



Prediction of Surface Roughness in Non-Traditional Machining Using Machine Learning Techniques

Sneha Patted [1], Ruchita Saraf [2], Surabhi Kappgal Srinath [3], Supraja [4]

How to Cite this Article:

Patted, S., Saraf, R., Srinath, S. K. & Supraja, (2026). Prediction of Surface Roughness in Non-Traditional Machining Using Machine Learning Techniques. International Journal of Creative and Open Research in Engineering and Management, 2(10), 1-9.
<https://doi.org/10.55041/ijcope.v2i10.166>

License:

This article is published under the terms of the Creative Commons Attribution 4.0 International License (CC BY 4.0), which permits unrestricted use, distribution, and reproduction in any medium, provided the original author(s) and the source are credited.

© The Author(s). Published by International Journal of Creative and Open Research in Engineering and Management.



<https://doi.org/10.55041/ijcope.v2i10.166>

1. Abstract

Surface roughness decides how a machined part behaves in service. It affects fatigue life, wear, sealing, friction and, in many cases, whether a part is accepted at inspection at all. Non-traditional machining (NTM) processes such as electrical discharge machining, wire EDM, electrochemical machining, laser beam machining, abrasive water jet machining and ultrasonic machining are now routine choices for hard, brittle and geometrically complex parts. Their surface texture, however, comes from thermal, chemical or erosive mechanisms that are stochastic and strongly coupled, so it is hard to predict with classical physics-based models or with simple regression equations. Over the last two decades, machine learning (ML) has become a practical alternative. Artificial neural networks, support vector regression, tree-based ensembles, fuzzy and neuro-fuzzy systems, and more recently deep learning have all been used to map process parameters and sensor signals to roughness values.

This paper reviews that body of work. It first outlines the main NTM processes and the way roughness arises in each, then summarises the factors that influence it and the traditional prediction approaches (empirical, statistical and analytical). The discussion then turns to the ML techniques most often applied, a survey of representative studies, a side-by-side comparison of the techniques, and the benefits that ML brings. The review

also looks honestly at the obstacles: small datasets, limited transferability, poor interpretability and inconsistent reporting. From this analysis, the main research gaps are identified and directions for future work are proposed, including hybrid physics-informed models, transfer learning, explainable AI and real-time in-process prediction.

2. Keywords

Surface roughness; non-traditional machining; machine learning; artificial neural network; support vector regression; random forest; electrical discharge machining; wire EDM; laser machining; abrasive water jet; predictive modelling; Industry 4.0.

3. Introduction

Manufacturing has always been a negotiation between what a design asks for and what a process can deliver. Surface finish is one of the places where that negotiation is most visible. Two parts with identical dimensions can behave very differently if one has a smoother surface: the rougher one may crack earlier under cyclic loading, wear its mating component faster, or leak where a seal should hold. For this reason, roughness parameters such as the arithmetic mean roughness (R_a), the maximum height (R_z) and the root-mean-square roughness (R_q) are specified on drawings and checked on almost every precision component [10, 11].

Conventional cutting methods rely on a hard tool removing material by mechanical shear. That approach becomes uneconomical, or simply impossible, for very hard alloys, ceramics, composites, thin sections and intricate micro-features. Non-traditional machining was developed to fill this gap. Instead of a cutting edge, these processes



use thermal energy, electrochemical dissolution, high-velocity abrasive jets or ultrasonic vibration to remove material [1, 2, 3]. They are widely used in aerospace, tooling, medical devices, automotive and electronics manufacturing.

The trade-off is that the surface produced by NTM is not governed by feed marks and tool geometry, as it is in turning or milling. In electrical discharge machining, for example, the surface is a field of overlapping craters formed by thousands of tiny sparks per second, topped by a recast layer [4, 5]. In abrasive water jet cutting, the texture changes with depth, with a smoother upper zone and a striated lower zone [8, 9]. Because these mechanisms involve randomness, rapid heating and cooling, and many interacting variables, even experienced operators find roughness hard to forecast.

Early prediction work leaned on design of experiments, response surface methodology (RSM) and Taguchi analysis [14, 15]. These methods are valuable and still widely used, but they usually give a low-order polynomial that is valid only inside the tested parameter window. As datasets grew and computing became cheaper, researchers began to apply ML, which can learn nonlinear relationships directly from data without assuming their form [20, 22]. The result is a steadily growing literature, but one that is scattered across processes, materials and algorithms, and rarely compared on equal terms.

The purpose of this review is to bring that literature together. The paper is organised as follows. Section 4 describes the principal NTM processes. Section 5 explains how surface roughness is defined and generated in them, and Section 6 lists the factors that influence it. Section 7 covers traditional prediction methods, Section 8 discusses the general role of ML in machining, and Section 9 introduces the ML techniques used for roughness prediction. Section 10 reviews representative studies, Section 11 compares the techniques, and Sections 12 to 15 discuss advantages, challenges, research gaps and future scope. Section 16 concludes the paper.

