

Review

The Role of Machine Learning in Minimum Quantity Lubrication for Sustainable Machining: A Review

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Abstract

Sustainable machining is gaining attention in modern manufacturing due to its cleaner operations, improved resource utilization, and reduced environmental impact. Among sustainable machining methods, minimum quantity lubrication (MQL) successfully minimizes cutting fluid consumption while maintaining adequate cooling and lubrication. This review examines recent developments and future directions in MQL-assisted machining, with particular emphasis on machine learning (ML)-based modeling and optimization techniques. A systematic review comprising literature identification, screening, scientometric analysis, and critical evaluation was employed to analyze 120 papers published mainly between 2010 and 2026. The reviewed studies employed ML models such as artificial neural networks, support vector machines, random forests, gradient boosting, and hybrid optimization approaches to predict machinability parameters, including surface roughness, tool wear, cutting force, cutting temperature, energy consumption, and chip morphology. The findings indicate that ML-assisted MQL processes improve prediction accuracy, machining efficiency, process monitoring, and sustainability performance by reducing energy consumption, minimizing cutting fluid usage, and improving machining quality. The analysis also identifies key research gaps and prospects for intelligent and sustainable machining.

Keywords: minimum quantity lubrication; machine learning; artificial intelligence; sustainable machining; machinability prediction; process optimization



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1. Introduction

Sustainable machining focuses on minimizing the environmental and societal impacts of machining processes while ensuring economic viability and maintaining product quality. It includes the adoption of energy-efficient, resource-optimized, and eco-friendly practices such as metal cutting, grinding, and turning [1,2]. In contrast, traditional machining methods have long been associated with high energy consumption, excessive use of metal cutting fluids, and substantial material waste. Considering that the manufacturing sector is one of the major consumers of global energy and natural resources, the transition toward sustainable machining practices has become necessary. This shift not only aims to reduce waste and emissions but also contributes to sustainable manufacturing for present and

future generations. In response to increasing environmental regulations and societal demands, sustainable machining has emerged as a strategy to improve productivity, enhance process efficiency, and contribute to a better quality of life.

Several techniques have been developed to support sustainable machining by reducing environmental impact, improving process performance, and maintaining economic viability. Among these methods, dry machining has gained considerable attention because it eliminates the use of cutting fluids, thereby minimizing environmental risks and reducing manufacturing and cleaning costs [3–6]. It also reduces health risks to operators and helps prevent air and water pollution. Because of these benefits, dry machining has been widely explored in recent years. To comply with environmental regulations associated with the use and disposal of cutting fluids, researchers are exploring alternative lubrication approaches. One such method is minimum quantity lubrication (MQL), which uses a very small amount of lubricant applied directly at the tool-workpiece interface [7,8]. MQL provides a practical balance between dry and conventional machining by significantly reducing cutting fluid consumption and minimizing related environmental concerns. In sustainable machining, the use of eco-friendly lubricants, along with reduced lubricant consumption, plays an important role. Vegetable-based oils used in MQL systems are appropriate alternatives because they are biodegradable, non-toxic, renewable, and easily available [9]. These oils provide effective lubrication while minimizing the environmental concerns associated with conventional cutting fluids. Cryogenic machining is another sustainable approach that utilizes cryogenic fluids such as liquid nitrogen or carbon dioxide for cooling [10,11]. This method reduces cutting temperature, minimizes tool wear, improves surface quality, and enhances productivity. High-speed machining (HSM) is used to increase productivity and reduce machining costs by employing high cutting speeds and feed rates compared to conventional machining. It minimizes machining time, cutting forces, power consumption, and overall energy use. However, its application in machining lightweight and high-temperature alloys is often limited by machine tool capabilities and increased tool wear [12]. Advanced coatings can improve cutting tool performance by improving wear resistance, reducing friction, and increasing tool life. Cutting tools coated with TiN, TiAlN, TiCN, DLC, and NDC show superior performance compared to uncoated tools under dry machining conditions [13,14]. DLC-coated tools reduce cutting temperature, chip thickness, and surface roughness. Among these coatings, DLC/TiAlN shows excellent wear resistance and a long tool life. Another important approach is hybrid machining using solid lubricants in the form of nano- and microparticles [15,16]. These particles form a protective tribo-film at the tool-chip and tool-workpiece interfaces, reducing friction, wear, and cutting temperature, thereby increasing tool life and improving surface quality.

MQL has emerged as a favorable technique among the various machining approaches discussed above because of its ability to effectively balance machining performance, economic benefits, and environmental sustainability. Unlike conventional machining, which requires substantial volumes of cutting fluid and creates problems such as waste disposal issues, increased operating costs, and health risks to operators, MQL supplies a minimal quantity of lubricant directly to the tool-workpiece interface [17]. This significantly reduces cutting fluid usage while ensuring effective cooling and lubrication. As a result, MQL decreases the cutting temperature, reduces tool wear, improves surface finish, and lowers operating costs. MQL demonstrates excellent machining options compared to dry and conventional flood cooling methods, particularly in the machining of difficult-to-cut materials [18,19]. Advanced forms such as cryo-MQL and nano-MQL further reduce cutting forces and the cutting temperature while improving surface quality. Cryo-MQL techniques have also been shown in recent studies to extend tool life, reduce energy consumption, and increase productivity while providing environmental and economic benefits compared with

standalone MQL systems [20]. Although the MQL system offers considerable benefits, the process remains highly complex due to the involvement of multiple factors, including fluid flow, heat transfer, tribology, chip formation, and material removal mechanisms [21,22]. Further, MQL performance depends on many parameters, including lubricant type, flow rate, air pressure, nozzle position, spray angle, cutting speed, feed rate, and depth of cut. These parameters often interact in a nonlinear manner, making the prediction of machinability characteristics difficult. In addition, localized aerosol lubrication and the short interaction time among the tool, workpiece, lubricant droplets, and chips further increase the complexity of the MQL process. To explore these relationships, researchers have used many methods such as design of experiments (DOE), Taguchi methods, analysis of variance (ANOVA), and response surface methodology (RSM) [23,24]. These methods are useful for parameter optimization and understanding process relationships, but they are often limited to specific machining conditions and are generally more suitable for linear and controlled processes. As a result, they cannot fully capture the complex nonlinear interactions among parameters involved in MQL processes.

The nonlinear behavior of MQL machining is strongly influenced by several coupled physical phenomena, including lubricant atomization, aerosol droplet penetration into the cutting zone, heat transfer at the tool-chip interface, tribological interactions, and chip formation dynamics. The effectiveness of MQL largely depends on the ability of fine lubricant droplets to penetrate the high-temperature cutting region and form a stable lubricating tribo-film, which directly affects friction, heat generation, tool wear, and surface quality. These highly coupled thermo-fluid and tribological interactions further increase the complexity of modeling and optimizing MQL-assisted machining processes.

Due to the above limitations, machine learning (ML) has emerged as an effective tool for modeling and optimizing MQL machining processes. Unlike statistical techniques, ML algorithms can learn complex and nonlinear relationships directly from experimental data and often provide more accurate predictions [25]. In MQL machining, ML has been successfully applied to predict machining performance in terms of surface roughness, tool wear, cutting forces, cutting temperature, and energy consumption. Several studies have shown that ML algorithms can accurately predict process performance, even for difficult-to-machine materials, with strong agreement observed between predicted and experimental results [26,27]. Furthermore, the integration of ML with genetic algorithms, the gray wolf optimizer, and teaching–learning-based optimization can further enhance machining performance and process efficiency [28–31]. These hybrid methods can improve surface finish, extend tool life, reduce energy consumption, and support sustainable manufacturing. Therefore, ML has significant potential to enable intelligent and high-performance MQL machining processes.

This review presents a comprehensive analysis of ML techniques in MQL machining by examining widely used ML models, machining input parameters, output responses, optimization strategies, hybrid intelligent algorithms, and future research directions. It also discusses the role of AI techniques in enhancing machining efficiency, process control, and sustainability. To the best of the authors' knowledge, although many studies have applied ML techniques in MQL machining, a comprehensive comparative evaluation of ML models, input parameters, prediction targets, performance metrics, workpiece materials, optimization strategies, and sustainability indicators is still lacking. Most existing studies are restricted to specific materials, machining conditions, or individual ML models, thereby limiting the identification of suitable approaches for various MQL applications. Unlike previous review studies that mainly focused on general MQL techniques, the present review provides a comprehensive evaluation of ML models employed in MQL-assisted machining. Furthermore, the review identifies existing research gaps and highlights future

research opportunities for the development of intelligent, adaptive, and sustainable MQL systems. The proposed approach aims to bridge theoretical advancements and practical industrial applications, thereby facilitating the effective and environmentally sustainable integration of ML techniques into MQL processes. In addition, the review seeks to support future innovations aimed at improving machining productivity while minimizing the environmental impact of manufacturing operations.

2. Overview of Existing Research

MQL has become an important technique in sustainable machining because it uses a minimal amount of lubricant while maintaining effective cooling and lubrication. Compared with conventional flood cooling, MQL reduces cutting fluid consumption, lowers the environmental impact, enhances tool life, and improves surface quality. However, analyzing MQL machining is complex because multiple process parameters simultaneously affect machining performance. Machining conditions such as cutting speed, feed rate, and depth of cut, along with MQL parameters such as lubricant flow rate, spray angle, and nozzle orientation, interact with machinability characteristics such as the cutting temperature, tool life, chip formation, and surface finish, thereby influencing machining performance and productivity. These interactions are often nonlinear, making process modeling and machining performance prediction difficult. Previous studies mainly used statistical methods such as design of experiments (DOE), the Taguchi method, analysis of variance (ANOVA), and response surface methodology (RSM) to analyze machining processes. These methods helped researchers understand how process parameters influence outputs such as surface finish, cutting force, temperature, and tool life. However, these methods are more suitable when the number of process parameters is limited and may not effectively handle the complex behavior of MQL processes involving multiple interacting parameters.

