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A Review on Predicting Wear and Friction of PTFE Composites - Fillers to Machine Learning Models

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Abstract

Polytetrafluoroethylene (PTFE) composites, a self-lubricating material with low friction, became an indispensable material in engineering applications where load carrying capacity and wear are crucial. The pure PTFE has poor mechanical strength and wear resistance which can be enhanced by the addition of fillers in appropriate volume fraction. The wear performance is dependent on various factors such as fillers, operating parameters, environmental conditions as well as manufacturing attributes. This makes the analysis of any tribological system more complex with nonlinear interactions with different influencing elements. This limitation focuses the need of adopting a data driven machine learning (ML) approach to provide more accurate understanding of the tribo-system and provide more accurate prediction of wear.ML techniques have emerged as an effective tool for understanding wear mechanisms and accurately predicting the wear rate and coefficient of friction (COF). These ML algorithms are data driven, learn from the experimental data finds the trends in material composition with different fillers and operating circumstances for accurate forecasts. Gradient boosting model (GB) shown high predictive accuracy (R^2 values up to 0.95) for PTFE composites, outperforming traditional models by capturing non-linear interactions and adapting to varied conditions. ML techniques offer interpretability, critical for understanding the impact of each material parameter as well as providing robustness with smaller datasets, making it suitable for applications where data availability is limited. These models provide stability and accuracy in forecasting wear behaviour, which is essential in real-world applications where complex material interactions are present This review identifies current challenges, such as data quality and model validation, and emphasizes the need for hybrid models that combine the strengths of ML and numerical methods. Future research should focus on expanding the predictive capability of these models through more comprehensive datasets and advanced algorithms, aiming for sustainable, cost-effective, and high-performance tribological solutions in PTFE composite applications across automotive, aerospace, and medical industries.

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INTRODUCTION

PTFE with its distinctive properties such as low friction, chemical resistance and thermal stability is widely used as a high-performance polymer. It is synthetic fluoropolymer of tetrafluoroethylene which can withstand extreme temperatures. Its carbon-fluorine bond is responsible for these properties which has earned PTFE an indispensable role in many engineering applications, but notably, it is among the preferable tribological material available to date. Tribological applications are virtually found in all mechanical devices from automobiles to massive industrial machinery.[1] It has an impact on performance, efficiency as well as the lifespan of the various parts of these machines, hence tribology, plays a very important role in modern engineering systems. PTFE based on its inherent property of low friction and self-lubricating ability has been extensively used in many tribological applications. Although the pure form of PTFE has poor mechanical strength, wear resistance, and load-bearing capacity, it must be reinforced with fillers. [2] PTFE is often reinforced with glass fibers, carbon fibers, graphite, bronze, molybdenum disulfide (MoS_2), and other materials to form PTFE composites. These composites display enhanced wear resistance, improved load bearing capability, better mechanical performance, and maintain low friction characteristics. Fillers incorporated into the PTFE matrix changed its tribological properties significantly, lowering the wear rate and considerably expanding the scope of applications. PTFE composites are employed in a huge extent across the automotive, aerospace, chemical processing, and medical devices industries in a variety of elements such as bearings, seals, gaskets, bushings, etc. [3] The various kinds of wear appear; such include adhesive wear, abrasive wear, fatigue wear, and tribo-chemical wear. However, working under extreme conditions like high temperatures, corrosive environment, and dry or lubrication conditions it is critical to maintain the long life and high efficiency of the composite material.[4]

The wear behaviour of PTFE composites remains sensitive to both operating conditions and the nature of filler materials, thereby challenging accurate prediction of wear rates through traditional experimental methods. The prediction of wear rates of PTFE composite is necessary for sustainable operation under specific conditions without precocious failure.[5] Predictive wear models enable engineers to predict the lifespan of components, optimize material selection, and minimize extensive experimental testing, eventually reducing cost and downtime. Though the performance of PTFE is enhanced by addition of fillers, wear remains a complex phenomenon, hence making its accurate prediction remains a challenge. ML, a data driven technique is one of the most promising advancements in predictive modelling which analyse complex wear behaviours and improve forecasting accuracy.

ML approaches have witnessed a major revolution in the field of predictive modelling across various domains-including tribology. The ML algorithms involved with the overall approach represent artificial neural networks (ANNs), support vector machines (SVMs), random forests (RF), and deep learning models for predicting wear rates based on historical data. This is one of the main advantages of the ML approach since it can learn complex patterns and relationships from large datasets without explicit knowledge of the underlying physical mechanism. Therefore, ML may be applied to predict the wear rates in PTFE composites by analysing a wide set of input variables, such as composition of material, operating conditions.[6] The ML approach prove helpful in the case of complex nonlinear relationships between variables, which cannot be easily captured by empirical or numerical models. Furthermore, ML models can be continuously improved with new data, which makes it very adaptable to changes in condition or new material formulations. Although ML has proved valuable in wear prediction, there are also challenges such as it requires large volumes of high-quality data to be used for training and model validation.[7] Such data might be difficult to obtain for specific materials or specific conditions.

