SEMARAK ILMU PUBLISHING

Journal of Advanced Research in Fluid Mechanics and Thermal Sciences

Journal homepage:
https://semarakilmu.com.my/journals/index.php/fluid_mechanics_thermal_sciences/index
ISSN: 2289-7879

# Swarm Optimisation to Model the Surface Roughness of an AISI 4340 Turning using the Hot Machining Process

Ismail Thamrin[1,*], Amrifan Saladin Mohruni[1], Irsyadi Yani[1], Riman Sipahutar[1], Zulkarnain Ali Leman[1]

[1] Department of Mechanical Engineering, Faculty of Engineering, Universitas Sriwijaya, Palembang, Indonesia

**ARTICLE INFO**

***Article history:***
Received 19 December 2023
Received in revised form 25 April 2024
Accepted 12 May 2024
Available online 30 May 2024

***Keywords:***
Swarm optimization; surface roughness; hot machining; turning; prediction model

**ABSTRACT**

Given that surface roughness is used to determine product quality, it is a crucial consideration in turning machining. Moreover, it considerably affects the cost of machining. This study forecasts surface roughness values for AISI 304 stainless-steel hot lathe machining using the particle swarm optimisation (PSO) methodology. The workpiece is heated to 100, 150 or 200 degrees Celsius before being turned. Afterwards, the depth, speed and feeding rate of cutting are adjusted to determine the surface roughness of the workpiece. The feeding rate is determined to be the most considerable influence in raising the surface roughness value, followed by cutting depth, cutting speed and workpiece temperature. In terms of accuracy, empirical modelling performs better. The PSO methodology illustrates an effective and straightforward method that can be applied to calibrate different empirical machining models.

## 1. Introduction

Machine tool usage is integrally related to the machining industry, whether small or large. A lathe is a machine tool that is used in small and large manufacturing operations. The two most common lathe machining processes are turning with cooling fluid (cutting fluid) and dry turning (dry cutting). Dry turning is becoming more common in the machining industry for the foreseeable future due to environmental concerns [1-3].

Various approaches, such as cooling fluid and hot machining procedures, have been utilised to improve the quality of metal turning processes. Hot machining is a technique for improving the quality of a turning operation by softening difficult-to-work-on workpieces. It is one of the most used methods for metal turning of difficult-to-cut materials, such as superalloys, titanium alloys and ceramics [4]. Cakir and Gurarda [5] outlined a method for determining machining conditions in turning operations with the objective of minimizing production costs. Their approach involved calculating production time and cost for various combinations of workpiece and tool materials under the same input parameters. Meng *et al.,* [6] introduced a machining theory aimed at identifying optimal cutting conditions in turning to either minimize costs or maximize production rates. Lee and

* *Corresponding author.*
*E-mail address: ismailthamrin@ft.unsri.ac.id*

https://doi.org/10.37934/arfmts.117.2.147156

Tarng [7] devised a self-organizing adaptive modeling technique to establish the correlations between cutting speed, feed rate, depth of cut, and surface roughness, as well as cutting force and tool longevity. In this technique, the material is heated during or before the machining process. In addition, it can be used at a low cost and with a simple design. The material is heated to recrystallisation temperature, at which point its shear strength is reduced, making it simpler to work with. As a result, the chisel's cutting force and wear are reduced [3].

Given the increased quality expectations, the surface roughness of any machining process has grown more prominently. Machining factors, including cutting speed, feed rate, cut depth, tool shape and specimen, are all important. Other factors influencing the manufacture of the appropriate surface quality of a piece of work include tool wear, vibrations, machine dynamics and temperature. The concept behind all optimisation algorithms is the same: optimal cutting conditions are required to reduce manufacturing costs. The simplest method to achieve this is to combine essential cutting parameters. During the turning process, cutting speed, feed rate and cutting depth are all widely described variables. The revolutions must increase as the cutting diameter decreases to retain the same cutting speed, which generally increases as the roughness decreases. It is the polar opposite in terms of feed rate [8].

Previously, machining settings were chosen by a time-consuming and costly trial-and-error procedure based on process planners' experience and machining handbooks [9]. A human process planner selects appropriate machining process parameters based on their own experience or the machining tables at hand. In most cases, the parameters chosen are standard and far from optimal. However, when it comes to machining, choosing the right settings is crucial. Excessive cutting tool wear is noticeable if the machining settings are not acceptable, and the choice may result in surface damage.

