machine
ASTM	American Standard for Testing of Materials
HRC	Rockwell Hardness C Scale unit
RMSE	Root Mean Square Error
MSE	Mean Square Error
MAE	Mean Absolute Error
SWR	Specific Wear Rate
CV	Cross Validation