This review aimed at offering a detailed and comprehensive analysis of the current state-of-the-art in the prediction of the wear rate of PTFE composites ML techniques. With more and more high-performance materials being used in wide varieties of industrial applications, it is becoming increasingly critical to understand the tribological behaviour of PTFE composites. Traditional modelling techniques always lack in accurate prediction of complex nonlinear interactions between the material properties, operating conditions and wear mechanism. It mostly dependent on experimental data which require extensive testing that is costly and time consuming. The scope of this review encompasses the ML approaches applied to PTFE composite wear prediction, including recent research, focusing on the latest advances in computational modelling techniques which are underexplored in tribology domain.

FILLER MATERIALS

PTFE composite's low friction and self-lubricating qualities make them popular in a various industrial application, especially tribological ones. However, pure PTFE has severe limitations in terms of wear resistance and mechanical strength, necessitating the use of fillers for reinforcement. This article addresses the use of several fillers to improve the mechanical and tribological characteristics of PTFE composites, such as carbon fibers, glass fibers, bronze, graphite, SiO_2, Al_2O_3, calcium carbonate, aramid fibers, and PEEK. Each filler contributes differently to the wear rate and coefficient of friction (COF) of the composites; the performance of the composite is mostly determined by the filler volume fraction, the environment, and the synergistic effects of hybrid fillers. Additionally, the review emphasizes how these fillers work together to provide protective transfer coatings, increase load-carrying capacity, and improve thermal stability, which significantly lower wear rates and coefficient of friction across a range of sliding circumstances. It is critical to understand the individual contribution, synergetic effect and specific conditions for the fillers which improves the tribological performance of PTFE composite.

Carbon, the most effective filler added to PTFE composites to improve its mechanical and tribological properties. It is a material with superior mechanical strength and thermal stability, often used in a wide application which requires high durability. Researchers observed that carbon enhance the performance of PTFE composite, however, properties of composite influenced by volume fraction of carbon as well as its collaboration with other fillers like bronze, glass, molybdenum disulfide (MoS_2), graphite, and various whiskers or oxides.[8] It is observed that wear rate of PTFE composite decreased by up to 80% with a moderate carbon volume fraction between 15–30%.[9] Low volume fraction (5%) of carbon, filler distribution is insufficient to form a robust load-bearing network within the polymer matrix.[10] However, as carbon content increases around 30% volume fraction, the wear rate decreases exponentially.[10] Excessive carbon content can lead to agglomeration, negatively affecting the wear rate and COF due to non-uniform dispersion. Carbon fiber prevent stress concentration resulting in better distribution of the applied load which enhances the wear life of the material. It is observed that carbon fiber-reinforced PTFE composites displayed enhanced wear resistance, particularly under high humidity conditions, where virgin PTFE typically suffers from higher wear rates. The presence of carbon fiber provided structural stability and prevented excessive deformation under sliding conditions, leading to a reduction in wear by nearly 60% compared to pure PTFE.[11] It is seen that the addition of carbon fiber in combination with graphite enhances load-carrying capacity as well as reduces friction in PTFE composites. The presence of graphite helps in building up a lubricating layer on the counter-face that helps in increasing the friction-reduction process.[12] The synergistic effect of carbon fiber and MoS_2 results in improved load-bearing capacity and effective solid lubrication, which reduces adhesive wear and minimizes surface damage during sliding contact. Similarly, combination of carbon fiber with other lubricating fillers like graphite or calcium carbonate whiskers results in the formation of a stable transfer film on the counterface, which significantly reduces wear. The study noted that a 15% volume fraction of carbon fiber combined with 5% MoS_2 resulted in up to a 60% reduction in wear rate and COF compared to pure PTFE. [13,14] It is found that carbon fiber combined with glass fiber effectively mitigated the detrimental effects of moisture and thermal aging on the wear properties. The wear rate was reduced by 40%, and COF decreased by 20% due to the synergistic reinforcement of glass fibers along with carbon in PTFE.[15] Moreover, the synergistic effects of carbon fillers combined with other reinforcements like MoS_2, graphite, and glass fiber can lead to a substantial reduction in wear rate (up to 80%) and COF (up to 50%), making PTFE composites more suitable for demanding tribological applications.[16] While carbon fiber significantly improves properties of PTFE composite, glass fiber also contribute to enhance its tribological performance under various conditions.

