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OPTIMIZATION OF CUTTING PARAMETERS IN THE FINISH TURNING OF AISI 420 STAINLESS STEEL USING AN ARTIFICIAL NEURAL NETWORK

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Abstract. *AISI 420 steel is a martensitic stainless steel alloy known for its high corrosion resistance, hardness, and wear resistance, making it suitable for applications requiring protection against aggressive environments. However, due to its properties, this material is considered to have low machinability, resulting in challenges in chip formation and high cutting forces, which adversely affect the quality of the machined surface, particularly in turning processes. Evaluating cutting parameters and their effects is crucial for enhancing machinability and reducing average roughness (R_a). However, there is limited research that comprehensively addresses all input variables and promotes simultaneous optimization. Thus, this study collected various data from the literature and developed a comprehensive algorithm that utilizes an artificial neural network (ANN) to optimize R_a values based on cutting parameters for AISI 420 turning. The collected data were validated and revealed a disparity between the predicted values and the experimental results, which could be attributed to variations in experimental configurations reported in the literature. Nonetheless, the experimentally obtained data yielded remarkably low roughness values (R_a = 0.43 ± 0.01 μm) for the turning process. This proposal demonstrates a viable alternative for achieving low roughness without requiring extensive prior experimental procedures.*

Keywords: *ANN, AISI 420, Turning, Optimization, Roughness*

1. INTRODUCTION

AISI 420 is a martensitic stainless steel widely used in various industries such as food, chemical, petroleum, medical, and automotive, thanks to its excellent corrosion and wear resistance properties. Machining processes are commonly employed to produce components from this alloy, where the tool moves linearly while the workpiece rotates (Ferraresi, 1977; Lo et al., 2009). However, turning AISI 420 steel can cause challenges due to its high hardness and ductility, leading to difficulties in chip formation and high cutting forces, which affect the machined surface quality (Diniz et al., 2010).

Surface roughness is the microscopic texture resulting from the machining process, predominantly influenced by the method rather than the machine tool. Various factors can impact roughness generation on the machined surface, such as tool marks and fragments, which may exhibit periodic or random characteristics depending on the process. Additionally, the formation of material burrs, residue from the cutting tool, and the tool chip-breaker geometry contribute to surface roughness (Machado et al., 2009). Roughness parameters are employed to assess the surface texture of machined components, with average roughness (R_a) being the most commonly used. The turning process is influenced by several factors, including machine conditions, workpiece characteristics, tool clamping devices, and mainly, the feed rate f [mm/rev] and the tool-nose radius $r\varepsilon$ [mm] (Kalpakjian and Schmid, 2010; Machado et al., 2015).

The surface roughness exhibits variations depending on the machining process employed. The NBR 8404/84 standard defines 12 roughness classes (Tab. 1), each corresponding to a range of average roughness (R_a) values (ABNT, 1984). According to Machado et al. (2009), turning processes can achieve finishing classes N5 and N6 with careful attention to details. On the other hand, roughness values between N7 and N10 are more commonly obtained during the turning.

Aiming to enhance the quality of machined surfaces, some research has focused on optimizing cutting parameters such as cutting speed, feed rate, depth of cut, lubricooling conditions, and developing suitable tool geometries (Kopack et al., 2002; Lu, 2008). However, simultaneously optimizing all these variables is challenging, and only a few studies have comprehensively addressed all the factors involved (Zerti et al., 2019). An emerging approach for optimizing cutting parameters is the utilization of algorithms based on artificial neural networks (ANNs). ANNs are computational models inspired by the functioning of the human brain that are capable of learning data patterns and making accurate predictions without depending on complex physical models. These algorithms can predict the roughness of machined surfaces based on cutting parameters, enabling the simultaneous optimization of multiple factors (Corso et al., 2013).

Table 1. Classification of roughness classes (ABNT, 1984).

Roughness Class	Range of R_a values [µm]	Roughness Class	Range of R_a values [µm]
N12	25 - 50	N6	0.4 - 0.8
N11	12.5 - 25	N5	0.2 - 0.4
N10	6.3 - 12.5	N4	0.1 - 0.2
N9	3.2 - 6.3	N3	0.05 - 0.1
N8	1.6 - 3.2	N2	0.025 - 0.05
N7	0.8 - 1.6	N1	0 - 0.025

Lu (2008) highlights the advantages of ANNs over classical programming, like eliminating the need to explicitly formulate solution algorithms, develop specific code, and ensure information processing in parallel through interconnected neurons. However, the author notes that ANNs require a significant amount of experimental data for proper training, and their generalization capacity is limited, leading to substantial errors when applied to inputs outside the range of the training dataset. Improperly trained networks may also fall into overfitting, wherein the network is overly specialized to the training data. Hubner (2016) states that multilayer perceptron networks (MLP) are the most commonly used type of network in machining studies, typically considering input parameters such as cutting speed, feed rate, and depth of cut while evaluating average roughness (R_a) as output variable.

