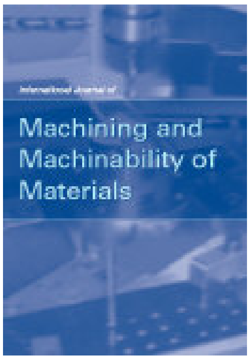

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Productivity improvement in hard turning of AISI 4340 with response surface methodology and machine learning

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Abstract: This study aims to optimise the hard turning of AISI 4340 steel to improve productivity using response surface methodology (RSM) and machine learning (ML) techniques. The novelty lies in integrating these methods to enhance material removal rate (MRR) while maintaining surface roughness (Ra) quality. Experiments were conducted with an uncoated carbide tool under dry and minimum quantity lubrication (MQL) conditions, varying cutting speed, feed, and depth of cut. RSM identified feed as the most significant factor affecting Ra, while ML, specifically linear regression (LR), predicted optimal cutting conditions. Key findings include achieving an optimum MRR of 5.2 cm^3/min under dry and 7.2 cm^3/min under MQL conditions, with Ra within the acceptable range (1.6 µm–3.2 µm). Validation confirmed the model's accuracy, demonstrating high agreement between predicted and experimental Ra values. This integrated approach offers a robust solution for optimising hard-turning processes in industrial applications.

Keywords: surface roughness; Ra; material removal rate; MRR; linear regression; LR; minimum quantity lubrication; MQL.

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1 Introduction

The background of the study reported in this paper is the application of hard machining technology in producing post-harvest machinery parts. As one of the world's major agricultural countries, Indonesia needs post-harvest machinery to process harvest products. Many players, from small and medium enterprises (SMEs) up to high-investment industries, contribute to the various aspects of manufacturing businesses to provide the availability of post-harvest machinery in the country. As steel is mainly the raw material for machinery parts, the metal-cutting industry is vital in manufacturing machinery. In line with the increasing demand for machinery parts in the country, the metal-cutting industries must increase their productivity. The strategies for increasing productivity in metal cutting technology can be applied by hard machining technology (Koenig et al., 1984; Astakhov, 2011) and cooling conditions during machining (Klocke and Eisenblaetter, 1997; Weinert et al., 2004; Goindi and Sarkar, 2017).

As hard machining technology can be used for any machining operation, particularly for post-harvest machinery, hard turning is mostly taken operation for production. Astakhov (2011) recommended the simple rule for the key success in applying hard turning by minimising the overhangs, tool and part extensions, eliminating shims and spacers when turning operation. In short, the setup of the turning operation must be kept as close as possible to the turret or spindle head of the lathe. For cooling conditions, although most hard turning operations are carried out under dry conditions (Sarma and Rajbongshi, 2021; Ginting et al., 2020), if a coolant is needed, high pressure is recommended. In this case, applying the minimum quantity of lubrication (MQL) cooling conditions is recommended, as reported in Weinert et al. (2004) and Goindi and Sarkar (2017). The last but prime recommendation is selecting the proper tool material, including tool geometry, tool accessories (insert shape, tool holder, etc.), and the appropriate or optimal cutting condition when possible. As highlighted in Koenig et al. (1984) and König et al. (1990), three tool materials are recommended, i.e., carbide, ceramic, and cubic boron nitride (CBN). Carbide can machine ferrous alloys of hardness up to 58 HRC, ceramic for up to 63 HRC, and CBN for up to 70 HRC.

Turning hardened steel at a certain magnitude of cutting parameters (cutting speed, feed, and depth of cut) and resulting in an acceptable value of objective (response) parameters (i.e., surface roughness, tool life, etc.) are the ways of finding the appropriate cutting condition. In this case, the acceptable level can be higher, better, or lower, depending on the objective parameter's nature; for instance, the higher, the better when the objective is tool life, but the lower, the better when the objective is surface roughness. Based on this understanding, finding the appropriate cutting condition is commonly done by utilising optimalisation technique. Therefore, to find the appropriate cutting condition with the objective of surface roughness, various statistical approaches, from classical regression to today's machine learning (ML) technique, have been utilised (Dubey et al., 2022; Motta et al., 2022; Mazid et al., 2023; Ahmad et al., 2015; Chatterjee et al., 2021).

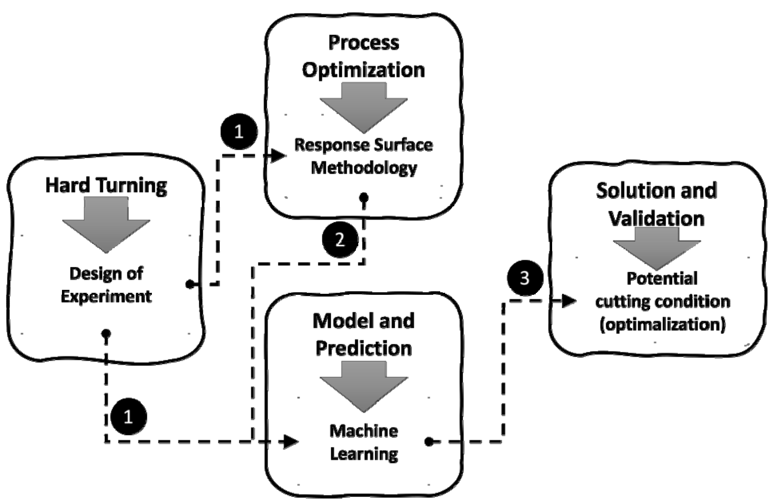
There is useful fundamental information related to ML applied in manufacturing and machining that can be obtained from Kim et al. (2018), Aggogeri et al. (2020), Nasir and Sassani (2021) and Arinez et al. (2020). ML is a subset of artificial intelligence that empowers systems to learn and improve from experience without explicit programming. Standard techniques include supervised learning, semi-supervised, and unsupervised learning. Supervised learning is a ML paradigm where a model is trained on labelled data, associating input features with corresponding output labels. It involves algorithms that enable computers to recognise patterns, make predictions, and adapt to new data. Mostly, the research in machining with the design of experiment (DoE), such as the study reported in this paper, adopted supervised learning and algorithms such as linear regression (LR), random forest (RF), support vector regression (SVR), and Gaussian process regression (GPR) (Motta et al., 2022; Mazid et al., 2023; Ahmad et al., 2015; Brillinger et al., 2021).