To improve the prediction accuracy of machining processes, researchers have explored artificial intelligence methods, particularly artificial neural networks (ANNs). Neural network models are able to predict machining performance more accurately than statistical models because they can learn nonlinear relationships from experimental data. In addition, advanced ML models such as support vector machines (SVMs), random forests (RFs), decision trees (DTs), gradient boosting (GB), and deep learning (DL) have been successfully applied. These models have been used to predict machining performance in terms of tool wear, cutting temperature, surface roughness, chip formation, and energy consumption. Studies have reported accurate predictions, particularly for difficult-to-machine materials such as titanium alloys and nickel-based superalloys. Researchers have also combined ML models with optimization techniques such as genetic algorithms (GAs), particle swarm optimization (PSO), and gray wolf optimization (GWO). These hybrid methods help identify optimal machining conditions to improve tool life, reduce energy consumption, and achieve better surface quality. Despite these improvements, several challenges still exist. Most studies use small experimental datasets and have not been extensively validated in industrial environments. In addition, many ML models function as black boxes, making their predictions difficult to interpret. Important factors such as ambient temperature, lubricant degradation, and machine condition are also often ignored. Therefore, further research is needed to develop reliable, explainable, and practical ML models for MQL machining.

3. Review Methodology

The main objective of this paper is to present a comprehensive review of different ML methods used in MQL machining. For this purpose, a structured review methodology consisting of six key steps was adopted to ensure the quality and depth of the study. These

steps included defining the research questions and scope, collecting relevant literature, screening studies based on inclusion and exclusion criteria, performing bibliometric and scientometric analyses, extracting and organizing key information, and critically evaluating the findings to identify research gaps and future research directions. The framework of the proposed methodology and its sequential steps are illustrated in Figure 1.

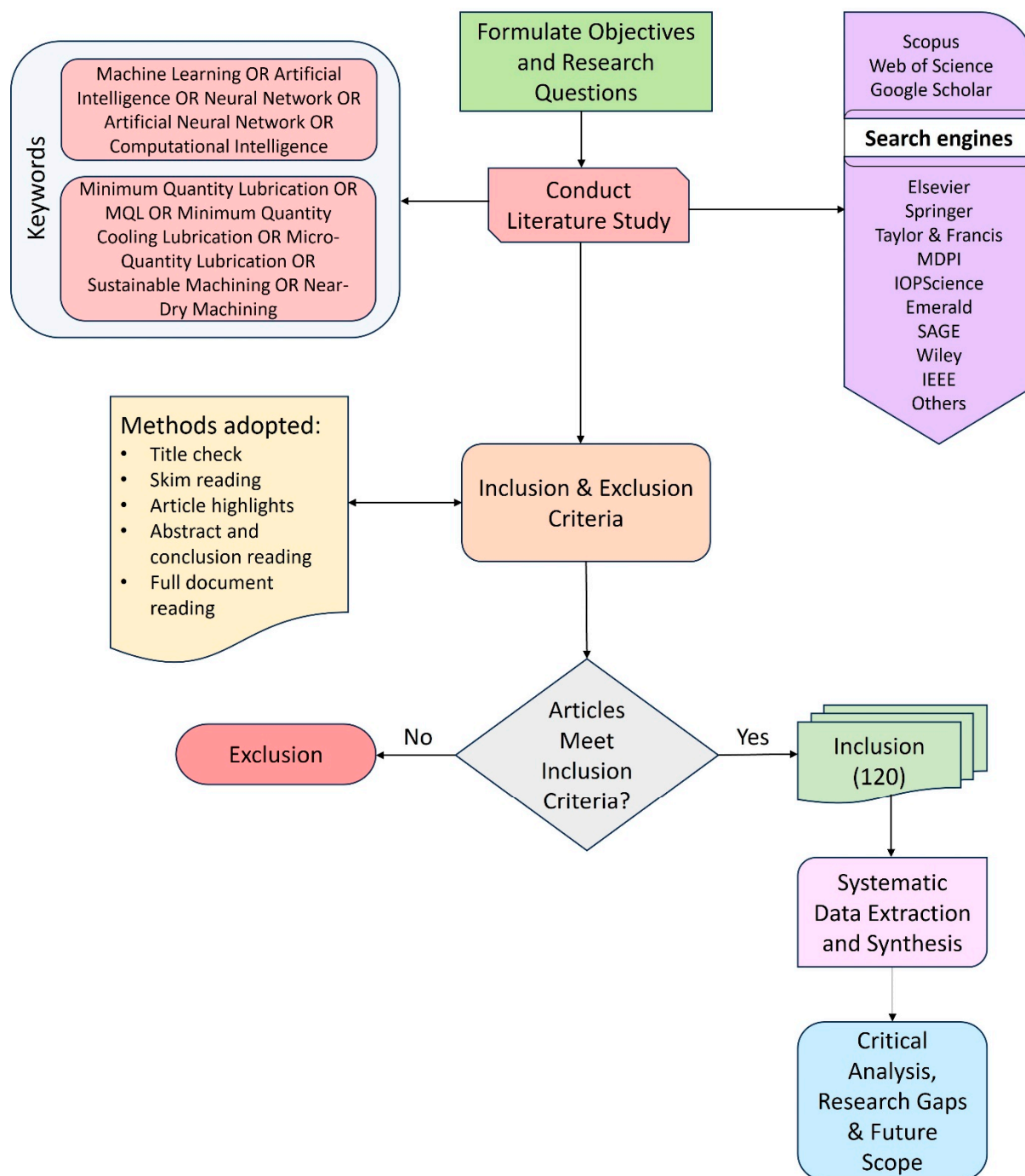


Figure 1. Proposed research methodology framework.

3.1. Formation of Research Questions

The first and most important step in conducting a review is the formulation of focused research questions, which help identify research gaps and provide future directions. Clear and well-structured questions also provide a coherent framework for readers, making the study easier to follow. In this review, eight research questions were developed to

systematically examine the use of ML models in MQL machining. These questions aim to evaluate the role of ML techniques in enhancing MQL systems, assess the effectiveness of existing models, identify key challenges in modeling complex MQL processes, and explore pathways for improving sustainable and practical machining applications. The questions include the types of ML models used; the problems these models solve; the role of MQL in sustainable machining; the challenges in understanding complex machining processes; the methods used to evaluate ML performance; the ability of ML models to predict machining outputs such as tool wear, cutting force, surface finish, and temperature; consideration of sustainability factors such as energy efficiency and environmental impact; and the identification of research gaps and future research directions. These research questions provide a structured basis for systematically analyzing the literature and understanding current trends, limitations, and future directions in ML-based MQL machining.

3.2. Literature Sources

The present review draws upon a wide range of research databases, including Scopus, Web of Science, and others, covering literature published over more than a decade. To ensure comprehensive coverage, publications from leading publishers were included, such as Elsevier, Springer, MDPI, Taylor & Francis, Wiley, IEEE, Emerald, SAGE, Inderscience, AIP Publishing, IOPScience, and Cambridge University Press, as well as papers from the Indian Society for Education and Environment and SAE International. The literature search was conducted using a combination of topic-specific and methodology-specific keywords to identify relevant studies on ML applications in MQL machining. The detailed search parameters and keyword combinations used in the study are listed in Table 1. Furthermore, scientometric visualization and science mapping techniques were employed to analyze research trends; identify influential authors, key journals, and collaboration patterns; and assess recent advances in the field. This approach ensures that the review is both comprehensive and systematic, providing a robust foundation for evaluating the state-of-the-art in ML-based MQL machining.

Table 1. Literature search strategy and selection criteria.

Database and Search Period	Scopus, Web of Science, Google Scholar (2010–2026)
Search string	("machine learning" OR "artificial intelligence" OR "deep learning" OR "neural network" OR "artificial neural network" OR "support vector machine" OR "random forest" OR "decision tree" OR "genetic algorithm" OR "fuzzy logic" OR "ANFIS" OR "Bayesian network") AND ("minimum quantity lubrication" OR "MQL" OR "MQL machining" OR "sustainable machining" OR "cryo-MQL" OR "nano-MQL")
Inclusion criteria	(i) Studies on MQL-assisted machining processes; (ii) studies applying ML, AI, or hybrid intelligent models for prediction, classification, monitoring, or optimization; (iii) studies reporting machining parameters such as surface finish, tool life, cutting force, cutting temperature, energy consumption, or chip formation; (iv) studies involving experimental validation or industrial case data; and (v) studies indexed in major scientific databases
Exclusion criteria	(i) Studies based only on conventional statistical methods without ML or AI techniques; (ii) pure review papers, editorials, reports, theses, patents, and unpublished manuscripts; (iii) studies lacking sufficient methodological details or validation results; (iv) non-English publications; and (v) duplicate records across databases

Table 1. *Cont.*

Database and Search Period	Scopus, Web of Science, Google Scholar (2010–2026)
Objective of search	To identify, classify, and critically evaluate ML applications in MQL machining with respect to prediction accuracy, optimization capability, sustainability contribution, and future research opportunities
Search fields	Title, abstract, keywords
Document types	Articles, conference papers, review papers, book chapters
Language	English

3.3. Criteria for Inclusion and Exclusion

Studies were included in this review if they focused on MQL-assisted machining and applied techniques such as ML, AI, or hybrid intelligent methods for prediction, monitoring, classification, or optimization. The studies reported important machining responses such as surface finish, cutting force, cutting temperature, tool life, chip formation, and energy consumption. Only studies published in English and indexed in leading databases such as Scopus, Web of Science, Google Scholar, and related publisher databases were considered. Journal articles, conference papers, technical papers, and relevant book chapters published between 2010 and 2026 were included.

