USING ARTIFICIAL INTELLIGENCE (AI) TO IMPROVE LUBRICANT TECHNOLOGY

Introduction

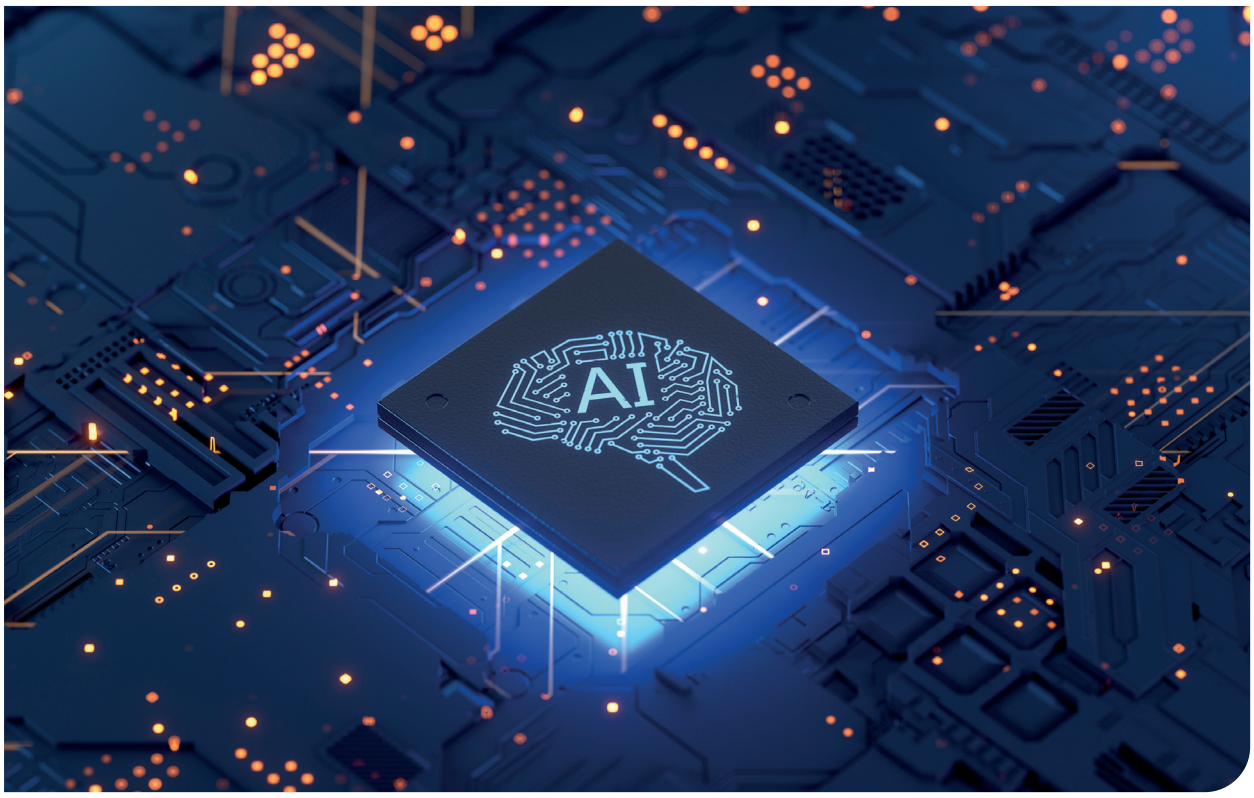
The rise of artificial intelligence (AI) has revolutionized numerous industries by enhancing the way processes are developed, evaluated, and optimized. One such industry is that of lubricants, which are essential for reducing friction and preventing machine wear [1]. Historically, analyzing these substances has required manual methods that are often laborious, time-consuming, and costly. Furthermore, testing methods such as the rotating pressure vessel oxidation test (RPVOT) are outdated designs that are tailored towards older types of lubricants commonly used in the industry that differ in sulfur and saturate concentrations, influencing properties such as viscosity, wear, oxidation, thermal stability, shear, and corrosion resistance [2][3].

The integration of AI presents a promising solution to these limitations by enhancing data analysis and organization, thereby facilitating the early identification of lubrication issues. This is critical, given that lubrication problems account for approximately 75% of repair costs and 66% of machine failures [4]. Proactive detection and signaling of lubrication issues can mitigate machine failures through scheduled maintenance leading to minimized downtime. Consequently, leading companies like Shell and ExxonMobil are adopting AI technologies to identify specific issues such as lubricant degradation, wear patterns, and operational anomalies, enabling more precise predictive maintenance and reducing unexpected failures [5]. Other recent emerging studies and applications are examined in this paper, providing a comprehensive overview of the utilization of AI models such as artificial neural networks (ANNs), convolutional neural network (CNN), and fuzzy logic, which offer alternatives to the costly and labor-intensive traditional methods used in the lubricant industry for testing and developing new formulations.