The objective of this paper is to find the appropriate and optimum cutting condition applied for hard turning of AISI 4340 through response surface methodology (RSM) and ML techniques to increase productivity, showcase enhanced material removal rates (MRRs), and maintain surface roughness (Ra) within acceptable quality ranges. Unlike the selection of the ML algorithm in the other studies, the selection of LR as the ML algorithm for model development in this study is based on the result of the RSM analysis.

2 Materials and method

Figure 1 is the illustration of a strategy designed for this study. The study started with a hard turning activity. In this activity, the AISI 4340 steel with a diameter of 70 mm, length of 350 mm, and hardness of 50 HRC is selected as the workpiece material. The workpiece is rigidly mounted onto a CNC Turning machine model CKA6136 spindle powered by a 4,000 rpm motor. As the turning experiment is carried out under dry and minimum quantity lubrication (MQL) conditions, the CNC Turning machine is equipped with the MQL systems (see Figure 2 for the setup). The MQL systems work constantly at a pressure of 4 bar, with a cutting fluid capacity of 100 mL/h, and the ECOCUT 1012 ID is used as the cutting fluid.

Figure 1 The strategy developed to achieve the objective of the study



The uncoated carbide coded DCMT11T304-F2 HX is selected as the cutting tool and attached to the tool holder coded SDJCR1616H11. Since the results of this study will benefit our industrial partner, the workpiece material and the cutting tool used in this study are provided and received from them. Even the CBN cutting tool is superior for hard turning. However, we support the decision of our industrial partner to select the uncoated carbide tool used in this study for 2 (two) reasons. Firstly, the hardness number of material to be cut is at the entry-level of hard machining application (50 HRc). Carbide showed a good performance for turning hardened ferrous alloys up to 58 HRc (Koenig et al., 1984). Secondly, our industrial partner is in the SME industry; the small investment and low production cost have to be considered. The CBN insert cutting tool is more costly than carbide.

Figure 2 Setup of the turning experiment under dry and MQL conditions

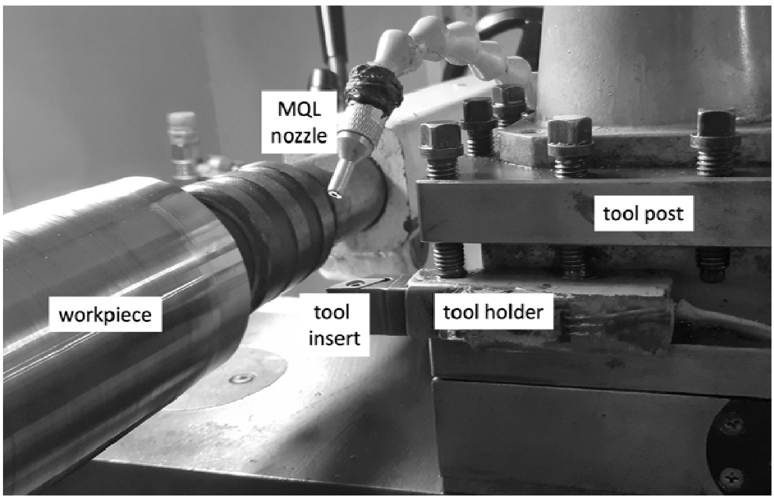


Table 1 The DoE of Box-Behnken design: factors and values

Factor		*Unit*	*Lower value*	*Upper value*
v	Cutting speed	(m/min)	90	120
f	Feed	(mm/rev)	0.10	0.20
a	Depth of cut	(mm)	0.25	0.50

As the method of process optimisation in this study is RSM, the Box-Behnken design is then taken as the DoE for hard turning activity. The turning parameter, factors, and values used for the DoE are identified and result from the preliminary study (see Table 1). The baseline turning parameter used by the industry is cutting speed (v) of 60 m/min, feed (f) of 0.1 mm/rev, depth of cut (a) of 0.2 mm, and the process is only under dry condition. The surface roughness quality ranges from medium finish with a roughness grade number of N8 (~3.2 μm) to finish with a roughness grade number of N7 (~1.6 μm). If the productivity is measured by *MRR*, which mathematically can be given as:

$$MRR = v \times f \times a \tag{1}$$

thus, the *MRR* of the baseline turning parameter is 1.2 cm^3/min. The hard turning activity is conducted as per design, with the response variable being surface roughness under the Ra (average roughness) parameter. The surface roughness tester Surftest SJ-210 is utilised to measure the response. The measurement of Ra is taken five times/pass until the cutting tool reaches the flank wear at VB of about (0.20–0.23) mm, and finally, the Ra average is recorded for each cutting condition (run) as per the DoE of Box-Behnken design (➊).

RSM then analyses the data (➊) from the hard turning activity for process optimisation. The quadratic model is developed, and the adequacy is checked. The RSM analysis could be continued once the best-fit model is obtained and confirmed. The goal of this activity is a set of potential cutting conditions (➋) with high *MRR* value and good Ra value in which quality ranges from medium finish (N8) to finish (N7) (ISO 4288, 1998). Simultaneously, the data (➊) is also used as a set of data to be trained for creating the model using the ML approach. A supervised ML technique is adopted, and the computer code is developed using Python. Using supervised learning, input variables in the labelled datasets (*v*, *f*, *a*) are trained to learn the relationship between the input and output variables. Once the training phase has been completed, the ML model can process new input data (➋) and provide the predicted Ra values. The result of the ML activity (model and prediction) is a set of potential cutting conditions, including the predicted Ra values (➌). This dataset will be the solution to cutting conditions that can be applied to improving the productivity of the hard turning process in producing the post-harvest machinery parts for our industrial partner. As for the final adjustment, from the set of data in (➌), the cutting conditions are classified as potential optimum cutting conditions, which are characterised by high *MRR* value with accepted Ra value at roughness grade number (N8) and (N7). The potential optimum cutting conditions are then validated by re-hard turning testing.

