



(Review Article)

# Optimization of the Hard Turning Process by Artificial Neural Networks: A Review

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## ABSTRACT

Hard turning is a precision machining process employed as a finish operation on hardened alloy steels (42–68 HRC), widely used as an alternative to cylindrical grinding. The complexity and non-linearity of the hard turning process—governing surface roughness, cutting forces, tool wear, and cutting temperature—make traditional analytical modeling inadequate. Artificial neural networks (ANNs) have emerged as powerful data-driven tools capable of modeling and optimizing these intricate relationships with high predictive accuracy. This review systematically surveys peer-reviewed research published between 2005 and 2025, with emphasis on studies from 2018–2025, examining the application of ANN-based models to optimize hard turning parameters. The review covers ANN architectures employed (feedforward, radial basis function, deep neural networks, and hybrid approaches such as ANN–GA, ANN–PSO, and CNN–LSTM), training algorithms (back-propagation, Levenberg–Marquardt, Bayesian regularization), workpiece materials (AISI 52100, AISI H13, AISI D2, AISI 4340), cutting tool types (CBN, PCBN, coated carbides), and performance indicators (surface roughness Ra, cutting forces F<sub>x</sub>/F<sub>y</sub>/F<sub>z</sub>, tool flank wear VB, cutting temperature). Key findings confirm that ANN models consistently outperform regression-based models in capturing non-linear input–output relationships, with prediction errors frequently below 5%. Recent trends toward hybrid ANN–genetic algorithm models, explainable machine learning (XAI), and real-time CNN–LSTM architectures signal a move toward intelligent and autonomous hard turning optimization systems.

**Keywords:** Artificial Neural Network (ANN); Hard Turning; Surface Roughness; Tool Wear; Optimization; Machine Learning; CBN Tool

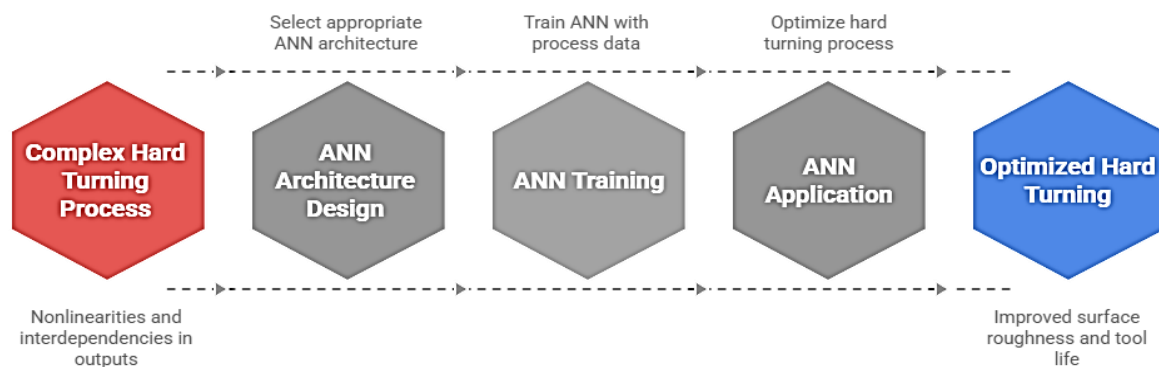
## I. INTRODUCTION

Hard turning represents single point cutting operations conducted on metallic components having typical Rockwell C hardness values of 42-68HRC using cutting tool materials characterized as cubic boron nitride (CBN), polycrystalline cubic boron nitride (PCBN), mixed ceramic cutting inserts and coated carbide cutting tool inserts [1]. The increased popularity of hard turning as a finish machining operation for hardened components including bearing race surfaces, gear shafts, camshaft lobes and hydraulic cylinder bores in place of traditional cylindrical grinding stems primarily from its inherent competitive advantages relative to grinding [2], namely; decreased set-up time requirements, versatility in terms of work-piece geometry, decreased need for cutting fluid usage, decrease in required energy input per unit volume removed and increased rate of material removal [3]—advantages that support current trends toward sustainable and smart manufacturing practices [3].