4. Non-Traditional Machining Processes

Non-traditional machining covers processes in which material is removed without a conventional cutting tool in direct mechanical contact with the workpiece. They are usually grouped by the main form of energy that does the removal: mechanical, thermal, electrochemical or chemical [1, 3]. The ones that appear most often in roughness-prediction research are described below.

4.1 Electrical Discharge Machining (EDM)

In EDM, a pulsed voltage is applied across a small gap between a shaped electrode and a conductive workpiece, both immersed in dielectric fluid. Each discharge creates a plasma channel with extremely high local temperature that melts and partly vaporises a tiny volume of the workpiece, leaving a crater [4, 5]. Repeated over many cycles, this reproduces the electrode shape in the workpiece. EDM can machine any electrically conductive material regardless of hardness, which makes it a standard method for dies, moulds and hardened tool steels. The price is a heat-affected zone, a recast layer and a surface that is inherently textured by craters.

4.2 Wire Electrical Discharge Machining (WEDM)

WEDM uses a continuously moving thin wire, typically brass or coated wire, as the electrode. It can cut complex two-dimensional and tapered profiles through thick hard materials with good accuracy.

Because the wire is thin and constantly renewed, the process is well suited to intricate profiles, but wire vibration, flushing conditions and the choice of multiple trim cuts all have a strong effect on roughness [13].

4.3 Electrochemical Machining (ECM)

ECM removes material by controlled anodic dissolution. The workpiece is the anode, the tool is the cathode, and electrolyte flows through the narrow gap between them. Since there is no thermal damage and no tool wear in principle, ECM can give stress-free, burr-free surfaces on difficult alloys [6]. Roughness depends largely on current density, electrolyte composition and flow, and on the microstructure of the alloy being dissolved.

4.4 Laser Beam Machining (LBM)



In LBM, a focused laser beam heats the material to the point of melting or vaporisation, and an assist gas helps remove the molten material. LBM is used for cutting, drilling, micro-machining and surface texturing across metals, ceramics and polymers [7]. Surface quality depends on beam power, pulse characteristics, scanning speed, focal position and gas conditions, and it is often visibly striated in laser-cut edges.

4.5 Abrasive Water Jet Machining (AWJM)

AWJM accelerates abrasive particles in a high-pressure water stream to erode the workpiece. It is a cold process, which avoids heat-affected zones, and it can cut almost any material, including stone, glass, composites and metals [8, 9]. Roughness in AWJM depends on pressure, traverse speed, abrasive type and flow rate, and stand-off distance, and it normally increases with depth of cut.

4.6 Ultrasonic Machining (USM) and Others

Ultrasonic machining uses a vibrating tool and an abrasive slurry to chip away hard and brittle materials such as glass and ceramics. Other processes, including plasma arc machining, electron beam machining, chemical machining and electrochemical discharge machining, are also in use, although they appear less often in ML-based roughness studies [1, 3].

Table 1. Overview of common non-traditional machining processes

Process	Main removal mechanism	Typical materials	Typical roughness drivers
EDM	Spark erosion (melting/vaporisation)	Conductive metals, hardened steels	Pulse current, pulse-on time, voltage, dielectric
WEDM	Spark erosion with moving wire	Conductive metals, thick hard alloys	Pulse parameters, wire speed and tension, flushing, trim cuts
ECM	Anodic dissolution	Difficult-to-cut alloys	Current density, electrolyte, gap, feed rate
LBM	Melting/vaporisation by laser	Metals, ceramics, polymers	Power, scan speed, frequency, focus, assist gas
AWJM	Abrasive erosion	Almost any material	Pressure, traverse speed, abrasive flow, stand-off distance
USM	Abrasive impact with vibration	Glass, ceramics, brittle materials	Amplitude, frequency, grit size, slurry concentration

5. Surface Roughness in Non-Traditional Machining

5.1 Definition and Measurement

Surface roughness describes the fine, closely spaced irregularities left on a surface by the manufacturing process. It is quantified using parameters defined in standards such as ISO 4287 [11]. R_a , the arithmetic average of absolute profile deviations from the mean line, is by far the most reported parameter. R_z and R_t describe peak-to-valley heights and are more sensitive to isolated defects, while R_q weights large deviations more heavily. Areal parameters such as S_a are increasingly used because they capture the full three-dimensional topography [10]. Measurement is usually done with a contact stylus profilometer, although optical profilers, confocal and white-light interferometers, and atomic force microscopes are used when contact might damage the surface or when finer resolution is needed.

5.2 How Roughness Forms in NTM

In thermal processes the surface is shaped by repeated melting, ejection and resolidification. In EDM and WEDM, each spark produces a crater whose size grows with discharge energy, so higher current and longer pulse-on time



generally lead to deeper craters and a rougher surface [4, 5, 13]. Some molten material resolidifies on the surface as a recast layer, often with micro-cracks and globules. In laser machining, similar melt dynamics and the pulsating nature of the beam create ripples and dross.