Surface roughness, when paired with surface quality, refers to the contour of the surface to be machined. The surface roughness mechanism has a complex look that is based on highly analytical formulae. Two primary characteristics, average roughness (Ra) and maximum peak-to-valley height can be used to describe the surface finish (Rt). These parameters were calculated using theoretical models [10]. Eq. (1) provides a fundamental theoretical model for surface roughness.

$$R_a = \frac{1000f^2}{32r_e} \tag{1}$$

$$R_t = \frac{1000f^2}{8r_e} \tag{2}$$

Linear and exponential empirical models for surface roughness (Eq. (2)) as functions of cutting speed (V), feed (f), and depth of cut (d) are presented by Fang and Safi-Jahanshahi. According to this model, the feed rate must be reduced or the tool nose radius must be increased to obtain the appropriate surface roughness. This model assumes a big nose radius and a slow feed to some extent.

$$R_a = C_0 V^a f^b d^c \tag{3}$$

Empirical models are developed in this study by using traditional methods, such as factorial design, statistical regression and response surface methodology. Nonconventional methodologies, such as the artificial neural network (ANN), fuzzy logic, support vector regression and genetic algorithm, are used to introduce artificial intelligence-based models [11].

To address the trade-off analysis between the material removal rate, specific cutting energy and surface roughness, Nguyen [12] used a micro genetic algorithm for dry milling. For wire-cut EDM, Camposeco-Negrete [13] adopted a comprehensive design technique to regulate the results and contributions of four machining factors on the response variables listed above. To regulate and anticipate the ideal parameters in the drilling KFRP, Soepangkat *et al.,* [14] suggested a fuzzy analysis and BPNN-based GA. For the boring process, Rao and Murthy [15] used predictive methods, such as response surface technique, ANNs and support vector machines, to predict surface roughness and the root mean square of workpiece vibration. Prasath *et al.,* [16] used Taguchi and response surface methodology to construct a mathematical model for response prediction. The model was validated, and it accurately predicted surface roughness and MRR with less than 6% margin of error.

Although substantial research has been conducted on machining AISI 4340 lathes, studies on the surface roughness of workpieces in the lathe machining process using hot machining methods on the AISI 4340 are lacking. The swarm optimisation approach is used to study the surface roughness modelling of AISI 4340 lathe machining via the hot machining technique. This research aims to see how well the particle swarm optimisation (PSO) technique predicts the surface roughness of AISI 4340 lathe machining using hot machining methods.

## 2. Methodology

AISI 4340 is a high-strength, low-alloy steel that is primarily used in the automotive and aerospace sectors for shafts, gears, couplings and other components [17]. The independent variables in this study were cutting speed, feeding rate, cutting depth and workpiece temperature, whereas the dependent variable was the workpiece's surface roughness. The surface roughness of samples by hot lathe machining was measured using a Handysurf Accretech E-35B.

The central composite design (CCD) is utilised to reduce the amount of experimental data. The CCD model serves as a pivotal component within response surface methodology, offering notable advantages over traditional optimization models. One significant benefit is its heightened accuracy, obviating the necessity for a three-level factorial experiment to construct a second-order quadratic model. Following the implementation of the CCD model in experiments, a linear regression model is typically employed to formulate the model, utilizing combined values. Additionally recognized as the Box-Wilson Central Composite Design, this model augments center points with a set of "star points," facilitating the estimation of curvature within the design space. Unlike factorial points which maintain a distance of ±1 unit from the center, star points are situated at a distance of $\pm \alpha$, where $|\alpha| > 1$, contingent upon specific design requirements. With the flexibility to accommodate numerous factors, the CCD model often includes multiple star points, representing extreme values at both lower and higher ends. Notably, the CCD model extends the applicability of 2-level factors, which are widely employed in response surface modeling and optimization endeavors [18]. Table 1 shows the level and coding of the independent variables used in the study. The independent variables in this study were coded using Eq. (1) whilst considering the lathe machining circumstances [18].

**Table 1**
The level and coding of the independent variables

| Level | Unit | Coded level | | |
|---|---|---|---|---|
| | | -1 | 0 | +1 |
| Cutting speed | m/min | 100 | 125 | 150 |
| Feed rate | Mm/tooth | 0.035 | 0.0875 | 0.14 |
| Depth of cut | mm | 0.5 | 1 | 1.5 |
| Heating temperature | °C | 100 | 150 | 200 |

In this study, the independent variable was coded using Eq. (3) whilst considering the lathe machining circumstances. In the equation, x is the code value of any factor that has the same value as the original. Furthermore, xn and xn1 are +1 level factors, but xn0 is the natural value of the base or zero level factors [10].

