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Impact of cutting parameters on surface roughness in aluminum alloys machining: a review of machine learning models for key parameter identification

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ABSTRACT

This paper provides a comprehensive review of research on the influence of machining parameters—depth of cut, feed rate, and cutting speed—on surface roughness, with a focus on aluminum alloys. Surface quality in CNC machining is significantly affected by these parameters, with numerous studies highlighting their impact on achieving desired surface roughness. The review analyzes findings from ten studies, emphasizing that feed rate is generally identified as the most influential parameter for surface roughness. While feed rate shows a dominant effect, cutting speed and depth of cut also contribute, though to a lesser extent. The research includes a discussion of various methodologies, including ANOVA, the Taguchi method, and more simple machine learning regression models, which demonstrate strong alignment with experimental results and highlight the effectiveness of advanced regression-based models in predicting surface roughness. The study concludes that optimizing feed rate is crucial for achieving high surface quality values, while cutting speed and depth of cut should be managed appropriately. The findings underscore the importance of machine learning tools in analyzing and optimizing machining parameters, offering practical guidance for CNC machine operators and engineers.

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1. INTRODUCTION

Machine learning, although present in the scientific world for more than seven decades [1], has gained significant attention in recent years and is becoming increasingly integrated into the daily lives of a growing number of people, particularly younger generations who aim to engage in various projects within the fields of computer science as well as other scientific disciplines [2], [3]. The automotive industry, architecture, medicine, biology, education, mechanical and petroleum industries are just a few sectors increasingly relying on the application of machine learning, which involves the implementation of large datasets in complex algorithms [4], [5]. Since 2014, machine learning has gained growing prominence in industrial production settings, particularly in the optimization of operating parameters [6], and has also found applications in reducing errors during manufacturing [7].

Despite the widespread presence of machine learning and artificial intelligence across all sectors, as noted in [8], the level of integration of artificial intelligence across different disciplines still largely depends on workers' trust in decisions made by AI systems. This trust significantly depends on the workers' understanding of the technologies underlying artificial intelligence and machine learning [9], the specific environment, and the technology itself [10]. A lack of transparency in machine learning models for certain groups of people can lead to uncertainty within these groups regarding the decisions made by such models [11]. However, production needs to stay up with advancements [12] and it must be accepted that artificial intelligence and machine learning are becoming integral components of every industry [13], especially when it comes to optimizing production time and, consequently, the economic aspects of production. This is confirmed by scientific achievements realized through the use of machine learning in recent years, which, before the intensive use of machine learning, were believed to require decades to achieve using traditional statistical methods [14], [15]. Therefore, it is important to familiarize the wider public with the fundamentals of machine learning, especially younger generations, who, according to [16], should be introduced to the basics of machine learning during secondary education.

The aim of this paper is to raise awareness among the broader population about the technical aspects of machine learning, particularly regression models, through their specific application in analyzing factors that influence the surface roughness during CNC milling.

2. FUNDAMENTAL PRINCIPLES OF MACHINE LEARNING

Although the terms machine learning and artificial intelligence are closely related, they do not have the exact same meaning [17]. Machine learning served as the foundation for the development of artificial intelligence [18]. Today, artificial intelligence is extensively used for advancing machine learning, and thus, these two disciplines complement each other.

Machine learning is based on the implementation and improvement of more or less complex algorithms (shallow or deep learning [19]), through which a computer (machine) can independently propose a solution to a given problem without prior programming for the specific query [18]. By enhancing these algorithms, the machine learns experientially, using a trial-and-error method, and begins to recognize certain patterns of reasoning based on the information entered into the system [20].

There are four basic techniques through which a machine learns [21], [22]:

1. Supervised Learning;
2. Unsupervised Learning;
3. Semi-Supervised Learning; and
4. Reinforcement Learning.

However, in addition to these four types of machine learning, it is important to mention self-supervised learning, which, according to authors [23], [24], has been intensively developed in recent years.

