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COMPUTATIONAL MODELLING AND SENSITIVITY – BASED OPTIMIZATION OF SURFACE ROUGHNESS IN CNC TURNING USING MATLAB

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Abstract- **This paper provides a computation model of optimizing surface roughness and analysing surface roughness in CNC turning with MATLAB. The proposed method combines a geometric surface roughness model and parametric simulation and sensitivity analysis in assessing the effect of the important machining parameters. The findings indicate that the surface roughness is nonlinearly dependent on feed rate and cutting speed has a relatively lesser influence in the range used. Sensitivity analysis reveals that the most influential parameter is the feed rate, and it has about 82% contribution to variation in the surface roughness. The results obtained are observed to be in good agreement with reference data and the normalized error value is less than 7%. Secondly, contour and surface plots are also applied to determine the best machining areas to enhance surface finish. The suggested framework is a computationally efficient and easy to use tool to analyse the preliminary process and select the parameters in CNC turning.**

Keywords- **Surface roughness prediction, CNC turning, MATLAB simulation, parametric analysis, sensitivity evaluation, process optimisation.**

I. INTRODUCTION

Surface roughness is an important parameter which dictates a surface integrity therefore it directly determines a tribological behaviour, fatigue life, and functional performance of machined parts. In CNC turning it is managed by machining parameters like feed rate, cutting speed, geometry of tool, and depth of cut, feed rate is the most important dispensation of machining parameter on surface profile generation, whereas cutting speed is the most important dispensation of machining parameter on chip formation and built-up edge properties.

Analytical and simulation-based techniques have become popular in order to minimize the use of expensive experimentation. The ideal classical geometric model describing the relationships between the feed rate and the nose radius of a tool is a first-order approximation of the model when conditions are ideal. Nevertheless, the literature typically addresses modelling, visualization, and sensitivity analysis separately, which does not allow gaining a full comprehension of the process. Moreover, data-driven techniques, despite their precision, are not physically interpretable and need large sizes of data [14, 20, 26 – 29]. In this regard, the current research is a guided and comprehensive method of predicting the parties of surface roughness of CNC turning based on geometric modelling, parametric analysis in MATLAB, multidimensional visualization, and sensitivity analysis scaled on norms. In contrast with alternative techniques, the proposed framework allows simultaneous prediction, interpretation, and optimization of surface roughness, and provides a practically relevant and industry application instrument of efficient machining parameter choice with an insignificant amount of experimental work.

II. LITERATURE REVIEW

The development of surface roughness prediction in CNC turning has been evolving away towards empirical and regression based models to an advanced form of hybrid and computational method. The previous research was based on experimental and statistical evidence, and the latest research emphasizes the nonlinear interrelations between cutting speed, feed rate, and depth of cut, and high-speed machining in particular [1]. Such techniques as machine learning and probabilistic have enhanced the quality of prediction, such as Dynamic Bayesian Networks [10], support vector regression, and adaptive neuro-fuzzy systems [7, 11, 16, 21]. SHAP-based methods of parameter comprehension [4] and hybrid ANN-based RSM models demonstrate the prevailing role of the feed rate [3]. The research of sustainable machining also proves strength in different conditions [5]. The state-of-the-art techniques, e.g., ensemble learning, gradient boosting, and deep learning are more effective in improving the reliability of predictions [8, 17, 18, 23, 25], whereas using multi-objective optimization with RSM and genetic algorithms is a better way to control the quality of predictions and efficiency concurrently [9, 24]. Although, they tend to be computationally intensive [15,25]. In comparison to these strategies, the current research provides a numerically efficient and physically explainable framework of modelling, simulation, and sensitivity analysis backed up within a single framework.

III. MATERIALS AND METHODS

The current research uses the computational strategy of simulation to examine how machining parameters affect the roughness of the surfaces in CNC turning, which is in line with model-based manufacturing optimisation procedures [2].

3.1 Research Framework

The model combines the geometric roughness modelling, MATLAB simulation, parametric variation and sensitivity analysis. It offers a computationally efficient and interpretable alternative to data-driven methods [6, 18], which allows multidimensional response analysis as illustrated in Fig.1.