Experiments were conducted with the values of four independent variables, and up to 30 data retrieval numbers were used. The CCD technique was utilised in this study because it offers more benefits than other design methods [19].

$$x_{in} = \frac{\xi_{in} - [max(\xi_{in}) + min(\xi_{in})]/2}{[max(\xi_{in}) - min(\xi_{in})]/2} \tag{4}$$

The swarm approach has been used in various research domains, including driverless cars, fisheries, underwater vehicles and optimal economic load dispatch [20-25]. The PSO technique is based on stochastic processes and is built around a population of organisms/particles. It is also based on a model of live creatures, such as flocks of birds. These creatures then interact based on social–psychological connections in the same manner as live species do, and they can adapt to diverse conditions.

To find the optimal solution, starting organisms/particles must be produced at random. The method follows a fundamental path established by utilising solution particle location and particle velocity vectors as a guide. We may decide that a certain solution, within a particular optimisation period, is now determined by the velocity vector, which defines our optimal solution [26].

This is computed using a fitness function for each species, often known as the ability to find a better solution. The personal best solution is a form of vector that represents the personal best values for each individual organism inside the system (pBest). By contrast, each particle swarm inside a solitary instant has its best global location, which is referred to as gBest [27].

Initial locations for each organism within the search space are created randomly. The algorithm then performs optimisation cycles, with each iteration searching for the current personal best solution (pBest) and global best solution (gBest). Eq. (5) shows the core of the optimisation algorithm, whereas Eq. (6) stands for updating the particle location after each optimisation cycle.

$$v_i = v_i + c_1 rand()(p_i - x_i) + c_2 rand()(p_g - x_i) \tag{5}$$

Particle location update

$$x_i = x_i + v_i \tag{6}$$

The findings below are merely typical values for the workspace. The designed system remains unchanged under various machining conditions, and the user only needs to prepare the new knowledge base. To configure a PSO algorithm correctly, some extra parameters must be chosen (Table 2), which in our instance are as follows [23,27,28]:

**Table 2**
Configuration of a PSO algorithm

| Parameters | Value |
|---|---|
| Number of iterations | 150 |
| Correction factor $c_1$ | 1.2 |
| Correction $c_2$ | 2.4 |
| swarm | 25 |
| particle | 8 |

Given that PSO was used to model the machining process, PSO parameters were used to regulate the optimisation method. The findings were to be displayed in the form of coefficients C0, a, b and c, which defined the specific combination and weight factor of each independent machining parameter according to the design of the PSO method [20,21].

The PSO algorithm is provided as a method for forecasting the surface roughness of hot turning processes. The study employs the Particle Swarm Optimization (PSO) method with a single objective function. This objective function, represented by Eq. (7), demonstrates the application of PSO in generating an approximation equation characterized by a minimized Root Mean Square Error (RMSE) value. The utilization of PSO in this context aims to refine the approximation equation to closely match the observed data, thus enhancing the predictive accuracy of the model. As the RMSE serves as a crucial metric for evaluating the fidelity of the approximation equation, achieving a smaller RMSE value signifies a higher level of agreement between the model predictions and the actual data points. Consequently, when the RMSE reaches a sufficiently low level, the approximation equation derived through PSO becomes a reliable tool for making accurate predictions and guiding decision-making processes in the studied domain. For the training data testing processes using Python software, experimental datasets were separated. A training split of 85% of the observed dataset was used, with a testing split of 15%. In addition, root mean square error (RMSE) was used to evaluate the performance of the model prediction accuracy, see Eq. (7) [22].

$$RMSE = \frac{\sqrt{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}}{n} \tag{7}$$

where $\hat{y}_i$ and $y_i$ denote the measured and predicted outputs, respectively.

## 3. Results and Discussion

The PSO algorithm was trained to forecast the surface roughness of the hot turning method using experimental data from Table 3. Table 3 demonstrates the experimental results for the hot turning process, which show 30 repetitions of each procedure to examine every combination of depth of cut, speed and feed rate.

The surface roughness condition for the experiment with preheating treatment on the workpiece is shown in Figure 1. Figure 1 shows that when the preheating temperature rises, the workpiece’s surface roughness decreases. At 100, 150 and 200 degrees Celsius, the workpiece’s surface roughness ranges from 0.6 µm to 1.65 µm, from 0.60 µm to 1.52 µm and from 0.61 µm to 1.17 µm, respectively.

Several alternative combinations of learning and testing datasets were used to develop prediction models. About 80% of the experimental findings were used in the learning phase, whereas the remaining 20% were used to test the prediction model. In terms of accuracy, different combinations of learning input datasets produced comparable outcomes.