Despite these advantages, hard turning possesses inherent complexities. Cutting speed, feed rate, depth of cut, work-piece hardness, tool nose radius, coatings, and environmental condition (i.e., dry, mist-cooled lubrication (MQL) or cryogenically cooled) interact simultaneously to create nonlinearities and interdependencies in process output variables (surface roughness (Ra), cutting forces (F<sub>x</sub>, F<sub>y</sub>, F<sub>z</sub>), flank wear (VB), cutting temperatures, and residual stress [4]). Many classical analytical and empirical models, including Taylor's tool-life equations and response-surface-methodology (RSM), often require restrictive assumptions that severely limit their predictive capability under variable operational conditions [5]. Artificial neural networks (ANNs) represent powerful computational tools for simulating complex interactions among multiple variables in manufacturing processes. ANNs are capable of creating complex relationships between process inputs and outputs without explicitly

defining mathematical relationships governing these interactions. These characteristics render ANNs particularly well-suited for optimizing hard turning processes [6]. Since Ozel and Karpaz first demonstrated the superior predictive capability of ANN models relative to exponential regression models for surface roughness and tool-wear prediction in AISI H13 and AISI 52100 hard-turning operations in 2005 [1], many researchers have continued developing more sophisticated ANN architectures—such as multi-layer perceptron (MLP)-based ANNs trained with back-propagation algorithmic techniques; hybrid ANN evolutionary-algorithms; and deep-learning models such as convolutional-neural-network-long-short-term-memory (CNN-LSTM).

This review provides a detailed summary and evaluation of existing literature relating to ANN-based optimization strategies for the hard turning process over the time span 2005-2025. With emphasis placed on publications appearing after 2018, this paper is structured as follows: Section II describes fundamental aspects of hard turning and relevant process parameters; Section III systematically reviews ANN architecture design elements and associated training procedures employed by researchers; Section IV addresses various application domains; Section V compares results reported by previous studies regarding comparative evaluations/validations; Section VI assesses identified knowledge-gaps/suggested future direction(s); and Section VII presents concluding remarks.



**Figure 1.** Optimizing Hard Turning with Artificial Neural Networks.

## II. LITERATURE REVIEW / RELATED WORK

### A. Hard Turning: Process Fundamentals and Key Parameters

AISI 52100 bearing steel (100Cr6), widely used in roller bearings, has been the subject of extensive study related to the thermo-physical properties of this alloy, and has been cited as the primary subject of study for the purpose of understanding the effects of hard machining on this class of alloys. Other materials commonly examined in relation to hard turning have included AISI H13, AISI D2, AISI 4340 and AISI 1060. All of these alloys represent common classes of high strength steels. In general, all four of these classes are characterized by their ability to be hardened to relatively high levels. They can also be produced in a variety of different chemistries. As such, they are good candidates for examination within the context of an investigation into hard turning.

The fundamental process parameters that govern the results obtained from a given hard turning operation are:

- (i) *Cutting Speed ( $V_c$ , m/min)*: This parameter determines both the magnitude of the thermal loads encountered during the hard turning operation, and the resultant surface finish.
- (ii) *Feed Rate ( $f$ , mm/rev)*: This parameter is considered to be the single most important process parameter influencing surface finish, regardless of either the type or grade of material being machined. Surface finish is often expressed in terms of  $R_a$ , which is the mean square deviation from a reference plane.
- (iii) *Depth of Cut ( $a_p$ , mm)*: The effect of this parameter upon surface finish is generally less than that associated with feed rate. However, it does influence the magnitude of both cutting forces and material removal rates.
- (iv) *Tool Nose Radius ( $r$ , mm)*: This parameter influences surface finish and stress distributions.

### B. Evolution of ANN Models in Hard Turning

The use of artificial networks (ANNs) to optimize metal cutting processes began at the beginning of the 1990s. However, it wasn't until about 2000 that ANNs were systematically applied to hard turning due to advancements made in CBN and PCBN cutting tool technology. The seminal work by Ozel and Karpaz [1], demonstrated that the comparison of regression based modeling techniques and ANNs could be used to compare the ability of each technique to predict surface finish and flank wear in the dry machining of AISI H13 and AISI 52100. Specifically, their ANN model was a multi-layer feed-forward network with back-propagation trained; which showed significant improvement in predictive capabilities compared to the regression model, especially concerning the