In this context, this article proposes developing an ANN-based algorithm to optimize cutting parameters in AISI 420 steel turning, aiming to enhance the quality of the machined surface. Considering the data available in the literature, the algorithm enables the prediction of R_a values based on input data and facilitates the optimization of cutting parameters. This versatile approach could be extended to other materials, utilizing existing data and eliminating preliminary tests.

2. MATERIALS AND METHODS

The initial stage involved a comprehensive literature review on the AISI 420 steel machining, mainly focusing on the turning process, dry-cutting condition, and standard tool geometry. A sum of 190 experimental runs was collected from the reviewed studies for training the algorithm. Table 2 shows the summarized data extracted from the literature. The roughness values were classified into their respective classes according to the NBR 8404/84 standard, as shown in Fig. 1. In this case, all the reported values fit into the range of N6 to N9.

Table 2. References used for algorithm training.

Year	Authors	Cutting Parameters			R_a (µm)	Number of Runs
		v_c (m/min)	f (mm/rev)	a_p (mm)		
2019	Zerti et al.	80 - 340	0.08 – 0.24	0.1 – 0.5	0.42 – 3.67	25
2019	Souza	200 - 300	0.15	1.0	1.76 – 1.87	2
2015	Bouzid et al.	120 - 280	0.08 – 0.20	0.2 – 0.6	0.51 – 1.93	64
2014	Rosa et al.	290	0.05 – 0.30	1.0 – 3.0	0.54 – 5.95	64
2013	Nassif et al.	290	0.10 – 0.20	0.5 – 1.0	1.00 – 3.50	4
2013	Silva	180	0.10 – 0.20	0.4 – 0.8	0.93 – 2.80	4
2013	Izquierdo et al.	290	0.10 – 0.20	0.4 – 1.5	0.78 – 3.88	27

An artificial neural network (ANN) model was utilized for the computational algorithm, employing a 3-9-1 architecture. This architecture was chosen based on its low mean square error (MSE) and a high coefficient of determination R^2 for roughness prediction, as reported by Zerti et al. (2019) (Fig. 2). The training process involved using the Levenberg-Marquardt algorithm for backpropagation, with the dataset divided into 70% for training, 15% for validation, and 15% for testing. Fifteen rounds of predictions were performed for optimization, and the differences between the obtained results were evaluated. The ANN algorithm was developed, trained and simulated using the Neural Network Toolbox of MATLAB® R2012b software.

Based on the best results achieved, an experimental evaluation was conducted to verify the algorithm's accuracy in predicting the real R_a value in the turning process. The validation procedure utilized the Mazak Quick Turn Nexus-II CNC lathe (Fig. 3a) and the Sandvik coated carbide insert (Fig. 3b) with a negative basic triangular shape (T-Max P). The insert had a tool-nose radius of r_ε = 0.4 mm and a chip breaker designed for finish turning (MF). Additionally, the inserts featured an MT-CVD coating (Medium Temperature Chemical Vapor Deposition) of $TiCN/Al_2O_3/TiN$ (GC4215). The fastening system of the insert in the support is of the wedge-clamp type to minimize vibrations. The used MTJNL 2020K tool holder has a side cutting edge angle κ_r = -3°.

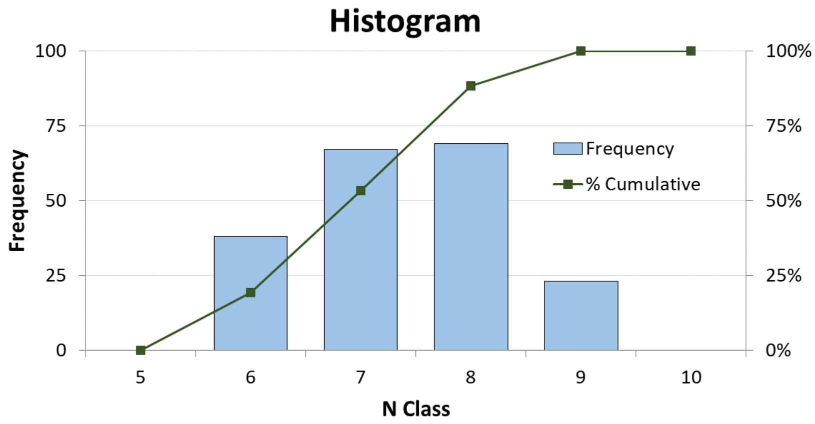


Figure 1. Classification of roughness classes.