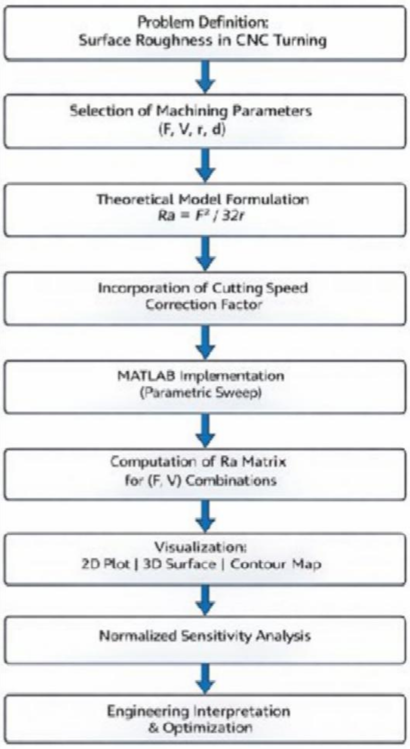

Fig.1. Computational workflow for surface roughness prediction

3.2 Selection of Machining Parameters

Machining parameters that are selected are feed rate (f), cutting speed (V), depth of cut (d), and tool nose radius (r) that control the roughness of surfaces in turning processes. The selected parameter ranges are realistic CNC turning parameters of medium carbon steel as shown in Table 1.

Table 1. Machining parameters & ranges used simulation

Parameter	Symbol	Range (mm/rev/m)	Description
Feed rate	f	0.05 – 0.30 mm/rev	Primary variable affecting surface profile
Cutting speed	V	100 – 300 m/min	Primary variable influencing cutting dynamics
Tool nose radius	r	0.8 mm (constant)	Geometric characteristic of cutting tool
Depth of cut	d	1 mm (constant)	Fixed to isolate feed and speed effects

Table 1 shows the machining parameters & ranges that are chosen in MATLAB simulation. Feed rate and cutting speed were kept constant and tool nose radius (0.8 mm) and depth of cut (1 mm) varied to determine their effects on surface roughness.

3.3 Surface Roughness Theoretical Modelling

Surface roughness may be estimated in ideal conditions of cutting under a geometric relationship between the feed rate and tool nose radius. The theoretical arithmetic average roughness (Ra) is given by Equation (1):

$$\mathrm{Ra} = \frac{f^2}{32r} \qquad (1)$$

Where,
Ra = average surface roughness of arithmetic mean (μm)
f = feed rate (mm/rev)
r = tool nose radius (mm)

The model overlooks the wear of tools, vibration and material deformation, and makes a first-order approximation of surface roughness [2]. Nevertheless, in spite of this idealization, the geometric model provides a sound foundation to be used together with parametric simulation and sensitivity analysis to allow systematic analysis of the interactions between parameters and effective determination of optimal machining conditions [2].

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3.4 Parametric Computational Implementation and Simulation

MATLAB is used to apply the analysis model to perform parametric sweeps of the feed rate and cutting speed and compute surface roughness at the discrete combinations. The results enable:

- 2D plots (Ra vs. feed rate)
- 3D surface plots (Ra versus f V)
- Optimisation interpretation contour maps.

In this model, machining behaviour can be studied systematically without involving repetitive experiments.

3.5 Sensitivity Analysis

In order to measure the predominance of parameters, normalised sensitivity coefficients were determined by Equation (2):

$$Si = \left(\frac{\partial Ra}{\partial xi}\right) \times \left(\frac{xi}{Ra}\right) \quad (2)$$

And x_i is a measure of either cutting speed or feed rate. Such a formulation allows comparing the contribution of the relative parameters directly, and contributes to finding the important control factors in optimising the surface finish.

3.6 Visualization Strategy

To increase the interpretability of the results of computer-based simulation, the use of graphical visualization was made. The hierarchical representation was taken:

- 2D plots to authenticate primary trends.
- 3D interaction analysis surfaces.
- Contour maps Optimisation region determination.

Structured visualisation will enhance the analytical transparency and aids engineering interpretation of machining parameters effects.

IV. RESULTS AND DISCUSSION

The influence of feed rate on surface roughness was examined at constant cutting speed and tool geometry, and it was found that the roughness increased nonlinearly with feed rate.

4.1 Effect of Feed Rate on Surface Roughness

The Ra values are nonlinearly dependent on the feed rate, and in agreement with the quadratic geometrical relationship and previous studies [22, 23]. This is due to the cusp formation in which the roughness of the surface varies with the square of the feed rate as in Fig. 2.