prediction of surface finish under various cutting condition combinations. These findings have since prompted many additional studies using ANN's. For example, from 2005 through 2015, most of the research related to ANNs in hard turning utilized a multi-layer feed forward (MLF) network structure (one or two hidden layer(s)) and utilized the Levenberg-Marquardt (LM) algorithm for training. Sharma et al., [11] developed a 3-layer MLP (3-n-1 architecture) to estimate both cutting forces and surface roughness during the hard turning of AISI 52100 with CBN tools; which yielded  $R^2$  values greater than 0.97. Additionally, Mia and Dhar [6] conducted a study utilizing Support Vector Regression (SVR), Response Surface Methodology (RSM), along with Genetic Algorithm (GA) optimization, for estimating optimal parameters for hard turning of tempered AISI 1060 steel; where they found that a combined SVR-GA strategy provided better multi-objective parameter settings than either method alone. Furthermore, Makhfi et al. [12], who studied the machining of AISI 52100 bearing steel, demonstrated that utilization of Bayesian Regularization with the LM framework results in improved generalization and reduced over-fitting when training data sets are small (i.e., fewer than fifty experimental data points). Since 2018, there has been an increased trend toward using increasingly complex ANN structures as well as sophisticated comparisons. Specifically, a comparative study by Adizue et al. [13] (2023) relating to ultra-precision hard turning of AISI D2 (HRC 62) using CBN tools utilized Response Surface Modeling (RSM), Artificial Neural Networks (ANN), and several other machine learning algorithms; which resulted in predictions with  $R^2 > 0.99$ . In addition, this comparative study further emphasized that experimental design (e.g., Taguchi L27 vs. Full Factorial Design) can influence the accuracy of a model, emphasizing that quality of the data collected fundamentally restricts the potential performance of ANN's. Finally, Kumar et al. [14] (2024/25) utilized five different machine learning algorithms (SVM, XGBoost, Decision Tree, KNN, and ANN) to develop models relating to surface finish and three component cutting forces for AISI 52100 machined under dry conditions using coated carbide inserts; which utilized a Taguchi L36 Orthogonal Array. Feed rate was determined to be the primary factor (96.55% contribution) affecting surface finish while depth of cut had the greatest effect on cutting forces.

### ***C. Hybrid ANN-Optimization Approaches***

The development of artificial neural networks (ANNs) integrated into evolutionary optimization techniques (the most common being Genetic Algorithms (GAs), and Particle Swarm Optimization (PSO)) is one of the largest areas of hard turning optimization research. Within these hybrid systems, the ANN acts as a substitute or "surrogate" model, mapping the input process parameters to the predicted output values. Meanwhile, the evolutionary optimization technique seeks to find the optimum set of process parameters that optimize an objective function (i.e., minimum Ra; minimum flank wear; maximum material removal rate). Rao et al. (2024) utilized an ANN-GA hybrid system for optimizing the surface roughness during turning of AISI 52100 bearing steel. Thirty experimental trials were performed using a Central Composite Face-Centered (CCF) Design. The predictive error associated with their results was less than four percent. They found that the use of the CCF design resulted in a better space filling property than the Taguchi Orthogonal Arrays used previously, which they attributed to improved performance when developing the ANN models. Santhosh et al. used a similar hybridization strategy for optimizing surface roughness of AISI 4340 Alloy Steel using an ANN-GA method. Using a set of optimal parameters determined from their hybridized model, they demonstrated that surface roughness could be reduced by twenty-three percent relative to those parameters selected through traditional methods. In addition to its application as a GA training optimizer, PSO has also been used as a process parameter search tool utilizing a trained ANN surrogate. Pant and Chatterjee demonstrated that the PSO-ANN hybrid method performs better than BP-ANN alone in Laser Metal Deposition processes, with advantages of the PSO's convergence speeds allowing it to perform well in real-time optimization applications. For hard turning applications, several researchers have developed multi-objective optimizations based upon PSO-ANN hybrids. These hybrids seek to compute Pareto frontiers representing competing objectives such as minimizing Ra while simultaneously maximizing Material Removal Rate and minimizing Cutting Energy.