In electrochemical machining the surface develops through uneven dissolution. Grain boundaries, inclusions and different phases dissolve at different rates, so roughness reflects both electrical conditions and the metallurgy of the material [6]. In abrasive water jet machining, particle impact produces cutting wear at the top of the kerf and deformation wear lower down, which explains the typical gradient of increasing roughness with depth [8, 9].

The key point for prediction is that roughness here is the cumulative outcome of many small random events rather than the result of a single deterministic tool path. That is the main reason why simple analytical formulas rarely transfer well from one machine, material or operating regime to another.

6. Factors Affecting Surface Roughness

The factors that influence roughness can be sorted into four groups: machine and process parameters, workpiece properties, tool or electrode properties, and environmental or medium conditions. Not all of them are equally controllable, and some are rarely recorded, which becomes a problem when building datasets.

6.1 Process Parameters

These are the inputs set by the operator and are the most common ML inputs. In EDM and WEDM they include peak current, pulse-on time, pulse-off time, gap voltage, servo settings, wire feed and wire tension. In laser processing they are laser power, pulse frequency, scanning speed and focal position. For ECM they are applied voltage, electrolyte concentration, flow rate and inter-electrode gap. For AWJM they are water pressure, traverse speed, abrasive mass flow rate and stand-off distance [4, 6, 7, 8].

6.2 Workpiece Material Properties

Thermal conductivity, melting point, hardness, microstructure, and electrical conductivity influence how much material is removed per unit energy and how it resolidifies. Two alloys machined with identical settings can give notably different roughness. Many ML studies train models for a single material, which limits how far their conclusions can be extended.

6.3 Tool or Electrode Characteristics

Electrode material (copper, graphite, brass, etc.), polarity, geometry and wear all affect discharge behaviour. In AWJM, the nozzle diameter and its wear state alter the jet. Progressive tool wear is one reason why a model trained early in a production run may drift later.

6.4 Medium and Environmental Conditions

The dielectric fluid type and flushing efficiency in EDM, electrolyte chemistry in ECM, assist gas in laser machining and abrasive type and size in AWJM all matter. Powder-mixed dielectrics, for example, change the discharge distribution and can substantially improve the finish [5]. Temperature, contamination of the medium and ageing of the electrolyte or dielectric are real-world effects that are seldom captured in laboratory datasets.

Table 2. Groups of factors influencing surface roughness in NTM

Factor group	Examples	Usually recorded in studies?
Process parameters	Current, pulse time, voltage, power, speed, pressure	Yes, almost always
Workpiece material	Hardness, conductivity, microstructure	Often only the material name
Tool / electrode	Electrode material, wire type, nozzle wear	Partly; wear seldom quantified
Medium	/ Dielectric, electrolyte, abrasive, flushing,	Rarely in detail



environment	temperature	
Process signals	Discharge voltage/current, acoustic emission, vibration	Only in few recent studies

7. Traditional Methods for Surface Roughness Prediction

7.1 Empirical and Experimental Approaches

The oldest approach is simply to run experiments, measure the roughness and tabulate the outcome. Handbooks and machine-tool manufacturers provide technology tables that link settings to expected finish. This is useful as a starting point, but the tables are generic and do not account for specific materials or machine condition.

7.2 Statistical Design of Experiments

Taguchi's orthogonal-array method reduces the number of trials required and uses signal-to-noise ratios to identify robust settings [14]. Response surface methodology goes further by fitting a second-order polynomial between inputs and output, which allows interaction effects and curvature to be explored [15]. Analysis of variance (ANOVA) is then used to rank the contribution of each factor. These methods have been applied to practically every NTM process and are valued for being transparent and cheap to implement [16, 17].

Their limitations are well known. The polynomial form is a strong assumption, accuracy outside the experimental region is poor, and the number of required runs grows quickly as factors are added. They also treat the process as a static system and do not easily absorb new data from later production.

7.3 Analytical and Numerical Models

Physics-based models try to describe the process mechanism directly. For EDM and WEDM, thermal models of single and multiple discharges estimate crater dimensions from heat-flux assumptions, and finite element or finite difference methods are used to simulate temperature fields [13]. In AWJM, erosion models relate particle energy to material removal [9]. These models improve understanding and can guide design, but they depend on simplifying assumptions (spherical craters, constant plasma radius, uniform flushing, and so on) and on parameters that are hard to measure. Real surfaces, which are shaped by debris, arcing and instabilities, often deviate from the idealised prediction.

7.4 Optimisation Heuristics

Metaheuristic algorithms such as genetic algorithms and particle swarm optimisation are often combined with regression equations to search for parameter settings that minimise roughness [16, 18, 19]. Strictly speaking they are optimisers rather than predictors, but they are discussed here because they are frequently paired with ML models in later work.

