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Experimental analysis and machine learning with IoT monitor in two-way abrasive flow machine polishing on P20 mold components

Theerapong Maneepen[1], Parinya Srisattayakul[2], Narong Mungkung[3], Wittawat Poonthong[4], Tanapon Tamrongkunanan[5]

[1]Program in Engineering and Technology Management, Faculty of Engineering, Rajamangala University of Technology Krungthep, 10120, Thailand, 659041810089@mail.rmutk.ac.th (T.M.)
[2]Department of Industrial Engineering, Faculty of Engineering, Rajamangala University of Technology Krungthep, 10120, Thailand; parinya.sr@mail.rmutk.ac.th (P.S.)
[3]Faculty of Industrial Education and Technology, King Mongkut's University of Technology Thonburi, 10140, Bangkok, Thailand; narong_kmutt@hotmail.com (N.M.)
[4]King Mongkut's University of Technology Thonburi, Thailand; (KMUTT), 10140; poonthong.golf2538@gmail.com (W.P.)
[5]King Mongkut University of Technolgy Thonburi, Thailand; nathwut.kow@kmutt.ac.th (T.T.)

Abstract: The purpose of this paper was to reveal the effects of pressure and time on the surface roughness (Ra) and compare the experimental design (Factorial Regression) and machine learning (ML) of steel mold workpieces. Methodology began with turning, and fine sandpaper P180 to P1200 and measured with an initial value of Ra compared with the final value of Ra at the end of the two-way prototype AFM process. The process parameters are as follows; abrasive particle size (alumina; Al_2O_3) 5.0 μm in Silicone Oil (concentration 50% by weight) at pressures (p) of 10 bar and 20 bar, processing time (t) 5, 15, and 25 min, specimens P20 Mold steel. The experimental results show that under these conditions. The average surface roughness of the specimens differed from the initial value by Ra 0.034 to 0.021 μm, with delta values ranging from 0.011 μm to 0.005 μm. The results showed a smoother profile between before and after polishing. The approach to the topic is DOE and ML, and the theoretical or subject scope of the paper is Statistical and AI. The original value of the paper is applied to the ESP32 Arduino to control and display critical parameters. A General Factorial Regression statistical value of 76.39% is acceptable. A pressure factor of 20 bars and a time of 25 minutes gives the best effect on surface roughness. ML assisted in predicting the Surface Roughness for optimization based on the experiment.

Keywords: *Abrasive flow machining (AFM), Factorial regression, Machine learning (ML), Polishing, Surface roughness (SR).*

1. Introduction

The systematic investigation of factors influencing the abrasive flow machining (AFM) process and its outcomes: AFM typically involves investigating the effects of two critical factors or process parameters on the performance metrics of interest. These factors can include Pressure applied to the abrasive media, Media flow rate, Abrasive particle concentration in the media, Cycle time, or number of cycles. The goal is to understand how varying these key input factors impacts the output responses such as Surface finish quality (e.g. roughness), Material removal rates, and Other performance metrics like deburring capability. By systematically studying the effects of changing pressures, flow rates, abrasive concentrations, cycle times, etc., researchers and manufacturers can optimize the AFM process to achieve the desired surface characteristics, material removal rates, and overall process efficiency on complex internal geometries and workpiece materials.

* Correspondence: parinya.sr@mail.rmutk.ac.th

The formation of a dispersive particle phase under pressure facilitates particle-surface interactions that govern the material removal mechanisms in AFM. Experiments have demonstrated widely varying removal rates based on the input factors investigated. In essence, understanding the relationship between critical AFM input parameters and output performance is crucial for process control and achieving the intended surface quality/geometry specifications (J.J. Hann, P.S. Steif, 1998) [1]. AFM was polishing the contemporary and small removal surfaces with the flow of the slurry medium. The abrasive flow machining process provides a high level of surface finish. It closes tolerances with an economically acceptable rate of surface generation for a wide range of industrial components (Rajendra K. Jain, Vijay K. Jain, P.M. Dixit, 1999) [2].

AFM was the high-end cutting process with deburring, radius, polish, removal recast layer, and made compressive residual stresses. This process was widely used in the 1960s and was interesting in consistency production and prediction of results output. AMS process was developed by Extrude Hone Co., ltd. in 1996. Process Parameters mention the orbital amplitude to find the material removal rate in higher amplitudes yielding, higher material removal rates but the orbital amplitude must not be bigger than the minimum internal feature of the workpiece. To find the material removal rate must focus on both the oscillation speed and the orbital amplitude and not get the effect from the geometrical dimension of the workpiece between 400 to 1200 RPM (Jun Wang, et all, 1999) [3]. High-precision abrasive flow machining has two sub-systems: a high-viscosity media; the range of between 150-1,000,000 centipoise a viscous-elastic-plastic media (a semisolid polymer composition) and a low-viscosity media; 1-50 centipoise was a liquid abrasive slurry involve to abrasive uspended or slurried in fluid media by cutting fluids of honing fluids consisted of a thixotropic slurry plus a rheological additive and finely divided abrasive particles incorporate therein with mixed pressure and flow between 4,000 psi. V.K. Jain, and S.G. Adsul, 2000 [4] this research study on the effects of parameters of the different processes of AFM such as the number of cycles, the concentration of abrasive, abrasive mesh size, and media flow speed. Study in material removal and surface finish. To find the dominant parameters such as medium percentage concentration, abrasive media mesh size, cycle time or machining time, and speed of media flow. Test with Brass and Aluminum by comparing experimental and theoretical of workpiece surface with Scanning electron microscopy: SEM, experiment on Lath by setup on turret steady rests so that Parameter planning is shown in Table 1 (Geoffrey Boothroyd, 1996) [5]. Neelesh K. Jain, V.K. Jain, Kalyanmoy Deb, 2007, "Optimization of process parameters of the mechanical type advanced machining processes using genetic algorithms" to study between 4 processes; USM, AJM, WJM, AWJM (Neelesh K. Jain, V.K. Jain, Kalyanmoy Deb, 2007) [6]. AFM and Stereolithography (SL), to minimize the time to develop a finished prototype, simulation, and neural network. Results indicated that media pressure, grit size, percentage concentration, reduction ratio, and build orientation were significant [7], [8], [9]. The results of Rotating Abrasive flow finishing (R-AFF) show that the rotational speed of the workpiece has a significant effect on delta Ra [10]. The material removal rate model and the maximum error between theoretical and experimental values is 13.1% Cconsistent with the experimental results of S.M. Basha, et. Al., [13, 14]. Demonstrates good production efficiency. There are many types of materials and shapes (complex holes [21, 32]) used in past experiments such as Mild steel [15, 18], AISI D2 [22], Bevel gear [25], and SLM [31, 33], ABS LM and PLA parts [35]. Simulation with models, such as NN, models, to predict polishing results [16, 24, 27, 30, 34]. Using a magnetic field to help with polishing, such as [17, 23, 28]. Use ultrasonication in experiments such as [26]. As well as using the rotation of the workpiece while experimenting, including [19, 20]. Wear [29].