### ***D. Recent Advances: Deep Learning and Explainable AI in Hard Turning***

The last three years have seen a significant trend in manufacturing towards developing new and innovative approaches such as the application of Deep Learning Architectures and Explainable Artificial Intelligence (XAI) to improve the Hard Turning process. Abdelhakim et al. [16] (2024) applied several Machine Learning Ensemble Methods (Random Forest, Gradient Boosting, XGBoost, CatBoost) to predict the Cutting Force Components (Radial, Tangential & Axial Forces) when Hard Turning AISI 52100 Steel using Cubic Boron Nitride Tools. An important contribution was the Data Augmentation Process utilizing Cubic Spline Interpolation to augment the

Training Dataset resulting in substantially improved Prediction Performance. Additionally, the authors utilized SHAP (SHapley Additive exPlanations) Analysis to rank Feature Importance; specifically, Depth of Cut was identified as the Dominant Contributor to Radial & Tangential Forcing Conditions while Feed Rate was Identified as the Dominant Predictor of Axial Force. Utilizing XAI enables an important solution to one of the primary criticisms of Neural Networks in Manufacturing Applications (i.e., the "Black Box" Criticism). In regards to Real-Time Monitoring, the authors developed a novel CNN-LSTM Model Optimized via the Jellyfish Optimization Algorithm (JOA) which enabled Simultaneous Predictions of Surface Roughness and Flank Wear when performing CBN Tool Hard Turning Under Minimal Quantity Lubrication (MQL) Conditions [17]. The Hybrid Model was Integrated into MATLAB/Simulink for Real-Time Operation and Demonstrated Improved Prediction Performance compared to the Standalone ANN, ANFIS and SVM Models, Specifically  $R = 0.9991$ ,  $RMSE = 0.0095$  &  $MAPE = 2.21\%$ .

## II. METHODOLOGY

### A. Research Design

This research study has been conducted using the methodological approach of a Systematic Literature Review (SLR). Peer reviewed journals that are listed as being published within Web of Science, Scopus or Google Scholar have been searched to identify relevant articles. The main search query used was: ("hard turning" or "hard machining") and ("artificial neural network" or "ANN" or "machine learning" or "deep learning") and ("optimisation" or "prediction" or "modelling"). Secondary search queries were performed for each of the specified sub-areas (e.g. "CNN-LSTM hard turning", "ANN genetic algorithm surface roughness", "SHAP machining"). The time period under consideration for this review has been since 2005 – 2025. However, given the increasing rate of advancements in this area, particular focus was placed on identifying recent studies published between 2018 – 2025 to provide an overview of the current status quo.