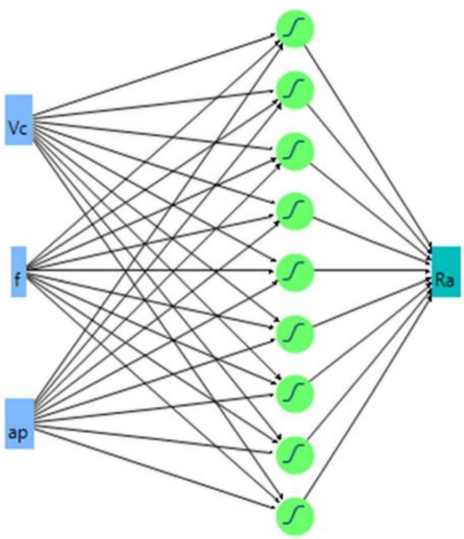


Figure 2. A 3-9-1 network architecture (Zerti et al., 2019).

(a) (b)

Figure 3. (a) Mazak QTN 100-II CNC Lathe; (b) TNMG 160404-MF coated carbide insert.

After machining, surface roughness values were measured using a portable Mitutoyo Surftest SJ-201P roughness meter with a resolution of 0.01 µm. A sampling length l_e = 0.8 mm and an evaluation length $l_m = 5 \cdot l_e$ = 4.0 mm were assumed according to DIN EN ISO 4288 ($0.1 < R_a \leq 2.0$ µm). The workpiece was removed from the CNC lathe and affixed to a magnetic base for the roughness readings to ensure measurement accuracy. The roughness values were collected in four planes, each approximately 90º out of phase with the others.

3. RESULTS AND DISCUSSION

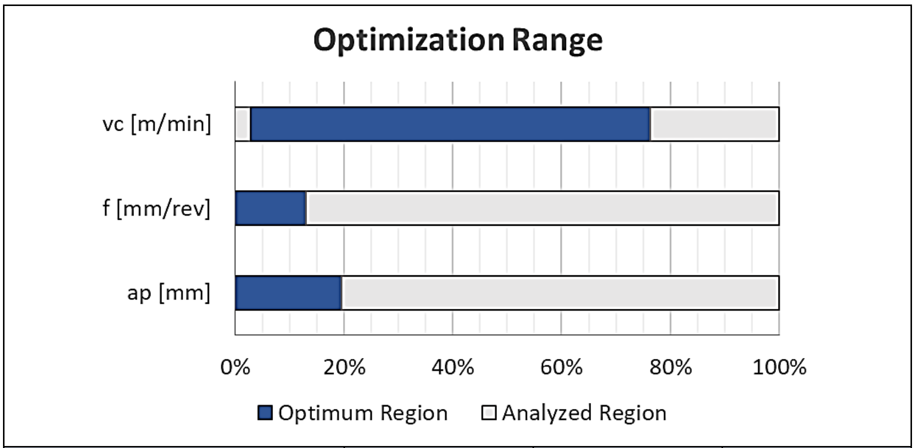
The algorithm was applied in fifteen simulation runs to evaluate its robustness and compare the predictions. Table 3 presents the results, showing the mean and standard deviation of each variable. It is observed that all runs resulted in R_a values into class N6 or lower, which is the minor class used for training the algorithm. In two runs (7 and 11), the generated combinations of parameters resulted in low roughness values (class N5), which are even better than those reported in the literature. These combinations had in common the lowest feed rate (f = 0.05 mm/rev) and a low depth of cut (a_p < 0.3 mm), while the cutting speed varied but tended to reduce R_a when it closed to the average value.

Table 3. Optimization predictions run.

Run	v_c [m/min]	f [mm/rev]	a_p [mm]	R_a [µm]	N Class	MSE
1	238	0.05	0.2	0.56	6	0.013
2	270	0.05	0.1	0.45	6	0.021
3	224	0.05	0.4	0.67	6	0.032
4	84	0.1	0.7	0.59	6	0.019
5	335	0.1	0.1	0.61	6	0.016
6	113	0.07	0.1	0.53	6	0.003
7	279	0.05	0.2	0.37	5	0.024
8	100	0.07	0.3	0.63	6	0.018
9	83	0.08	0.2	0.66	6	0.011
10	258	0.06	0.9	0.80	6	0.054
11	199	0.05	0.3	0.35	5	0.014
12	81	0.08	0.3	0.54	6	0.020
13	95	0.05	1.0	0.56	6	0.022
14	233	0.05	0.5	0.61	6	0.001
15	334	0.05	0.6	0.45	6	0.021
Mean	195.07	0.06	0.39	0.56	-	0.019
Std. Deviation	93.86	0.02	0.29	0.11	-	0.010

When evaluating the average values of the runs, it was observed that the cutting speed was very close to the mean value of the range used, with an expressive variation in the standard deviation. Then, the cutting speed has little influence on the surface roughness obtained by turning of AISI 420. On the other hand, the depth of cut and feed rate were concentrated in the lower regions within the parameter range. The feed rate showed slight variation and indicated a minimum value in a significant portion of the optimized results. Figure 4 illustrates the parameter region obtained from the optimization runs of the algorithm, considering the range covered by the literature. This analysis is consistent with previous research findings. According to Bouzid et al. (2015), the feed rate had an effect of 81.69% over the average roughness, while Zerti et al. (2019) reported that the feed rate represents 80.71% of the contribution, and it is the main cutting parameter that influences R_a. Therefore, the low variation in the feed rate during the optimization runs demonstrates its strong influence on the process, followed by the depth of cut. In contrast, the optimal cutting speed range is vast and weakly defined.

