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Optimization and Prediction of Surface Roughness in Turning Operations: A Review of Modern Techniques

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Abstract: *Surface roughness is a critical quality metric in metal cutting, particularly in the manufacturing industry, where high surface quality is essential. Optimizing machining parameters, such as cutting speed, feed rate, and tool materials, is crucial for achieving the desired surface roughness. However, this optimization process is challenging due to constraints related to time, cost, and skill levels. Recent advancements in surface roughness prediction techniques, including the Taguchi method, Grey Relational Analysis, and Artificial Neural Networks, have simplified the selection of cutting parameters, reduced costs, and ensured superior surface quality. This study reviews these methods and their applications in various machining processes. The Taguchi method employs orthogonal arrays to minimize the number of experiments while effectively identifying critical parameters. Grey Relational Analysis optimizes multiple response characteristics simultaneously, such as surface roughness, material removal rate, and tool wear. Artificial Neural Networks excel at modeling nonlinear relationships and learning from data, demonstrating superior performance in predicting surface roughness compared to other methods. This review highlights the significance of modern statistical and computational models in achieving efficient and high-quality machining processes, ultimately benefiting industries that require precise and reliable manufacturing techniques.*

Keywords: Artificial Neural Networks, Taguchi Method, Manufacturing, Speed, Feed rate

I. INTRODUCTION

Surface Roughness (SR) refers to the irregularities or deviations present on the surface of a material, typically resulting from machining or manufacturing processes. It is a critical measure of surface texture and is quantified by the vertical variations of the surface profile from its ideal form. (SR) is crucial in metal cutting, especially in the aerospace industry, where high Surface Quality (SQ) is essential. To achieve optimal SR, it is important to carefully choose cutting parameters (CP), tool properties, and workpiece characteristics. Common finishing methods include turning, milling, and polishing, but optimizing CP can be challenging due to constraints related to time, cost, and skill levels. SR prediction techniques help overcome these challenges by simplifying the selection of CP, reducing costs, and ensuring quality. This study highlights advancements in SR prediction, emphasizing the benefits of improved SR, cost efficiency, optimized cutting conditions, and superior quality.

Managing manufacturing costs while ensuring quality is a significant challenge in machining. Researchers analyze machinability characteristics, noting that cutting fluids can enhance surface quality and tool longevity. However, overuse of cutting fluids leads to increased machining expenses [2]. Typical parameters for cutting, such as cutting speed, feed rate, and depth, influence surface roughness. However, optimizing these parameters for surface quality is complex and relies on the material grade [3]. Choosing the right cutting inserts is essential for achieving high precision and a superior surface finish. Advances in cutting tools, including CBN, ceramic, coated carbide, and coated ceramic inserts, facilitate hard turning on hardened steels [4]. A smooth surface finish achieved through machining can enhance corrosion resistance, fatigue strength, creep life, and various other properties. The goal of optimizing machining parameters is to lower production costs while maintaining the desired quality. Surface roughness (Ra) serves as an important quality indicator and is often a critical requirement for mechanical components [5]. Grey relational analysis is

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used to evaluate the effects of cutting factors on cutting force (F), surface roughness (Ra), and material removal rate (MRR) [6].

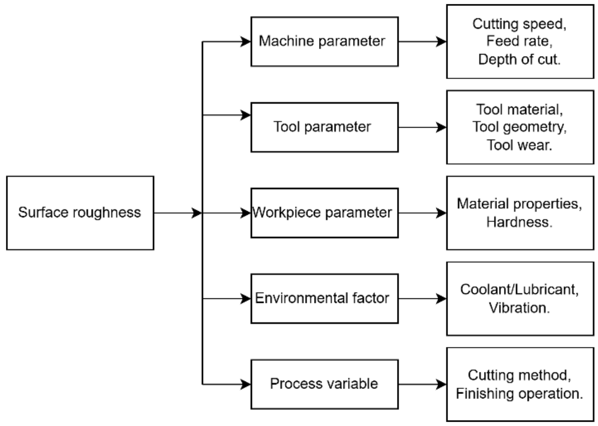

Fig. 1. Parameters affecting surface roughness [1]