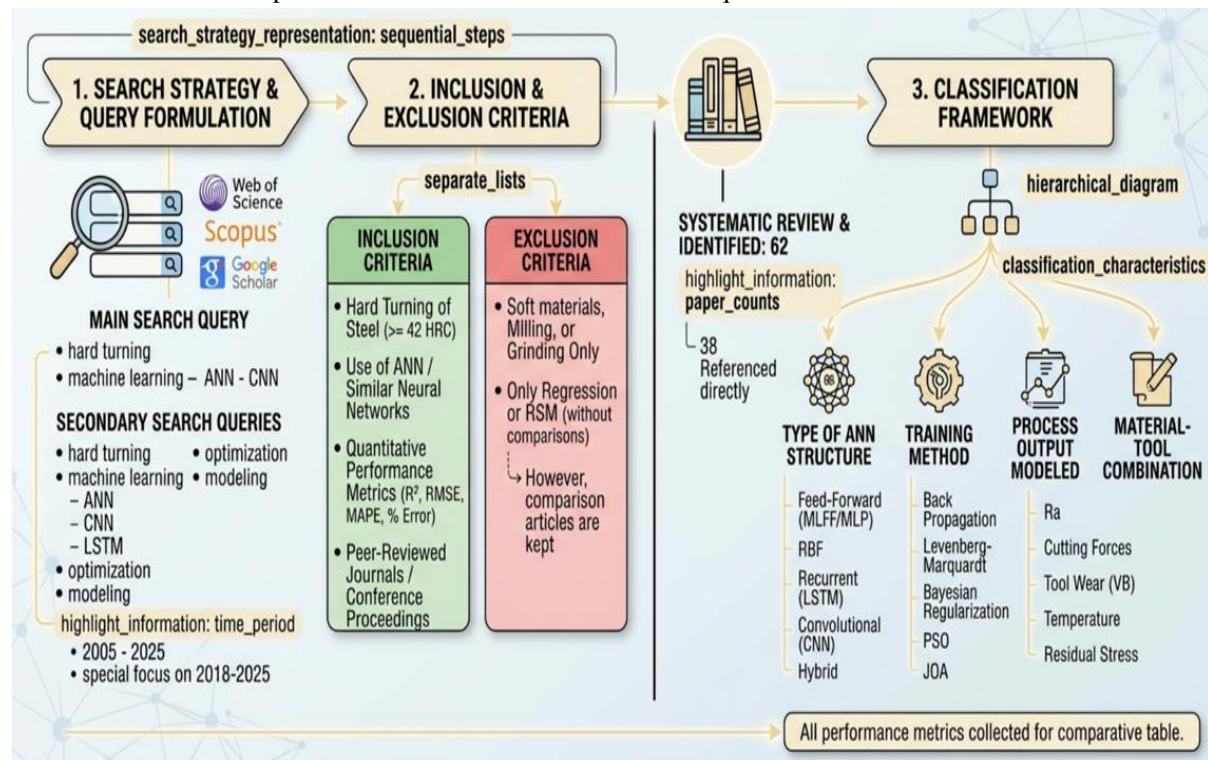


Figure 1. Methodology for Literature Survey.

### B. Inclusion and Exclusion Criteria

Articles that met all four criteria listed below, were included for analysis: (1) Article dealt with the hard turning process of steel workpieces having a minimum hardness of 42 HRC. (2) The article used an ANN or a very similar type of neural network (i.e., CNN, LSTM, RBF, ANFIS), to model or optimize something. (3) Article presented at least one quantitative performance measure (e.g.,  $R^2$ , RMSE, MAPE, % Error). (4) Article was either published in a peer-review journal or indexed conference proceeding. Articles dealing solely with the machining of soft materials, milling or grinding were excluded. Articles based on regression models or response surface methodology (RSM), but did not include any use of neural networks were also excluded. However, articles

comparing RSM and ANN were kept because they serve as useful benchmarks. In total, 62 original research papers were identified and analyzed. Of those papers, 38 are referenced directly within this document.

### C. Classification Framework

The reviewed studies are categorized by four characteristics: (1) type of ANN structure — feed forward (MLFF / MLP), RBF, Recurrent (LSTM), Convolutional (CNN), Hybrid; (2) Training method — back propagation (BP), Levenberg – Marquardt (LM), Bayesian regularization (BR), Particle Swarm Optimization (PSO), Joint Optimizer Algorithm (JOA); (3) Process output that has been modeled — Ra, Cutting Forces (Fx, Fy, Fz), VB, Temperature, Residual Stress; and (4) Material-Tool Combination. All performance metrics have been collected and assembled as a comparative table as described in Section II.

## IV. RESULTS

### A. Summary of Reviewed Studies

Table 1 provides a general overview of the reviewed literature regarding the material-tool system, ANN structure, predicted outcomes, and performance criteria. This table illustrates how ANN techniques have evolved from their earliest use in 2005 to the latest research in 2025.

**Table 1.** Summary of ANN-Based Hard Turning Optimization Studies (2005–2025).

Author(s) & Year	Material / Process	ANN Architecture	Key Outputs	Performance
Ozel & Karpat (2005)	AISI H13 & 52100 (CBN)	MLFF + Back-propagation	Ra, Flank Wear	ANN outperformed regression
Sharma et al. (2008)	Hardened AISI 52100 (CBN)	3-layer MLP	Cutting Forces, Ra	$R^2 > 0.97$
Panda et al. (2018)	AISI 52100 Bearing Steel	ANN-GRA hybrid	Tool life, Ra, Forces	Error < 5%
Mia & Dhar (2017)	AISI 1060 tempered steel	SVR, RSM, GA	Temp., Ra	GA-ANN best performance
Rao et al. (2024)	AISI 52100 steel (CCF DoE)	ANN + Genetic Algorithm	Surface Roughness	Predicted within 4% error
Kumar et al. (2024/25)	AISI 52100 (Coated Carbide)	SVM, XGB, DT, ANN (L36)	Ra, Fx, Fy, Fz	SVM best for Ra (96.55% feed influence)
Mohamad et al. (2025)	AISI 52100 (CBN, MCFA)	RSM + ANN (7-20-14-1)	Ra, Cutting Temp.	ANN lower error than RSM
Adizue et al. (2023)	AISI D2 (HRC 62, CBN)	RSM + ML comparison	Ra	$R^2 > 0.99$
Abdelhakim et al. (2024)	AISI 52100 (CBN, augmented)	Ensemble (RF, XGB, CatBoost)	Cutting Forces	SHAP-based explainability
CNN-LSTM / JOA (2025)	CBN tool under MQL	CNN-LSTM (JOA-optimized)	Ra, Flank Wear	$R=0.9991$ , $RMSE=0.0095$