8. Role of Machine Learning in Machining

Machine learning is a family of methods that build a model from data instead of from explicit rules. Given a set of examples, each with input variables and a measured outcome, a supervised learning algorithm tunes its internal parameters to reproduce the outcome and, ideally, to generalise to unseen cases [22]. In manufacturing, ML has been applied to tool condition monitoring, process planning, quality prediction, anomaly detection, energy optimisation and predictive maintenance [20, 21].

Machining is a natural field for this approach for several reasons. The processes are nonlinear and multivariable, sensors and CNC controllers can now record large quantities of data, and the cost of a poor prediction (scrap, rework, or a failed part) is high. A model that can estimate roughness before or during a cut could help operators choose settings without trial runs, trigger corrections when the process drifts, and cut down on final inspection.

The theoretical foundation is also reassuring. Feed-forward neural networks with enough hidden units can



approximate any continuous function on a bounded domain to arbitrary accuracy [24], which is why they were the first ML models to be widely used in this domain. The practical caution is that approximation capacity does not guarantee good generalisation, particularly with small experimental datasets.

A typical workflow for ML-based roughness prediction has five stages. First, experiments are designed and run, and roughness is measured. Second, inputs are selected and cleaned, and features may be scaled or engineered. Third, one or more models are trained, with hyperparameters tuned by cross-validation. Fourth, the model is evaluated on held-out data using metrics such as RMSE, MAE, mean absolute percentage error and R^2 . Fifth, the model is deployed for prediction or coupled with an optimiser. Each stage affects the reliability of the final result, and weaknesses at any point (for example, data leakage between training and test sets) can inflate reported accuracy.

9. Machine Learning Techniques Used for Surface Roughness Prediction

9.1 Artificial Neural Networks (ANN)

ANNs consist of layers of interconnected nodes, with weights adjusted by back-propagation of the prediction error [23]. Multilayer perceptrons trained with back-propagation are the most frequently used model for roughness prediction in NTM. Variants include radial basis function networks, generalised regression neural networks and, more recently, deep architectures. ANNs handle strong nonlinearity well and can model several outputs together (for example roughness, material removal rate and tool wear), but they need sufficient data and careful control of overfitting.

9.2 Support Vector Machines and Support Vector Regression

Support vector machines find a decision function that maximises the margin between classes; their regression form, support vector regression (SVR), fits a function within a tolerance band around the data [28, 29]. Kernel functions allow nonlinear relationships to be modelled in a transformed space. SVR is attractive for small to medium datasets because its structural risk minimisation principle tends to give good generalisation, although the kernel and its parameters must be selected carefully [29, 30].

9.3 Decision Trees, Random Forest and Gradient Boosting

Decision trees partition the input space through a series of splits and are easy to interpret. Random forests average many trees built on random subsets of the data and features, which greatly reduces variance [31]. Gradient boosting builds trees sequentially, each correcting the errors of the previous ones [32], and implementations such as XGBoost have become strong baselines for tabular data [33]. Tree ensembles handle mixed variable types, do not need feature scaling, and offer built-in measures of feature importance.

9.4 Fuzzy Logic and Neuro-Fuzzy Systems

Fuzzy inference uses linguistic rules (for example, if current is high and pulse-on time is long then roughness is high) with membership functions to handle imprecision. The adaptive neuro-fuzzy inference system (ANFIS) merges this with neural network learning to tune the membership functions automatically [34]. It offers a degree of interpretability through its rule base, which is a useful property in process engineering.

9.5 Other Regression and Instance-Based Methods

Methods such as k-nearest neighbours, Gaussian process regression, multiple linear regression, ridge and LASSO regression, and Bayesian models are used as baselines or for particular purposes. Gaussian process regression is notable because it supplies an uncertainty estimate with each prediction, which suits small experimental datasets [40].

9.6 Deep Learning

Deep learning uses networks with many layers to learn features automatically [36]. Convolutional neural networks can extract information directly from images of machined surfaces or from time-frequency representations of sensor signals, while recurrent architectures such as long short-term memory networks handle time-series signals,



such as discharge waveforms or acoustic emission [37]. These models are powerful but demand far more data than most NTM experiments produce.

9.7 Hybrid and Ensemble Approaches

Many studies combine a predictor with an optimiser, for instance ANN with a genetic algorithm to tune weights or to search the parameter space, or ANN with particle swarm optimisation [18, 19, 27]. Others combine predictions from several different models (stacking or voting) to reduce error. Hybrids with physics-based simulations, where finite element results supplement scarce experimental data, are another route [27, 43].

10. Review of Existing Studies

This section discusses representative contributions. It is not an exhaustive census; the intention is to show how methods and results have developed. Where studies in conventional machining have shaped NTM practice, they are mentioned for context and identified as such.

10.1 Foundations in Roughness Prediction

Benardos and Vosniakos reviewed approaches to predicting surface roughness in machining, grouping them into machining-theory-based, experimental, designed-experiment and artificial-intelligence-based methods [12]. They observed that AI-based models were promising because of their capacity to handle complex relationships, an observation that has largely been borne out in the years since. Mukherjee and Ray similarly surveyed optimisation techniques for metal cutting and noted the increasing use of soft computing [16].