The application of the LR algorithm in this study is carried out by writing a set of Python code and utilising the Scikit-Learn library for ML programming (Müller and Guido, 2015; Hastie et al., 2009). The pseudo-code of the LR algorithm can be given as follows:

Step 1 Assume *X* is the input feature, and y is the target variable. In this study, *X* is the cutting condition (*v*, *f*, *a*), and *y* is the response (Ra).

Step 2 Split the data in Table 2 into training and testing sets.

Step 3 Train the model on the training set.

Step 4 Predict the test set. Data in Table 2 was used as the testing sets.

Step 5 Evaluate the model performance using mean squared error (MSE), root mean squared error (RMSE), and R^2 (coefficient of determination).

MSE and RMSE are commonly used metrics to evaluate the performance of a regression model (step 5). The MSE measures the average squared difference between the experiment and predicted values and quantifies how well the model performs regarding the average magnitude of the error. A lower MSE indicates better model performance, which means the model's prediction is closer to the experimental values. The RMSE is the square root of the MSE and measures the average magnitude of errors in the same units as the target variable. It is beneficial for understanding the typical size of errors the model makes. As MSE, a lower RMSE indicates better model performance. In addition to MSE and RMSE, the R^2, also known as the coefficient of determination, is used to evaluate the model performance. The coefficient of determination is a measure that indicates the percentage of the response parameter variation that a regression model explains. A higher R^2 score indicates that the regression model explains more variability and the regression model fits the data better.

3 Result and discussion

3.1 Hard turning

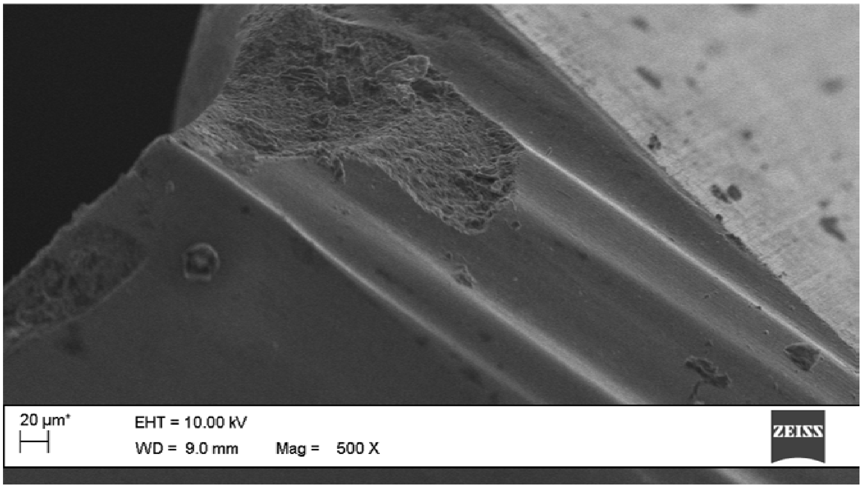
The results of hard turning activity as per DoE Box-Behnken design under dry and MQL conditions are presented in Table 2. Table 2 shows that all *MRR* values are more significant than the *MRR* of the baseline turning parameter (1.2 cm^3/min). All *MRR* values indicate that the cutting conditions can improve productivity. Besides, the Ra values resulting both under dry and MQL conditions seem promising where the surface roughness with quality of medium finish (N8~3.2 μm) and finish (N7~1.6 μm) are covered.

As mentioned, Ra was measured per pass (cutting length of 330 mm/pass), five times of measurement/pass, until the cutting tool reached flank wear at VB of (0.20–0.23) mm. This VB limit was chosen because, above the limit, the cutting tool experienced excessive chipping (Figure 3). At the VB limit, the flank wear was generally observed in the vicinity of the active cutting tool edge (within the cutting tool nose radius). The flank wear condition was believed because the cutting condition variables where *f* (0.1 to 0.2 mm/rev) and *a* (0.25 to 0.5 mm) were about the same dimension as the cutting tool nose radius (0.4 mm). After all, the cutting condition variables *f* and *a* are both assigned at the active cutting tool edge, where chip formation actively occurs during the turning.

Table 2 The results of the hard turning experiment under dry and MQL conditions

Run	*v*	*f*	*a*	*MRR*	*Ra dry*	*Ra MQL*
	m/min	*mm/rev*	*mm*	*cm^3/min*	*μm*	*μm*
1	90	0.10	0.375	3.4	2.125	1.640
2	120	0.10	0.375	4.5	2.664	2.166
3	90	0.20	0.375	6.8	5.802	4.881
4	120	0.20	0.375	9.0	5.565	6.014
5	90	0.15	0.250	3.4	3.788	2.854
6	120	0.15	0.250	4.5	4.514	3.980
7	90	0.15	0.500	6.8	4.253	3.434
8	120	0.15	0.500	9.0	4.922	4.049
9	105	0.10	0.250	2.6	2.461	1.856
10	105	0.20	0.250	5.3	5.682	4.592
11	105	0.10	0.500	5.3	3.012	2.125
12	105	0.20	0.500	10.5	6.403	5.639
13	105	0.15	0.375	5.9	4.233	3.904
14	105	0.15	0.375	5.9	3.893	3.806
15	105	0.15	0.375	5.9	4.384	3.578

Figure 3 Excessive chipping (dry, *v* 120 m/min, *f* 0.20 mm/rev, *a* 0.375 mm)



3.2 Process optimisation

Prior to analysing the data in Table 2 using the RSM technique, the distribution data was checked, and the goodness-of-fit was assessed. Understanding data distribution would help us choose the appropriate statistical methods and make valid inferences. For this purpose, the probability plot with a 95% confidence interval (CI) was studied. The plots are shown in Figures 4 and 5 for the data resulting under dry and MQL conditions, respectively.