Glass fibers, having high tensile strength and modulus, are widely used for reinforcement of PTFE. The incorporation of glass fibers may significantly enhance the wear resistance and reduce the coefficient of friction (COF) for PTFE composites. The volume fraction of the glass filler is one of the key factors affecting the tribological performance of PTFE composites. Researchers observed that the glass fibre with 20% volume fraction in PTFE shows outstanding performance in tribological applications, however with increased volume fraction performance of composite decreases due to agglomeration or weak adhesion between the matrix and filler.[17] The blending of glass with fillers like SiO_2, MoS_2, graphite in a balanced combination allowed the wear rate to be minimized by about 15%. [18] The temperature and humidity influence performance of glass filled PTFE composite significantly. The PTFE composite tend to absorb water which increases wear rate by 10-20%, however the elevated temperature softens the matrix material accelerating the wear rate by 20-30%. [7] It is found that due to the high mobility of polymer chains, at elevated temperatures leads to change in the wear rate as well as thermal degradation because of the increase in temperature. [19,20] Glass fiber provides improvement in tribological properties of PTFE, researchers have also considered other fillers to further improve performance. Bronze is one such alternative which different advantages when amalgamated with PTFE matrix.

Bronze-filled PTFE composites, shows improved wear resistance, load bearing capacity as well as frictional behaviour which makes them suitable for applications like bearings and seals. It also dissipates the heat generated during sliding, reduce the degradation of the PTFE.[14] It is seen that, PTFE with bronze filler improves load distribution and reduces direct contact between matrix and counterface, hence show reduction in wear rate up to 80%.[21] However, selection of optimal bronze volume faction is crucial. Researchers found that higher bronze content improves wear resistance at the cost of increased surface hardness, conversely, insufficient bronze content provides inadequate reinforcement. Soft counterface shows better results with bronze volume fraction between 15 – 20%. [16] It is also evident that bronze blended with graphite as well as MoS2 shows considerable reduction in wear rate especially at elevated temperature conditions. [22,23] Harder counterface require higher bronze content for optimal performance, however it can lead to excessive hardness, increasing COF and the risk of abrasive wear, particularly on softer counterface. Furthermore, high bronze content can lead to particle agglomeration, potentially compromising the composite structure. [24,25] The applications requiring better mechanical and tribological properties, bronze content may reach up to 60% of volume fraction in combination with fillers like MoS_2, graphite. Higher volume fraction of bronze maximises load bearing capacity, wear resistance and thermal stability, making it suitable for high stress applications at higher temperature environment as in case of seals, piston rings etc. [26,27] Therefore, careful consideration of bronze content, counterface material, and other fillers is crucial for optimizing the performance of bronze-filled PTFE composites in specific tribological applications.

Graphite, a self-lubricating filler act as solid lubricant significantly reduces COF in PTFE composites. A transfer film formed on the counterface avoids direct contact between two interacting surfaces which leads to lower the wear rate. [18] Graphite having better heat conductivity helps in dissipating heat generated during friction, which prevents thermal degradation of PTFE matrix. It possesses lower hardness and strength compared with other fillers which limit its use for high load and abrasive conditions. The usual volume fraction of graphite is around 5-20%, higher volume fraction is desirable where lubricity is demanded in applications such as seals, bearings. If the graphite is used in lower volume fraction the properties of composites shall be balanced using other fillers in appropriate volume fraction.[22] It is seen that better wear resistance can be obtained when it is used together with SiO_2 and MoS_2. These filled composites show wear reduction to 50-70% compared to unfilled PTFE.[22]

Beyond the tribological enhancements achieved with fillers like bronze and graphite, incorporating hard particle reinforcements such as SiO_2 offers another avenue for tailoring PTFE composite performance. SiO_2, due to its hardness, plays a crucial role in restricting the deformation and abrasion of the relatively soft PTFE matrix, leading to a substantial reduction in wear rate. Research indicates that even small additions of SiO_2 (5-10%) can decrease the wear rate of PTFE composites by approximately 60% under water lubrication, demonstrating its effectiveness in enhancing wear resistance.[18] This improvement stems from the SiO_2 particles providing support and hardness to the PTFE matrix, preventing direct contact between the PTFE and the sliding surface. This, in turn, minimizes material loss and reduces the wear rate. However, exceeding a critical concentration of SiO_2 (around 15 vol.%) can have detrimental effects. An excessive amount of these hard particles creates a significantly more abrasive composite, leading to increase COF and wear rates. Therefore, careful control of SiO_2 content is essential. The influence of SiO_2 on COF is somewhat complex and depends heavily on the lubrication conditions. In dry contact scenarios, the inherent hardness of SiO_2 particles can contribute to increased micro-abrasion at the sliding interface, potentially raising the COF. Conversely, in water-lubricated environments, SiO_2 particles often have little to no impact on COF or may even slightly reduce it.[19] This is likely due to the formation of a uniform transfer film, influenced in part by the SiO_2 particles, which reduces surface roughness and facilitates smoother sliding. The benefits of SiO_2 can be further amplified by combining it with other solid lubricants. A synergistic effect is observed when SiO_2 is used in conjunction with materials like graphite or molybdenum disulfide (MoS_2). For instance, a ternary blend of 5% SiO_2, 5% MoS_2, and 5% graphite has demonstrated outstanding tribological performance under seawater lubrication.[19] In this combination, SiO_2 contributes hardness and abrasion resistance, while graphite and MoS_2 provide lubricity by forming lubricating layers, resulting in a composite with both low friction and high wear resistance.