2.1 Supervised Learning

Supervised machine learning represents a type of machine learning in which the model is trained to understand the relationship between input (features) and output (label) data [25] and to learn a certain regularity that connects the given data, thus being able during the test or when it is deployed to make specific numerical predictions or classifications for queries directed to it [26]. This form of machine learning is called supervised because the data fed into the model are supervised by humans or a team of experts who create it [27]. Without data to feed into the model, it is impossible to create a model, making data collection a necessary operation before starting any training of the model [28]. To ensure that the model, after training, testing, and deployment, performs its task at the highest level of accuracy, it is essential to provide precise real-world data during programming, as the quality of decisions and solutions offered by the machine learning model directly depends on the quality and quantity of data entered during its creation [29]. According to [30], data collection represents an extensive task, consuming 80-90% of the time required for the development of a machine learning model. Great attention must be paid to the quality of the input data, as incorrect data could negatively impact the quality of the final product, so both feature and label data accuracy must not be overlooked [31], [32].

Supervised machine learning is generally divided into two areas: regression and classification [33]. This paper will primarily focus on regression models of supervised machine learning and their practical application in analyzing parameters that affect the surface roughness.

2.1.1 Regression Models in Machine Learning

Regression models are among the fundamental and, according to [34], some of the most important machine learning models. They are often the starting point for solving mathematical and statistical problems across various industrial sectors [35]. There are numerous regression models or higher machine learning models based on regression, as noted by the author in [36], who identifies 77 different regression models, grouped into 19 categories. Furthermore, regression models are among the fastest-developing models when it comes to improving machine learning techniques.

At their core, regression models represent a statistical method based on mathematical functions and input (feature) and output (label) data used to generate the machine learning model [35], [37]. The mathematical functions are created by the model itself as it identifies the interaction between input (independent) and output (dependent) data [38], [39].

Based on the input and output data entered during model creation and the mathematical relationships formed, the final model is expected to provide certain predictions, forecasting changes in the dependent variable in relation to changes in independent variables [35]. Typically, once created to solve a particular problem, regression models are used to compute regression coefficients and evaluate the accuracy of the model through squared error analysis [37].

In the following sections, the practical application of regression models in machining processes will be discussed.

3. PARAMETERS AFFECTING SURFACE ROUGHNESS

An important parameter in the manufacturing industry is the surface roughness. This parameter can significantly influence the quality of the product, noise and vibration during operation in a mechanical assembly, corrosion resistance, wear resistance, and more [40], [41], [42].

According to [43], the surface roughness during milling largely depends on three parameters: feed rate, depth of cut, and cutting speed. Variations in these parameters are typically used to achieve the desired surface quality. The selection of these parameters must be done wisely, as in addition to achieving the desired surface roughness, the condition of the cutting tool itself must be considered, as the state of the tool can directly affect surface roughness [44]. Increasing cutting forces to achieve high-intensity production can place significant stress on the cutting tool, leading to overheating due to increased friction, especially during the machining of high-hardness steel, which can result in damage to the cutting elements [45].

Additionally, authors [46], [47], [48] emphasize the importance of coolant characteristics and the cutting tool itself—such as the characteristics of the cutting edges (angle), tool wear (sharpness), tool positioning, etc.—in influencing surface quality during milling operations. However, according to [43], varying the cutting parameters (feed rate, cutting speed, and depth of cut) is considerably more effective in achieving the desired surface quality than varying other factors that affect the surface roughness (e.g., cutting tools, coolants, lubricants). Inadequate cutting speed is cited by [49], [50] as one of the primary causes of tool vibrations, which negatively impact surface roughness. Inappropriate cutting parameters can also lead to tool damage and breakage, which, according to [51], [52], accounts for 7-20% of all machine downtimes during CNC machining processes. Therefore, it is necessary to precisely determine cutting parameters and adequately select tools before machining operation. According to [53], once the cutting tool for a particular operation has been selected, it is essential to adjust key parameters to achieve higher surface quality for a workpiece made from a specifically selected material. Otherwise, poor selection of machining parameters may extend production time, negatively affect the surface roughness, and increase production costs (in the case of scrap) [41].

Every cutting tool comes with manufacturer-prescribed specifications. Programming a machine according to the parameters for optimal tool operation within the manufacturer's recommended range will not always yield the desired surface roughness for every material, as surface roughness is not solely dependent on cutting parameters, but also on the material from which the workpiece is made [54].