The probability plots in Figures 4 and 5 show that the resulting Ra data under dry and MQL conditions follow the normal distribution. The legends in Figures 4 and 5 show that the Anderson-Darling (AD) test gives a low value of 0.227 for dry and 0.255 for MQL. In this case, a lower value suggests a better fit. The P-value (closer to 1) is associated with the AD test values and indicates a better fit to the normal distribution. In this case, the P-values of 0.775 and 0.676 are the results for dry and MQL conditions, respectively. The high P-value suggests insufficient evidence to reject the hypothesis that the data comes from a normal distribution. The analysis results through the probability plot confirm that the Ra data that resulted both under dry and MQL conditions are suitable for further statistical testing and model development.

The results of hard turning activity per DoE Box-Behnken design under dry and MQL conditions in Table 2 were then analysed using the RSM technique. As the probability plot, this analysis was done using the commercial statistical software Minitab. The first step in the analysis under the RSM technique was finding the best-fit model for the data. After developing a full quadratic model, calculating all coefficients, and retrieving the result of ANOVA of response surface regression (Ra versus *v*, *f*, *a*), the results showed that a linear model was the best-fit model to represent the data both for dry and MQL conditions with a coefficient of determination (R^2) of 96.64% and 97.56%, respectively. The square and two-way interaction models were not significant. Figures 6 and 7 show the result of ANOVA for the response surface regression linear model in detail. From the figures, it can be seen that the contribution (effect) of independent variables (*v*, *f*, *a*) on a response variable (Ra) is mainly dominated by *f* (92.66% under dry and 89.78% under

MQL conditions). It is followed by *a* and *v* for turning under dry condition and *v* and *a* for turning under MQL condition.

Figure 4 The probability plot of Ra (dry) (see online version for colours)

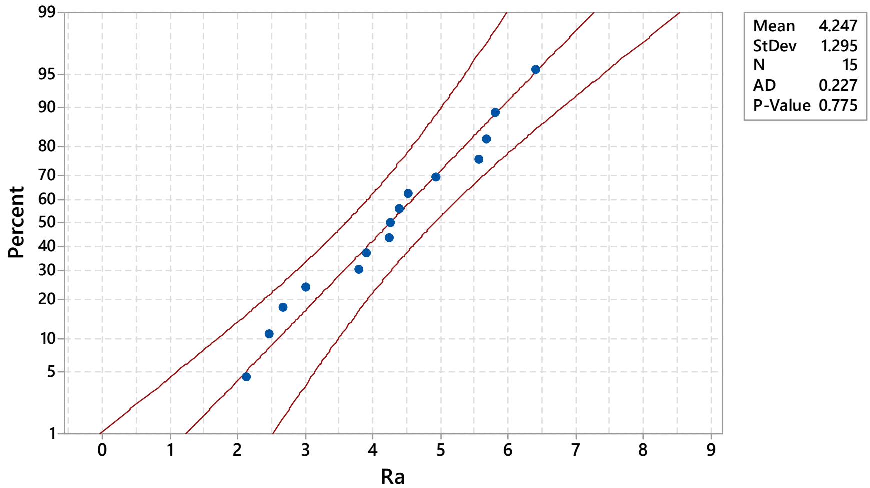
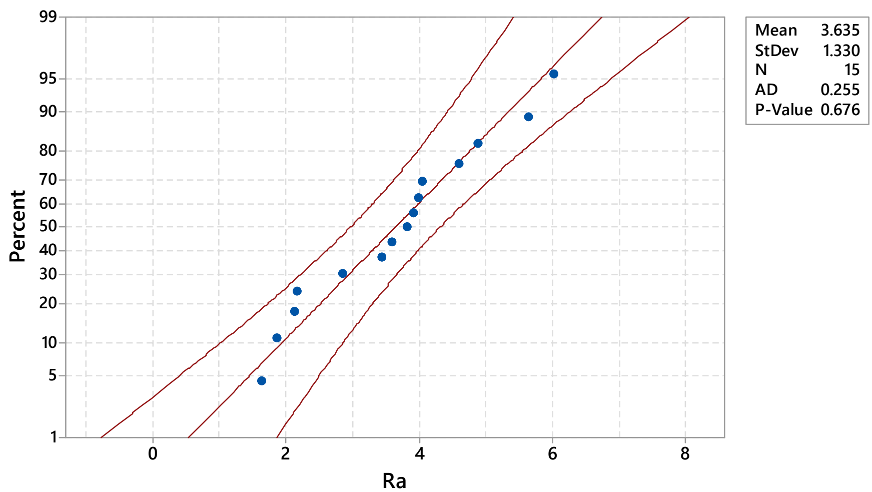


Figure 5 The probability plot of Ra (MQL) (see online version for colours)



The next step in the analysis under the RSM technique is finding the optimum value of the response variable (Ra). In this case, the optimum value of Ra is at the extremum minimum. For this purpose, the surface plots of Ra, as shown in Figure 8, were examined. The red arrows in Figure 8 show the position of Ra minimum, and based on the ANOVA results, that linear model was the best-fit model for the response surface regression (Ra versus *v*, *f*, *a*); thus, it can be concluded that the optimum value of Ra (minimum) could be found at the lowest value of the cutting condition (*v*, *f*, *a*).