The coefficients obtained via the PSO approach for surface roughness were indicative and would represent for preparing the computing models referring to Eq. (2). Given the removal of specific coefficients, minor variations may be observed between the starting polynomial (Eq. (2)) and the final polynomials; hence, the partial result was negligible for the final result.

**Table 3**
Data for demonstrates the experimental results for the hot turning process

| No | Type | Variables | | | | Ra (µm) |
|---|---|---|---|---|---|---|
| | | $V_c$ | f | a | $T_w$ | |
| 1 | Factorial | 100 | 0.035 | 0.5 | 100 | 1.1821 |
| 2 | | 150 | 0.035 | 0.5 | 100 | 0.6288 |
| 3 | | 100 | 0.14 | 0.5 | 100 | 1.4666 |
| 4 | | 150 | 0.14 | 0.5 | 100 | 1.2557 |
| 5 | | 100 | 0.035 | 1.5 | 100 | 0.9212 |
| 6 | | 150 | 0.035 | 1.5 | 100 | 0.6034 |
| 7 | | 100 | 0.14 | 1.5 | 100 | 1.3388 |
| 8 | | 150 | 0.14 | 1.5 | 100 | 1.6466 |
| 9 | | 100 | 0.035 | 0.5 | 200 | 0.6766 |
| 10 | | 150 | 0.035 | 0.5 | 200 | 1.0166 |
| 11 | | 100 | 0.14 | 0.5 | 200 | 1.0466 |
| 12 | | 150 | 0.14 | 0.5 | 200 | 1.29 |
| 13 | | 100 | 0.035 | 1.5 | 200 | 1.11 |
| 14 | | 150 | 0.035 | 1.5 | 200 | 1.02 |
| 15 | | 100 | 0.14 | 1.5 | 200 | 1.1166 |
| 16 | | 150 | 0.14 | 1.5 | 200 | 1.4266 |
| 17 | Axial | 100 | 0.0875 | 1 | 150 | 1.5232 |
| 18 | | 150 | 0.0875 | 1 | 150 | 0.9532 |
| 19 | | 125 | 0.035 | 1 | 150 | 0.5968 |
| 20 | | 125 | 0.14 | 1 | 150 | 1.22 |
| 21 | | 125 | 0.0875 | 0.5 | 150 | 0.69 |
| 22 | | 125 | 0.0875 | 1.5 | 150 | 0.89 |
| 23 | | 125 | 0.0875 | 1 | 100 | 1.1734 |
| 24 | | 125 | 0.0875 | 1 | 200 | 1.0466 |
| 25 | Center | 125 | 0.0875 | 1 | 150 | 0.9289 |
| 26 | | 125 | 0.0875 | 1 | 150 | 0.6746 |
| 27 | | 125 | 0.0875 | 1 | 150 | 0.6066 |
| 28 | | 125 | 0.0875 | 1 | 150 | 0.9621 |
| 29 | | 125 | 0.0875 | 1 | 150 | 0.9523 |
| 30 | | 125 | 0.0875 | 1 | 150 | 0.6877 |