10.2 EDM and Die-Sinking EDM

Tsai and Wang compared several neural network models for predicting the surface finish of EDM across different work materials and concluded that network-based models could capture the relationship between discharge conditions and finish more effectively than conventional approaches [25]. Pradhan and Biswas used neural network and neuro-fuzzy models to predict responses including roughness in EDM of AISI D2 tool steel, and reported that the learning-based models gave useful predictions within the experimental range [26]. Joshi and Pande took a hybrid route: they built a thermal finite element model of single-spark EDM, used its output to train a neural network, and then employed an evolutionary algorithm to optimise process parameters [27]. That study is often cited as an example of using simulation to ease the data burden.

10.3 Wire EDM

Spedding and Wang developed an early empirical-and-neural model of wire EDM, linking cutting parameters to surface roughness and waviness [13]. More recent work has broadened the range of algorithms. Ulas and co-workers compared several ML algorithms for predicting Ra in wire EDM of an aluminium alloy, illustrating how algorithm choice influences accuracy on the same dataset [35]. In general, wire EDM studies show that nonlinear models outperform linear regression, with the best performer varying with the data size and quality.

10.4 Laser, ECM and AWJM

The literature on laser, electrochemical and abrasive water jet machining is thinner than that on EDM, but the pattern is similar. Regression, ANN and SVR models have been built to relate laser power, speed and frequency to edge roughness, to estimate surface finish in ECM from current density and electrolyte conditions, and to predict kerf roughness in AWJM from pressure, traverse speed and abrasive flow [6, 7, 8]. A recurring feature of AWJM work is that depth-dependent roughness is difficult to capture with a single average value, which suggests that models should predict roughness profiles or zone-wise values rather than a single Ra.

10.5 Evidence from Conventional Machining

Because ML methodology transfers across processes, results from turning and milling are informative. Caydas and Ekici used support vector machines to predict roughness in CNC turning of stainless steel and compared them with neural network models, with encouraging results for SVM [30]. Kumar and Chauhan compared RSM and ANN for



turning of aluminium-based composites and found that the neural model generally fitted the data better [38]. Mia and Dhar applied ANN to roughness prediction in hard turning under high-pressure coolant [39]. These studies established modelling practices (input selection, normalisation, cross-validation) that NTM researchers have since adopted.

10.6 Emerging Trends

Recent literature points toward tree ensembles and gradient boosting as strong, low-effort baselines on small tabular datasets [31, 33], toward deep learning for signal- and image-based prediction [36, 37], and toward model-explanation tools such as SHAP to show which inputs drive predictions [41]. Smart machining reviews also highlight a shift from offline prediction to in-process monitoring where sensor data feed models that update continuously [21].

Table 3. Summary of representative studies reviewed

Study (ref.)	Process	Technique(s)	Main takeaway
Tsai and Wang [25]	EDM	Several neural network models	Neural models predicted EDM finish better than conventional approaches
Pradhan and Biswas [26]	EDM (AISI D2)	ANN, neuro-fuzzy	Learning-based models gave useful multi-response predictions
Joshi and Pande [27]	Die-sinking EDM	FE model + ANN + evolutionary optimiser	Simulation data can reduce experimental effort
Spedding and Wang [13]	WEDM	Empirical + neural modelling	Early evidence of ANN suitability for WEDM roughness
Ulas et al. [35]	WEDM (Al alloy)	Several ML algorithms compared	Algorithm choice significantly affects accuracy
Caydas and Ekici [30]	CNC turning (context)	SVM vs. ANN	SVM competitive with ANN on limited data
Kumar and Chauhan [38]	Turning of composites (context)	RSM vs. ANN	ANN fitted nonlinear data better than RSM
Mia and Dhar [39]	Hard turning (context)	ANN	ANN effective under high-pressure coolant

11. Comparison of Machine Learning Techniques

No single algorithm is best for every roughness-prediction task. The comparison below is qualitative and based on the general characteristics of the methods and on trends in the literature reviewed above, rather than on a head-to-head benchmark under identical conditions, which does not yet exist for NTM.

Table 4. Qualitative comparison of ML techniques for roughness prediction

Technique	Data need	Handles nonlinearity	Interpretability	Typical strength	Typical weakness
Linear / RSM regression	Low	Limited	High	Simple, transparent	Poor outside tested range
ANN (MLP)	Medium	Very good	Low	Flexible, multi-output	Overfitting; black box