The development of a precise and convenient two-way abrasive flow machining setup for achieving high surface smoothness: The goal was to develop a specialized machine for polishing workpiece surfaces to a high degree of smoothness through the unidirectional flow concept of abrasive media. This involved relying on knowledge and skills to create and optimize such a machine setup. The application differed from previous research by focusing on the use of a two-way flow approach. Experiments were conducted using an abrasive media consisting of aluminum oxide mixed with silicone oil. Key aspects included integrating inspection sensors for monitoring parameters like pressure or flow rate, which would be further developed. Due to the high construction costs, a prototype underwent development stages. The effects of the clearance between the specimen and tooling on the surface roughness (Ra) of P20 mold steel were investigated. Factorial regression statistical principles were applied to analyze the results and achieve the desired surface roughness specifications. Additionally, experimental findings were compared with machine learning (ML) models to validate the approach. The overall objective was to obtain insights that would aid in further improving and differentiating the prototype unidirectional abrasive flow machining setup for precise surface polishing applications.

Table 1. Improvement in Process parameters of Abrasive flow machining (Nitin Dixit, et. al., 2021) [11, 12]

2. Materials and Methodology

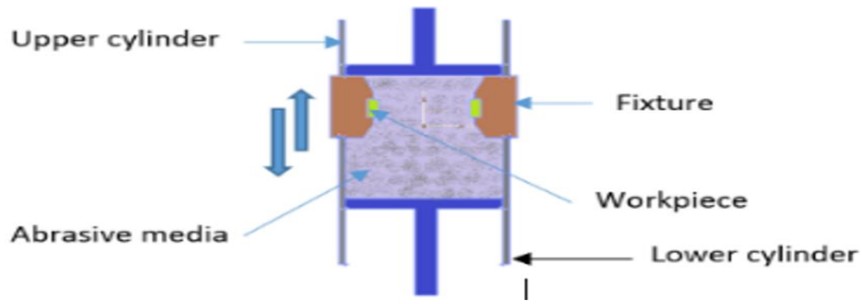

Figure 1.
Schematic of the Two-way prototyping AFM.

2.1. *Experimental Set-Up*

The experimental setup of the power plant is driven by bi-directional hydraulics. As shown in Figure 2, it has been designed and developed to be able to store the abrasive in each cylinder from two cylinders so that it can work in two directions to continuously polish the workpiece. Hold the workpiece with a C-Clamp, there is a seal to withstand the pressure of the polishing system.

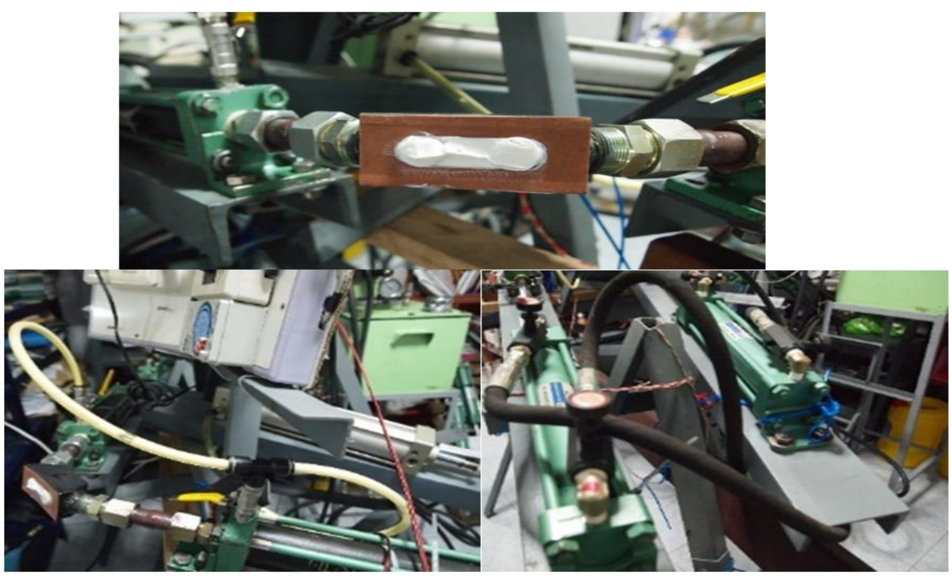

Figure 2.
Shows the prototyping AFM machine.