Figure 6 The ANOVA for response surface regression linear model (dry)

Response Surface Regression: Ra versus v, f, a (Dry technique)

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Model	3	22.6818	96.64%	22.6818	7.5606	105.58	0.000
Linear	**3**	**22.6818**	**96.64%**	**22.6818**	**7.5606**	**105.58**	**0.000**
v	1	0.3605	1.54%	0.3605	0.3605	5.03	0.046
f	1	21.7463	92.66%	21.7463	21.7463	303.68	0.000
a	1	0.5750	2.45%	0.5750	0.5750	8.03	0.016
Error	11	0.7877	3.36%	0.7877	0.0716		
Lack-of-Fit	**9**	**0.6610**	**2.82%**	**0.6610**	**0.0734**	**1.16**	**0.546**
Pure Error	2	0.1267	0.54%	0.1267	0.0633		
Total	14	23.4695	100.00%				

Model Summary

S	R-sq	R-sq(adj)	PRESS	R-sq(pred)
0.267599	**96.64%**	**95.73%**	**1.54354**	**93.42%**

Regression Equation in Uncoded Units

Ra(Dry) = -2.990 + 0.01415 v + 32.97 f + 2.145 a

Figure 7 The ANOVA for response surface regression linear model (MQL)

Response Surface Regression: Ra versus v, f, a (MQL technique)

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Model	3	24.1651	97.56%	24.1651	8.0550	146.68	0.000
Linear	**3**	**24.1651**	**97.56%**	**24.1651**	**8.0550**	**146.68**	**0.000**
v	1	1.4444	5.83%	1.4444	1.4444	26.30	0.000
f	1	22.2378	89.78%	22.2378	22.2378	404.96	0.000
a	1	0.4829	1.95%	0.4829	0.4829	8.79	0.013
Error	11	0.6041	2.44%	0.6041	0.0549		
Lack-of-Fit	**9**	**0.5483**	**2.21%**	**0.5483**	**0.0609**	**2.19**	**0.353**
Pure Error	2	0.0557	0.23%	0.0557	0.0279		
Total	14	24.7691	100.00%				

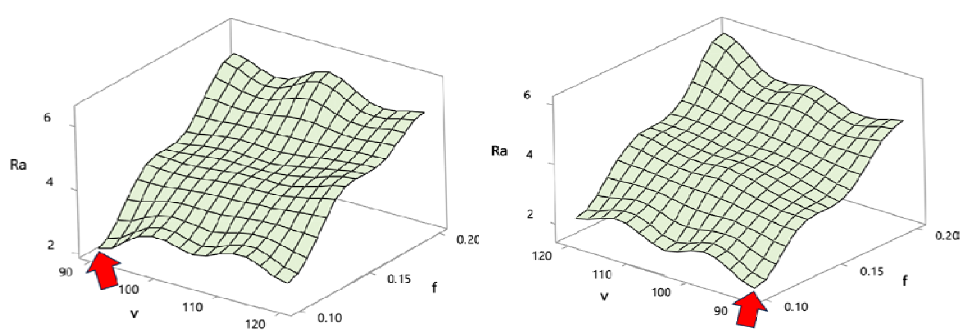
Model Summary

S	R-sq	R-sq(adj)	PRESS	R-sq(pred)
0.234338	**97.56%**	**96.90%**	**1.18915**	**95.20%**

Regression Equation in Uncoded Units

Ra(MQL)= -5.078 + 0.02833 v + 33.34 f + 1.966 a

Figure 8 Surface plot of Ra data, (a) dry (b) MQL conditions (see online version for colours)



(a) (b)

The Minitab menu under DoE RSM was executed to find the optimum value with minimum criterion (extremum minimum) and validate the conclusion. The results showed that the optimum Ra (minimum) under the dry condition was 2.117 µm, and under the MQL condition was 1.297 µm. Both were obtained at *v* 90 m/min, *f* 0.10 mm/rev, and 2.50 mm (the lowest value of the cutting condition). This result confirms the conclusion.

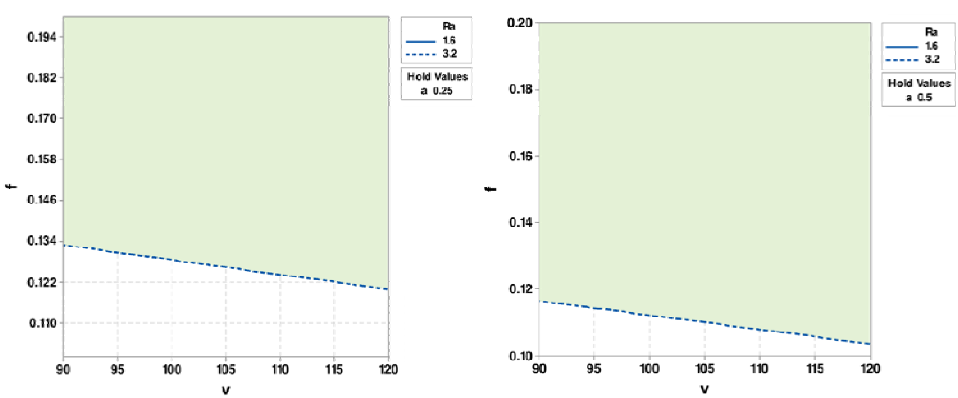
The value of Ra minimum at 2.117 µm for dry and 1.297 µm for MQL are both in the range of the expected surface finish (1.6–3.2 µm) and even better (1.297 µm). When this result is related to the *MRR* value as the indicator of productivity in this study, the Ra minimum for hard turning under dry and MQL conditions is obtained at an *MRR* value of 2.25 cm^3/min. This result is promising since the *MRR* of 2.25 cm^3/min is higher than the origin turning parameter practiced by the industrial partner (1.2 cm^3/min). Even when the range of surface roughness quality from medium finish (N8~3.2 µm) to finish (N7~1.6 µm) is concerned, it is possible to raise productivity higher than *MRR* of 2.25 cm^3/min. To address this possibility, the menu for the resulting predicted value in the Minitab application was utilised, and the results are presented in Table 3.