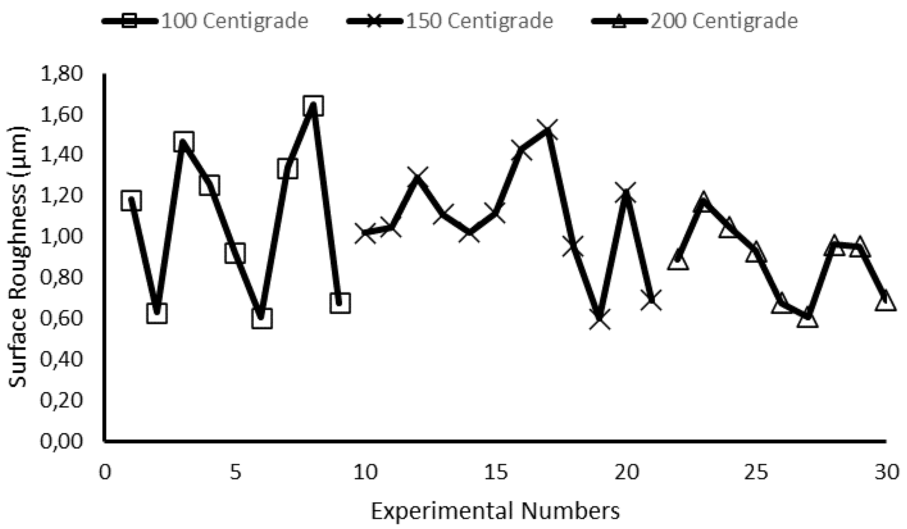



**Fig. 1.** Effect of preheating temperature on surface roughness

Figure 2 shows a surface plot for cutting parameters and surface roughness. A trend surface graph is a visual representation of a fitted surface that describes the general trend or pattern of variation in a dataset. These graphs are commonly used in surface modeling to illustrate the overall behavior of a continuous variable across a spatial or temporal domain. The link between surface roughness and cutting settings can be examined. Low cutting speed (100 mm/min) and low feed rate (0.0035 mm/s) generate roughness of about 1.4 m, as shown in Figure 2(a). As illustrated in Figure 2(b), a combination of low cutting speed (100 mm/min) and shallow cut depth (0.5 mm) produces a rough surface (1.54 µm). As illustrated in Figure 2(c), the situation is considerably different, that is, a combination of fast feed rate (0.14 mm/teeth) and low cut (1.5 mm) produces larger roughness values (1.56 µm).

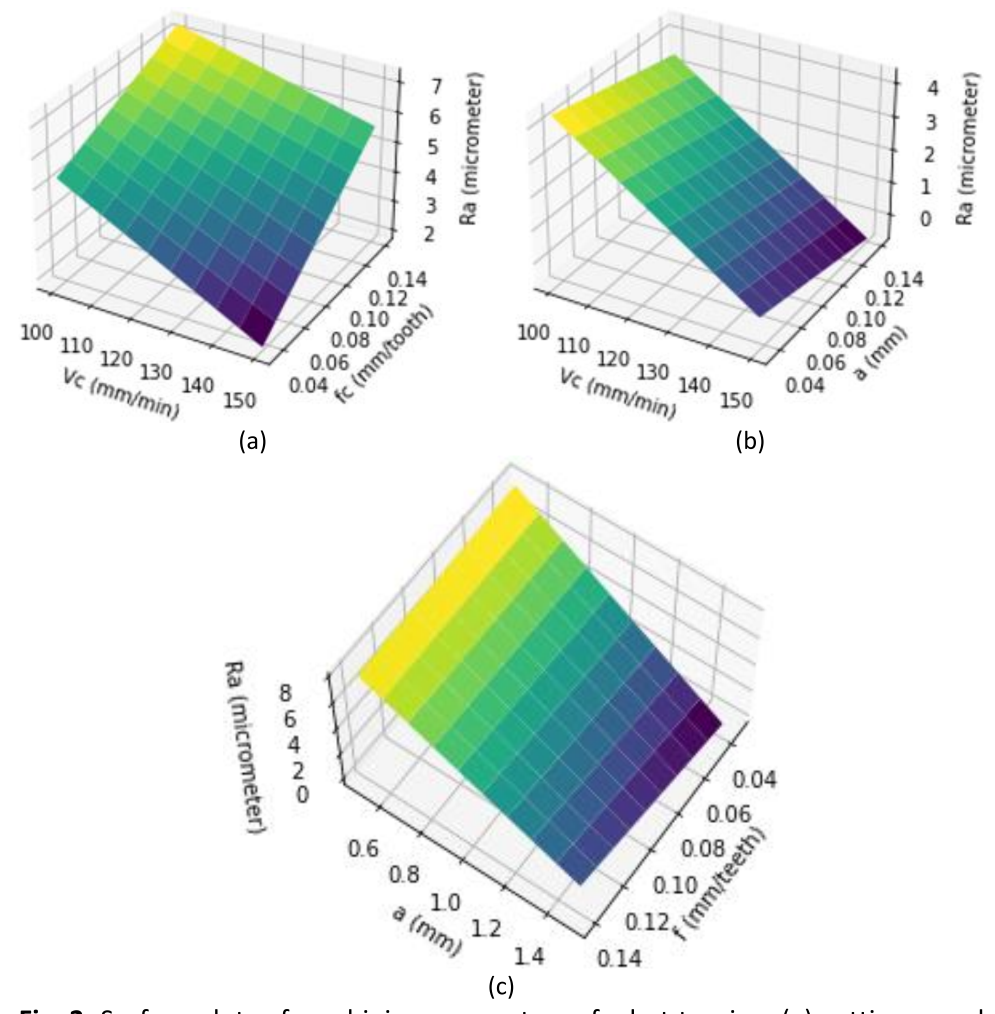
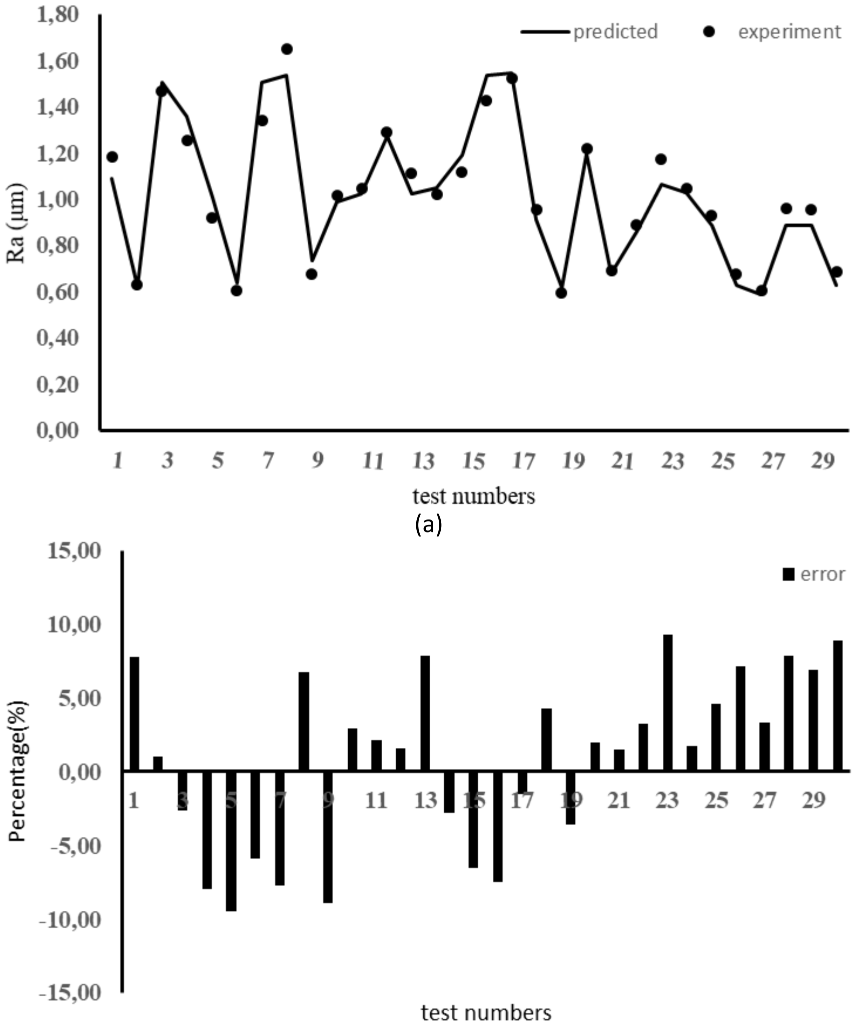