This study explores the application of the Taguchi method in conjunction with fuzzy logic reasoning to optimize multiple outputs in high-speed CNC turning of AISI P-20 tool steel using TiN-coated tungsten carbide inserts. Additionally, it emphasizes that a cryogenic environment is the most effective cutting parameter for this process [7]. A linear regression equation has been developed to predict surface roughness values based on cutting parameters, with a comparison to experimental results that fall within a reasonable range. The main effects plots and the signal-to-noise ratio (S/N) derived from the Taguchi method were utilized to identify the optimal cutting parameter levels for surface roughness among the three levels considered [8]. Surface roughness (Ra) is a crucial quality characteristic in engineering that significantly influences properties such as wear and corrosion resistance, fatigue strength, lubricant retention, and distribution, as well as heat generation and transfer. This paper demonstrates the application of the Taguchi design of experiments (DOE) method to identify the optimal turning parameters for producing rough surfaces on aluminum alloy without the use of cutting fluid. Taguchi's DOE is a well- established statistical approach for designing robust products and processes [9]. Hard turning is a machining process that shapes materials while they are in a hardened state (typically between 50 and 70 HRC). This technique is employed to achieve high precision and excellent surface quality. It is often used on hardened steels, which are in high demand for manufacturing components such as bearings, camshafts, gear shafts, cutting tools, dies, and molds [10]. A study conducted with an uncoated CBN tool revealed that the feed rate and depth of cut were the most significant factors affecting cutting forces. Meanwhile, surface roughness was predominantly influenced by the depth of cut. In the hard turning process of AISI 52100 steel using a PCBN tool, it was found that the feed rate had a major impact on surface finish, whereas cutting speed and depth of cut had only a minor effect [11]. The substrate material of the cutting tool must remain chemically and physically stable at high temperatures.

The tool material must be able to withstand the high temperatures generated at the chip-tool interface.

To ensure effective abrasion and adhesion resistance, the tool material should exhibit a low wear ratio. Additionally, it must possess sufficient toughness to prevent fracture during interrupted or intermittent cutting.

Tool materials can be classified in order of increasing hardness as follows:

- High-Speed Steel (HSS)
- Sintered Carbide
- Ceramics
- Extra Hard Materials [12].

All experiments were conducted using the L9 design matrix, which focused on the effects of cutting speed, feed rate, and depth of cut on the average surface roughness (Ra). The experimental data were analyzed using the analysis of variance (ANOVA) technique, which identifies the most influential turning parameters [13]. The MINITAB software was utilized to analyze the mean effect of the signal-to-noise (S/N) ratio in achieving multiple objective features [14]. Materials with a hardness greater than 45 Rockwell are frequently utilized in various engineering industries, such as

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machine tools, bearing steels, forging, high-speed steels, and the automotive and aerospace sectors. Products from these industries typically undergo finishing in the final stage, usually through a grinding process [15]. Modern machining industries face the challenge of balancing high quality, precision, production rates, cost efficiency, and environmental impact. While research indicates that factors such as cutting speed, feed rate, and depth of cut influence surface roughness, cutting forces, and chip formation, there is limited research available on the hard turning of EN-31 steel, which is difficult to machine when hardened [16]. The main objective in production is to lower costs while enhancing product quality and reducing production time. Automation is crucial in achieving this goal, with Computer Numerical Control (CNC) machines being favored for their ability to produce high-quality surfaces, accelerate production, and decrease costs [17]. The feed rate greatly influences surface roughness, which is highly sensitive to changes in the feed rate while being less affected by variations in cutting speed and depth of cut. This study demonstrates that in the dry hard turning of this type of steel, the surface roughness achieved under all tested conditions is comparable to that obtained through grinding [18]. A Taguchi L9 design and ANOVA are utilized to analyze the impact of each parameter on the response [19]. Response Surface Methodology (RSM) integrates experimental and statistical techniques to model and optimize the effects of input variables on outcomes. This approach assists researchers in determining the best combination of machining parameters to achieve an optimal surface finish. Additionally, models based on Artificial Neural Networks (ANN) have demonstrated superior performance compared to RSM when predicting the Ra value in various machining processes [20].