Table 3 Predicted cutting condition and *MRR* at expected Ra value

Condition	*Ra**	*v^*	*f^*	*a^*	*MRR^*
	µm	*m/min*	*mm/rev*	*mm*	*cm^3/min*
Dry	1.6	90	0.100	0.250	2.25
	3.2	105	0.125	0.250	3.28
MQL	1.6	90	0.100	0.400	3.60
	3.2	105	0.145	0.250	3.81

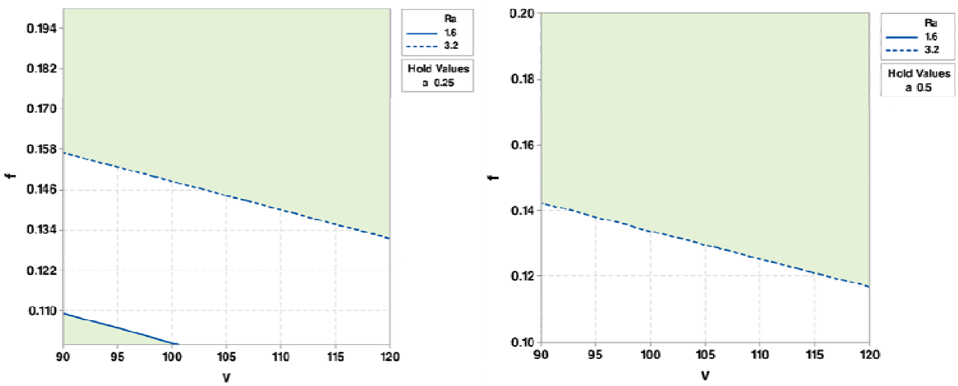
Notes: *expected; ^predicted.

Figure 9 Overlaid contour plot for Ra (1.6–3.2) µm (dry) (see online version for colours)



Further analysis with Minitab for finding the predicted cutting condition and *MRR* with Ra is in the range of the expected values of (1.6–3.2 µm). The overlaid contour plot can be extended, as shown in Figures 9 and 10. The overlaid contour plots in Figures 9 and 10 were plotted based on input cutting conditions in the range from *v* 90–120 m/min, *f* 0.1–0.2 mm/rev, but a was kept constant at 0.25 mm (for the overlaid contour plot at the left side) and 0.50 mm (for the overlaid contour plot at the right side) while the value of surface roughness (Ra) was also in range (1.6–3.2 µm). As shown in Figures 9 and 10, the results of the overlaid contour plots show that the white areas of those plots are the feasible areas for having surface roughness (Ra) values between 1.6 µm and 3.2 mm. The cutting conditions in Table 3 are also inside the feasible areas of the overlaid contour plots.

Figure 10 Overlaid contour plot for Ra (1.6–3.2) µm (MQL) (see online version for colours)



Figures 9 and 10 show the boundary-cutting condition for the feasible areas of expected surface roughness (Ra) between 1.6 µm to 3.2 µm can be provided and presented in Table 4. Referring to the boundary cutting condition in Table 4, there are many possibilities of cutting conditions that can now be arranged rather than what we have previously in Table 3. However, the question now is about the best way to obtain the predicted surface roughness (Ra) value for those cutting conditions within the boundary in Table 4. Moreover, the Ra value should be associated with high *MRR* so that the study's objective, productivity improvement, could be achieved. A ML technique was introduced in this study to answer the question.

Table 4 The boundary-cutting condition for the feasible areas of expected surface roughness (Ra) between 1.6 µm and 3.2 µm

Condition	*Boundary*	*v*	*f*	*a*
		m/min	*mm/rev*	*mm*
Dry	Low	90	0.100	0.250
	High	120	0.135	
	Low	90	0.100	0.500
	High	120	0.120	
MQL	Low	90	0.110	0.250
	High	120	0.160	
	Low	90	0.100	0.500
	High	120	0.140	

3.3 Model and prediction

The Ra value (experiment) result in Table 2 is plotted with the predicted Ra value resulting from the LR model and presented in Figures 11 for the dry condition and 12 for the MQL condition.

Figure 11 Plot of experiment and predicted of Ra under dry condition

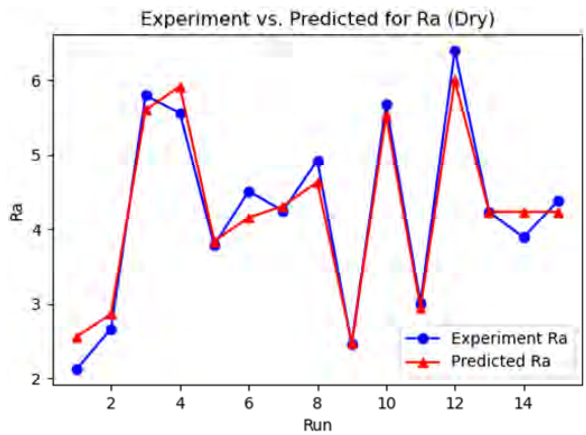
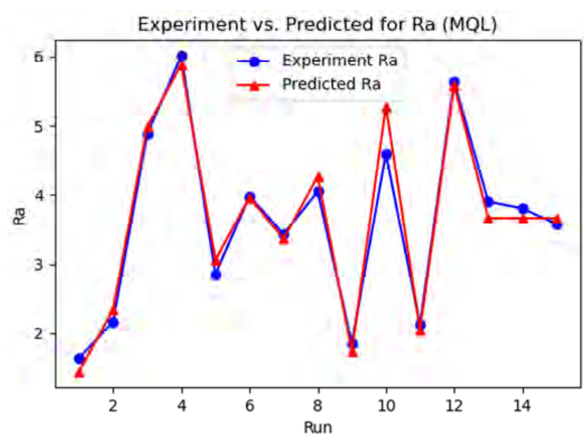


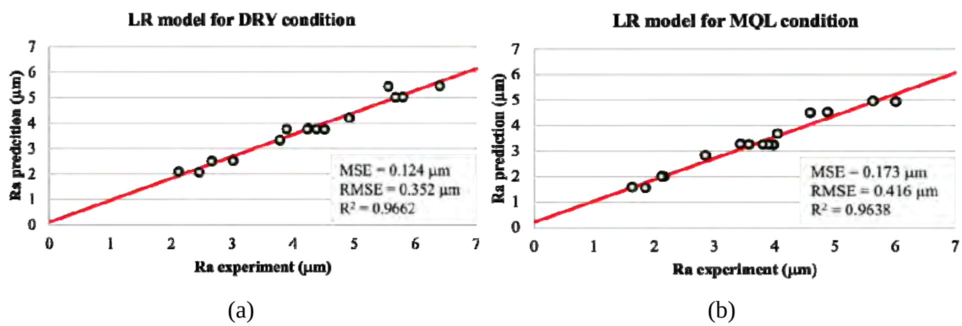
Figure 12 Plot of experiment and predicted of Ra under MQL condition (see online version for colours)



As shown in Figure 11, the plot of the Ra experiment and prediction show that the trend and value agree. Both models' MSE and RMSE values are calculated to assess the model performance. The value of MSE and RMSE of the LR model for dry condition are recorded at 0.124 µm and 0.352 µm, respectively. In Figure 12, the plot of the Ra experiment and prediction for MQL are also in good agreement. The MSE and RMSE values of the LR model are recorded at 0.173 µm and 0.416 µm, respectively.