Another hard particle reinforcement, Al_2O_3, offers distinct advantages for enhancing the tribological properties of PTFE. Al_2O_3-filled PTFE composites exhibit high hardness and thermal conductivity, which significantly reduces deformation and material loss during sliding. This often translates to a 50-60% reduction in wear rates compared to unfilled PTFE.[28] The Al_2O_3 filler creates a robust surface layer that protects the composite and resists wear, making it particularly beneficial in dry sliding conditions where its hardness is advantageous. However, the influence of Al_2O_3 on the coefficient of friction (COF) is more nuanced. It often leads to a modest increase in COF, likely due to abrasive interactions at the sliding interface. Furthermore, higher Al_2O_3 content (above 10-15%) can exacerbate this issue, potentially leading to increased abrasive wear, especially on softer counterface materials.[28] To mitigate the increase in COF associated with Al_2O_3, combining it with solid lubricants like graphite proves effective. Graphite, by forming a lubricating film on the surface, counteracts the increased friction caused by Al_2O_3. Simultaneously, the presence of Al_2O_3 reinforces the composite, providing the necessary wear resistance. This synergistic combination results in hybrid composites that exhibit both low COF and excellent wear resistance. While both SiO_2 and Al_2O_3 enhance wear resistance, Al_2O_3 is generally more suitable for dry or high-temperature environments due to its superior hardness. SiO_2, on the other hand, demonstrates more stable COF behaviour under such conditions. Ultimately, combining either Al_2O_3 or SiO_2 with additional fillers, such as solid lubricants, creates hybrid systems with synergistic effects, significantly improving overall tribological performance.[17] These tailored composites can be effectively utilized in a wide range of applications, from simple to complex.

In addition to the fillers, calcium carbonate ($CaCO_3$) presents another option for modifying the properties of PTFE composites, particularly when cost-effectiveness is a consideration. $CaCO_3$, typically added in volume fractions ranging from 5 to 15%, contributes to improved mechanical properties, thermal stability, and, to a lesser extent, wear resistance in PTFE.[19] As an inexpensive filler, $CaCO_3$ functions by dispersing stress under load, minimizing deformation. This, in turn, reduces material loss during sliding wear. The protective layer formed by $CaCO_3$ particles also helps prevent direct contact between the composite and its counterface, further contributing to wear reduction.

Incorporating polymeric fillers like aramid fibers and PEEK offers another approach to enhancing the performance of PTFE composites. Aramid fibers, known for their excellent abrasion resistance, thermal stability, and mechanical strength, form a durable network within the PTFE matrix when added in volume fractions of 5 to 10%.[29] This network significantly improves wear resistance and reduces the coefficient of friction (COF). Even when amalgamated with PTFE, aramid fibers maintain the composite's flexibility while providing effective mechanical reinforcement. The fibers contribute to the formation of a stable transfer film on the counterface, preventing direct contact between the moving elements and further reducing wear. [29] However, under harsh operating conditions with excessive friction, the generated heat can degrade the PTFE matrix, limiting the effectiveness of the aramid fibers. Therefore, optimizing operating parameters to minimize mechanical and thermal damage is crucial for realizing the full potential of aramid fiber reinforcement.

Similarly, Polyetheretherketone (PEEK) fillers have a significant impact on the tribological performance of PTFE composites. PEEK, with its inherent wear resistance, high mechanical strength, and thermal stability, enhances the functionality of PTFE composites. Studies have shown that PEEK increases the load-carrying capacity of PTFE and promotes the formation of a stable transfer film, drastically reducing wear rates. PEEK also facilitates a more even distribution of applied load across the interacting surfaces, minimizing localized stresses and contributing to lower wear. The optimal volume fraction of PEEK in PTFE composites depends on both operating parameters and environmental factors. Research suggests that adding 10-20% PEEK can lead to a 40-60% reduction in wear rate and a 10-15% reduction in COF, although these improvements are contingent upon the specific test parameters.[30] Exceeding 20% PEEK, however, can increase micro-abrasion, leading to increased surface roughness and potentially negatively affecting the composite's overall performance. [31] Notably, PEEK-filled composites demonstrate more pronounced improvements under dry sliding conditions compared to lubricated environments.

Table 1. Effect of environmental and working conditions on different fillers.