Surface Roughness (SR) is a key quality metric in metal cutting, especially in aerospace, where high Surface Quality (SQ) is vital. Optimizing machining parameters like cutting speed, feed rate, and tool materials is essential but challenging due to time and cost constraints.

Advancements in SR prediction methods, such as the Taguchi method, Grey Relational Analysis, and Artificial Neural Networks (ANN), simplify parameter selection, improve SR, reduce costs, and enhance product quality. These techniques also address challenges like tool wear and cutting forces.

This study highlights the importance of process parameters like depth of cut, feed rate, and tool nose radius to improve material surface roughness, showcasing the value of modern statistical and computational models in efficient machining.

II. CLASSIFICATION

Surface roughness (SR) prediction models can generally be divided into two main approaches:

2.1 Based on cutting theory which involves developing analytical models and numerical algorithms to tackle the SR issue in machining and those based on experimental design—

2.2 method based on Taguchi,

2.3. ANN,

2.4. Grey relation analysis.

Metal cutting theory: Metal cutting is an essential process that involves the removal of material using multiple cutting edges to create desired shapes, dimensions, and surface finishes. While there have been advancements in machining tools and process control, there are still opportunities for improvement, making it a significant area for research within the metal-forming industry [21]. Optimization techniques are essential for identifying the best cutting conditions, enhancing productivity, and improving product quality. A bibliometric analysis underscores the use of various optimization methods in metal cutting operations, particularly highlighting the growing importance of machine learning approaches in recent years. These machine-learning techniques focus on machining theory to predict the surface roughness (SR) of manufactured components. Several factors include tool characteristics, process kinematics, and chip formation mechanisms. Physical models (PMs) are developed using computational tools, such as computer-aided design (CAD), computer-aided manufacturing (CAM), and computer-aided engineering (CAE), to analyze and simulate cutting behavior. The ultimate goal is to assess the surface roughness of machined components [22]. In the machining process using machine tools, the cutting state significantly impacts the overall operation, particularly in relation to cutting chatter. This type of cutting state greatly affects both the surface quality and machining efficiency of the workpiece. It can even lead to damage to the tool and the machine itself. Therefore, monitoring and identifying the cutting state is of utmost importance [23].

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Taguchi method: The Taguchi method provides an efficient approach to experimental design, simplifying the complexities associated with traditional techniques. Conventional methods often require numerous trials as the number of machining parameters increases. In contrast, the Taguchi method employs orthogonal arrays to significantly reduce the number of tests while minimizing the impact of uncontrollable factors. This approach offers several advantages: it decreases the time needed for experimentation, lowers costs, and more effectively identifies critical parameters in a shorter period [24]. The Design of Experiments (DoE) is commonly used to structure and assess machining processes effectively. The Taguchi Method (TM) is effective in predicting and optimizing surface roughness (SR) by strategically selecting cutting parameters (CP), thereby minimizing the number of experiments needed [25]. TM facilitates the creation of models that help engineers optimize manufacturing performance [26]. The Design of Experiments (DoE) framework using Taguchi methods (TM) is structured into three main stages: planning, execution, and analysis. During the planning phase, researchers define the problem, establish objectives, identify relevant factors and their levels, and design orthogonal arrays to systematically explore interactions. In the execution phase, experiments are conducted based on these arrays. Finally, the analysis phase interprets the results to determine the optimal conditions. Orthogonal arrays not only reduce the number of experiments needed but also facilitate effective analysis of interactions, often utilizing linear graphs and tables. Overall, Taguchi- based models demonstrate their effectiveness in optimizing signal-to-noise ratios (SR) and assisting engineers in selecting the best machining parameters [27]

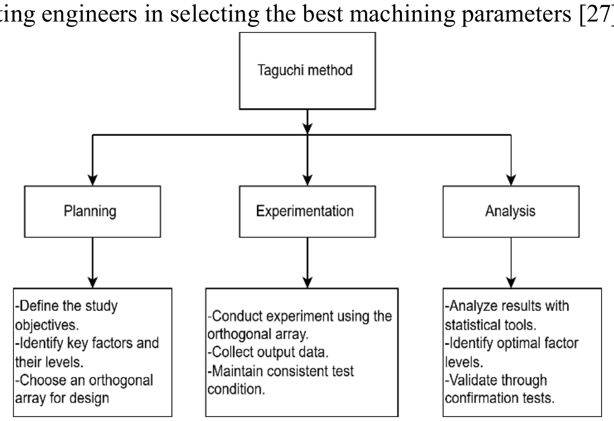

Fig 2 The diagram of the Taguchi method with basic three-stage [28]