Further assessment of model performance is using coefficient of determination (R^2). The visualisation of prediction quality provided by the LR model is presented in the scatter plot of the Ra experiment versus Ra prediction (Figure 13). A line corresponding to the equality between the values of the Ra experiment and Ra prediction is plotted for reference. It is also a trendline used to determine the R^2 score. In Figure 13(a), the LR model for the dry condition shows that $R^2 = 0.9662$, and in Figure 13(b), the LR model for the MQL condition shows that $R^2 = 0.9638$. These R^2 scores indicate that about 96% variability is explained by both LR models. The values and scores of MSE, RMSE, and R^2 are mentioned in Figure 13 to summarise the model assessment results. Based on these, as both MSE and RMSE metrics are relatively low while R^2 is relatively high, both LR models predict the surface roughness (Ra) values well.

Figure 13 Scatter plot of Ra experiment vs. Ra prediction, (a) dry (b) MQL conditions (see online version for colours)



So far, the LR model has been successfully generated and well performed. Using both LR models, the cutting conditions in Table 4 were used as the testing set to obtain the predicted Ra value for improved productivity. For this purpose, the boundary-cutting condition in Table 4 was arranged as in Table 5, and the new testing set was designed using DoE full factorial. From Table 5, there were 2 (two) new testing sets generated (dry and MQL) with 64 cutting conditions (runs) for each testing set.

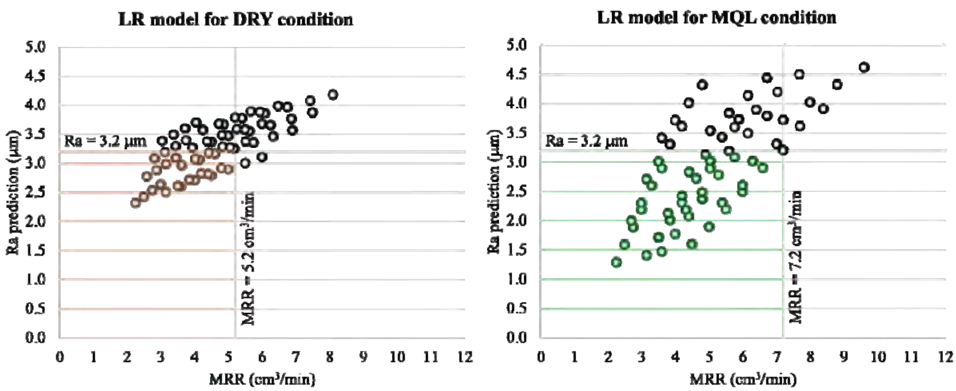
Table 5 Factors and levels of the new testing sets designed by DoE full factorial

Condition	*Levels*	*v*	*f*	*a*
		m/min	*mm/rev*	*mm*
Dry	1	90	0.100	0.250
	2	100	0.115	0.350
	3	110	0.125	0.400
	4	120	0.135	0.500
MQL	1	90	0.100	0.250
	2	100	0.120	0.350
	3	110	0.140	0.400
	4	120	0.160	0.500

3.4 Solution and validation

Both new testing datasets (dry and MQL) were then made as the input data to the dry and MQL models, resulting in the LR algorithm described in the former paragraph. After executing the Python code for each new testing dataset and model, the predicted Ra value for dry and MQL results are plotted and shown in Figure 14. The scatter plots in Figure 14 present the MRR values versus the corresponding Ra prediction values for 64 cutting conditions (for each plot) as per Table 5. Regarding this study's surface roughness quality of medium finish (N8~3.2 μm) to finish (N7~1.6 μm), the horizontal line at Ra = 3.2 μm is plotted as the borderline of the scatter plots in Figure 14. As a result, 28 MRR values in Figure 14(a) and 39 MRR values in Figure 14(b) are acceptable for further analysis. Among 28 MRR values in Figure 14(a), the highest is recorded at MRR = 5.2 cm^3/min, and among 39 MRR values in Figure 14(b), the highest is recorded at MRR = 7.2 cm^3/min. It indicates that the MQL condition is affected by the MRR. The corresponding cutting conditions of those accepted MRR and the Ra prediction values for dry and MQL conditions are listed in Tables 6 and 7, respectively.

Figure 14 Scatter plot of MRR vs. Ra prediction, (a) dry (b) MQL conditions (see online version for colours)



(a) (b)

In Table 6, the prediction result for dry condition shows that 28 out of 64 cutting conditions can be accepted with predicted Ra values ranging from 1.6 μm to 3.2 μm. However, the lowest predicted Ra is noted at 2.3 μm. The *MRR* is also listed, and the value is associated with the predicted Ra. The lowest predicted Ra, 2.3 μm, could result in an *MRR* of 2.3 cm^3/min. Moreover, the predicted Ra value of 3.2 μm could result in *MRR* of 3.1, 4.4, 4.6, and 5.2 cm^3/min. When *MRR* is concerned, 2.3 cm^3/min and 6.0 cm^3/min are the lowest and the highest *MRR* that could be achieved.

In Table 7, the prediction result for the MQL condition shows that 39 out of 64 cutting conditions can be accepted with predicted Ra values ranging from 1.6 μm to 3.2 μm. In this case, the lowest predicted Ra is noted at 1.3 μm. The lowest predicted Ra value is associated with an *MRR* value of 2.3 cm^3/min. Regarding the predicted Ra value of 3.2 μm, there are 2 *MRR* values associated with it, which are 5.6 and 7.2 cm^3/min. The *MRR* of 7.2 cm^3/min is the highest *MRR* value that could be achieved under MQL condition with the acceptable value of predicted Ra.