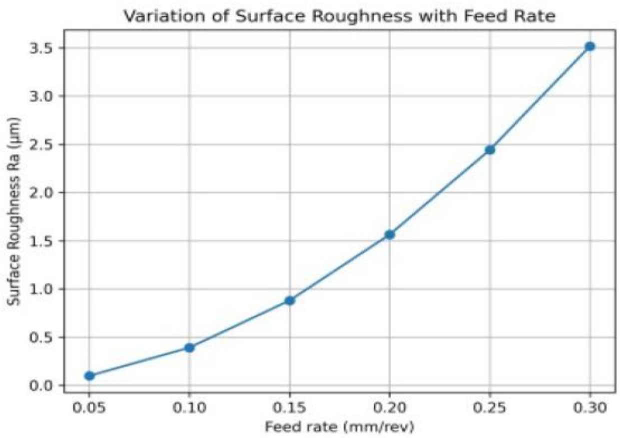

Fig.2. Variation of surface roughness with feed rate (mm/rev)

Fig. 2 indicates a nonlinear growth of surface roughness with the feed rate in constant conditions, which validates the quadratic dependence ($Ra \propto f^2$) of Equation (1). The sharp slope means that it is very sensitive to the feed rate, which is in line with machining theory and confirmed by the sensitivity analysis Table 2.

4.2 Combined Influence of Feed Rate and Cutting Speed

A two-parameter sweep was performed to test the effects of interaction among parameters and visualised in the form of a three-dimensional surface plot.

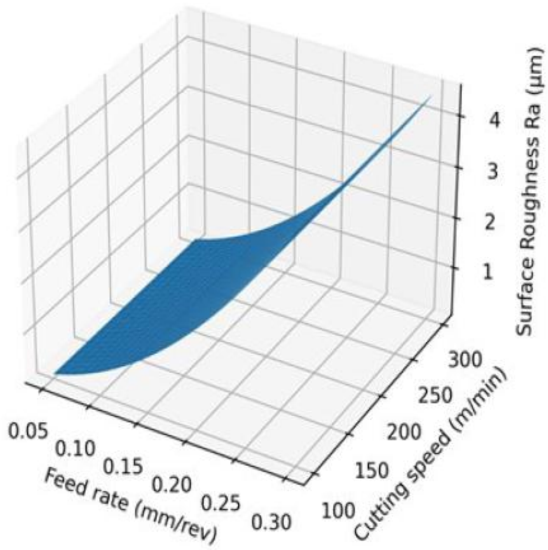

Fig.3. 3D surface plot of surface roughness

Fig. 3 represents a 3D surface plot of a twoparameter sweep (feed rate and cutting speed) with a steep gradient on the axis of feed rate and a relatively mild gradient on the axis of cutting speed. This confirms that feed rate dominates surface

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roughness, with cutting speed having a secondary influence on surface roughness through reduced BUE and thermal softening, which is in line with the previous literature [9, 22] and sensitivity analysis Table 2.

4.3 Contour-Based Optimization Interpretation

The MATLAB contour mapping was applied to the data to determine possible low-roughness operating zones, which is more engineering interpretable. This is in line with multi-objective optimization methods that have been reported in turning studies [9, 24].

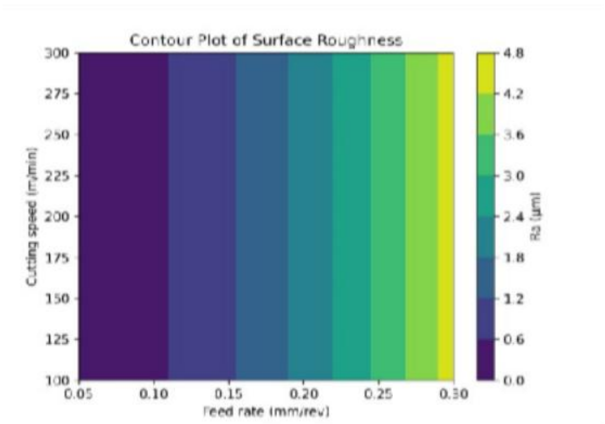

Fig.4. Contour plot of surface roughness distribution

Fig. 4 illustrates contour plots of surface roughness versus feed rate as well as cutting speed, and it shows the best low-roughness of surfaces at low feed and moderate-to-high cutting speed. The high gradient in the feed axis implies that it is more sensitive and the contour patterns reveal that high feed rates cannot be countered by increasing cutting speed and this helps in effective process planning.

4.4 Sensitivity Analysis and Dominating Parameters

In order to determine a quantitative effect of any parameter, normalised sensitivity coefficients were calculated in accordance with the methodology outlined in Section 3.5.

Table 2. Normalized sensitivity coefficients and contribution of machining parameters

Parameter	Symbol	Sensitivity Coefficient (Si)	Relative Contribution (%)
Feed Rate	f	2.000	82.35
Cutting Speed	V	0.429	17.65

The sensitivity analysis Table 2 reveals that the feed rate is the most significant ~82.35% compared to cutting speed, which is similar to the 3D and contour results. The nonlinear trend is consistent with experimental and hybrid investigations [22, 23] and optimization results [9, 24], which prove the model even though the effects of tool wear, vibration, and deformation are not taken into account.