**Fig. 2.** Surface plots of machining parameters of a hot turning: (a) cutting speed vs. feed rate influence on surface roughness, (b) cutting speed vs. depth of cut influence on surface roughness, (c) depth of cut vs. feed rate influence on surface roughness

A phase of testing and deviation analysis of the developed models must be confirmed during the experimentation step. Figure 3 shows the graphical representation of the output value of surface roughness Ra acquired in the experiment. The experimental surface roughness values are categorised in accordance with how much heat was applied to the workpiece prior to the machining operation. The predicted surface roughness findings are shown in Figure 3. A comparison plot of experimental and predicted surface roughness levels is shown in Figure 3(a).

The RMSE of the workpiece surface roughness between predicted and experimental is less than 10%, as shown in Figure 3(b). The findings of this RMSE comparison suggest the accuracy of the curve fitting and coefficient optimisation of the workpiece's surface roughness model.




(b)

**Fig. 3.** (a) Comparison of the predicted and experimental surface roughness and (b) the RMSE between predicted and experimental surface roughness

## 4. Conclusions

In this work, the PSO machine learning technique was used to predict the surface roughness of AISI 304 stainless steel during the hot turning process. The PSO system was trained using an experimental dataset that included cutting speed, feed rate and cut depth. These PSO algorithm features are critical for estimating surface roughness with a given set of machine settings, thus saving money and time on experimental runs. To illustrate the effectiveness of PSO, the predicted surface roughness values were compared with the measured values. The predicted results were found to be close to the experimental results. Furthermore, the difference between testing and predicted surface roughness levels during the hot turning process was less than 10%.