SVR	Low to medium	Good (kernels)	Low to medium	Robust on small data	Kernel and parameter tuning
Decision tree	Low to medium	Good	High	Easy to explain	Unstable, overfits
Random forest / boosting	Medium	Very good	Medium (feature importance)	Strong tabular baseline	Less smooth predictions
Fuzzy / ANFIS	Low to medium	Good	Medium to high	Rule-based insight	Rule explosion with many inputs
Technique	Data need	Handles nonlinearity	Interpretability	Typical strength	Typical weakness
Gaussian process	Low	Good	Medium	Gives uncertainty	Scales poorly to large data
Deep learning (CNN/LSTM)	High	Excellent	Very low	Learns from signals/images	Data hungry, costly
Hybrid (ML + optimiser / physics)	Varies	Very good	Varies	Can reduce data needs	Complex to build and validate

A few practical points follow from this comparison. When only a few dozen experimental points are available, which is common in EDM and WEDM studies, SVR, Gaussian process regression and well-regularised small ANNs are reasonable choices. When a few hundred or more points exist, tree ensembles and boosted trees are often very competitive and are easier to tune. Deep learning is justified mainly when raw signals or images are available in large quantity. Finally, because small datasets give noisy performance estimates, results should be validated with repeated cross-validation instead of a single train-test split.

12. Advantages of Machine Learning-Based Prediction

Ability to model complex nonlinear behaviour. ML models do not require a predefined equation. They learn interactions between current, pulse duration, material and flushing conditions without the analyst specifying them in advance [24].

Better accuracy within the training domain. Across many studies, learning-based models fit experimental data more closely than low-order polynomials, as shown in comparisons between ANN and RSM [38].

Multi-output modelling. A single network can predict roughness along with material removal rate, tool wear and dimensional accuracy, which supports trade-off analysis [26].

Reduced experimentation. Once trained, a model can estimate outcomes for untested settings, saving time, material and machine hours. Combining ML with simulation data can reduce experimental needs further [27].

Compatibility with optimisation. Trained models can serve as fast objective functions for genetic algorithms or particle swarm methods, enabling automated search for settings that give the desired finish [18, 19].

Potential for real-time use. After training, inference is very fast. When linked to sensors, models can support in-process monitoring and adaptive control, a core idea of smart manufacturing [20, 21].

Continuous improvement. Models can be retrained as more production data accumulates, so they can adapt to new materials, machine ageing or process changes in a way that fixed analytical equations cannot.

13. Challenges and Limitations

Small and costly datasets. NTM experiments are slow and expensive, so most published datasets contain only a few dozen to a few hundred observations. With so little data, complex models overfit easily, and reported accuracies can



be optimistic [20].

Limited generalisation. Most models are trained for a single machine, material and parameter window. Their performance on a different machine or alloy is often untested and may be poor. The transferability problem is one of the biggest barriers to industrial uptake.

Black-box behaviour. Neural networks and ensembles provide predictions without clear physical explanations. Engineers who must justify decisions in regulated sectors such as aerospace and medical devices may be reluctant to trust them [41].

Measurement variability and noise. Roughness depends on where and how it is measured: stylus radius, cut-off length, evaluation length and measurement direction all alter the result. NTM surfaces, especially recast layers and laser-cut edges, can be heterogeneous, so a single Ra reading may not represent the surface [10, 11].

Inconsistent reporting and benchmarking. Studies differ in their choice of inputs, ranges, data splits and error metrics, which makes direct comparison almost impossible. Many do not release their data or code, limiting reproducibility.

Process drift and non-stationarity. Electrode wear, dielectric ageing, wire condition and temperature change over time. A model trained on fresh conditions may degrade without retraining.

Limited input features. Most studies use only machine settings as inputs. The actual discharge or jet conditions, which are the real drivers of roughness, are rarely captured, so unexplained variance remains.

Hyperparameter tuning and overfitting risks. Poor validation design, such as tuning on the test set, can inflate performance. Without careful practice, a model can look excellent on paper and fail on the shop floor.

14. Research Gaps

The review of the literature points to several gaps that deserve attention.

Table 5. Research gaps identified from the review

No.	Research gap	Why it matters
1	Heavy concentration on EDM and WEDM; limited work on ECM, LBM, USM and hybrid NTM	Findings may not apply to processes with different mechanisms
2	Absence of standard benchmark datasets and reporting protocols	Results from different papers cannot be fairly compared
3	Few models validated on new machines, materials or conditions	Unknown real-world transferability
4	Little use of in-process sensor signals as inputs	Models miss the actual process state
5	Lack of uncertainty quantification in predictions	Users cannot judge the reliability of a given prediction
6	Weak integration between physics-based and data-driven models	Data demand stays high; physical consistency is not enforced
7	Roughness is mostly treated as a single Ra value	Ignores profile shape, areal parameters and depth variation
8	Limited explainability analysis	Slows industrial acceptance
9	Few studies on long-term drift and online model updating	Models may become unreliable in production



15. Future Scope

Physics-informed machine learning. Embedding known physical relationships (for example, energy-crater size relations in EDM) in the model structure or loss function can reduce data requirements and keep predictions physically plausible [43]. This is probably the most promising direction for NTM, where physical understanding is substantial but incomplete.