		Parameters					
		Temperature	**Humidity**	**Lubrication**	**Abrasive Environment**	**Counterface Material**	**Reference**
Fillers	**Carbon**	Reduces thermal expansion	Improves wear resistance	Effective in Dry and Lubricated conditions	High wear resistance	Effective with hard and soft counterface	8,9,10, 11,12, 13,14,
	Glass	Degrade at very high temperatures	Moisture-sensitive	Effective in Lubricated conditions	Moderate wear resistance	Effective with hard counterface	7,17,18, 19,20
	MoS_2	Maintains lubrication under high temperature; reduces wear	Moisture-sensitive	Effective in Dry conditions	High wear resistance	Effective with hard and soft counterface	22,26,27,
	Bronze	Prevents overheating	Improves wear resistance	Effective in Lubricated conditions	High wear resistance	Effective with hard counterface	14,18,21, 22
	Graphite	Reduces friction by forming lubricating layers	Improves wear resistance	Effective in Lubricated conditions	High wear resistance	Effective with soft counterface	18,19,22
	SiO_2	Enhances thermal stability	Increase abrasiveness	Slight improvement in wear under lubrication	High wear resistance	Effective with hard counterface	18,19,23,
	Al_2O_3	High thermal stability	Increase abrasiveness	Slight improvement in wear under lubrication	High wear resistance	Effective with hard counterface	17,28,
	$CaCO_3$	Degrade at very high temperatures	Moisture-sensitive	Slight improvement in wear under lubrication	Become brittle in extreme abrasive conditions	Effective with hard counterface	17,23
	Aramid Fibers	Degrade at very high temperatures	Moisture-sensitive	Effective in Lubricated conditions	High wear resistance	Effective with hard and soft counterface	29
	PEEK	Enhances thermal stability	Maintains structural stability	Effective in Dry and Lubricated conditions	High wear resistance	Effective with hard and soft counterface	30,31

In summary, the research highlights the importance of carefully selecting fillers to enhance the mechanical strength and tribological performance of PTFE composites. While each filler offers unique advantages, the optimal choice and content depend heavily on the specific application and operating conditions. Effect of few environmental and operating conditions on the fillers is shown in *Table. 1* Combining PTFE with appropriate fillers opens possibilities for tailoring the composite's properties for a wide range of high-performance applications. However, predicting the tribological performance of these composites remains a challenge due to the nonlinear behaviour of these materials under varying operating conditions. In this context, ML techniques have proven valuable for analysing experimental datasets and complex wear patterns, enabling more accurate predictions of PTFE composite performance under diverse conditions.

MACHINE LEARNING APPROACH

ML, a highly effective tool is used to understand wear phenomenon widely applied in aerospace bearing, automobile seals, and biomedical implants. These applications required high wear resistance, low friction reliable materials under extreme working conditions. Traditional empirical model fails to understand the nonlinear interactions between operating parameters as well as filler compositions. For instance, aerospace bearing uses PTFE self-lubricating material subjected to extreme load and temperature conditions, traditional models are not able to successfully simulate these dynamic conditions. Similarly, automobile seal performance is influenced by lubricating conditions as well as surface roughness, which traditional models oversimplify. However, ML models can identify intricate wear patterns and predicts wear behaviour with better accuracy. Similarly, ML models learn and understand new data interruptions and constantly adapts other influencing conditions as well as material formulations. Hence, ML model has a batter approach to optimize the PTFE composite performance for the real-world applications.

Based on input characteristics including hardness, roughness, and applied force, these ML approaches categorize the various wear mechanisms into groups of abrasive, adhesive, or fatigue wear. This will help the researchers to easily identify the wear mechanisms that dominate the system, which also helps to choose materials and modify designs to improve wear behaviour. ML is effective in downtime and cost reduction due to its ability to recognize patterns and generate predictions. The interpretability of ML models in tribology is improved by using explainable Artificial Intelligence deployment as it not only yields accurate forecasts but also enlightens the fundamental causes of wear behaviour. *Fig. 1* gives ML workflow, progressing from data collection to prediction. In tribological applications the data is collected through experimentation using various operating conditions like load, speed, temperature, and wear rate. The performance of ML model is dependent on large-scale high-quality data.

The collected data is then cleaned and formatted before being processed by ML algorithms. Data preprocessing includes addressing missing data, removing outliers, standardizing or normalizing numbers, and feature selection. The minimization of the error caused by dataset oddities can be handled by effective pre-processing of data which helps the model to learn the data effectively.

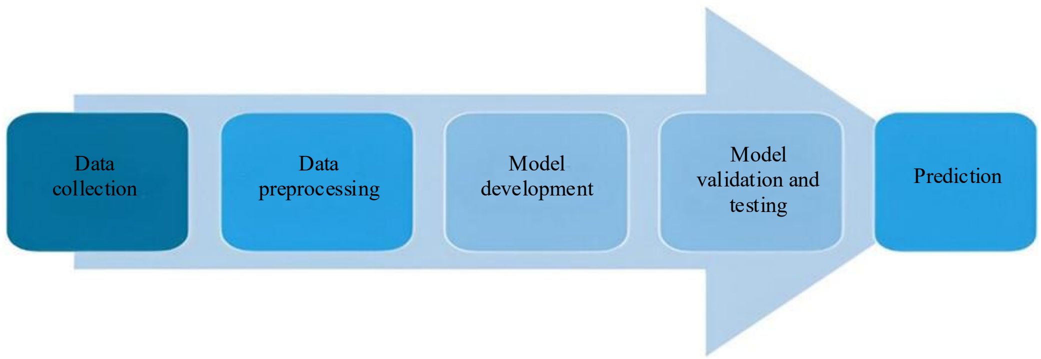

Figure 1. ML workflow.