Studies were excluded if they relied only on conventional statistical methods without incorporating ML or AI techniques. Review papers, editorials, theses, patents, unpublished manuscripts, and duplicate records were also excluded. In addition, research articles without sufficient methodological details, validation results, or clear information about the machining process and ML models were not considered. After the initial screening based on titles, abstracts, and keywords, the full texts of the remaining articles were examined to ensure their relevance, quality, and consistency with the objectives of the review.

3.4. Scientometric Analysis of the Literature

Scientometrics, introduced by Vasily Nalimov and Zinaida Mulchenko in the 1960s, refers to the quantitative evaluation of scientific research, research performance, and patterns of knowledge communication [32,33]. Over time, scientometric techniques have been widely used to identify important publications, examine collaboration networks, identify emerging research areas, and evaluate the development of a research field. In the present review, VOSviewer 1.6.20 was used as the primary tool for scientometric analysis to provide a deeper understanding of the research landscape in ML-based MQL systems.

The scientometric analysis was performed in two stages. In the first stage, relational networks were developed using keyword co-occurrence analysis, document co-citation analysis, citation analysis, and co-authorship network analysis. These methods provide insights into the relationships among authors, publications, keywords, and research themes. In the second stage, visualization maps were generated to identify the conceptual, intellectual, and social structure of the selected literature [34]. Figure 2 illustrates the clustered keyword co-occurrence map representing the main research themes and their interrelationships in ML-assisted MQL machining. Frequently occurring keywords are grouped into different color-coded clusters based on their co-occurrence strength, where closely related terms appear closer to each other. The map highlights strong associations among keywords such as machine learning, artificial intelligence, MQL, sustainable machining, tool wear, surface roughness, cutting force, temperature, lubrication, nanoparticles, neural networks, support vector machines, deep learning, random forests, and optimization. These interconnections indicate the increasing research focus on integrating intelligent techniques with

sustainable machining applications and demonstrate the strong relationship between ML algorithms and machinability characteristics in current research.

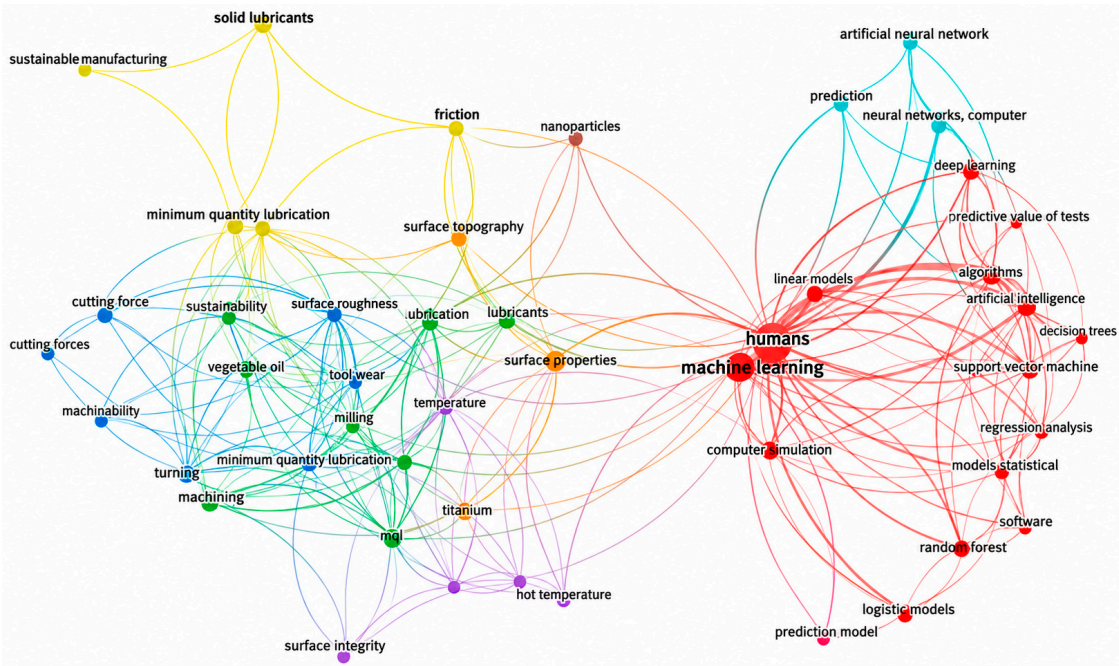


Figure 2. Keyword co-occurrence network in ML-based MQL literature.

3.5. Data Analysis and Evaluation

A total of 300 documents were initially identified during the literature review. After a comprehensive screening and exclusion process, 120 articles were selected. Figure 3 shows the distribution of articles among different publishers. Studies using ML models for the analysis of MQL machining parameters have been published across a wide range of journals and conference proceedings. As shown in Figure 3, most publications originate from three to four leading publishers, while the “Others” category includes publishers with a smaller number of publications.

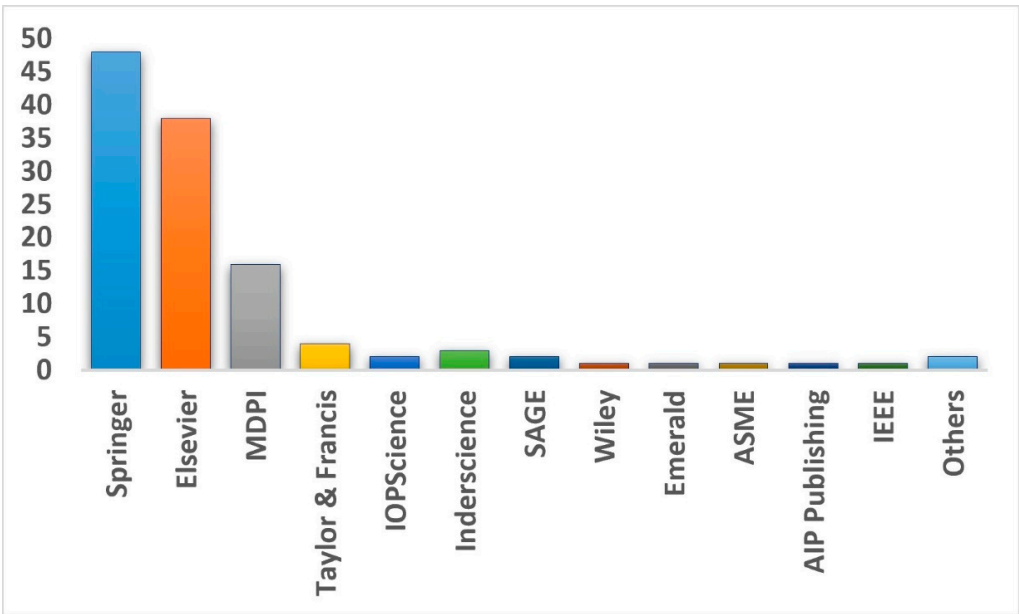


Figure 3. Article distribution among publishers.

Figure 4 presents the distribution of articles along the publication timeline, highlighting the chronological progression of research in this domain. The timeline depicts the publication pattern from 2009 to 2026 in two-year intervals. Although research in this area began in the late 2000s, the application of ML techniques to capture the nonlinear relationships in MQL machining parameters gained noticeable momentum around 2012. As shown in Figure 4, the research scope has expanded significantly in recent years, with more than half of the selected articles published within the last three years. This increasing trend reflects the rapid adoption of ML techniques in complex engineering applications, driven by their self-adaptive and dynamic capabilities.

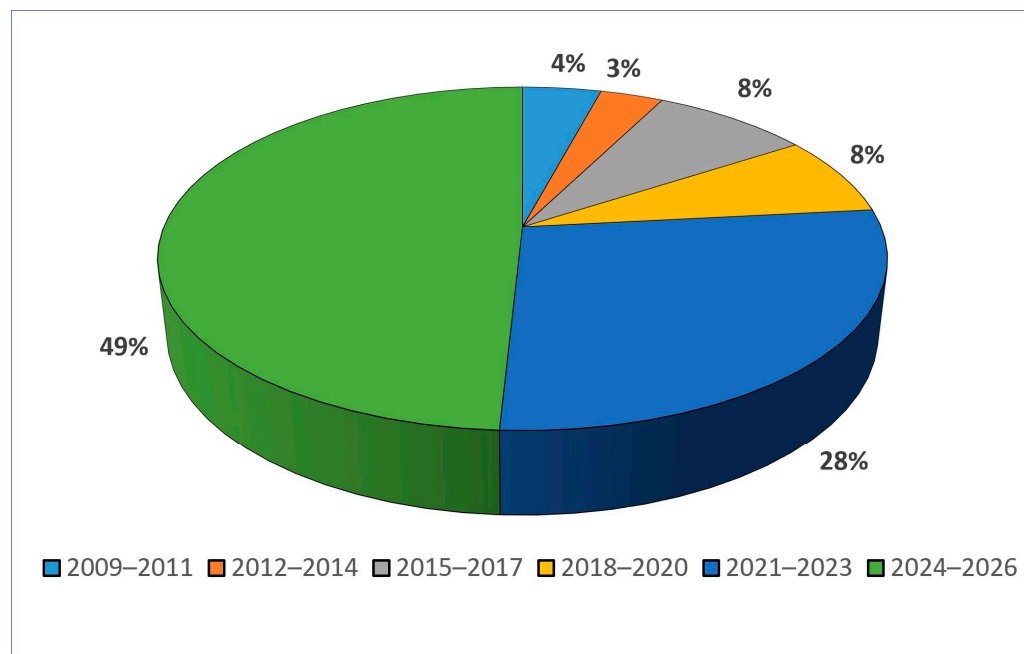


Figure 4. Article distribution along the timeline.