Different AIs in Performance Prediction and Alert

Machine learning is widely used in the lubricant industry, particularly for predicting the degradation of lubrication properties and issuing alerts for timely reapplication. One notable type of machine learning model is ANNs, which were first employed in 1998 to classify wear particles from lubricated ball-on-disc experiments. Since then, ANNs have been applied to various tribology testing methods [6,7]. ANNs are designed to predict relationships between experimental conditions and particle features by self-organizing and analyzing data without supervision. To do this, ANNs require comprehensive data on material properties, operating conditions, and surface characteristics. They can assess how lubricants perform under different conditions such as temperature, pressure, load, and sliding speed. By correlating these conditions with experimental data, ANNs can predict performance metrics including the friction coefficient, wear rate, and thermal degradation, as shown in Figure 1. The training of ANNs involves several steps. Initially, the model makes predictions based on input data. A loss function then calculates the difference between these predictions and the actual outcomes. Optimization algorithms, such as gradient descent, are used to adjust the model's parameters to minimize this loss. This iterative process continues until the model's performance aligns with the desired accuracy [8][9].

Furthermore, Rosenkranz et al. described other types of systems besides ANNs, such as fuzzy logic, which offers a more human-like way of prediction [6]. Fuzzy logic helps manage the imprecision and uncertainty in lubricant behavior by converting data into fuzzy sets [7]. These fuzzy sets use if-then rules to interpret input variables, such as temperature, and translate them into output variables, such as viscosity.



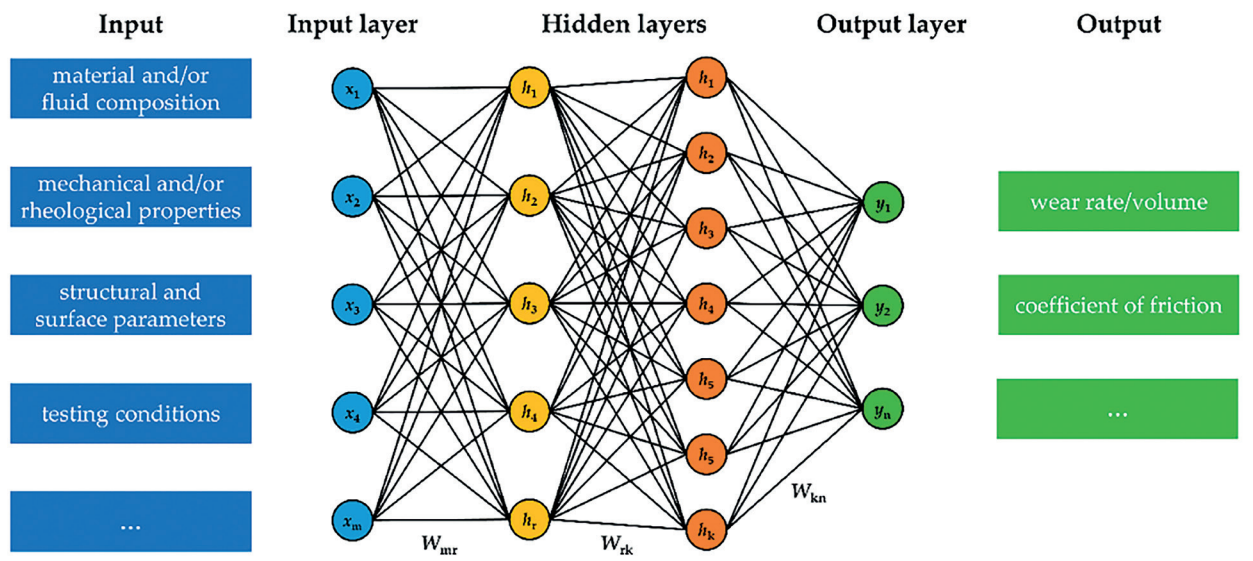


Figure 1: Relationship between testing conditions and properties of materials using artificial neural networks (ANNs) [6].