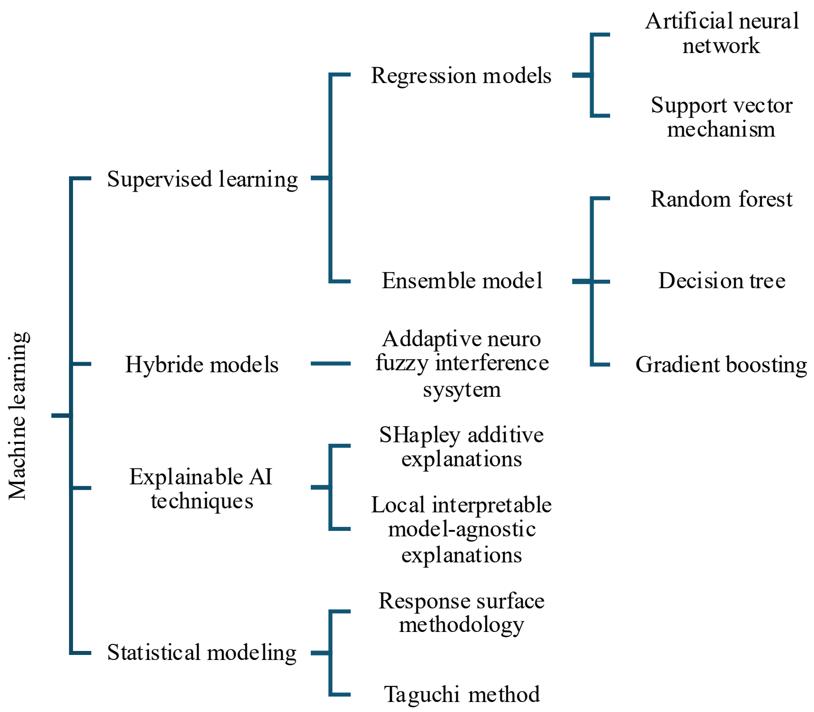

Figure 2. Hierarchical framework of ML.

The one or more ML algorithms are then trained using the clean pre-processed data. It is observed that in tribological studies models like ANN, SVM, Decision Trees (DT), RF or Gradient Boosting (GB) are generally used to predict wear and/or categorize wear mechanisms. At this stage, the right techniques and parameters are chosen to allow the algorithm to capture the data's patterns with as much precision as possible. After training the suitable model, it is validated and tested using a test subset of the dataset. The accuracy measurements, such as root mean squared error (RMSE), or R-squared values employed to calculate the model's predictive accuracy. After validation and optimization, predictions are made for previously unknown data by using the ML model. This will help the researchers to optimize material properties as well as operating parameters. The hierarchical framework of ML is shown in Figure 2.

Across the range of composite materials, the use of ANN has become increasingly prominent, offering valuable insights into wear mechanisms, coefficient of friction, and overall tribological behaviour. ANN is suitable for predicting wear and frictional characteristics of composites, it is also proven to be effective in modelling complex, non-linear relationships in materials' performance. [32,6] It is observed that ANN can replace traditional empirical models, which often fail to capture the complex interactions in composites. In feed-forward propagation, data flows in a single direction from the input layer to output layer through hidden layers. Initially the weights are randomly assigned, hence the network's predictions unlikely to be accurate. However, the error in the model is reduced through back propagation, which often gives high prediction for complex tribological problems with the error margin up to 5%. [33,34]

These models can use experimental data from various materials for training which makes it more versatile wear and COF of different material combinations as well as operating conditions. [35] Generally, ANN model showed high predictive accuracy with a correlation coefficient (R^2) of 0.93, This indicates a close agreement between experimental and predicted values, indicating the robustness of the model and its ability to be effectively used in different industrial applications for precise wear predictions.[36] The ANN yields a lower mean squared error compared to the traditional statistical models and also making ANN a superior choice for predicting wear materials with heterogeneous compositions in applications such as aerospace, automotive, and manufacturing. [37-39] Similarly, researchers used Adaptive Neuro-Fuzzy Inference System (ANFIS) model on experimental data of the composites containing varied the composition content of each filler. The model shows its effectiveness in capturing the influence of fillers on the wear performance of the composites. Notably, the ANFIS model also achieved a considerable level of accuracy, tuning closely with experimental data and offers a reliable alternative for traditional empirical methods.[40]