4. Role of Machine Learning in Minimum Quantity Lubrication

AI and ML techniques are increasingly applied for parameter optimization in machining processes, including turning, milling, drilling, and grinding [35,36]. ML, a major branch of AI, has become an important tool for analyzing, modeling, and optimizing parameters in complex MQL machining processes [37,38]. MQL machining has gained substantial recognition as a sustainable cooling and lubrication approach over conventional flood cooling methods. In MQL machining, a very small amount of lubricant is delivered directly to the cutting interface as a fine aerosol mist, which helps reduce cutting fluid use while improving tool life, surface finish, and productivity. However, the performance of MQL systems is influenced by numerous process and operating factors, such as cutting speed, feed rate, depth of cut, lubricant flow rate, air pressure, nozzle position, droplet size, workpiece material, and cutting tool characteristics. Since these factors interact in a complex and nonlinear manner, traditional statistical techniques often fail to provide accurate predictions under different conditions. ML techniques can effectively model complex nonlinear interactions from experimental data, making them highly suitable for MQL process modeling and optimization.

ML algorithms used in MQL systems are generally classified into supervised, unsupervised, and reinforcement learning methods. Among these, supervised learning is the most commonly used because it can predict machining process outputs from known input variables. Algorithms such as ANN, SVM, RF, DT, GPR, and XGBoost have been widely ap-

plied in MQL studies. These models have been used to estimate important responses such as surface quality, cutting force, cutting temperature, tool life, material removal rate, energy consumption, and chip morphology [39–41]. In many cases, ML models have demonstrated superior prediction accuracy compared with conventional regression and response surface methods due to their better capability to capture nonlinear process behavior.

Different ML models utilized in MQL machining demonstrate distinct advantages and limitations depending on the machining application, dataset size, and prediction objectives. ANN and deep learning models are highly effective in capturing complex nonlinear relationships and process behavior; however, they generally require large datasets and high computational effort and may be prone to overfitting when trained with limited data. In particular, deep learning models require large training datasets and substantial computational resources, which may limit their practical applicability in machining studies with small experimental datasets. SVM and GPR models provide reliable prediction accuracy for smaller datasets, although their performance is influenced by parameter selection and computational complexity. Ensemble methods such as random forest, gradient boosting, XGBoost, and CatBoost offer robust prediction capability, improved feature importance analysis, reduced overfitting, and enhanced generalization performance. In many studies, k-fold cross-validation has been employed to improve model reliability and avoid biased prediction results; however, external validation using industrial-scale datasets remains limited in current MQL research. Furthermore, the explainability and interpretability of complex ML and deep learning models still require greater attention for practical industrial implementation. Hybrid intelligent approaches integrating ML models with optimization techniques such as GA, PSO, NSGA-II, GWO, and TLBO have demonstrated significant potential for the multi-objective optimization of machining performance, energy efficiency, and sustainability indicators. Therefore, the selection of an appropriate ML model depends on machining requirements, data availability, computational cost, model interpretability, and the desired prediction accuracy.

Another important role of ML in MQL machining is process optimization. ML models are frequently integrated with optimization methods such as GA, PSO, GWO, NSGA-II, and ANFIS. These hybrid methods help identify optimal machining conditions by simultaneously reducing surface roughness, cutting force, and energy consumption while improving tool life, productivity, and machining performance. Such optimization is especially important in lubrication methods such as nano-MQL, cryo-MQL, and hybrid lubrication systems. ML-based optimization, therefore, plays a significant role in improving both machining performance and sustainability. Although MQL is widely recognized as a sustainable machining method because of its lower cutting fluid consumption and improved machining efficiency, most reviewed studies focused on machinability indicators such as surface roughness, tool wear, cutting temperature, cutting force, chip morphology, and energy consumption. Only a few studies explored broader sustainability metrics such as carbon emissions, life-cycle assessment (LCA), and overall energy usage. According to the literature assessment, only a limited number of studies included carbon emission analysis, energy consumption, or LCA-based sustainability assessments, while most investigations focused on machining performance prediction and optimization. As a result, future ML-assisted MQL research should incorporate broader sustainability metrics along with machining performance indicators to provide a more comprehensive evaluation of sustainable manufacturing systems. Table 2 summarizes the ML models applied in MQL-assisted machining systems, along with their machining applications, predicted responses, sustainability-related outcomes, and predictive capabilities reported in the literature.

Table 2. Machine learning models and their applications in MQL machining.

Ref.	MQL/Machining Type	Material	Machinability/Processes Responses	ML/Statistical Models	Performance Metrics	Sustainability Benefits and Outcomes	Review Observations
[42]	Dry and MQL-assisted turning	AISI 4140 steel	Surface roughness, tool wear, cutting force, chip morphology, cutting temperature, carbon emission, energy consumption	DT	RMSE	Carbon emissions increased by up to 60% at high speeds; energy consumption reduced by 42% at lower cutting parameters	DT successfully predicted machining responses. Lowest RMSE obtained for surface roughness (0.16) and cutting temperature (1.15) in MQL machining, demonstrating reliable ML-assisted machining
[43]	Dry, MQL, nano-MQL, and cryogenic CO ₂ -assisted machining	Inconel 718	Cutting force, tool wear, surface roughness, cutting temperature	ANN, ANN-GA, ANN-PSO	R ²	Cryogenic CO ₂ reduced machining responses by up to 43%; reduced fluid usage and improved sustainable machining performance	ANN achieved high prediction accuracy (R ² > 0.97). ANN-GA outperformed ANN-PSO with 86.7% optimization success, while ANN-PSO showed faster convergence
[44]	MQL-assisted end milling	Multiple workpiece materials	Tool wear	One-class SVM, LightGBM	RMSE	Supporting resource-efficient and sustainable tool condition monitoring	One-class SVM achieved RMSE of 16.9 µm, comparable to supervised LightGBM (16.4 µm), demonstrating an effective low-data unsupervised tool wear prediction
[45]	MQL-assisted hard turning	C45 steel	Surface roughness, energy consumption, CO ₂ emissions, machining cost	ANN, ANOVA, k-fold cross-validation, WOFSMPSO	Correlation	Lubricant flow rate contributed 39.18% to CO ₂ emissions; cooling conditions contributed 34.19%; reduced energy consumption and machining cost	ANN integrated with WOFSMPSO effectively optimized hard turning
[46]	MQL-assisted turning	SS304 alloy	Surface roughness, cutting force	ANN, Taguchi-GRA	R ² , gray relational grade (GRG), S/N ratio	Eco-friendly fluids reduced harmful environmental impact; optimized lubrication improved machining efficiency and sustainable cooling performance	ANN with 3-4-2 architecture achieved R ² of 0.99 for training/testing

Table 2. Cont.

Ref.	MQL/Machining Type	Material	Machinability/Processes Responses	ML/Statistical Models	Performance Metrics	Sustainability Benefits and Outcomes	Review Observations
[47]	Dry, flood cooling, MQL, ICT, and ICT + MQL high-speed turning	AISI 304 stainless steel	Tool wear	XGBoost, RFECV, SHAP, ANOVA	Accuracy, precision, recall, F1-score, AUC-ROC, KS	Low fluid MQL and ICT reduced environmental burden and fluid consumption while maintaining machining performance	XGBoost achieved high end-of-life prediction accuracy (95.9% test, 93.3% validation; AUC-ROC > 0.95)
[48]	Dry, MQL (vegetable oils), fluid-assisted grinding	AA6061 aluminum alloy	Surface roughness	GPR, ANN, XGBoost, Stacking Ensemble, SHAP, PSO, ANOVA	RMSE, MAPE, R ²	Fluid and MQL cooling improved surface quality and reduced thermal damage compared to dry grinding	GPR achieved the best single-model accuracy (97.50%, R ² = 0.99, MAPE = 2.49%). ANN-XGB: GPR stacking improved generalization, and SHAP effectively identified dominant grinding parameters
[49]	Dry, flood, coconut oil-based MQL (Co-MQL), and rice bran oil-based MQL (Rb-MQL) turning	Monel-500 alloy	Surface finish, cutting temperature	RFR, DT	Prediction accuracy	Rb-MQL reduced the tooltip temperature by 39.5% and surface roughness by 60.49%, improving eco-friendly and energy-efficient machining	Random forest regression achieved 99.8% prediction accuracy, outperforming logistic regression; decision tree analysis effectively optimized cooling-condition selection
[50]	Alumina nanofluid-assisted MQL turning	AISI 304 steel	Surface roughness	LR, RF, SVM, RSM	R ² , MAPE, MSE	Nanofluid MQL improved lubrication, reduced material wastage and energy use, supporting sustainable machining	Random forest outperformed LR and SVM in predicting surface roughness, achieving the highest R ² values of 0.8176 (30 nm) and 0.7231 (40 nm)
[51]	MQL-assisted milling	Inconel 690	Tool wear	GEP, ANN, MEP, ANOVA	Training/testing accuracy, statistical comparison	Optimized MQL flow rate reduced tool wear and machining cost, supporting sustainable and resource-efficient machining	GEP outperformed ANN in predicting flank wear under MQL conditions,

Table 2. Cont.