2.2. Workpiece and Medium

Figure 3.
The workpiece, AFM nozzle, and abrasive media (Al_2O_3+Silicon Oil).

2.3. Experimental Procedure

Steps followed: A step-by-step guide on how might conduct experimental two-way AFM:

1. Define Objectives: Trying to optimize surface finish

2. Identify Factors: Select two key factors to study. These could be, pressure (p) and cycle/processing time (t).

3. Define Factor Levels and Experimental Design: Determine the levels for each factor. For instance, choose two levels of pressure (10, 20 bar) and three levels of cycle time (t) (5, 15, and 25 min.) Use a factorial experimental design to systematically combine the different levels of the two factors. For a full factorial design, test all possible combinations of factor levels (Minitab 19).

4. Conduct Experiments: Implement AFM experiments for each combination of factor levels. Ensure that the experiments are conducted under controlled and consistent conditions. Prepare the workpiece surface with sandpaper from P40 to P1200. To measure initial surface roughness (SR); Ra micron before AFM process. To polish by AFM prototype within cycle time ranges of 5, 15, and 25 minutes consequently.

5. Data Collection: Measure and record the responses of interest after each experiment. This could involve quantifying surface roughness, or assessing other relevant performance indicators. To measure surface roughness after being polished by AFM (Final SR). To measure the raw profile and modified profile of the workpiece with the surface roughness machine (Olympus).

6. Statistical Analysis: An analysis of variance (ANOVA), to analyze the data. This will help identify significant main effects and interactions between the two factors. Here are some common statistical analyses used in AFM: 1) Regression Analysis: Regression analysis is used to model the relationship between independent variables (e.g., process parameters) and dependent variables (e.g., surface roughness). By performing regression analysis, researchers can quantify the effect of each factor on the response variable and develop predictive models for AFM processes. Regression analysis can help optimize process parameters and predict the expected outcome of AFM based on given input variables. 2) Design of Experiments (DOE): DOE involves planning and conducting a set of well-designed experiments to evaluate the effects of different factors and their interactions. By using statistical

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analyses like ANOVA and regression analysis, researchers can identify significant factors, optimize process parameters, and understand their impact on AFM performance. Applying statistical methods in AFM research helps in data-driven decision-making and the continuous improvement of the machining process.

7. Validation: Validate your findings by conducting additional experiments or using a separate dataset. This ensures the reliability and generalizability of results.

8. Interpretation and Conclusion: Interpret the results in the context of objectives. Conclude the effects of the selected factors on the AFM process.

9. Documentation and Reporting: Document the experimental setup, procedures, and results thoroughly. Prepare a comprehensive report or presentation summarizing findings. By systematically varying two key factors and observing their effects on the AFM process, can gain valuable insights into the optimization and performance characteristics of AFM for specific objectives.

3. Results and Discussion

3.1. Roughness and Profile Detection

The results of the experiment were as follows: Displays Figure 4 the relationship between surface roughness; (micron) and polishing with AFM prototype at 10 bar, 20 bar, and interval time from 0 to 5, 15, and 25 minutes step by step consequently.

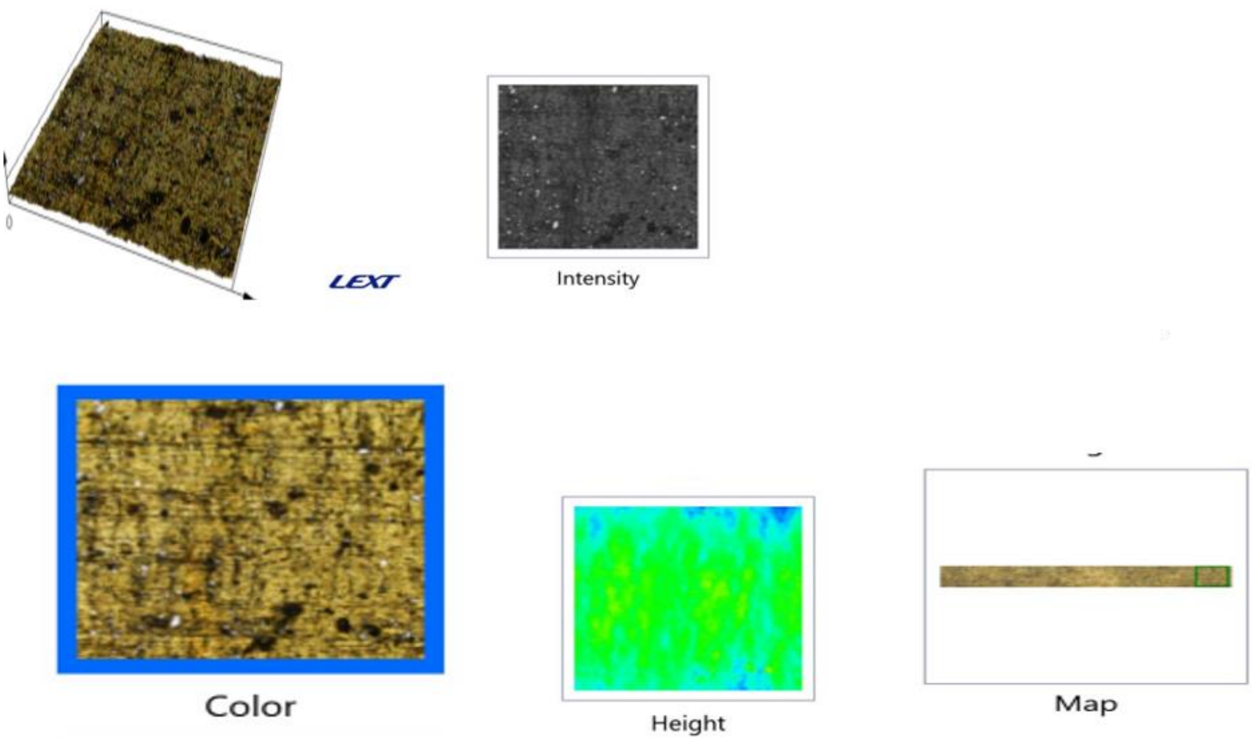

Figure 3.
The surface roughness 3D polishing.