ANN: Artificial Neural Networks (ANN) are computing systems designed to mimic the structure and function of the human brain's neural network. They consist of interconnected nodes that work together to solve complex tasks such as function approximation, classification, and time series forecasting [29]. The studies on surface roughness using artificial neural networks (ANN) focus on the turning process of AISI H13 steel[30]. Artificial Neural Network (ANN) models have been developed to predict and understand the machinability performance of Inconel 718, taking into account cutting conditions and tool geometry. These models aim to predict surface quality, specifically surface roughness, during both Minimum Quantity Lubrication (MQL) turning and MQL turning assisted by WS2 solid lubricant [31]. The study examines the reliability of Artificial Neural Networks (ANN) in predicting surface roughness values when machining Brass C26000 under dry cutting conditions on a CNC turning machine. The surface roughness was measured and compared with experimental data. The findings concluded that ANN can be implemented accurately and reliably to predict surface roughness in the turning operations of Brass C26000 material [32].

Grey relation analysis: Machining is a crucial manufacturing process that continues to offer opportunities for improvement. The efficiency and performance of the process are largely influenced by cutting parameters such as feed rate, cutting speed, depth of cut, and tool geometry, which play a key role in determining both process efficiency and product quality [33]. The optimal turning parameters were identified using Grey Relational Analysis (GRA). Furthermore, the exploration of compressed air was conducted as a sustainable and environmentally friendly machining solution to minimize negative environmental impacts [34]. Improving machining processes is essential for boosting productivity and maintaining product quality. The response characteristics, such as surface roughness, material

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removal rate, tool wear, and cutting time, have been optimized simultaneously in the finish-turning process [35]. Surface quality is an important requirement for customers in part production, as surface roughness impacts factors such as fatigue strength, wear rate, and corrosion resistance. Grey Relational Analysis (GRA) is a valuable tool for optimizing machining parameters to improve surface roughness. By enhancing these attributes, GRA ensures better performance and durability of the parts produced [36].

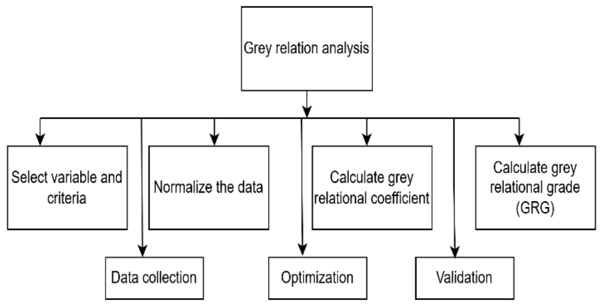

Fig 3 Method of grey relation analysis

III. CONCLUSION

This paper reviews recent methods for predicting surface roughness in machining processes. Predicting surface roughness is a critical aspect of finishing machining processes, as it directly influences product quality, functionality, and performance. Based on findings from numerous research studies, this review has analysed various methods, including metal cutting theory, Taguchi methods, Artificial Neural Networks (ANN), and grey relation analysis.

Metal Cutting Theory: Offers a theoretical framework for predicting surface roughness; however, it is limited by idealized conditions and simplified assumptions that do not always reflect real-world scenarios.

Taguchi Method: A statistically robust approach for optimizing machining parameters with minimal trials, though it is less adaptable to dynamic conditions.

Artificial Neural Networks (ANNs): These excel at modeling nonlinear relationships and learning from data, but they require large datasets, significant computational resources, and specialized expertise.

Grey relation analysis: Machining processes significantly affect productivity and quality, with key parameters like feed rate and cutting speed. Grey Relational Analysis (GRA) optimizes these factors, improving surface roughness and fatigue strength. Sustainable methods, such as compressed air machining, enhance efficiency while minimizing environmental impact

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