SVM is a sophisticated ML technology that has been used successfully in tribology to predict complicated behaviours such as wear rate and mass loss in a wide range of composite materials. SVM becomes efficient in dealing with non-linear relationships characteristic of tribological research due to its capacity to handle data in high dimensionality and give good findings from much smaller datasets. Recent studies on composites and applications demonstrate the effectiveness of SVM for material optimization and predictive modelling in tribology.[41] The researchers discovered that SVM provides a well-defined framework for forecasting tribological behaviour while also opening up options for further modification and optimization of PTFE formulations within specific applications for durability and effectiveness across operational situations.[34] The utility of SVM was effectively represented in applications requiring precise classifications. This suggests that SVM has a wide range of applications in tribological studies of metal composites, particularly in complex relationships between compositional and surface properties. Furthermore, SVM provides critical information for predicting discrete wear stages, which is possibly appropriate for tribo applications in smart manufacturing. [39] Other significant advantages of SVM include its adaptability for dealing with high-dimensional datasets, which is typical in tribology because multiple factors influence material behaviour at the same time.[34] However, when experimental data is insufficient, it is shown that SVM can generalize datasets better than most algorithms, making it useful in early-stage material testing or specialized applications where collecting a huge number of data is difficult to apply in practice.[37] The competitive accuracy that SVM may achieve when compared to other ML methods like RFs and GB underscores its utility. RFs have several advantages when working with very noisy input data. On the other hand, SVM frequently maintains an outstanding balance of accuracy and efficiency, making it an excellent candidate for future study and applications in material design, industrial lubrication, and wear resistance.

DT have also been effective at forecasting tribological actions and distinguishing the most relevant factors driving them. As expected, literature studies have shown that DT perform well for identifying crucial variables such as material composition and operating circumstances, which is thus extremely valuable in understanding the role that such elements play in the outcomes of wear and friction. However, one fundamental weakness of DT is that they are prone to overfitting complicated data, particularly when there are numerous interacting variables.[43] Overfitting occurs when the model becomes too accurate to the training data and does not generalize well to new data. Among numerous countermeasures, several academics believe that model tailoring and hybrid models should be utilized to improve generalization. [38,44]

To improve predictions, ensemble methods, particularly RFs and GB, are commonly used in tribological studies. In these strategies, multiple DT are joined to improve stability and reduce the impact of overfitting. For example, RFs generate many uncorrelated trees, and the projected results are pooled to reinforce the model during cross validation for various material compositions. [37,39] GB generates numerous following trees that successively minimize the mistakes committed by preceding trees, resulting in enhanced accuracy by lowering prediction errors.

DT's overfitting propensity is overcome by using ensemble approaches with prediction robustness while remaining interpretable. RF and GB are more suitable for reliable forecasting wear in more complex industrial applications. [34] In general, RF and GB are the primary strategies that improve accuracy and dependability and so are extremely effective in practical applications of tribology investigations.

RF has become a prominent tool in tribological study, due to its strength and ability for accurately predicting material qualities such as wear rate and COF. Ensemble approaches refer to the use of many independent DT to produce predictions in unison.[43] In this case, each tree in the forest is trained on a separate subset of the data and features, and the results are then averaged to generate a more accurate and stable outcome prediction. [42] The researcher's findings revealed that RF algorithms outperformed other ML approaches in dealing with the intricacy of interconnections between composition and tribological performance. [34,45] Thus, it is indisputably obvious that the model identifies the primary influencing aspects of wear behaviour, such as filler material percentage, surface treatment, and ambient circumstances. Other notable findings from the study included the fact that RFs are better at isolating influential parameters, which can lead to insights into the causes that may be influencing these outcomes. [39] The model's ability to detect this detail resulted in a high R^2 score, indicating great prediction dependability. The research of smart manufacturing approaches revealed that RFs outperformed other ML methods such as SVMs and neural networks. The algorithm's strength is its ability to handle noisy data and complex feature interactions.[32] The system adjusts for variances in wear patterns using numerous DT, resulting in a high degree of accuracy in wear forecasts. RFs improve accuracy and prevent overfitting with light into essential material features, making them ideal for use not just in research but also in practical tribology applications.

GB is an ensemble ML method that develops predictive models by building several DT that are trained successively in such a way that the faults of the prior trees are corrected, resulting in an iterative model. It produces very accurate models, particularly for complex, nonlinear relationships, because each tree incrementally enhances the model's performance. [42] The study indicated that GB could extract significant elements from material and operating characteristics that have a strong impact on wear performance. This study extended GB's ability to capture intricate interactions between materials and fillers, which linear models typically ignore. [44] In terms of stability, GB performed well but was only surpassed by RFs. GB showed interpretability advantages and detected nonlinear interactions between variables involved in wear with coefficient of determination of 0.95.[7]. The GB model also effectively manages variances in PTFE formulations, which capture the material's complicated, nonlinear responses to varied fillers.[39] It also demonstrates its utility in predictive modelling for composite material optimization by providing detailed advice on how filler adjustments can increase wear resistance.

The approach has a significant advantage in terms of accuracy; hence GB remains a viable methodology for applications requiring precision. Other algorithms further enhance the process by increasing computation speed and regularizing the model to prevent overfitting.[2] However, GB is computationally more expensive than other techniques, and it is prone to overfitting with small datasets when sufficient hyperparameter tweaking is not performed.