Ref.	MQL/Machining Type	Material	Machinability/Processes Responses	ML/Statistical Models	Performance Metrics	Sustainability Benefits and Outcomes	Review Observations
[52]	Tri-hybrid nanofluid-assisted MQL turning	SS304 steel	Surface roughness, cutting temperature	ANN, ANOVA, RSM, regression analysis, CCD	R, R ² , MSE	Tri-hybrid nano-MQL reduced cutting temperature by 76% and improved surface quality by 16%, enhancing sustainable machining efficiency	ANN predictions were more accurate than regression analysis, achieving correlation values of 0.88–0.89 for surface roughness and temperature prediction
[53]	MQL-assisted tribological testing	Stainless Steel 316L	Wear rate, friction force, wear behavior	J48 DT, RF, BFT	Accuracy, precision, recall, F1-score, cross-validation	MQL reduced friction and wear, lowering lubricant consumption and improving sustainable tribological performance	J48 outperformed random forest and best-first tree, achieving 100% accuracy under low wear and 99.27% under high wear conditions
[54]	MQL-assisted milling	Inconel 718	Surface roughness, cutting temperature, tool wear, chip morphology, surface topography	LR, RFR, PR, DT	RMSE, R ² , MSE, MAE, 95% CI	MQL improved sustainability by reducing cutting temperature, tool wear, friction, and lubricant consumption with superior machining efficiency	Random forest and linear regression predicted roughness and temperature with R ² up to 0.98 and low RMSE
[55]	MQL turning	Ti-6Al-4V	Surface roughness, chip morphology	SVR	MAPE, APE, predictive accuracy	Reduced cutting fluid usage, lower waste generation, improved machining efficiency, safer working conditions, enhanced sustainable machining performance	SVR predicted surface roughness with a low MAPE of 4.68%, while Jaya optimization demonstrated a minimum roughness of 0.4812 μm
[56]	Dual MQL-assisted milling	316L Stainless Steel	Surface roughness, flank wear, surface integrity, tool wear classification	MLP, RF, SVM, LR	R ² , MAE, RMSE, RAE, RRSE, accuracy, precision, recall, F1-score, specificity	Reduced lubricant consumption, reduced tool wear, improved surface finish, biodegradable oil usage, and increased machining efficiency	MLP outperformed LR, SVM, and RF in predicting surface roughness and flank wear, attaining R ² > 0.99 with minimal MAE and RMSE. However, RF and MLP showed superior classification

Table 2. Cont.

Ref.	MQL/Machining Type	Material	Machinability/Processes Responses	ML/Statistical Models	Performance Metrics	Sustainability Benefits and Outcomes	Review Observations
[57]	MQL milling	Ti-6Al-4V Alloy	Cutting force, torque, surface roughness	MLP-ANN, DOE, ANOVA, desirability function	Prediction accuracy, statistical validation	Supported eco-friendly machining, reduced cutting fluid use, lower cutting forces, and enhanced surface finish	MLP-based ANNs have shown prediction capabilities that are comparable to DOE models, highlighting the suitability of ANNs for machining optimization and the enhancement of predictive performance
[58]	MQL and NF-MQL milling	Inconel 718	Power consumption	KNN, GR, DT, LogR, RSM, ANOVA	R ² , MSE, RMSE, MAE, MaxError, MedAE	Minimized energy usage, decreased carbon emissions, environmentally friendly lubrication, and sustainable power-efficient machining	DT attained the highest prediction accuracy, achieving R ² values of 0.915 for MQL and 0.931 for NF-MQL, surpassing both KNN and LR in power prediction performance
[59]	MQL-TNL hard turning	AISI 4340 steel	Cutting force, surface roughness, tool wear	RVFL, RVFL-PSO, RVFL-PO, Taguchi L16	R ² , RMSE, MAE, EC, VC, OI	Eco-friendly vegetable oil, minimized fluid consumption, decreased tool wear, enhanced energy-efficient sustainable machining	RVFL-PO demonstrated exceptional prediction accuracy with an R ² range of 0.961 to 0.998, surpassing both RVFL and RVFL-PSO in the prediction of cutting force, roughness, and tool wear
[60]	MQL, cryogenic CO ₂ , and S-MQL milling	AM-SS 316L	Tool wear, flank wear, surface roughness	LR, SVR, RF, MLP, SVM	R ² , MAE, MSE, RMSE, accuracy, recall, precision, F1-score	Minimized coolant consumption, decreased energy usage, enhanced tool longevity, and environmentally conscious machining practices	MLP achieved over 95% classification accuracy and surpassed LR, SVR, and RF in tool wear prediction, showcasing its effectiveness for machining optimization

Table 2. Cont.

Ref.	MQL/Machining Type	Material	Machinability/Processes Responses	ML/Statistical Models	Performance Metrics	Sustainability Benefits and Outcomes	Review Observations
[61]	MQL and HPC-assisted turning	AISI 1045 steel	Machining force, cutting power, cutting pressure	PR, SVR, GPR, ANN	MAPE, MaxAPE, MAE, NRMSE, R ²	Less cutting fluid usage, reduced energy consumption, minimized environmental impact, sustainable cooling and lubrication, and lowered machining costs	ANN achieved the highest prediction accuracy, with MAPE as low as 0.7% and R ² reaching up to 0.9999, surpassing PR, SVR, and GPR in the prediction of machining force, cutting power, and cutting pressure
[62]	MQL-assisted turning using	Al-Mg-Zr alloy	Surface roughness, cutting temperature	ANN, ANFIS, Taguchi, DFA, ANOVA	MAPE, R ²	LCA-based sustainability focuses on minimizing energy consumption, decreasing CO ₂ emissions, reducing the carbon footprint, and optimizing processing time and tool changes	ANFIS demonstrated superior performance over ANN in predicting surface roughness and cutting temperature, achieving lower MAPE values of 1.072% and 1.172%, respectively, compared with ANN's values of 3.95% and 3.45%
[63]	MQL-assisted grinding	Inconel 751 alloy	Grinding force, grinding temperature, surface roughness	SVM, GPR, BTE, K-fold validation	R ² , RMSE	Optimized cooling reduces coolant usage, energy-intensive grinding, and environmental impact	GPR outperformed SVM and boosted tree models in predicting grinding forces and interface temperature, with greater R ² and lower RMSE
[64]	MQL-assisted orthogonal cutting	AZ91 magnesium alloy	Flank tool wear, chip contact length, chip morphology, segmentation ratio, compression ratio, shear angle	DTR, BO, RF, RFR, XGB	MSE, MAE, R ²	Enhanced MQL machining efficiency, reduced waste and resource use, sustainable lightweight alloy machining	XGBoost demonstrated superior predictive accuracy, achieving a 34.1% reduction in MSE and a 17.1% reduction in MAE compared to decision tree models, and outperformed random forest-based models in predicting tool wear and chip morphology

Table 2. Cont.

Ref.	MQL/Machining Type	Material	Machinability/Processes Responses	ML/Statistical Models	Performance Metrics	Sustainability Benefits and Outcomes	Review Observations
[65]	MQL, nano-graphene + MQL, nano-hBN + MQL, Cryo + MQL-assisted milling	PH13-8Mo stainless steel	Power consumption, energy distribution, machining power signals	LR, MLP, GBR, ABR	R^2 , MAPE, MAE, MSE, RMSE	Reduced energy usage, decreased power demand, sustainable lubrication/cooling, increased energy efficiency, cleaner machining	Gradient Boosting Regression outperformed Linear Regression, MLP, and AdaBoost models in predicting power use, with an R^2 of 0.996
[66]	Pulsed MQL-assisted hard turning	Hardened steel	Surface roughness	ANN, statistical analysis	Prediction accuracy, statistical validation	Reduced coolant usage, lower environmental impact, cost-effective, sustainable lubrication approach	ANN-based predictive modeling estimated surface roughness with 97.5% accuracy during pulsed MQL hard turning
[67]	MQL-assisted face milling	SM45C structural steel	Specific cutting energy	ANN, PSO	Regression coefficient	Reduced specific cutting energy by up to 70%; reduced cutting oil usage, energy consumption, and increased ecologically conscious machining	ANN-PSO accurately predicted and optimized specific cutting energy for MQL milling, attaining >97% regression accuracy and <1% prediction error, resulting in energy reduction
[68]	Dry, wet, and MQL turning	X210Cr12 steel	Surface roughness, cutting force	ANN, RSM, BBD	Correlation coefficient, MPE, RMSE	Reduced cutting fluid usage, lower environmental effect, and eco-friendly machining under MQL conditions	ANN outperformed RSM in predicting surface roughness and tangential force, with lower RMSE and MPE and higher correlation coefficients
[69]	Dry, MQL, CO ₂ cryogenic, and NMQL turning	Monel 400 alloy	Carbon emission (CE), energy consumption, power consumption, sustainability assessment	DT, NB, RF, SVM, SMOTE	Accuracy, precision, recall, F1-score, cross-validation/testing performance	NMQL reduces carbon emissions from 0.0051 to 0.0014 kg-CO ₂ , resulting in lower energy usage and higher sustainability performance	SVM with SMOTE demonstrated the best CE classification accuracy (~99–100%), surpassing DT, RF, and Naïve Bayes

Table 2. Cont.

Ref.	MQL/Machining Type	Material	Machinability/Processes Responses	ML/Statistical Models	Performance Metrics	Sustainability Benefits and Outcomes	Review Observations
[70]	Face turning under dry, MQL, and flood cooling	AISI 1045 steel	Tool life	RT, KNN, ANN, Bagging, RF	RMSE	MQL decreased coolant usage, while experimental repetition increased prediction accuracy by up to 23%	RBF-ANN provided the highest tool-life prediction accuracy (11.4 mm RMSE), while Random forest performed fairly well (12.8 mm RMSE)
[71]	High-speed deep drilling under traditional coolant and MQL conditions	Steel components	Surface roughness quality, axial cutting force	BN	Classification performance, model suitability, interpretability	MQL lowered conventional coolant usage and promoted environmentally friendly deep drilling	Bayesian networks accurately predicted roughness quality in MQL-assisted deep drilling using cutting parameters and axial force data
[72]	MQL-assisted milling	Ti-6Al-4V titanium alloy	Cutting forces, acoustic emissions	v-SVM, MI, LDA	Prediction accuracy	MQL lowered lubricant usage and increased tool-life monitoring efficiency	v-SVM achieved 98.9% prediction accuracy for multi-state tool wear monitoring, indicating effective intelligence and predictive capabilities
[73]	Turning under MQL and HPC conditions	AISI D6 steel	Machining force, cutting power, cutting pressure	PR, SVR, GPR, ANN	MAPE, MaxAPE, MAE, NRMSE, R ²	MQL lowered machining costs and experimentation time; optimized machining at 210 m/min, 1.5 mm, and 0.224 mm/rev	ANN surpassed PR, SVR, and GPR for forecasting machining force, cutting power, and pressure, with MAPE of 0.8% and R ² of 0.9998
[74]	Turning under dry, MQL, nano-MQL, cryogenic, and cryo-nano-MQL conditions	Inconel 601 alloy	Specific cutting energy (SCE), power consumption, material removal rate	MLR, Lasso, BRR, VR	R ² , MAPE, MAE, MSE, RMSE	Cryo-nano-MQL lowered SCE by 2.7%, while SCE decreased by 35.5% with increasing cutting speed	Bayesian ridge regression performed better than MLR, Lasso, and voting regressor, with lower prediction errors and similar R ² values

Table 2. Cont.