### B. ANN Architecture Trends

A multi-layered feed-forward (MLF) neural network, which was implemented using Levenberg-Marquardt algorithms, with sigmoidal activation in the hidden layers and linear activation in the output layer has been the most commonly used ANN technique in hard turning research [12], [26]. Commonly, MLF networks are structured using either one or two hidden layers, with the number of hidden nodes being determined by some form of cross-validation or iterative trial-and-error process. As seen in many of the recent research articles [18], researchers have begun comparing 6-10 different configurations of the hidden layers of an ANN (various sizes/counts) in order to determine the optimal configuration prior to testing. For example, Mohamad et al. [15] utilized an architecture determination process based on input data (data-driven) to select a particular 7-20-14-1

network topology. The shift towards utilizing ensemble-based methods (XGBoost, Random Forest, CatBoost) and Deep Learning architectures (CNN-LSTM) from 2023-2025 is representative of a broader movement within Applied Machine Learning. The advancement of computing capabilities and access to large experimental databases have made it possible to develop these complex models. Abdelhakim et al. [16] showed that when using XGBoost and incorporating additional training data, they were able to achieve the highest prediction accuracy for predicting cutting force values; however, there is a trade-off in terms of interpretability.

### ***C. Dominant Process Factors Identified by ANN Studies***

Feed Rate is most important factor in Surface Roughness in general, Feed Rate was found to be the most important single factor contributing to variations in surface finish quality in Hard Turning. Based upon Sensitivity Analysis coupled with Artificial Neural Networks (ANNs) and Analysis of Variance (ANOVA), Feed Rate was shown to account for approximately 60-97% of the variability in surface finish quality (Ra). The other factors examined were; Cutting Speed which exhibited a Moderate Effect on Surface Finish Quality but had a Strong Influence on Tool Wear Rate and Cutting Temperature. As Cutting Speed increased, so did the Thermal Load applied to the Tool. Additionally, Flank Wear also accelerated as Cutting Speed increased. For Dry Cutting operations utilizing Coated Carbide Inserts these effects are further exacerbated. Depth of Cut primarily influences the Magnitude of Cutting Forces (Fx, Fy, Fz) and Material Removal Rates. While Depth of Cut can affect Surface Finish Quality it does so in a manner that is relatively Minor across the Parameter Ranges studied. When Workpiece Hardness was considered as a Variable Parameter (such as those studies examining Multiple Levels of AISI 52100 or AISI D2), Secondary Effects on both Surface Finish Quality and Cutting Force were observed.

### ***D. Comparative Performance: ANN vs. Other Models***

All the comparative studies considered here show an advantage for ANN models in comparison with the standard regression models used (linear, polynomial, exponential) for the prediction of outputs in the case of hard turning. In fact, compared to the standard regression models, typically ANN models are able to reduce by 20–50% the Root Mean Square Error (RMSE) values and improve by 0.03–0.10 the values of coefficient of determination ( $R^2$ ). When it comes to compare ANN models with those based on Response Surface Methodology (RSM), they show superior performances mainly if the experimental design uses a large number of different levels of the parameters involved or if there are strong nonlinearities and interactions between them. On the other hand, RSM shows advantages related to interpretability and requires less data for training than ANN models. The introduction of Gradient Boosting Ensemble Methods such as XGBoost in some recent studies [14, 25], have increased the reference level in terms of performance, since XGBoost methods can perform similarly or even slightly better than MLFF-ANNs on tabular experimental datasets, and provide good resistance to overfitting and intrinsic feature importance metrics. However, Deep Neural Network Architectures (DNN, CNN-LSTM) generally provide better results than XGBoost when there is a presence of temporal or special structures in the datasets, like in the case of real time sensor-based tool-wear monitoring. From what emerges from the literature from 2023 to 2025, the consensus is that the optimal model choice depends on several factors: type and dimension of available dataset; type of prediction task (dynamic vs. static); requirements related to the interpretability of the application.