This method allows for more flexible and nuanced modeling of how lubricants perform under varying conditions. According to Sitek et al., fuzzy logic is particularly adept at dealing with uncertainty and linguistic variables, which are often encountered in materials engineering and lubricant optimization [6]. Fuzzy logic systems use membership functions to represent the degrees of truth rather than the binary true or false values of classical logic. This allows for a more nuanced evaluation of how various additives and base oils impact lubricant performance. By integrating fuzzy logic with ANNs, the predictive models can leverage both quantitative and qualitative insights, improving the accuracy of forecasts and ensuring that lubricant formulations perform optimally across diverse conditions [6].

Furthermore, advances in AI have also improved real-time monitoring and alert systems, addressing limitations found in traditional approaches. For example, multiple consumers using OEM-based alerts were reporting false positives for downtime agents when their systems are functioning correctly. Holzer proposed a solution where AI models are trained to differentiate between normal rates of soot accumulation and rapid accumulation due to engine issues, thereby increasing alert precision by 3.9 times compared to OEM-based and statistical-based alerts. This improvement results in longer-lasting machinery and more reliable maintenance scheduling [9]. Similarly, Hassan et al. introduced an alternative approach to detecting contamination accumulation in grease using a deep CNN [10]. The CNN model (Figure 2) was designed with several convolutional layers to extract relevant features from images, such as edges, textures, and shapes. Rectified Linear Unit activation functions were used to introduce non-linearity into the model, allowing it to capture complex patterns. Batch normalization was further applied to stabilize and accelerate the training process by normalizing the output of each convolutional layer. Following the convolutional layers, fully connected layers were used to integrate the learned features and assess contamination within the grease. This trained CNN model was then integrated into a real-time monitoring system that continuously analyzed the images from machine-environment interactions.

ANNs, fuzzy logic, and CNNs highlight the potential of AI and machine learning to improve operational efficiency. Due to their predictive capabilities, many industries reliant on lubricants are adopting machine learning and AI to plan cost-effective maintenance and optimize machine performance. For example, the Swedish-based automobile company Volvo has incorporated a new AI platform-driven analysis called "Fluid Analysis," which is used to identifies metal wear and changes in fluid conditions within the vehicles [4]. Through historical data, the AI can identify trends and predict lubricant reapplication needs, reducing downtime by 15% [4]. Similarly, the American aerospace company Pratt & Whitney (P&WC) utilizes machine learning for fluid analysis to conduct oil analysis on their aircraft [11]. By integrating AI to analyze patterns with ANNs, hundreds of types of lubricants can be quickly compared. This method aims to reduce maintenance