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Table 2.
Run order and results with MiniTab 19.

↓	C1 StdOrder	C2 RunOrder	C3 PtType	C4 Blocks	C5 pressure	C6 time	C7 delta SR
1	7	1	1	1	10	5	0.005
2	2	2	1	1	10	15	0.006
3	11	3	1	1	20	15	0.008
4	3	4	1	1	10	25	0.007
5	1	5	1	1	10	5	0.005
6	9	6	1	1	10	25	0.008
7	12	7	1	1	20	25	0.010
8	18	8	1	1	20	25	0.011
9	14	9	1	1	10	15	0.005
10	17	10	1	1	20	15	0.009
11	5	11	1	1	20	15	0.007
12	15	12	1	1	10	25	0.007
13	4	13	1	1	20	5	0.006
14	16	14	1	1	20	5	0.007
15	13	15	1	1	10	5	0.004
16	8	16	1	1	10	15	0.006
17	10	17	1	1	20	5	0.007
18	6	18	1	1	20	25	0.008

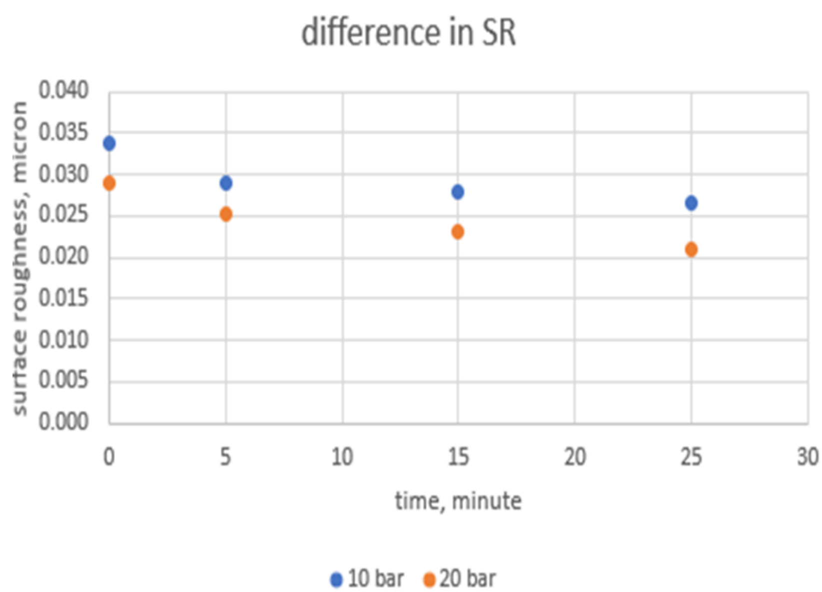

Figure 4.
Difference in surface roughness before and after polishing with the AFM prototype.

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Table 3.
Results delta SR, time 5, 15, and 25 minutes.

10 bar		20 bar	
Time	**Delta SR**	**Time**	**Delta SR**
5	0.005	5	0.006
	0.006		0.007
	0.007		0.008
15	0.005	15	0.007
	0.006		0.008
	0.008		0.010
25	0.004	25	0.007
	0.005		0.009
	0.007		0.011

Table 3 displays the relationship between surface roughness; (micron) and polishing with AFM prototype at 10 bar, 20 bar, and interval time 0 to 5, 15, and 25 minutes.