Machining experiments were conducted to validate the predicted data using the cutting parameters from the runs that generated the lowest roughness values compared to the others (Tab. 4). The roughness values measured during the validation runs were higher than the parameters predicted by the algorithm. However, in run 11, the experimentally obtained value was close to the simulated one ($R_a = 0.43 \pm 0.01$ µm). In run 7, there was a significant difference between the experimental and predicted results. This may be attributed to unanticipated interferences (non-controllable variables) such as vibrations in the process, tool and workpiece geometry variations, and chip formation. The experimental value from run 7 ($R_a = 0.63 \pm 0.04$ µm) stayed within the average error range ($R_a = 0.56 \pm 0.11$ µm) obtained through the prediction of machining parameters, remaining within the N6 class, similar to most optimization runs.



Range of Parameters	v_c [m/min]	f [mm/rev]	a_p [mm]
Minimum Literature	80	0.05	0.1
Minimum Optimization	101	0.05	0.1
Maximum Optimization	289	0.08	0.7
Maximum Literature	340	0.30	3.0

Figure 4. Optimum range variation.

Table 4. Comparison between prediction and validation.

Run	Cutting Parameters			Prediction		Validation	
	v_c [m/min]	f [mm/rev]	a_p [mm]	R_a [µm]	Class	R_a [µm]	Class
7	279	0.05	0.2	0.37	N5	0.63 ± 0.04	N6
11	199	0.05	0.3	0.35	N5	0.43 ± 0.01	N6

Several errors are associated with the ANN prediction method based on literature data, as there is heterogeneity in the experimental conditions of each bibliographic reference. Variations in tool and workpiece geometry, tool and workpiece fixation, machine tool performance and precision, and chip morphology can differ in each research study, potentially influencing the algorithm's training data and introducing errors. Therefore, the differences between the experimental and literature configurations can significantly explain the observed variations between the predicted and measured roughness values in the validation process. However, the experimental validation configurations used in this study were consistent with those used in previous works by Izquierdo et al. (2013), Nassif et al. (2013), Rosa et al. (2014), Silva (2013) and Souza (2019), where the same machine tool, cutting tool, and workpiece were employed. In these studies, the lowest average roughness value observed was R_a = 0.54 µm, while the experimental validation configuration in the present work achieved R_a = 0.43± 0.01 µm (validation run 11). Despite the few associated errors, this approach demonstrates the effectiveness of the ANN optimization process using secondary data.

4. CONCLUSIONS

The present study aimed to optimize the average roughness (R_a) in AISI 420 austenitic stainless steel turning using the ANN algorithm based on published literature data. The main conclusions of the study are as follows:

- The ANN algorithm generated combinations of cutting parameters that resulted in lower roughness values than those reported in the literature, achieving a finishing class N5. In contrast, the training data for the algorithm ranged between N6 and N9.
- The feed rate was identified as the most influential parameter in R_a during the turning process, as the optimization consistently suggested minimizing this parameter to achieve a better surface finish. On the other hand, cutting speed did not significantly contribute to the process, showing a considerable variation in the optimized predictions.
- The experimental validation did not precisely match the predicted roughness values, yielding higher values. However, the measured R_a values remained within the N6 class. The discrepancy between predicted and validated results can be attributed to the inherent physical differences in the experimental configurations of each reference study, such as variations in machine, tool, and workpiece conditions.

- When comparing the optimized parameters (R_a = 0.43 ± 0.01 μm) with the best results reported in the literature for the same experimental configurations (R_a = 0.54 μm), the ANN optimization reduced the roughness values, indicating the algorithm's accuracy when experimental differences are minimal.
- The proposed methodology eliminated the need for initial experimental tests by relying on secondary data from the literature. This is advantageous in situations where resources for preliminary tests are limited. This approach proved desirable and effective despite the errors associated with the physical differences in the literature data used for algorithm training.
- For future studies, it is recommended to expand the number of input parameters to include factors related to tool and workpiece geometry, as these factors also influence the machining process. This expansion will reduce the associated errors and enhance the algorithm's robustness.
- Finally, the study demonstrates the potential of using the ANN algorithm to optimize cutting parameters in the turning process based on secondary data from the literature.

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