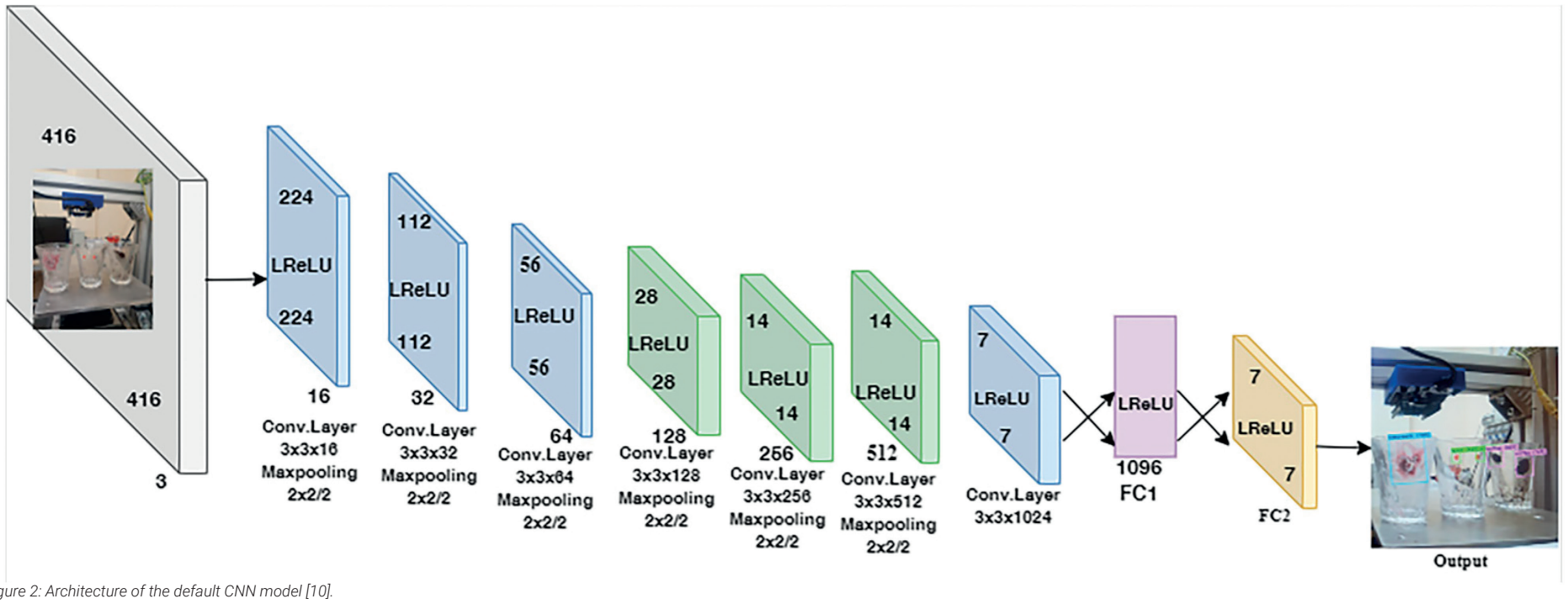


Figure 2: Architecture of the default CNN model [10].

costs and detect early signs of engine wear without the labor-intensive processes and process fees. This method has already been demonstrated to be effective, with a major government agency using P&WC's AI technology as its primary tool for monitoring their helicopters [11].

AIs in Formulations

Furthermore, both ANNs and fuzzy logic play a crucial role analyzing extensive datasets of chemical properties and performance metrics to perform complex calculations, aiding in the evaluation of various combinations of base oils, additives, and performance enhancers to meet specific requirements for reducing friction, extending service life, and improving thermal stability. For example, a study by Rosenkranz et al. demonstrated the use of ANNs and genetic algorithms to optimize lubricant formulations containing vegetable oils and carbon nanotubes or graphene, effectively reducing the friction coefficient (COF) [6]. As shown in Figure 3a, the ANNs was trained using experimental data with various oil concentrations and their corresponding COF values, adjusting the network's weights to minimize the prediction error through backpropagation. The ANNs predicted that a mixture with 4 wt% sunflower oil and no rapeseed oil would have a lower COF compared to a mixture with no sunflower oil and 20 wt% rapeseed oil. It also predicted a mixture with 6.5 wt% sunflower oil and no rapeseed oil would exhibit a lower COF than one with no sunflower or rapeseed oil. This training process was then visualized using a 3D surface plot to illustrate how different formulations affected the COF. Complementing the ANNs, a genetic algorithm was used to further optimize the formulations by systematically exploring and selecting the best oil concentration combinations to minimize COF. This algorithm employs principles of natural selection and evolution to iteratively improve the solutions, enhancing the lubricant's performance [6].

In a different approach, Wang et al. utilized ANNs, along with Support Vector Machines (SVMs), Random Forests (RFs), and Gradient Boosting Machines (GBMs), to design grease formulations incorporating graphene and carbon nanotubes. The ANNs model predicted the frictional coefficient based on additive concentrations and zinc oxide nanoparticles. The study also employed SVMs for classification, RFs to enhance predictive accuracy, and GBMs to improve the model's performance by sequentially correcting errors. A similar genetic algorithm to Rosenkranz was used to optimize the concentrations of the additives, resulting in a formulation with a friction modifier of 2 wt% and 0.66 wt% for each additive. The newly formulated grease achieved a 50% reduction in friction. The study highlighted that functionalized graphene (FGR) effectively filled surface irregularities and created a protective film, while functionalized carbon nanotubes (FCNT) shifted the friction mode from sliding to rolling, leading to reduced friction and wear.

Both studies highlight the versatility of AI models, such as ANNs and genetic algorithms, in optimizing lubricant formulations. While Rosenkranz et al. focused on reducing friction in vegetable oil-based lubricants with carbon nanotubes and graphene, Wang et al. explored grease formulations with similar AI techniques to incorporate advanced additives like graphene and carbon nanotubes. This synergy of AI-driven approaches underscores the potential for these technologies to enhance the performance of various lubricant formulations across different applications.

Application of AI in Lubricant Testing and Simulation

Additionally, AI was used to design a testing process for evaluating FGR and FCNT greases. The greases were assessed using a four-ball test, which measures tribological properties such as wear scar diameter and average friction coefficient. In this test, one stationary ball and three rotating balls are immersed in the lubricant and spun at 1,200 RPM for one hour. The results, including wear scar diameter and average friction coefficient, are summarized in Table 1.