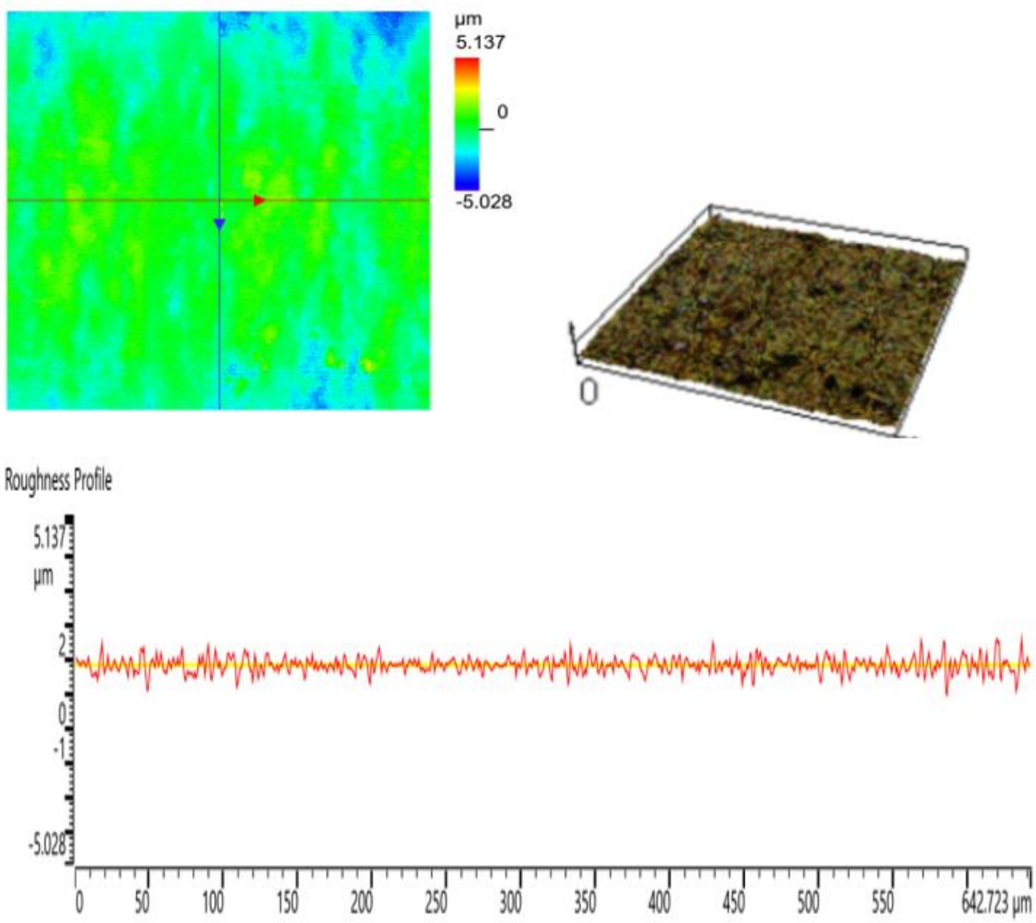

Figure 5.
Displays the Initial profile and final profile of the workpiece that was polished 25 minutes.

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Figure 6.
ESP32 arduino controller (SWU).

This ESP32 Arduino control kit was developed to control the operation of the control system, and sensors to measure pressure, temperature, etc., as well as collect results, analyze, monitor, and summarize the results of the prototype.

3.2. Statistical Analysis and Discussion

Design of Experiments (DOE) is a systematic approach used to optimize process parameters in Abrasive Flow Machining. By conducting a DOE, researchers can identify the optimal combination of factors that will yield the desired surface finish, material removal rates, or other performance measures.

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General Factorial Regression: delta SR versus pressure, time

Factor Information

Factor	Levels	Values
pressure	2	10, 20
time	3	5, 15, 25

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	5	0.000047	0.000009	12.00	0.000
Linear	3	0.000047	0.000016	19.95	0.000
pressure	1	0.000022	0.000022	28.57	0.000
time	2	0.000024	0.000012	15.64	0.000
2-Way Interactions	2	0.000000	0.000000	0.07	0.931
pressure*time	2	0.000000	0.000000	0.07	0.931
Error	12	0.000009	0.000001		
Total	17	0.000056			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
0.0008819	83.33%	76.39%	62.50%

General Factorial Regression: delta SR versus pressure, time

Factor Information

Factor	Levels	Values
pressure	2	10, 20
time	3	5, 15, 25

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	5	0.000047	0.000009	12.00	0.000
Linear	3	0.000047	0.000016	19.95	0.000
pressure	1	0.000022	0.000022	28.57	0.000
time	2	0.000024	0.000012	15.64	0.000
2-Way Interactions	2	0.000000	0.000000	0.07	0.931
pressure*time	2	0.000000	0.000000	0.07	0.931
Error	12	0.000009	0.000001		
Total	17	0.000056			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
0.0008819	83.33%	76.39%	62.50%

Figure 7.
Factor information and ANOVA.

The results of the analysis are shown as follows. The analysis of the variance table shows that the P-value is less than 0.05, indicating that Pressure and Time significantly affect the response. The correlation coefficient (r2) can be found in the regression analysis chapter where R-Sq(adj) = 76.39%, less than 70% is considered acceptable.

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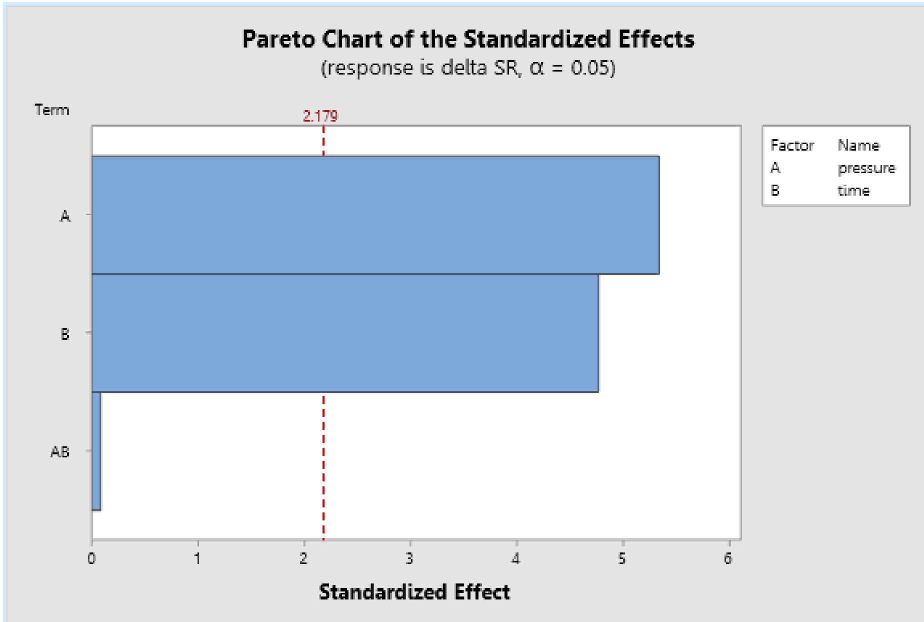

Figure 8.
Pareto chart of the standard effects.

The relationship equation between factor and response is. Graph Pareto, notice that the bar graph of factors A, and B is past the critical line, indicating that they all have a significant effect on the results. The error variance is uniform. Independence is a characteristic of a good control plan. Main effect graph; factors, pressure, and time affect SR. Where a pressure factor of 20 bar and a time of 25 minutes give the best effect on surface smoothness.