4.5 Model Validation and Error Analysis

To test the predictive power of the suggested computational model, the values of roughness of the simulated surfaces were compared with the literature reported data of the experiment under the same machining conditions [22, 23]. The data in the literature are considered to be experimental (literature-based) values, which allow partial experimental validation of the model. Comparison was done with a range of feed rates and constant tool geometry and cutting conditions. To determine the agreement between simulated and experimental values, it was measured in terms of normalized error as illustrated in the Eq. (3) below:

$$\text{Normalized Error (\%)} = \left| Rasim - \frac{Raexp}{Raexp} \right| * 100 \quad (3)$$

Where, R_a^{sim} represents the simulated values and R_a^{exp} denotes the experimental (literature-based) values. The comparative results are shown in Table 3, which indicates that there is a close agreement between the simulated and reported values.

Table 3. Comparison of simulated and experimental (literature-based) surface roughness

Feed Rate (mm/rev)	Ra (Simulated) (µm)	Ra (Experimental -Literature) (µm)	Normalized Error (%)
0.05	0.098	0.105	6.67
0.10	0.391	0.410	4.63
0.15	0.879	0.910	3.41
0.20	1.563	1.620	3.52
0.25	2.441	2.520	3.13
0.30	3.516	3.600	2.33

The fact that the simulated and experimental (literature-based) values are close with the normalized error being less than 7% indicates reliability of the proposed model. This illustrates that the model can represent realistic machining trends, and thus offers partial experimental validation although it is not directly tested in the laboratory.

4.6 Comparative Validation and Model Reliability

To further show how consistent the model is, a comparative analysis between the simulated and experimental (literature-based) values of surface roughness is shown in Fig. 5.

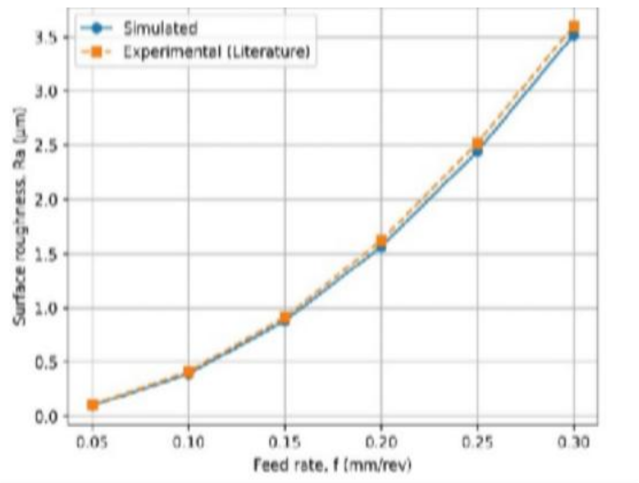

Fig.5. Comparison of simulated and experimental (literature-based) surface roughness

The comparison in Fig.5 indicates that there is a high similarity between the simulated and experimental trends throughout the feed range. The two datasets display nonlinear growth in the surface roughness with the feed rate, which is in line with the theoretical relationship. The observed minor deviations are explained by the fact that the simplified model does not consider secondary effects like tool wear, vibration and material heterogeneity.

The empirical consistency and predictability of the proposed framework is confirmed by the observed agreement. Although simplified, the model is able to reproduce the prevailing machining behaviour and therefore it can be used in initial process planning and parameter choice without the need to go through a lengthy series of experiments. This adds to the partial experimental validation of the proposed computational framework.

V. CONCLUSION

A computational framework for predicting surface roughness in CNC turning has been created. It shows that feed rate is the most important factor and cutting speed is the second most important factor. The most important aspect of this work is the creation of an interpretable and computationally efficient framework that combines modelling, simulation, and sensitivity analysis into a platform. It allows successful initial process design and parameter optimization without the need to do widespread experimental trials. The framework developed exhibits benefits in terms of simplicity, interpretability and computational efficiency over traditional methods. Secondary effects including tool wear, vibration, and material plastic deformation, are not considered in the current model, and could affect surface roughness in real world machining.

The research directions of the future will based on the expansion of the suggested computational framework in the direction of multi-objective optimization methods and hybrid intelligent algorithms to select the most optimal machining parameters. Moreover, controlled experimental validation will be carried out to harness actual machining phenomena like tool wear, chatter and plastic deformation of the material and thus enhance predictive capability and industrial practicability of model.

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Data Availability

The data used to support the findings of this study are available from the corresponding author upon reasonable request.

Competing Interests

The authors declare no financial or organizational conflicts of interest.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

AI tools were used for language refinement and figure generation; all scientific content and analysis are original and the authors assume full responsibility.

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