Ref.	MQL/Machining Type	Material	Machinability/Processes Responses	ML/Statistical Models	Performance Metrics	Sustainability Benefits and Outcomes	Review Observations
[75]	Turning under hybrid MQL vortex tube cooling	Hardened SKD11 steel	Surface roughness, carbon emission, tool wear	RF, RSM, NSGA-III, TOPSIS-Entropy	R^2 , Adjusted R^2 , MAPE, RMSE, MAE	Hybrid MQL cooling provided optimal conditions with $R_a = 0.264 \mu\text{m}$ and $CE = 0.032 \text{ g/min}$	RSM demonstrated superior prediction accuracy compared to random forest for R_a ($R^2 = 0.997$) and CE ($R^2 = 0.994$), while NSGA-III-TOPSIS effectively optimized hybrid MQL machining conditions
[76]	MQL-assisted milling	S50C hardened steel	Surface roughness, cutting force	SVR, GA, NSGA-II, Taguchi	R-score, prediction deviation (%)	Optimal MQL obtained $R_a = 0.066 \mu\text{m}$, cutting force = 167.126 N, and reduced lubricant consumption	SVR predicted surface roughness for 97.3% and cutting force for 99.9% better than RSM, whereas NSGA-II optimized MQL milling parameters
[77]	MQL milling	Ti-6Al-4V	Surface roughness, production rate	SVM, ANN-based NSGA-II, ANOVA	Regression prediction capability, multi-objective optimization accuracy, factor significance analysis	Lower lubricant use and higher productivity under MQL	SVM accurately predicted machining responses, while ANN-based NSGA-II optimized surface roughness and production rate
[78]	MQL surface grinding	UNS S34700 steel	Surface roughness, grinding force	SVR, GPR, ANN, GA, ANOVA	R^2 , RMSE, MAPE	MQL reduced surface roughness and grinding pressures, providing lower friction, energy consumption and sustainable grinding performance	GPR surpassed SVR and ANN in predicting surface roughness and grinding forces, with R^2 as high as 1.0 and prediction accuracy of ~97%
[79]	MQL turning and hybrid cooling (MQL + LN2) conditions	Ti-3Al-2.5V alloy	Energy consumption	RF, KNN, SVM, MLP, AdaBoost, KR	R^2 , MAPE, MAE, MSE, RMSE, recall, F1-score	MQL lowered energy usage by 2.6%, whereas hybrid cooling used 68.14% less total energy than dry machining	RF outperformed KR, AdaBoost, and MLP in energy monitoring with optimal prediction and classification performance (96.3% R^2 and 100% testing accuracy)

Table 2. Cont.

Ref.	MQL/Machining Type	Material	Machinability/Processes Responses	ML/Statistical Models	Performance Metrics	Sustainability Benefits and Outcomes	Review Observations
[80]	Nanofluid-assisted MQL milling	Hastelloy C276	Tool wear	DNN, XGB, SVR, Spearman correlation	R^2 , RMSE, MAE, MAPE	Compared to dry machining, 0.6% alumina nanofluid reduced flank wear by 23.5%, improving tool life and sustainability	XGBoost outperformed DNN and SVR with $R^2 = 0.9924$, RMSE = 0.002, and MAPE = 0.6%, providing precise tool wear prediction
[81]	MQL-assisted milling (dry, flood, MQL)	Hardox 400 steel	Tool wear, surface roughness, cutting temperature, energy consumption, chip morphology	DT	RMSE, MSE, MAE, correlation analysis	In comparison to dry machining, MQL reduced flank wear by 16–21%, improved surface quality, and reduced cutting energy	RMSE, MSE, and MAE values were low for machine learning models, and heat maps close to +1 demonstrated reliable machinability prediction
[82]	Turning under dry, MQL and nano-MQL	Bohler K490 steel	Flank wear	RR, DT, RF, SVR	R^2 , MAE, MSE, RMSE	Nano-MQL improved tool life and sustainable machining efficiency by 25% over dry machining by reducing flank wear	Under nano-MQL, Ridge Regression outperformed RF and SVR with 98% R^2 , while DT demonstrated superior tool wear monitoring prediction
[83]	Milling under dry, flood, MQL, and cryogenic CO ₂ environments	Nimonic 80A alloy	Flank wear, surface roughness, tool wear classification, surface morphology	Inception-V3, AlexNet, VGG-16, ResNet, MobileNet	Accuracy, precision, recall, F1-score, R^2	MQL and cryo reduced tool wear, machining time, surface roughness, and energy demand; cryo achieved the least wear and enhanced sustainable machining	Inception-V3 surpassed AlexNet, ResNet, VGG-16, and MobileNet with 99.4% accuracy, allowing for reliable tool wear categorization
[84]	Dry, MQL, and cryogenic CO ₂ -assisted milling	Ti-6Al-4V alloy	Surface roughness, surface waviness, surface morphology, roughness profile classification	RF, DT, SVM, MLP, BLSTM, 2D-CNN, CGAN	Accuracy, precision, recall, F1-score, R^2	MQL and cryo reduced surface roughness, friction, heat generation, and tool wear, enhancing long-term machining performance	For intelligent MQL surface profile classification and monitoring, MarkovGAN-2D-CNN performed better than MLP and BLSTM, with 99.6% testing accuracy and 99.4% F1-score

Table 2. Cont.

Ref.	MQL/Machining Type	Material	Machinability/Processes Responses	ML/Statistical Models	Performance Metrics	Sustainability Benefits and Outcomes	Review Observations
[85]	MQL-assisted near-dry EDM	Duplex stainless steel 2205	Material removal rate, electrode wear rate, surface roughness	ANN, gray relational analysis (GRA), Taguchi method	Multi-response optimization, prediction accuracy, gray relational grade	Near-dry MQL-EDM enhanced sustainability by increasing MRR, decreasing EWR, reducing lubricant usage, and improving machining efficiency	ANN-GRA optimized near-dry EDM responses, resulting in MRR of 6.1287 mm ³ /min and EWR of 0.0698 mm ³ /min
[86]	MQL nanofluid-assisted turning	Inconel 718	Flank wear, surface roughness, energy consumption	ANN, ANFIS, GP, NSGA-II, ANOVA, Taguchi OA	MSE, R ² , hypervolume indicator (HV), prediction accuracy	MQL nanofluids lowered energy consumption by 5–7%, enhanced sustainability, lowered lubricant usage, and decreased environmental/health burden	GP outperformed ANN and ANFIS with the lowest MSE and R ² > 0.99. MWCNT-MQL decreased flank wear by 45.6% and enhanced energy-efficient machining capabilities
[87]	Dry, MQL, LN ₂ , and hybrid MQL + LN ₂ milling	Hastelloy C276	Specific cutting energy, cutting force, machinability, energy consumption	GEP, ANN, RSM, ANOVA, Taguchi OA	RMSE, R ² , MAPE, validation error	Hybrid MQL + LN ₂ reduced SCE by 46.04% compared to dry cutting, resulting in lower energy usage and highly sustainable machining	GEP outperformed ANN and RSM with lower RMSE (0.799%), MAPE (2.457%), and validation error (0.25–1.52%), providing accurate sustainable energy prediction in MQL + LN ₂ machining
[88]	MQL and wet grinding	Inconel 738 alloy	Surface roughness, grinding performance	ANN, GPR, RT, ANOVA	MSE, RMSE, MAE, R, R ² , absolute accuracy, cross-validation	MQL decreased coolant use from 4 L/min to 200 mL/h, reducing fluid usage while promoting sustainable grinding	Deep ANN predicted surface roughness better than GPR and RT, enabling intelligent MQL grinding and IIoT-based smart machining
[89]	Dry, wet, and MQL-assisted hard turning	AISI 52100 steel	Tool wear	ANN, Taguchi OA	MSE, AE, correlation coefficient, absolute percentage error	MQL improved machining efficiency and lowered environmental impact over wet machining by reducing tool wear and lubricant use	ANN predicted tool wear with R-values up to 0.99999 and mean absolute error ~1.001%, proving AI-assisted sustainable MQL hard turning

Table 2. Cont.