Regression Equation

delta SR = 0.007000 - 0.001111 pressure_10 + 0.001111 pressure_20 - 0.001333 time_5
- 0.000167 time_15 + 0.001500 time_25 + 0.000111 pressure*time_10 5
- 0.000056 pressure*time_10 15 - 0.000056 pressure*time_10 25
- 0.000111 pressure*time_20 5 + 0.000056 pressure*time_20 15
+ 0.000056 pressure*time_20 25

Figure 9.
Regression equation for general factorial regression.

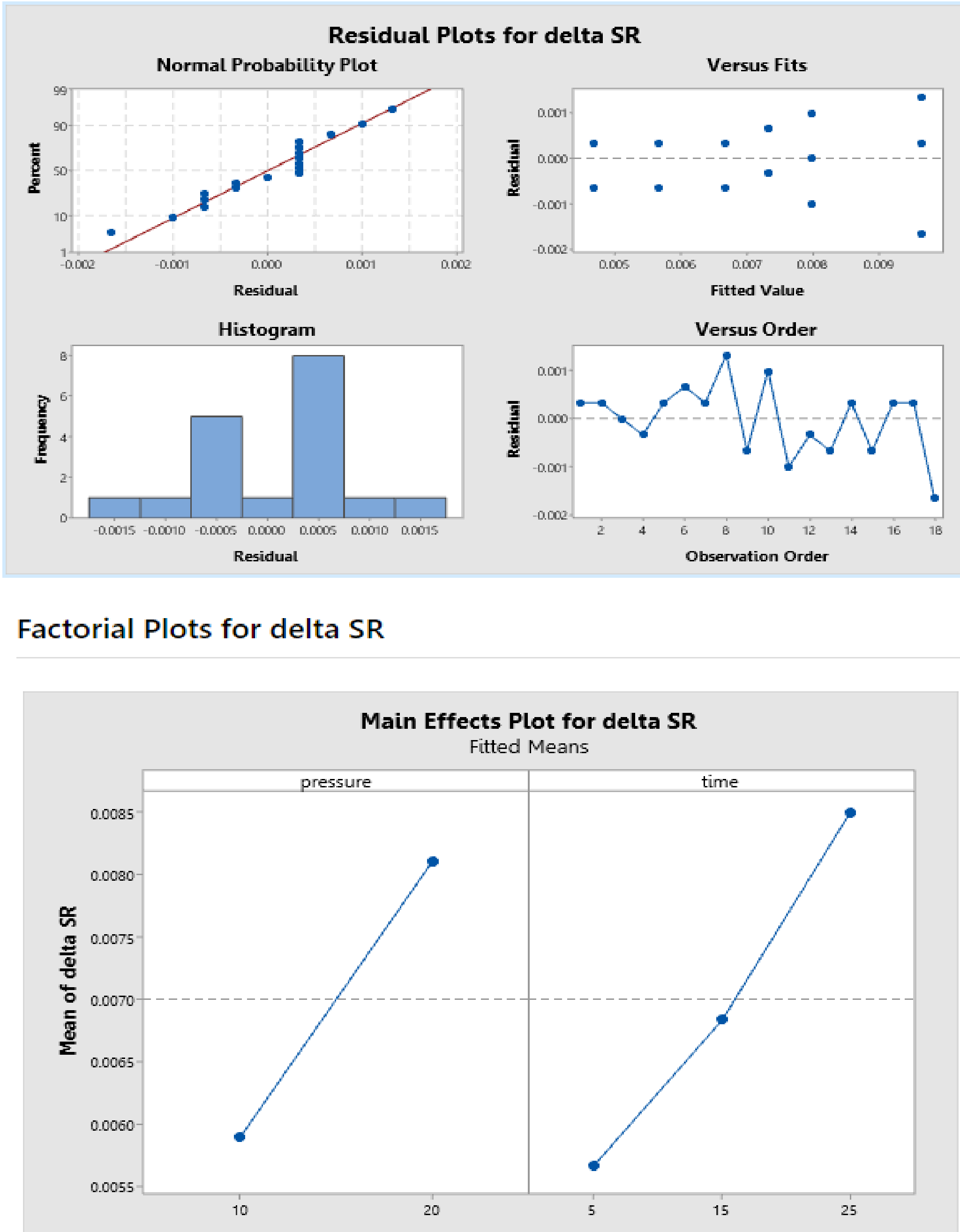

Figure 10.
Residual Plots & Main Effects Plot for Δ SR.

Relationship equation of factors and responses error analysis Check the normal distribution of the error values. The data has a normal distribution of error values.