Interpretability of ML predictive model can be enhanced by using powerful tools like feature importance ranking and SHAP (SHapley Additive exPlanations) values. These tools identify the key factors influencing the wear behaviour which helps in better material optimisation eventually reducing dependency on extensive experimental testing. Feature importance ranking gives a generalised view how different variables which interact in complex way such as load, fillers, sliding speed, distance travelled etc, influence the model prediction.[46] ML models assign an importance score/ranking to these variables based on their impact on prediction accuracy. This gives an insight to the researchers to optimise these variables in composite formulation to improve material performance. This approach improves efficiency by focusing research efforts on the most influential factors rather than testing all variables equally. SHAP values, unlike feature importance ranking, quantify how much each parameter influence the predicted wear rate under specified operating conditions. For instance, SHAP values indicate positive or negative contribution of load on wear behaviour of composite. This helps the researchers to understand nonlinear interactions of individual variable and make precise adjustments to composite design. Combining Feature Importance Ranking for global insights and SHAP values for individual explanations, researchers can optimize PTFE composites to achieve better wear resistance, minimize experimental costs, and improve material performance in tribological applications in aerospace, automotive, and medical devices. Such methods make ML-based wear prediction more transparent, reliable, and actionable.

In experimental approach, statistical methods are widely used to optimize input factors. These statistical tools help in identifying the suitable levels of variables like load, speed, and temperature. The pre-processed data used for training the ML model can be effectively generated through statistical modelling. [47,48] The researchers find it helpful to eliminate irrelevant or redundant variables and focus on the factors most likely to influence outcomes, making ML models more efficient and interpretable.

The effective experimental design in statistical methods helps to generate datasets that capture the essential relationships between the responses with minimal experimental runs. This reduces the extensive data collection required for training the ML models. High quality of dataset can be generated by the researchers by effectively designing experiments using statistical techniques, which enhance the accuracy and reliability of ML models without needing a prohibitively large number of samples.[17] It is also observed that statistical methods aid in feature engineering, helping to identify interactions between factors that may not be obvious. It can model interactions between factors and generate interaction terms that represent how variables jointly influence the output.[49] These interaction terms can then be added to the ML model as new features, improving the model's predictive power.

Generally, statistical models use polynomial functions, however, it can struggle with highly nonlinear data. ML models can build on statistical model outputs to capture these nonlinearities more effectively. Combining ML models with the statistical methods allow for a robust approach that is both noise-resistant and flexible enough to capture complex interactions.[50] ML algorithms like RFs and GB inherently handle noise better, as they aggregate multiple models to provide stable predictions. Statistical models might be used to determine the optimal parameter ranges for a process, after which a ML model like SVM can be trained on these optimized conditions to generalize the findings to new, unseen data. This approach enhances the model's predictive accuracy and its ability to generalize across different conditions.

CONCLUSIONS

PTFE is a versatile material for various industrial applications due to self-lubricating and low-friction properties. To improve low wear resistance and load bearing capacity, certain fillers are incorporated in it. However, to ensure the performance of the composite the fillers need to be added in specific volume fraction, sometimes even in combination with other fillers. Traditional empirical models are generally used for interpretation of the behaviour of the composite under different operating conditions as well as fillers. However, these models fail to capture the complex relationship in the tribo-system. It is observed that effective use of ML techniques can help in overcoming this limitation of traditional modelling. ML models show the remarkable predictive accuracy of wear and frictional behaviour of composites. The advanced XAI aids in optimizing composite formulation pertaining to interplay of fillers, material properties as well as operating conditions. This review focuses on the need of using these advancements for effective solution for prediction of tribological behaviour of PTFE composite for various industrial applications. Following conclusions can be drawn from the present review

1. Fillers like carbon, glass, and bronze enhance PTFE's tribological properties, improving wear resistance and load-bearing capacity for diverse industrial applications. Optimizing filler volume fraction and combinations is crucial to avoid agglomeration and ensure effective performance.
2. Traditional empirical models are inadequate for capturing the complex interactions within PTFE composite tribo-systems. ML models, particularly GB, offer significantly higher predictive accuracy (e.g., R^2 of 0.95) for wear and friction behavior compared to traditional methods. ML models like ANN, SVM, RF, and DT effectively manage non-linear relationships and complex interactions between material properties and operating conditions.

3. Explainable AI (XAI) facilitates understanding the influence of fillers and operating parameters on PTFE composite wear. XAI enables optimization of composite formulations for improved tribological performance, contributing to cost reduction and improved efficiency/lifespan in applications across various industries.

FUTURE SCOPE

The present review explores the use of different fillers as well as machine learning techniques to improve performance of PTFE composite. Future studies can focus on the tactical use of XAI to explore wear mechanism. Further, machine learning models can be incorporated with life cycle assessment for sustainability of composites under various industrial applications.

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