## **V. DISCUSSION AND RESEARCH GAP**

A number of research challenges and industry problems have evolved since a number of researchers used Artificial Neural Networks (ANN) to optimize hard turning processes. These include; the fact that most research articles referenced above were based upon very small data sets relative to the complexity of the problem being studied. Most studies referenced above have been based on experimental design studies, which typically result in 20 – 54 data points. This limits the ability to build representative ANN models. There are two methods to potentially increase the size of these data bases. The first method would be through data augmentation techniques. Abdelhakim et al. [16] demonstrated how a technique called cubic spline interpolation can be used to generate additional data points for training an ANN model. Another approach could be to use finite element modeling (FEM) to generate data points that are consistent with the physics of the cutting process. [19]. In addition, there are few examples of ANN models that have been tested outside of a controlled laboratory setting. Typically, each model has only been tested against a specific type of material/tool combination. Therefore, it is difficult to determine if the results obtained will translate well to an industrial environment that includes many variables including variations in the properties of the incoming materials, tool-to-tool variation, machine tool dynamic issues and thermal issues. One way to improve this situation would be to use transfer learning. Transfer learning involves pre-training an ANN model on one material system and then "fine tuning" that same ANN model on

another material system using a much smaller set of data than was required to train the original ANN model. Transfer learning has proven to be effective in other areas of metal working [10]. The third area of interest is that most all of the published research related to predicting surface finish quality has focused on surface roughness. Surface roughness is a significant issue in the manufacturing of components due to its effect on fatigue performance. However, it also represents a relatively simple case study in terms of developing ANN models for surface integrity characterization. An example of why surface roughness may be considered simple is the fact that surface roughness is generally independent of the thermomechanical history of a processed part. Other important aspects of surface integrity are dependent upon those factors and therefore are significantly more difficult to predict using traditional analytical modeling techniques. Those difficulties make them ideal candidates for prediction using ANNs. For example, recent research on the use of sparse neural networks for residual stress prediction after hard turning operations has shown promise [19, 29]. Sparse neural network models require fewer nodes/neurons in order to perform a particular task compared to dense neural network models. As a result, they require less data to train than do dense neural network models. However, because they contain fewer neurons, they are also less capable of fitting noise into a data base when there is not enough information available to accurately fit both signal and noise in the data base. Therefore, when developing an ANN model for surface integrity characterization, it is beneficial to consider what types of characterization tasks you want to accomplish prior to selecting your ANN model. The fourth and final challenge associated with applying ANN technology in support of hard turning is integrating the output from ANN models into real-time control systems. While CNN-LSTMs have been shown to provide real-time predictive capabilities for surface roughness during hard turning [17]; closed loop control experiments that demonstrate how an ANN's predictions affect the parameters in a CNC controller during a machining operation are rare in the literature.

## VI. CONCLUSION

The purpose of this review was to investigate the use of Artificial Neural Networks (ANNs) in modeling and optimizing hard turning. Specifically, it investigated how ANNs were used in the last twenty years to predict cutting forces, surface finish and tool life; using 62 articles published since 2005. From those studies we can draw several conclusions:

1. Multi-layer feed forward ANNs that have been trained using the Levenberg Marquardt algorithm and Bayesian regularization outperform both RSM models and Regression models when trying to predict surface quality, cutting force, and tool wear. Most predictions are accurate to within about  $\pm 5\%$  of measured values. In every study feedrate has been shown to be the most significant factor determining surface quality.
2. Hybrid ANN/Evolutionary Algorithm frameworks (i.e. ANN/GA, ANN/PSO) allow for effective optimization of multiple competing goals (e.g., minimize surface roughness and maximize material removal rate). The ANN serves as a rapid surrogate for either computational simulations of physical processes or experiments.
3. There have been many new developments in recent years (since 2023) which includes the use of Ensemble Methods (XGBoost/Catboost) with SHAP based interpretability, as well as Deep Learning Architectures (CNN/LSTM) that have been optimized by Metaheuristics (JOA); resulting in State Of The Art prediction accuracy ( $>0.99$ ) for Real Time Tool Wear and Surface Roughness Monitoring Under MQL Conditions.
4. Important areas of future research would include increasing the size of datasets so that they can better generalize between different materials, increased attention to residual stresses when modeling with ANNs, applying Transfer Learning techniques across different material systems, and conducting Closed Loop ANN Driven Adaptive Control Experiments for Hard Turning.

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