Ref.	MQL/Machining Type	Material	Machinability/Processes Responses	ML/Statistical Models	Performance Metrics	Sustainability Benefits and Outcomes	Review Observations
[90]	MQL-assisted turning	Brass	Specific cutting force, surface roughness	ANN	Prediction accuracy, response analysis	Comparatively, MQL reduced lubricant usage, improved machining efficiency, and promoted sustainable machining	Cutting force and surface roughness were predicted using ANN. Machine quality and turning performance are enhanced with higher MQL and optimized cutting speed/feed
[91]	Dry, air, MQL, and cryogenic milling	AlSi10Mg alloy	Power signals, surface roughness, surface quality, cutting power analysis	Swin Transformer, ViT, LWCNN, AlexNet, VGG16, ResNet	Accuracy, kappa, precision, recall, F1-score, learning rate convergence	MQL has effectively minimized power fluctuations and enhanced surface quality, while cryogenic cooling has resulted in the lowest power consumption and optimal surface finish	Swin Transformer demonstrated superior performance compared to CNN, AlexNet, VGG16, and ResNet, achieving the highest accuracy and kappa, resulting in dependable AI-driven monitoring
[92]	Ultrasonic-assisted machining (UAM) with MQL	Ti-6Al-4V alloy	Cutting force	ANN	Prediction rate, MAPE, MSE	MQL-UAM reduced cutting force and lubricant consumption, enabling cost- and time-efficient sustainable machining	ANN accurately predicted cutting forces with a prediction accuracy of 0.99, MAPE of 1.85%, and MSE of 13.1, demonstrating reliable AI-assisted UAM-MQL machining performance
[93]	Gnps-sesame oil nano-MQL end milling	AISI H11 steel	Cutting temperature, surface roughness	ANFIS, Taguchi S/N ratio, ANOVA	RMSE, ANOVA	Gnps-MQL reduced cutting temperature by 62.5% and surface roughness by 68.6%, while biodegradable sesame oil improved machining sustainability	ANFIS accurately predicted cutting temperature and surface roughness with 97.4% and 92.6% accuracy, respectively, supporting intelligent machining optimization
[94]	Dry, MQL, and graphene-based NMQL end milling	AISI H11 steel	Surface roughness	DT, XGB, SVR, CatBoost, ABR, RFR, MLR, Taguchi S/N, GDA	MAE, MSE, RMSE, MAPE, R ² , Accuracy	NMQL improved surface quality by 9.8% over MQL and reduced roughness by 75.2% compared to dry machining	CATBoost outperformed DT, SVR, XGB, RFR, ABR, and MLR with 90.8% accuracy and R ² of 0.94 for NMQL surface roughness prediction

Table 2. Cont.

Ref.	MQL/Machining Type	Material	Machinability/Processes Responses	ML/Statistical Models	Performance Metrics	Sustainability Benefits and Outcomes	Review Observations
[95]	Dry, MQL, and NMQL end milling	H11 steel	Cutting temperature	RLRM, DT, XGBR, SVM, KNN, GPR	MAE, RMSE, MAPE, R^2 , Accuracy	NMQL reduced cutting temperature, improving machining efficiency and reducing cooling and lubricant consumption	GPR outperformed RLRM, DT, XGBR, SVM, and KNN with an R^2 of 0.9, 85% accuracy, and 14% MAPE in cutting temperature prediction
[96]	Nanofluid MQL micro-drilling	Aluminum alloy	Torque, thrust force, material removal rate	ANFIS, GP	R^2 , RMSE, MAPE, goodness-of-fit tests	Nanofluid MQL reduced torque and thrust forces, minimized waste, and improved energy-efficient machining	GP outperformed ANFIS for thrust force and MRR prediction, with R^2 up to 0.94 and lower MAPE in micro-drilling optimization
[97]	MQL turning	Nimonic alloy	Cutting temperature, surface quality, chip morphology, tool wear	ML-based model	Prediction capability	Bio-based nano-MWFs reduced fossil-fuel dependence and tool wear, promoting sustainable machining	ML-based framework effectively optimized nano-bio-lubricants for sustainable MQL turning
[98]	MQL grinding,	Inconel 625	Tangential force, surface roughness, specific energy, coefficient of friction	RFR, GPR, TOPSIS, VIKOR, entropy method	R^2 , MAE, RMSE	MQL grinding reduced specific energy and friction, improving surface integrity compared to dry grinding	GPR outperformed random forest in predicting grinding responses for MQL grinding optimization
[99]	MQL-assisted turning	Polyoxymethylene copolymer	Surface roughness, total energy consumption, total carbon emissions, overall cost	ANN, ANOVA, k-fold CV, SHAMODE, RPBILDE	Prediction accuracy, k-fold validation, Pareto optimization performance	Biodegradable lubricant reduced energy consumption (0.0947 MJ) and carbon emissions (0.0583 kgCO ₂), supporting sustainable machining	ANN integrated with SHAMODE and RPBILDE effectively optimized MQL turning by balancing surface quality, energy consumption, emissions, and machining cost under biodegradable lubrication
[100]	Dry, flood, and MQL-assisted milling	Al6061-T6 alloy	Tool wear, milling forces, surface roughness	BNN	Prediction error	MQL reduced tool wear by 9–13%, lowered machining forces, and improved surface quality over dry machining	BNN predicted tool wear with 2–15% error, outperforming conventional models

Table 2. Cont.

Ref.	MQL/Machining Type	Material	Machinability/Processes Responses	ML/Statistical Models	Performance Metrics	Sustainability Benefits and Outcomes	Review Observations
[101]	Nano-MQL turning	AA2024 aluminum alloy	Surface roughness, tool wear	GBR, LR, RF	R ² , MAPE, MSE	Nano-MQL reduced surface roughness by 28%, minimized tool wear, and improved machining performance	Gradient boosting and linear regression achieved R ² values of 1.000 and 0.999, outperforming random forest (0.959) in predicting nano-MQL turning performance
[102]	MQL turning	Ti-6Al-4V alloy	Machining power	SVR, ANFIS, TLBO	Prediction accuracy	Reduced machining power and energy consumption, promoting sustainable machining	ANFIS and SVR effectively predicted machining power, while TLBO reduced power consumption to 334.24 W
[103]	MQL-assisted surface grinding	SKD 61 tool steel	Surface roughness, coefficient of friction	BPNN, TLBO	Prediction capability, fitness function	MQL reduced friction and surface roughness, lowering lubricant consumption and improving grinding performance	BPNN-TLBO optimized grinding parameters, achieving a minimum surface roughness of 0.376 µm and a coefficient of friction of 0.333
[104]	Hard turning under dry and MQL conditions	AISI 4340 steel	Surface roughness, material removal rate	LR, RSM, ANOVA, Box–Behnken design	MSE, RMSE, R ²	MQL improved surface finish and productivity, reduced lubricant usage, and enhanced machining efficiency	LR accurately predicted Ra under MQL with R ² = 0.9638, improving productivity with acceptable surface finish and higher MRR
[105]	Dry, MQL, and nanofluid MQL machining	UHSS S1100 steel	Tool wear, surface roughness, energy consumption, cutting temperature, chip morphology	ML-based model	correlation analysis	Nanofluid MQL reduced cutting temperature, tool wear, and energy consumption	Graphene nanoplatelet-based MQL and pure MQL achieved superior surface quality at low feed and high cutting speed
[106]	Cryogenic and Cryo + MQL tribological testing	SS 316L against 100Cr6 alloy	Friction force, wear rate, surface roughness, surface morphology	GPR	MSE, RMSE, MAE, MAPE, OFI	Cryo + MQL reduced the frictional force by up to 90%, reduced wear rate, and improved surface finish	GPR accurately predicted nonlinear friction behavior under cryo + MQL conditions, improving tribological performance prediction accuracy

Table 2. Cont.

Ref.	MQL/Machining Type	Material	Machinability/Processes Responses	ML/Statistical Models	Performance Metrics	Sustainability Benefits and Outcomes	Review Observations
[107]	Milling under dry, MQL, and cryogenic LN ₂ environments	Cu-Gr hybrid composites	Surface roughness, flank wear, cutting temperature, energy consumption	SVR, LR, KR, LSS, kNR, GPR, DT, GBDT, RFR, ANN	MAE, MSE, R ²	MQL and Cryo-LN ₂ machining reduce temperature, tool wear, and energy consumption, resulting in the lowest energy utilization of 54.18 kJ	GBDT outperformed the ANN, KR, and SVR, with the highest prediction accuracy for surface roughness (R ² = 0.9648), flank wear (0.9908), cutting temperature (0.9912), and energy consumption (0.9970)
[108]	Turning under dry and MQL conditions	Unreinforced polypropylene	Tangential force, cutting power, material removal rate, cutting energy, specific cutting energy	ANN, ANOVA, MOWCA, MOALO	K-fold cross-validation, prediction accuracy	MQL lowered both specific cutting energy and electricity consumption, enhancing the polymer machining performance	ANN-based predictive optimization was helpful in modeling machining energy responses, while MOALO and MOWCA improved SCE-oriented turning performance
[109]	Milling under Dry, MQL, CO ₂ cryogenic, and Hybrid (CO ₂ + MQL) cooling	LPBF-316L stainless steel	Surface roughness	TransGAN, MHA-AlexNet, AlexNet, AE-AlexNet	Accuracy, precision, recall, F1-score	Hybrid cooling reduced surface roughness by 52–56% compared with dry machining, enhancing surface quality	MHA-AlexNet outperformed AlexNet and AE-AlexNet with an accuracy of up to 0.998 and an F1-score of up to 0.991 for surface quality classification
[110]	Milling under dry, MQL, and solid lubricant-MQL (SL-MQL) conditions	Mg-AZ91D magnesium alloy	Surface roughness, tool wear	LR, SVM, RF	R ² , MAE, RMSE, RAE, RRSE	SL-MQL reduced surface roughness by 49–70% over dry and 8–13% over MQL, enhancing long-term machining performance	SVM outperformed LR and RF in predicting tool wear under SL-MQL machining conditions, whereas RF showed greater R ² and lower errors for surface roughness prediction
[111]	Dry, wet and coconut-oil MQL-assisted end milling	AL7049 alloy	Surface roughness	MLP, ReLU, K-fold cross-validation, KNN, LR, ANOVA	MSE, prediction error, K-fold validation	Coconut-oil MQL decreased surface roughness, machining cost, cleaning effort, and environmental impact while increasing machining efficiency	MLP with ReLU outperformed KNN and linear regression in surface roughness prediction, with a maximum prediction error of only 0.228% under MQL milling conditions

Table 2. Cont.