Some of the predicted Ra values in Table 6 (cutting condition numbers 1–4, 13–15, and 25–28) and 7 (cutting condition numbers 1–5, 15–18, and 36–39) were validated. The hard turning at those cutting conditions was repeated three times, and the measurements were taken. The results of the validation activity were also presented in Tables 6 (dry) and 7 (MQL). For the validation under dry condition, the validation value of Ra for cutting condition number 3 (*v* 90 m/min, *f* 0.115 mm/rev, *a* 0.50 mm), those validation values are higher than the predicted and the acceptable Ra values (>3.2 μm). Therefore, cutting condition three is excluded from the final solution for productivity improvement of hard turning under dry condition in this study.

Table 6 The results of predicted Ra and its validation (dry)

No.	*v*	*f*	*a*	*MRR*	*Predicted Ra*	*Validated Ra*		
	m/min	*mm/rev*	*mm*	*cm³/min*	*μm*	*μm*	*μm*	*μm*
1	120	0.100	0.50	6.0	3.109	3.219	3.263	3.217
2	110	0.100	0.50	5.5	3.003	3.121	3.147	3.118
*3**	*90*	*0.115*	*0.50*	*5.2*	*3.249*	*3.407*	*3.427*	*3.402*
4	100	0.100	0.50	5.0	2.897	3.023	3.032	3.019
…								
13	100	0.100	0.40	4.0	2.708	2.817	2.809	2.815
14	110	0.100	0.35	3.9	2.718	2.812	2.813	2.812
15	90	0.115	0.35	3.6	2.965	3.099	3.092	3.096
…								
25	110	0.100	0.25	2.8	2.529	2.607	2.590	2.609
26	90	0.115	0.25	2.6	2.775	2.893	2.869	2.892
27	100	0.100	0.25	2.5	2.423	2.509	2.474	2.510
28	90	0.100	0.25	2.3	2.317	2.411	2.359	2.410

Note: *excluded.

Table 7 The results of predicted Ra and its validation (MQL)

No.	*v*	*f*	*a*	*MRR*	*Predicted Ra*	*Validated Ra*		
	m/min	*mm/rev*	*mm*	*cm³/min*	*μm*	*μm*	*μm*	*μm*
*1**	*120*	*0.12*	*0.50*	*7.2*	*3.204*	*3.341*	*3.325*	*3.310*
2	110	0.12	0.50	6.6	2.904	3.028	3.015	3.000
3	90	0.14	0.50	6.3	3.013	3.131	3.118	3.112
4	120	0.10	0.50	6.0	2.495	2.610	2.603	2.577
5	100	0.12	0.50	6.0	2.604	2.714	2.706	2.690
…								
15	120	0.10	0.40	4.8	2.373	2.479	2.470	2.460
16	100	0.12	0.40	4.8	2.482	2.582	2.573	2.572
17	110	0.12	0.35	4.6	2.720	2.830	2.816	2.824
18	90	0.10	0.50	4.5	1.596	1.669	1.675	1.647
…								
36	110	0.10	0.25	2.8	1.889	1.968	1.962	1.973
37	90	0.12	0.25	2.7	1.998	2.071	2.064	2.085
38	100	0.10	0.25	2.5	1.589	1.654	1.652	1.663
39	90	0.10	0.25	2.3	1.290	1.340	1.343	1.353

Note: *excluded.

In the validation activity for the MQL condition, as presented in Table 7, cutting condition number 1 with the highest *MRR* for productivity improvement (7.2 cm^3/min) failed and was excluded from the final solution. This is because the validated Ra values from three times of re-hard turning validation activity were higher than the predicted Ra and also out of the gauge.

4 Conclusions

This study successfully integrates RSM and ML techniques to optimise the hard turning of AISI 4340 steel, demonstrating significant enhancements in productivity and surface quality. The key findings reveal that integrating RSM and ML allowed for precisely identifying optimal cutting conditions. Under MQL, the process achieved a minimum surface roughness (Ra) of 1.297 µm and a maximum MRR of 7.2 cm^3/min. For dry conditions, the optimal MRR was recorded at 5.2 cm^3/min, with Ra maintained within the acceptable range.

The cutting feed emerged as the most critical factor influencing Ra. This insight is crucial for setting parameters that balance productivity and surface quality.

The ML model, specifically LR, accurately predicted Ra for various cutting conditions. The model was assessed using MSE and RMSE, with lower values indicating better performance. The MSE and RMSE values were 0.124 and 0.352 µm, respectively, for the dry condition and 0.173 and 0.416 µm for the MQL condition. The coefficient of determination (R^2) values were 0.9662 for the dry condition and 0.9638 for the MQL condition. This indicates that the model explained about 96% of the variability in Ra, confirming the model's reliability and effectiveness.

The baseline conditions provided by the industrial partner included a cutting speed of 60 m/min, feed rate of 0.1 mm/rev, and depth of cut of 0.2 mm, resulting in an MRR of 1.2 cm^3/min and Ra ranging from 1.6 to 3.2 µm. The optimised conditions identified in this study significantly improved these metrics. The highest MRR of 7.2 cm^3/min was obtained under MQL conditions at a Ra of 3.2 µm. For dry condition, the maximum MRR recorded was 5.2 cm^3/min, with Ra maintained within the acceptable range.

However, the study has limitations that warrant further investigation. The focus on AISI 4340 steel and uncoated carbide tools may need to be fully generalised to other materials and tool types. Future research should explore a broader range of materials and tool types and validate the findings in diverse industrial settings to enhance the robustness and applicability of the optimisation framework.

Finally, this study demonstrates a robust method for optimising hard turning processes, significantly improving productivity and surface quality. The integration of RSM and ML techniques provides a valuable tool for the manufacturing industry, paving the way for further advancements in machining optimisation.

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