Transfer learning and domain adaptation. A model pre-trained on abundant data from one machine, material or simulation can be adapted to a new setting with few additional experiments [42]. This directly addresses both the small-data problem and the transferability problem.

Explainable AI. Techniques such as SHAP values, partial dependence plots and rule extraction should be a standard part of roughness-prediction studies, so that results can be examined against process knowledge [41].

In-process sensing and digital twins. Combining discharge waveforms, acoustic emission, vibration, current signals or machine-vision data with deep or hybrid models could enable real-time estimation and closed-loop adjustment of parameters. Linking such models to a digital twin of the machine would let engineers test settings virtually [21].

Active learning and Bayesian optimisation. Instead of running a fixed experimental design, algorithms can choose the next most informative experiment. This can reach good accuracy with far fewer runs, which is valuable when each experiment is expensive.

Open data and standardised benchmarking. Shared datasets, common error metrics, and clear descriptions of measurement conditions would let the community compare methods fairly and build on each other's work.

Wider process and material coverage. More work is needed on emerging and hybrid NTM processes, micro-machining, and advanced materials such as titanium alloys, nickel superalloys, ceramics and composites.

Multi-objective and sustainable machining. Future models should predict roughness together with energy consumption, tool wear and environmental impact, so that optimisation reflects practical and sustainability goals as well as surface quality.

16. Conclusion

Surface roughness in non-traditional machining is difficult to predict because it emerges from stochastic, strongly coupled thermal, chemical and erosive mechanisms. Traditional tools such as Taguchi design, response surface methodology and analytical models remain useful for understanding and for quick optimisation, but they are restricted by their assumed functional forms, narrow validity ranges and idealised physical assumptions.

Machine learning offers a strong complement. Across the studies reviewed, artificial neural networks, support vector regression, tree-based ensembles, neuro-fuzzy systems and hybrid approaches have repeatedly shown that they can capture nonlinear process behaviour and deliver useful predictions, often better than polynomial regression within the tested range. Which algorithm performs best depends on the quantity and quality of data, the process, and the need for interpretability, and no universal winner emerges.

At the same time, the field has not yet matured. Small datasets, narrow validation, limited generalisation, inconsistent reporting and the black-box nature of many models restrict industrial adoption. The most promising paths forward are physics-informed and hybrid models, transfer learning, explainable AI, uncertainty-aware prediction and sensor-based real-time monitoring, supported by open benchmark data. If these are pursued together, ML-based roughness prediction can move from a research exercise to a dependable part of intelligent, self-correcting NTM systems.

17. References

- [1] Pandey, P.C. and Shan, H.S. (1980). *Modern Machining Processes*. Tata McGraw-Hill, New Delhi.
- [2] McGeough, J.A. (1988). *Advanced Methods of Machining*. Chapman and Hall, London.



- [3] Jain, V.K. (2002). *Advanced Machining Processes*. Allied Publishers, New Delhi.
- [4] Ho, K.H. and Newman, S.T. (2003). State of the art electrical discharge machining (EDM). *International Journal of Machine Tools and Manufacture*, 43(13), 1287-1300.
- [5] Kunieda, M., Lauwers, B., Rajurkar, K.P. and Schumacher, B.M. (2005). Advancing EDM through fundamental insight into the process. *CIRP Annals*, 54(2), 64-87.
- [6] Rajurkar, K.P., Zhu, D., McGeough, J.A., Kozak, J. and De Silva, A. (1999). New developments in electro-chemical machining. *CIRP Annals*, 48(2), 567-579.
- [7] Dubey, A.K. and Yadava, V. (2008). Laser beam machining - a review. *International Journal of Machine Tools and Manufacture*, 48(6), 609-628.
- [8] Momber, A.W. and Kovacevic, R. (1998). *Principles of Abrasive Water Jet Machining*. Springer, London.
- [9] Hashish, M. (1989). A model for abrasive-waterjet (AWJ) machining. *Journal of Engineering Materials and Technology*, 111(2), 154-162.
- [10] Whitehouse, D.J. (2002). *Surfaces and their Measurement*. Hermes Penton Science, London.
- [11] ISO 4287:1997. *Geometrical Product Specifications (GPS) - Surface texture: Profile method - Terms, definitions and surface texture parameters*. International Organization for Standardization, Geneva.
- [12] Benardos, P.G. and Vosniakos, G.C. (2003). Predicting surface roughness in machining: a review. *International Journal of Machine Tools and Manufacture*, 43(8), 833-844.
- [13] Spedding, T.A. and Wang, Z.Q. (1997). Study on modeling of wire EDM process. *Journal of Materials Processing Technology*, 69(1-3), 18-28.
- [14] Taguchi, G. (1986). *Introduction to Quality Engineering*. Asian Productivity Organization, Tokyo.
- [15] Myers, R.H., Montgomery, D.C. and Anderson-Cook, C.M. (2016). *Response Surface Methodology: Process and Product Optimization Using Designed Experiments*. John Wiley and Sons.
- [16] Mukherjee, I. and Ray, P.K. (2006). A review of optimization techniques in metal cutting processes. *Computers and Industrial Engineering*, 50(1-2), 15-34.
- [17] Rao, R.V. (2011). *Advanced Modeling and Optimization of Manufacturing Processes*. Springer, London.
- [18] Goldberg, D.E. (1989). *Genetic Algorithms in Search, Optimization and Machine Learning*. Addison-Wesley, Reading, MA.
- [19] Kennedy, J. and Eberhart, R. (1995). Particle swarm optimization. *Proceedings of the IEEE International Conference on Neural Networks*, 4, 1942-1948.
- [20] Wuest, T., Weimer, D., Irgens, C. and Thoben, K.D. (2016). Machine learning in manufacturing: advantages, challenges, and applications. *Production and Manufacturing Research*, 4(1), 23-45.
- [21] Kim, D.H., Kim, T.J.Y., Wang, X., et al. (2018). Smart machining process using machine learning: a review and perspective on machining industry. *International Journal of Precision Engineering and Manufacturing-Green Technology*, 5, 555-568.
- [22] Jordan, M.I. and Mitchell, T.M. (2015). Machine learning: trends, perspectives, and prospects. *Science*, 349(6245), 255-260.
- [23] Rumelhart, D.E., Hinton, G.E. and Williams, R.J. (1986). Learning representations by back-propagating errors. *Nature*, 323, 533-536.
- [24] Hornik, K., Stinchcombe, M. and White, H. (1989). Multilayer feedforward networks are universal approximators. *Neural Networks*, 2(5), 359-366.
- [25] Tsai, K.M. and Wang, P.J. (2001). Predictions on surface finish in electrical discharge machining based upon neural network models. *International Journal of Machine Tools and Manufacture*, 41(10), 1385-1403.
- [26] Pradhan, M.K. and Biswas, C.K. (2010). Neuro-fuzzy and neural network-based prediction of various