High-throughput experimentation guided by AI models allows for the simultaneous testing of lubricant formulations, increasing the rate of discovery for new lubricants and reducing the need for extensive trial-and-error processes. Additionally, virtual screening techniques supported by AI can accurately simulate the behavior of lubricant formulations under different conditions, such as high temperatures and extreme pressures, to predict performance outcomes before physical testing. Simulation models further enable for the prediction of properties like performance in American Petroleum Institute or European Automobile Manufacturers' Association tests to ensure compliance with safety regulations [14]. These tests categorize oils based on their performance characteristics and suitability for different types of engines.

Performance metrics evaluated through these tests typically include viscosity, pour point, flash point, and wear resistance. Compliance with safety standards ensures that lubricants meet industry requirements for engine protection and efficiency. However, it is important to note that other performance metrics and safety standards set by different countries may also apply. AI-predicted formulations would not be perfected until predictive modeling in trained systems, such as ANNs, is refined to achieve a higher degree of accuracy and reliability in meeting these diverse standards.

Conclusion

Artificial Intelligence is revolutionizing the lubricant industry by enhancing formulation, testing, and optimization processes. Technologies such as ANNs and fuzzy logic improve the accuracy and efficiency of predicting lubricant performance and identifying issues, overcoming the limitations of traditional methods like the RPVOT. These advancements not only reduce downtime and maintenance costs but also enable faster discovery of new formulations and real-time analysis, driving significant improvements in lubrication practices and operational efficiency.

Looking ahead, future research in AI and lubricants will likely delve into several promising areas. One notable direction is the development of hybrid AI models that merge machine learning with physical chemistry principles, aiming to create more robust and interpretable models of lubricant behavior. Additionally, AI's transformative impact is expected to extend beyond lubricants to include coolant formulations and nanoparticle size prediction for additives, with companies like Shell Lubricants and ExxonMobil already exploring these applications [6][13]. As AI continues to advance, its role in optimizing various fluid systems will become increasingly significant, potentially reshaping industries that rely on lubrication technologies.

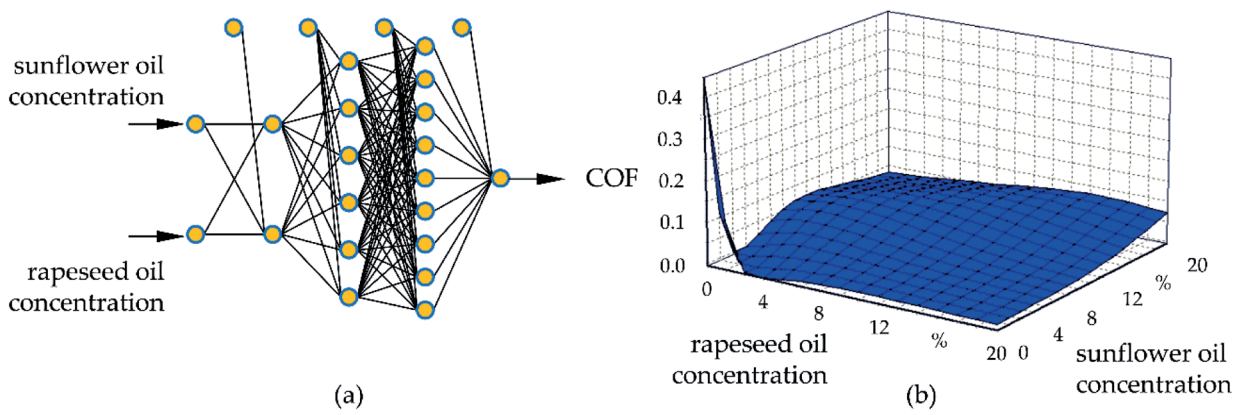


Figure 3: a) ANN; b) Friction coefficient of different vegetable oil concentrations [6].

Table 1: Summary of Four-ball test [12].

Test Element	Wear Scar Diameter (WSD)	Average Friction Coefficient (AFC)
Test Setup	Three stationary balls and one rotating ball in a cup.	Same as WSD but measures frictional force.
Measurement	The diameter of the wear scar on stationary balls.	The ratio of frictional force to normal load.
Performance	Lower WSD = Better wear protection.	Lower AFC = Better lubrication performance.
Example Data	WSD decreased by 25.66% in ANN grease compared to base grease.	AFC decreased by 29.34% in ANN grease compared to base grease.

However, to fully realize AI's potential in the lubricant industry, collaborative efforts between academia and industry stakeholders are essential. Continued investment in research and development, coupled with the establishment of industry standards for AI integration, will ensure that AI technologies are applied effectively and ethically. This will not only enhance the performance and sustainability of lubrication systems but also foster innovation and competitiveness in the global market.

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