Tool performance, when it comes to achieving high surface quality values, largely depends on tool wear, which is influenced by the time and method of tool use, as well as the quality of the coolant (if used during the machining process) [53]. However, if a coolant is not used during the machining process, the process must be strictly designed to minimize the heating of the workpiece and the tool, which can be achieved by reducing the cutting forces [55]. According to [56], the wear of the cutting tool affects the stability of the entire machining process, as an overly worn tool cannot achieve the required surface roughness, making premature tool replacement necessary [57]. In the process of identifying the most suitable cutting parameters that would extend the tool's lifespan while primarily ensuring the desired surface roughness for a specific material, regression models of supervised machine learning, as well as higher models based on regression, can be of significant help [7], [49]. According to [58], the machine learning model can predict the surface roughness based on cutting forces.

4. MACHINE LEARNING MODELS IN CNC MANUFACTURING PROCESSES

When discussing the application of machine learning in the manufacturing sector, regression models were among the first to be implemented for optimizing and better controlling material processing methods such as milling, turning, and drilling [37]. According to [56], regression models can be applied across various operations and phases of CNC machining: tool condition monitoring, surface roughness estimation, economic aspects of production processes, and more. Practice has shown that regression models perform well when the relationship between input and output parameters is nearly linear [59].

The implementation of a model developed to determine machining parameters for a specific material, based on the desired surface finish quality, can significantly accelerate both the preparation process for machining components and the programming process for CNC machines [48]. As the author [7] suggests, machine learning can enhance productivity and efficiency in the production of components during CNC manufacturing. Furthermore, according to [6], regression-based machine learning models could be used to optimize production time, reduce scrap, and minimize energy consumption during the production of machine elements, which, as noted by [60], is an imperative in many industries and enterprises. Any savings in energy and time during the production of any component can have a significant impact on the overall economic efficiency of the manufacturing process [7]. Such savings can be achieved by improving industrial processes, providing a competitive advantage to companies that implement modern technologies and production approaches (e.g., Lean production) over their competitors [61].

Additionally, regression models can predict the preventive replacement timing of cutting tools [44]. Replacing tools before they wear out positively affects machining speed and surface roughness [52]. Studies indicate that well-developed preventive replacement strategies can reduce downtime by up to 75% [44]. A worn tool will not provide the same surface roughness as a brand-new tool, so in the case of tool wear, it is necessary to stop the machine and replace the old tool with a new one. To achieve full automation in CNC milling, precise data on the tool's condition during the machining process are essential [51]. Developing a model for predicting the condition of the milling tool and estimating the remaining tool life is a challenging task because, according to [52], under different production conditions where cutting regimes and workpiece materials vary, it is not always easy to predict when the tool will become worn enough during the material removal process to produce an unsatisfactory surface finish or even generate scrap [44]. The preparation for developing such models may involve an extensive process of monitoring the condition of the milling tool to provide adequate and precise input data for creating machine learning models [62]. A detailed approach to determining the remaining tool life requires the application of advanced machine learning models (e.g., according to [63], the ANFIS (Adaptive Neural Fuzzy Inference System) model) [62]. However, according to [44], methods for addressing this issue are still under development and do not yet achieve the highest possible accuracy; therefore, this operation will not be given special attention in this paper. It is evident, as confirmed by the author [7], that there is a very broad range of applications for supervised machine learning regression models in CNC production, and this paper will focus on their consideration, emphasizing the analysis of parameters that influence surface roughness.