responses in electrical discharge machining of AISI D2 steel. *The International Journal of Advanced Manufacturing Technology*, 50, 591-610.

[27] Joshi, S.N. and Pande, S.S. (2011). Intelligent process modeling and optimization of die-sinking electric discharge machining. *Applied Soft Computing*, 11(2), 2743-2755.

[28] Cortes, C. and Vapnik, V. (1995). Support-vector networks. *Machine Learning*, 20, 273-297.

[29] Smola, A.J. and Scholkopf, B. (2004). A tutorial on support vector regression. *Statistics and Computing*, 14, 199-222.

[30] Caydas, U. and Ekici, S. (2012). Support vector machines models for surface roughness prediction in CNC turning of AISI 304 austenitic stainless steel. *Journal of Intelligent Manufacturing*, 23, 639-650.

[31] Breiman, L. (2001). Random forests. *Machine Learning*, 45, 5-32.

[32] Friedman, J.H. (2001). Greedy function approximation: a gradient boosting machine. *The Annals of Statistics*, 29(5), 1189-1232.

[33] Chen, T. and Guestrin, C. (2016). XGBoost: a scalable tree boosting system. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 785-794.

[34] Jang, J.-S.R. (1993). ANFIS: adaptive-network-based fuzzy inference system. *IEEE Transactions on Systems, Man, and Cybernetics*, 23(3), 665-685.

[35] Ulas, M., Aydur, O., Gurgenc, T. and Ozel, C. (2020). Surface roughness prediction of machined aluminum alloy with wire electrical discharge machining by different machine learning algorithms. *Journal of Materials Research and Technology*, 9(6), 12512-12524.

[36] LeCun, Y., Bengio, Y. and Hinton, G. (2015). Deep learning. *Nature*, 521, 436-444.

[37] Hochreiter, S. and Schmidhuber, J. (1997). Long short-term memory. *Neural Computation*, 9(8), 1735-1780.

[38] Kumar, R. and Chauhan, S. (2015). Study on surface roughness measurement for turning of Al 7075/10/SiCp and Al 7075 hybrid composites by using response surface methodology (RSM) and artificial neural networking (ANN). *Measurement*, 65, 166-180.

[39] Mia, M. and Dhar, N.R. (2016). Prediction of surface roughness in hard turning under high pressure coolant using artificial neural network. *Measurement*, 92, 464-474.

[40] Rasmussen, C.E. and Williams, C.K.I. (2006). *Gaussian Processes for Machine Learning*. MIT Press, Cambridge, MA.

[41] Lundberg, S.M. and Lee, S.-I. (2017). A unified approach to interpreting model predictions. *Advances in Neural Information Processing Systems*, 30.

[42] Pan, S.J. and Yang, Q. (2010). A survey on transfer learning. *IEEE Transactions on Knowledge and Data Engineering*, 22(10), 1345-1359.

[43] Raissi, M., Perdikaris, P. and Karniadakis, G.E. (2019). Physics-informed neural networks: a deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. *Journal of Computational Physics*, 378, 686-707.