Ref.	MQL/Machining Type	Material	Machinability/Processes Responses	ML/Statistical Models	Performance Metrics	Sustainability Benefits and Outcomes	Review Observations
[112]	Helical milling under flood emulsion and MQL	Inconel 718	Surface roughness, material removal rate	Cubist, SVR, KNN, neural network, DTR, ALO, Dragonfly algorithm, moth flame optimizer	Cross-validation error, RMSE	MQL lowered cutting fluid consumption and environmental contamination; sustainable lubrication with lower disposal and health implications	Cubist model outperformed SVR and other regression models in predicting roughness for MQL helical milling, while metaheuristic optimization improved the material removal rate
[113]	Nanofluid ultrasonic atomization MQL-assisted grinding	Ti-6Al-4V alloy	Force ratio, grinding temperature, surface roughness	CNN, VGG-19, GoogLeNet, ResNet-50, AlexNet, Taguchi design	Accuracy, precision, recall, F1-score, S/N ratio	Minimum cutting fluid consumption, enhanced lubrication efficiency, lowered grinding temperature, minimized nanoparticle agglomeration, and improved surface quality	ResNet-50 and VGG-19 attained superior grinding-quality classification after hyperparameter optimization, while CNN enabled automatic surface integrity monitoring for nanofluid UA-MQL grinding
[114]	Graphene oxide/rice bran oil-based nano-MQL turning	Nimonic 80A superalloy	Cutting force, flank wear, surface roughness	ANN, Taguchi, MOPSO, MOMA	Error prediction	Nano-MQL reduced cutting force, flank wear, and surface roughness by 51% compared to dry machining, while lowering fluid consumption and improving machining performance	ANN-MOMA outperformed ANN-MOPSO in multi-objective optimization, effectively minimizing cutting force, flank wear, and surface roughness
[115]	Dry, MQL, liquid nitrogen, and hybrid lubrication machining	Titanium alloy	Tool wear	LSTM, SCA	Classification accuracy, specificity, sensitivity, F1-score	MQL and hybrid lubrication improved process efficiency by reducing lubricant consumption and enhancing tool life	SCA-optimized LSTM achieved 98.08% tool wear classification accuracy, enabling robust monitoring under multiple lubrication conditions

Table 2. Cont.

Ref.	MQL/Machining Type	Material	Machinability/Processes Responses	ML/Statistical Models	Performance Metrics	Sustainability Benefits and Outcomes	Review Observations
[116]	Dry, flood, MQL, and Cryo + MQL milling	Incoloy 800 superalloy	Surface roughness, flank wear, cutting temperature	ANN, PSO-ANN	Relative error (RE)	Cryo + MQL improved surface roughness by 30%, reduced cutting temperature to 45 °C, and minimized tool wear	PSO-ANN effectively optimized milling parameters, while ANN achieved minimum RE of 1.46% for flank wear and identified Cryo + MQL as the optimum machining condition
[117]	MQL-assisted turning	AISI 304 stainless steel	Smoke diffusion	ELM, BPNN, Gaussian diffusion model, ANOVA	Absolute error	Reduced air pollution and operator exposure through eco-friendly castor oil-alcohol cutting fluid, with improved smoke diffusion control	ELM-BP integrated Gaussian model achieved over 90% MQL smoke prediction accuracy with prediction error below 10%, supporting safer and ecological machining
[118]	WS ₂ solid lubricant-assisted MQL turning	Inconel 718	Surface roughness	ANN, RSM	MSE, MAPE, AEP, R ²	WS ₂ -MQL improved surface finish and reduced cutting fluid consumption, promoting eco-friendly machining	ANN (3-5-1 architecture) outperformed RSM in predicting surface roughness, achieving R ² = 0.998 and lower MAPE of 0.813% in WS ₂ -assisted MQL turning
[119]	Dry, water-emulsified coconut-oil MQL, single, dual, and tri-hybrid nano-MQL CNC turning	SS304 stainless steel	Surface roughness, tool wear	DRNN, RSM, BBD	Regression value (R)	Dual hybrid nano-MQL reduced tool wear and improved surface finish while minimizing lubricant consumption	DRNN-BWO precisely predicted machining responses (R > 0.9), while dual hybrid nano-MQL achieved 0.11 µm surface roughness and 0.09 mm tool wear, surpassing dry and conventional MQL conditions
[120]	Dry, wet, and MQL drilling	6063-T6 aluminum alloy	Surface roughness, tool wear, cutting power	ANN	Prediction accuracy	MQL improved drilling performance, reduced cutting fluid consumption and cutting power, supporting environmentally friendly machining	Feed-forward ANN with backpropagation accurately predicted surface roughness and tool wear using chip thickness and cutting power inputs

5. Conclusions

MQL is a highly complex machining process characterized by nonlinear relationships among machining parameters, lubrication conditions, and workpiece-tool material behavior. This inherent complexity makes AI and ML models particularly suitable for modeling nonlinear relationships, capturing process behavior, and establishing correlations between process inputs and outputs beyond the capability of conventional analytical and statistical methods. The main objective of this review was to establish the significance and effectiveness of ML algorithms in modeling, predicting, optimizing, and monitoring MQL-assisted machining processes, thereby promoting the development of sustainable machining research. A thorough and systematic review methodology was adopted, involving the organized collection, inclusion, exclusion, and critical evaluation of the literature. In total, 120 publications were analyzed to synthesize research findings and present them in a logical manner for readers, including those new to AI-based approaches for modeling MQL processes. The examined studies demonstrate that ML plays a crucial role in understanding MQL behavior under different operating conditions, enabling accurate prediction, optimization, and monitoring of machining performance. The review systematically examined key MQL properties and applications, as well as the research directions explored using various ML techniques such as ANN, SVM, RF, GPR, ensemble methods, DL models, and hybrid ML optimization frameworks.

The key findings of the review are summarized as follows:

- MQL is one of the important sustainable machining methods, as it significantly reduces cutting fluid consumption compared with traditional machining methods.
- The MQL process involves complex nonlinear relationships among machining parameters, lubrication conditions, and material behavior, which are difficult to model using traditional analytical and statistical methods.
- ML models have demonstrated superior capability in modeling and predicting important machining responses such as tool life, cutting force, temperature, surface roughness, energy consumption, and emissions under MQL conditions.
- Ensemble and hybrid ML models such as random forest, XGBoost, ANN-PSO, GPR, and ANFIS have demonstrated superior prediction capability compared with conventional statistical models in many reviewed studies, particularly for predicting tool wear, surface roughness, cutting temperature, cutting force, power consumption, and energy utilization under complex MQL conditions.
- Several reviewed studies reported prediction accuracies greater than 95% and significant reductions in cutting temperature, tool wear, surface roughness, energy consumption, and carbon emissions through ML-assisted optimization of nano-MQL, cryo-MQL, and hybrid lubrication systems.
- Hybrid optimization methods integrating ML models with evolutionary algorithms such as GA, PSO, NSGA-II, GWO, and TLBO demonstrate considerable potential for multi-objective optimization of machining performance, productivity, sustainability, and energy efficiency.
- ML-based tool condition monitoring and fault diagnosis using sensor data enables real-time monitoring and improves machining performance and reliability. Deep learning architectures and advanced AI frameworks have also demonstrated excellent capability in tool wear monitoring, surface classification, and intelligent process control.
- Despite the significant progress achieved, several limitations remain, including small experimental datasets, overfitting issues, computational complexity, limited industrial-scale validation, and reduced interpretability of complex deep learning models.

- Emerging reinforcement learning-based adaptive control approaches show strong potential for intelligent optimization of lubrication and machining parameters, improving performance while reducing lubricant utilization.

Overall, the reviewed literature confirms that the integration of ML techniques with MQL systems has strong potential to support the development of intelligent, adaptive, energy-efficient, and environmentally sustainable machining processes for future manufacturing applications.

6. Future Research Direction

Based on the reviewed literature, future MQL research should increasingly focus on computational intelligence models rather than conventional statistical approaches for modeling, prediction, and optimization. ANNs have shown a strong capability in handling nonlinear machining behavior, while SVM, RF, DT, fuzzy logic, and hybrid ML frameworks also demonstrate significant potential depending on the application. Future studies should develop robust and generalized ML frameworks applicable to different materials, nanofluids, and machining conditions, thereby reducing experimental effort and cost. Large-scale industrial datasets, standardized benchmarking methods, and external industrial validation are also required, as most existing studies are limited to laboratory-scale datasets. In addition, improving the explainability and interpretability of ML and deep learning models is essential for reliable industrial implementation.

Research should further focus on real-time closed-loop intelligent MQL systems, since most current studies are limited to offline prediction and optimization. The integration of edge computing, digital twins, IIoT, cloud manufacturing, reinforcement learning, and smart sensor networks can support adaptive control, predictive analytics, and Industry 4.0-based smart machining. Advanced deep learning models such as CNN-LSTM hybrids and transformer-based architectures can further improve tool condition monitoring, fault diagnosis, predictive maintenance, and multi-sensor data fusion. Future systems should also include occupational health and air-quality monitoring, including aerosol and PM10 diffusion prediction during machining operations.

From a sustainability perspective, future research should extend beyond conventional machinability indicators and include life-cycle assessment, energy consumption, carbon emissions, cost analysis, and process stability. Further research is also needed on multi-objective optimization under hybrid lubrication environments and for difficult-to-machine materials. Emerging areas such as bio-based nanofluids, cryo-MQL, vortex-assisted MQL, nano-MQL, and hybrid lubrication systems also require deeper investigation. Collectively, these developments can transform MQL from a lubrication technique into an intelligent, adaptive, and sustainable manufacturing approach.

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