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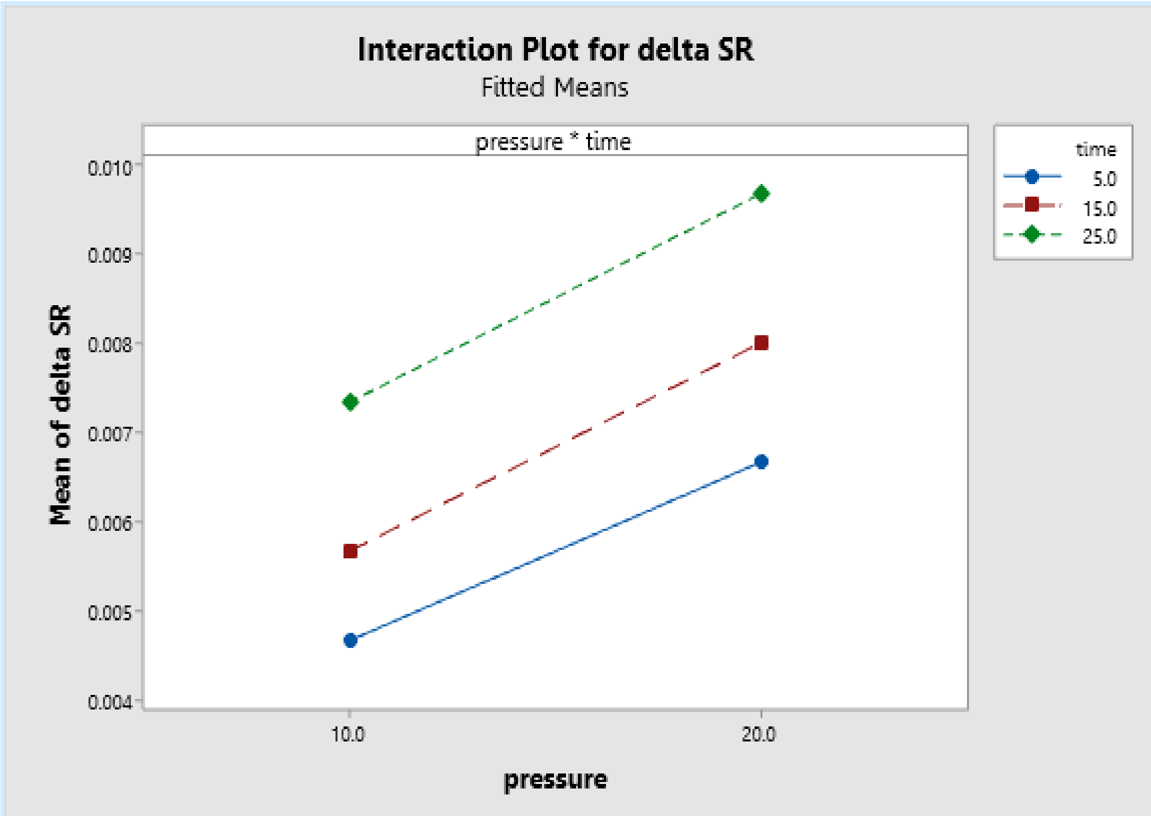

Figure 11.
Display linear model and related graphs.

Figure 11 illustrates the pressure and time data and Linear model results for SR. The delta Ra value tends to increase in line with the increase in pressure.

3.3. Machine Learning Prediction

Machine Learning Prediction with the Rapid Miner program to make predictions about expected experiment results from actual experimental results to compare with predictions. To make the selection of various parameters more accurate. The linear regression function is used with a flow chart and select attributes process Figure 12.

The sub-work steps that turn raw data into knowledge. It consists of the following steps: Data Cleaning, Data Integration, Data Selection, Data Transformation, Data Mining, Pattern Evaluation, and Knowledge representation. Input data from Minitab 19, and the result shows the prediction (Delta SR) Figure 13-14 and apply model, parameters; pressure, time, delta SR, and Cross-Validation as shows in Figure 15.