5. IMPACT OF MACHINING PARAMETERS ON SURFACE ROUGHNESS: A REVIEW OF EXISTING RESEARCHES

As previously noted, surface quality depends significantly on the workpiece material, cutting tool characteristics, and machining parameters [43], [44], [45], [54]. Numerous authors have concluded that three factors - depth of cut, feed rate, and cutting speed - are the most influential in achieving the desired surface quality. Authors [43], [46], [47], [48], [49], [50], [53], [64], [65], [66], [67], [68], [69], [70], [71], [72], [73], [74], [75], [76], [77] have used these parameters in experiments and machine learning models. Additionally, the fact that surface roughness solely depends on cutting parameters is confirmed by the observation that as much as 94% of all previous scientific studies dealing with surface roughness have used basic cutting parameters as input experimental data [43].
The optimization of cutting processes is a crucial aspect of machining elements, with significant impacts on time and economic savings. The analysis in this chapter is based on 10 studies that aimed to identify which of the three main milling parameters - depth of cut, feed rate, or cutting speed has the most significant impact on the surface roughness during the machining of the aluminum alloys. The reviewed studies aimed to improve machining process optimization, focusing on the parameter with the greatest impact on achieving high surface quality within a reasonable time frame. The research by all authors [49], [68], [69], [70], [71], [73], [74], [75], [76], [77] is based on an experimental approach aimed at providing input parameters for further research and statistical data processing using regression models or machine learning models based on regression (Taguchi method and ANOVA). The analysis of different authors' works strives to identify certain correlations among the results of the observed studies.
Y.-C. Lin et al. [49] used neural networks and multiple regression to conclude that cutting speed and depth of cut, in various combinations, had the most significant effect on the surface roughness of aluminum alloy Al6061. By applying the regression model to estimate surface rougness based on parameters obtained through experimental methods, the coefficient of determination was 0.82, and the root mean square error (RMSE) was 7.57%.
R. A. Salman Hussain et al. [68], through the experiments on aluminum alloy Al7075-T7351, applied various cutting parameter values to determine the optimal balance between cutting parameters that would provide the highest possible surface quality values while minimizing machining time. The paper describes the application of a predictive model for surface roughness based on input cutting parameters. By processing experimentally obtained data using Response Surface Methodology (RSM), they concluded that the key to process optimization is increasing cutting speed and feed rate while reducing depth of cut. The model predicted values of surface roughness relative to actual parameters with an error of 3.29%.
In addition to the three primary parameters being varied, A. Yeganefar et al. [69] also considered the type of cutting tool used for machining aluminum alloy AA 7075-T6. By applying various data processing methods, including a machine learning regression model, they concluded that, in most cases, the feed rate had the greatest impact on surface roughness, accounting for as much as 45.81%. They also found that predictions made by neural networks were significantly more accurate than those from traditional regression models, such as Support Vector Regression (SVR). Thus, they suggested that regression models could be used for surface roughness prediction when high precision is not required.
Similarly, S. Sakthivelu et al. [70], through experimentation on aluminum alloy Al 7075 T6 and using the ANOVA method to determine the contribution percentage of cutting parameters to surface roughness, concluded that feed rate is the most influential parameter in achieving high surface quality values. Specifically, feed rate impacts the surface quality by 51.26% compared to other cutting parameters. Therefore, in processes aimed at achieving the highest surface finish quality while also maximizing material removal rate, feed rate is the most critical factor.
During the experiment on aluminum alloy Al 7075 using a 10 mm wolfram-carbide milling cutter, R. N. Nimase and P. M. Khodke [71] aimed to determine which of the three cutting parameters has the greatest impact on surface roughness. By applying the ANOVA method, they concluded that feed rate, with a contribution of 46.36%, has the most significant influence on surface roughness among the observed parameters.
M. B. Kumar et al. [73], in their experiment on aluminum alloy Al–SiC–B4C, analyzed the measurement results using the ANOVA method and concluded that feed rate is the most significant cutting parameter for surface quality, with a contribution of 86.6%. The study also employed the Taguchi method, which corroborated this finding. The authors determined that the optimal cutting parameters for achieving the highest surface finish quality are: feed rate of 0.1 mm/rev, cutting speed of 3000 rpm, and depth of cut of 0.2 mm.
M. H. Raza et al. [74], by varying cutting parameters during the machining of aluminum alloy Al6082-T6 with

and without lubrication (MQL), found that feed rate has the most significant impact on surface roughness, contributing 60% in both cases, whether during dry machining or machining with lubrication. Cutting speed has a considerably smaller impact on surface roughness, around 30%, while the effect of varying depth of cut within the investigated range is nearly negligible. These results, obtained using ANOVA and Taguchi methods, also led to the conclusion that machining with lubrication yields a surface finish quality that is 26-30% higher compared to dry machining when the same cutting parameters are used.

C. David et al. [75] analyzed experimental results from machining aluminum alloy AlZn5.5MgCu and concluded that there is a direct relationship between cutting parameters (particularly depth of cut and feed rate), and surface roughness. Their experiment, which focused on milling, found that excessive values for depth of cut and feed rate could lead to overloading of the cutting tool, resulting in insufficient surface quality.

B. Öztürk and F. Kara [76], by varying cutting parameters (depth of cut, feed rate, and cutting speed), concluded using Taguchi and ANOVA methods that the most influential factor for achieving the highest surface quality values is cutting speed, with an influence of 36.18%. In contrast, the variation in depth of cut has the least significance, accounting for only 9.62% during the milling of aluminum alloy Al T6061.