## Acknowledgement
Thanks to Universitas Sriwijaya to facilities this research.

## References
[1] Sofuoğlu, Mehmet Alper, Fatih Hayati Çakır, Selim Gürgen, Sezan Orak, and Melih Cemal Kuşhan. "Numerical investigation of hot ultrasonic assisted turning of aviation alloys." *Journal of the Brazilian Society of Mechanical Sciences and Engineering* 40 (2018): 1-12. https://doi.org/10.1007/s40430-018-1037-4
[2] Alajmi, Mahdi S., and Abdullah M. Almeshal. "Prediction and optimization of surface roughness in a turning process using the ANFIS-QPSO method." *Materials* 13, no. 13 (2020): 2986. https://doi.org/10.3390/ma13132986
[3] Noor, M. M., K. Kadirgama, and M. M. Rahman. "Particle swarm optimisation prediction model for surface roughness." *International Journal of the Physical Sciences* 6, no. 13 (2011): 3082-3090.
[4] Parida, Asit Kumar, and Kalipada Maity. "Modeling of machining parameters affecting flank wear and surface roughness in hot turning of Monel-400 using response surface methodology (RSM)." *Measurement* 137 (2019): 375-381. https://doi.org/10.1016/j.measurement.2019.01.070
[5] Cakir, M. Cemal, and Adem Gurarda. "Optimization and graphical representation of machining conditions in multi-pass turning operations." *Computer Integrated Manufacturing Systems* 11, no. 3 (1998): 157-170. https://doi.org/10.1016/S0951-5240(98)00015-9
[6] Meng, Qinghui, J. A. Arsecularatne, and P. Mathew. "Calculation of optimum cutting conditions for turning operations using a machining theory." *International Journal of Machine Tools and Manufacture* 40, no. 12 (2000): 1709-1733. https://doi.org/10.1016/S0890-6955(00)00026-2
[7] Lee, B. Y., and Y. S. Tarng. "Cutting-parameter selection for maximizing production rate or minimizing production cost in multistage turning operations." *Journal of Materials Processing Technology* 105, no. 1-2 (2000): 61-66. https://doi.org/10.1016/S0924-0136(00)00582-3
[8] Kanth, V. Krishna, D. Sreeramulu, S. Srikiran, M. Pradeep Kumar, K. E. Jagdeesh, and B. Govindh. "Experimental investigation of cutting parameters using nano lubrication on turning AISI 1040 steel." *Materials Today: Proceedings* 18 (2019): 2095-2101. https://doi.org/10.1016/j.matpr.2019.06.323
[9] Mat Deris, Ashanira, Azlan Mohd Zain, and Roselina Sallehuddin. "Hybrid GR-SVM for prediction of surface roughness in abrasive water jet machining." *Meccanica* 48 (2013): 1937-1945. https://doi.org/10.1007/s11012-013-9710-2
[10] Petropoulos, G. P., C. N. Pandazaras, N. M. Vaxevanidis, and A. Antoniadis. "Multi-parameter identification and control of turned surface textures." *The International Journal of Advanced Manufacturing Technology* 29 (2006): 118-128. https://doi.org/10.1007/s00170-004-2483-y
[11] Boothroyd, Geoffrey, and Winston A. Knight. *Fundamentals of metal machining and machine tools*. New York: Marcel Dekker, 1989.
[12] Nguyen, Trung-Thanh. "Prediction and optimization of machining energy, surface roughness, and production rate in SKD61 milling." *Measurement* 136 (2019): 525-544. https://doi.org/10.1016/j.measurement.2019.01.009
[13] Camposeco-Negrete, Carmita. "Prediction and optimization of machining time and surface roughness of AISI O1 tool steel in wire-cut EDM using robust design and desirability approach." *The International Journal of Advanced Manufacturing Technology* 103 (2019): 2411-2422. https://doi.org/10.1007/s00170-019-03720-3
[14] Soepangkat, Bobby OP, Bambang Pramujati, Mohammad Khoirul Effendi, Rachmadi Norcahyo, and A. M. Mufarrih. "Multi-objective optimization in drilling kevlar fiber reinforced polymer using grey fuzzy analysis and Backpropagation Neural Network-Genetic Algorithm (BPNN-GA) Approaches." *International Journal of Precision Engineering and Manufacturing* 20 (2019): 593-607. https://doi.org/10.1007/s12541-019-00017-z
[15] Venkata Rao, K., and P. B. G. S. N. Murthy. "Modeling and optimization of tool vibration and surface roughness in boring of steel using RSM, ANN and SVM." *Journal of Intelligent Manufacturing* 29, no. 7 (2018): 1533-1543. https://doi.org/10.1007/s10845-016-1197-y
[16] Prasath, K. Manikanda, T. Pradheep, and S. Suresh. "Application of taguchi and response surface methodology (RSM) in steel turning process to improve surface roughness and material removal rate." *Materials Today: Proceedings* 5, no. 11 (2018): 24622-24631. https://doi.org/10.1016/j.matpr.2018.10.260
[17] Natasha, A. R., J. A. Ghani, CH Che Haron, J. Syarif, and A. H. Musfirah. "Temperature at the tool-chip interface in cryogenic and dry turning of AISI 4340 using carbide tool." *International Journal of Simulation Modelling* 15, no. 2 (2016): 201-212. https://doi.org/10.2507/IJSIMM15(2)1.314
[18] Siddique, Rifat Ahasan, Farhana Dilwar, and Rezaul Karim Nayeem. "Experimental investigation of the effect of cutting parameters on cutting temperature using Rsm and ANN in turning AISI 1040." *Global Scientific Journals* 6, no. 8 (2018): 47-60.

[19] Kant, Girish, and Kuldip Singh Sangwan. "Predictive modelling and optimization of machining parameters to minimize surface roughness using artificial neural network coupled with genetic algorithm." *Procedia CIRP* 31 (2015): 453-458. https://doi.org/10.1016/j.procir.2015.03.043

[20] Leman, Zulkarnain Ali, Mohd Hatta Mohammed Ariff, Hairi Zamzuri, Mohd Azizi Abdul Rahman, and Fitri Yakub. "Gain Scheduling Model Predictive Path Tracking Controller for Autonomous Vehicle on Highway Scenario." In *Proceedings of the 6th International Conference and Exhibition on Sustainable Energy and Advanced Materials: ICE-SEAM 2019*, 16-17 October 2019, Surakarta, Indonesia, pp. 461-473. Springer Singapore, 2020. https://doi.org/10.1007/978-981-15-4481-1_44

[21] Leman, Zulkarnain Ali, Mohd Hatta Mohammad Ariff, Hairi Zamzuri, Mohd Azizi Abdul Rahman, and Saiful Amri Mazlan. "Model predictive controller for path tracking and obstacle avoidance manoeuvre on autonomous vehicle." In *2019 12th Asian Control Conference (ASCC)*, pp. 1271-1276. IEEE, 2019.

[22] Amer, Noor Hafizah, Hairi Zamzuri, Khisbullah Hudha, and Zulkiffli Abdul Kadir. "Modelling and control strategies in path tracking control for autonomous ground vehicles: a review of state of the art and challenges." *Journal of Intelligent & Robotic Systems* 86 (2017): 225-254. https://doi.org/10.1007/s10846-016-0442-0

[23] Sari, Yuslena, Eka Setya Wijaya, Andreyan Rizky Baskara, and Rico Silas Dwi Kasanda. "PSO optimization on backpropagation for fish catch production prediction." *Telkomnika (Telecommunication Computing Electronics and Control)* 18, no. 2 (2020): 776-782. https://doi.org/10.12928/telkomnika.v18i2.14826

[24] Hasan, Mustafa Wassef, and Nizar Hadi Abbas. "An improved swarm intelligence algorithms-based nonlinear fractional order-PID controller for a trajectory tracking of underwater vehicles." *TELKOMNIKA (Telecommunication Computing Electronics and Control)* 18, no. 6 (2020): 3173-3183. https://doi.org/10.12928/telkomnika.v18i6.16282

[25] Ha, Phu Trieu, Hanh Minh Hoang, Thuan Thanh Nguyen, and Thang Trung Nguyen. "Modified moth swarm algorithm for optimal economic load dispatch problem." *TELKOMNIKA (Telecommunication Computing Electronics and Control)* 18, no. 4 (2020): 2140-2147. https://doi.org/10.12928/telkomnika.v18i4.15032

[26] Amer, Noor Hafizah, Khisbullah Hudha, Hairi Zamzuri, Vimal Rau Aparow, Amar Faiz Zainal Abidin, Zulkiffli Abd Kadir, and Muhamad Murrad. "Adaptive modified Stanley controller with fuzzy supervisory system for trajectory tracking of an autonomous armoured vehicle." *Robotics and Autonomous Systems* 105 (2018): 94-111. https://doi.org/10.1016/j.robot.2018.03.006

[27] El-Mounayri, Hazim, Zakir Dugla, and Haiyan Deng. "Prediction of surface roughness in end milling using swarm intelligence." In *Proceedings of the 2003 IEEE Swarm Intelligence Symposium. SIS'03 (Cat. No. 03EX706)*, pp. 220-227. IEEE, 2003.

[28] Tan, Qifan, Penglei Dai, Zhihao Zhang, and Jay Katupitiya. "MPC and PSO based control methodology for path tracking of 4WS4WD vehicles." *Applied Sciences* 8, no. 6 (2018): 1000. https://doi.org/10.3390/app8061000