I. P. Okokpujie et al. [77] aimed to develop a regression model using least squares approximation and RSM to predict the surface roughness of aluminum alloy Al 6061 during milling. Based on thirty measurements taken during the experiment, machine learning models were developed. The authors concluded that, within the domain of experimental research, the model based on least squares approximation achieved an accuracy of 99%, while the RSM model provided a precision of 99.6% in predicting surface quality. Additionally, using the ANOVA method, it was concluded that feed rate was the most influential factor on the surface roughness during the milling of this aluminum alloy, whereas variations in depth of cut had the least impact on the quality of the surface finish.

6. DISCUSSION OF RESEARCH RESULTS

Analyzing the data collected from ten different studies on the impact of cutting parameters on the surface roughness of aluminum alloys reveals a clear pattern among various authors. Most of the analyzed research highlights that feed rate is the most significant factor affecting surface quality. Feed rate has been identified as a key factor for achieving high surface quality values in seven of the studies reviewed. This conclusion suggests that particular attention should be paid to the precise determination and definition of feed rate values when programming the machine, in order to achieve the highest quality surface finish while optimizing machining time.

In addition to feed rate, several studies emphasize the significance of cutting speed and depth of cut. Although fewer research papers highlight these parameters as primary factors, the fact that cutting speed and depth of cut can significantly affect surface roughness, albeit to a lesser extent compared to feed rate, should not be overlooked. Detailed analysis of studies that suggest cutting speed and depth of cut as the most influential parameters indicates that cutting speed has a notably greater impact on surface roughness compared to depth of cut. Most authors suggest that variations in depth of cut have a negligible to moderately high effect on the quality of the surface finish in CNC milling within the tested range.

Analyzing the machine learning models used in the reviewed studies reveals that regression-based machine learning models, including more advanced regression-based models, are highly popular tools for analyzing and predicting surface finish quality. The studies reviewed employed various data analysis methods, including ANOVA, the Taguchi method, and regression-based machine learning models. Moreover, in most studies, the final results provided by the software closely match the actual experimental results. This strong alignment suggests that trust in decisions made by machine learning models should be elevated, recognizing their reliability in predicting and analyzing surface roughness.

To sum up, the analysis underscores the critical importance of feed rate as the most influential cutting parameter on the surface finish quality of aluminum alloys. While cutting speed and depth of cut are also significant, their impact is considerably less. To achieve high surface quality values in CNC milling, particular attention must be given to optimizing the feed rate. Properly setting this parameter can enhance surface quality while maximizing material removal rates. Furthermore, the use of basic regression models as well as advanced analytical tools based on regression, such as neural networks, can greatly aid in understanding the complexities of optimizing parameters in CNC machining.

7. CONCLUSION

Machine learning regression models, as well as more advanced models based on regression, find widespread application in CNC manufacturing. This research aimed to highlight the importance of understanding the principles behind regression models and to raise awareness of the pervasive role of machine learning in manufacturing engineering. In addition to these general goals, the study focused on the relatively narrow application of machine learning models in the analysis of cutting parameters and the assessment of surface quality.

The research concludes that the identification of feed rate as a key factor can provide significant guidance to engineers and operators working on CNC machines when processing aluminum alloys. Understanding the impact of cutting parameters can enable optimization of the machining process, leading to increased efficiency in production, reduced energy consumption, lower manufacturing costs, and decreased waste. Additionally, considering all these factors can directly contribute to enhanced market competitiveness.

Furthermore, this research could serve as a foundation for the development of more advanced systems aimed at achieving a high degree of automation in CNC machining, which could automatically adjust cutting parameter values to achieve the desired machining quality with optimal time consumption.

In addition to benefiting engineers and operators actively involved in CNC production, the findings of this study could also serve as valuable material for the education and training of new engineers and workers in manufacturing engineering, offering them a deeper understanding of machining processes and aluminum alloy cutting parameters. Education based on scientific research can significantly contribute to improving practical skills and knowledge, which in turn can result in enhanced efficiency during the production process.

Since this paper provides a detailed literature review on cutting parameters and their influence on the surface quality of aluminum alloys after machining, future research could be directed towards experimental work. Specifically, the conclusions drawn from the theoretical literature review in this study could serve as a solid foundation for developing independent research. The goal of such research would be to create a machine learning regression model to identify the impact of cutting parameters (cutting speed, depth of cut, and feed rate) on surface roughness.

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