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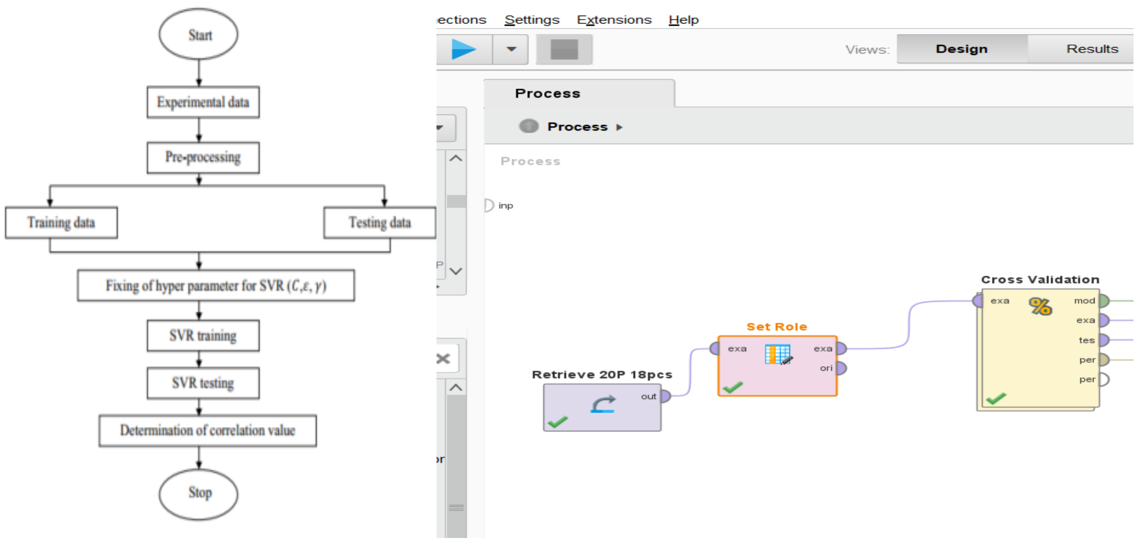
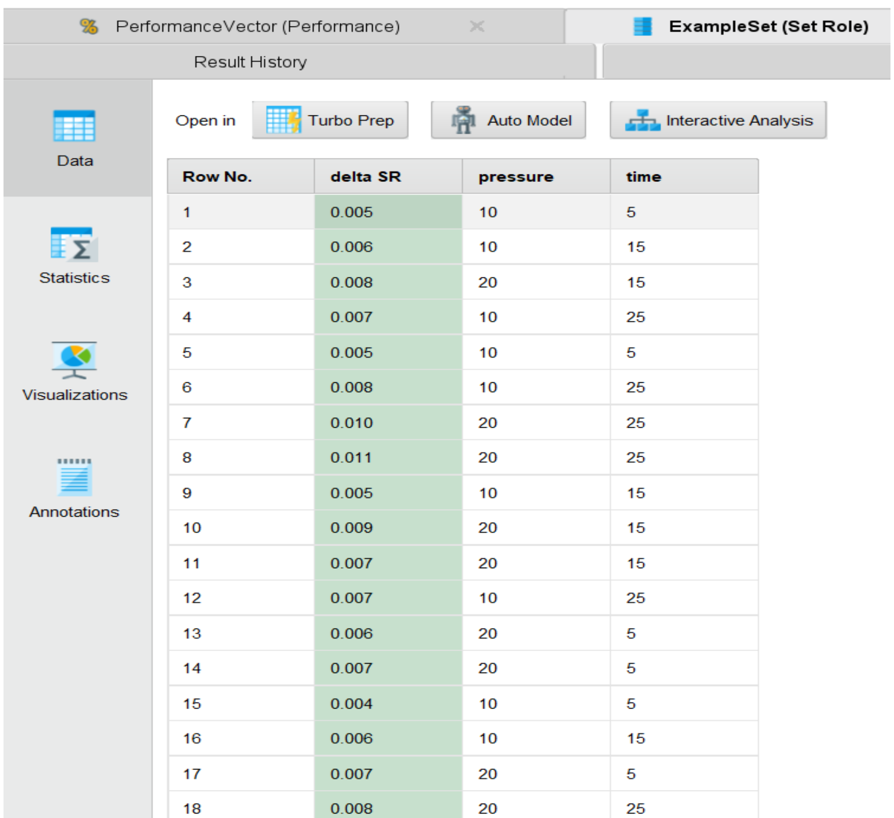
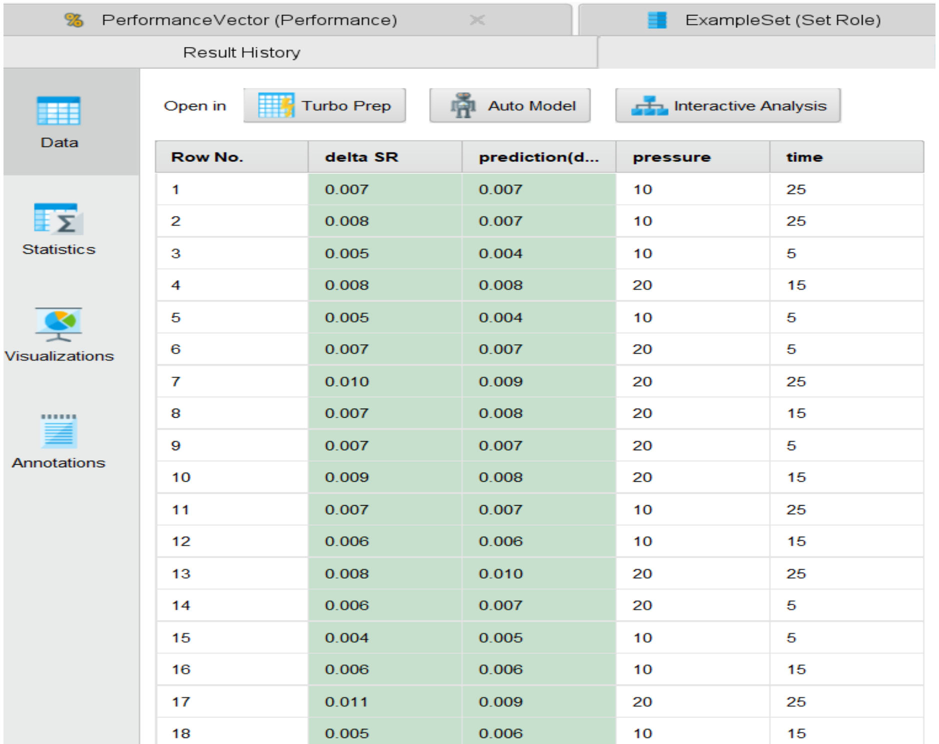


Figure 12.
Flow chart of a standard SVR model and select attributes process.



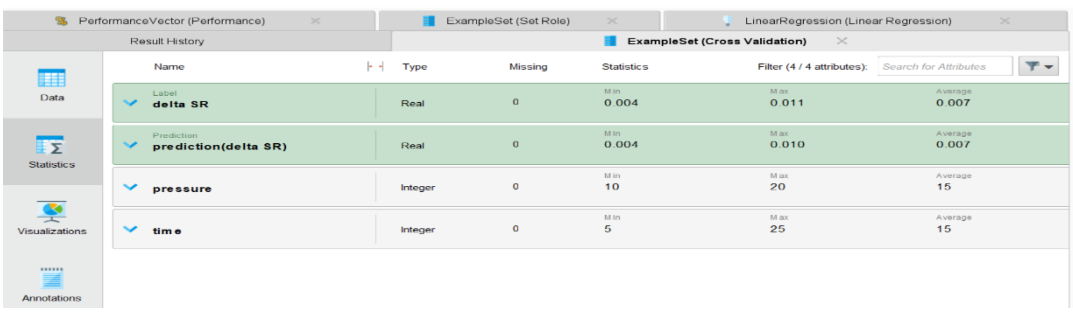
Row No.	delta SR	pressure	time
1	0.005	10	5
2	0.006	10	15
3	0.008	20	15
4	0.007	10	25
5	0.005	10	5
6	0.008	10	25
7	0.010	20	25
8	0.011	20	25
9	0.005	10	15
10	0.009	20	15
11	0.007	20	15
12	0.007	10	25
13	0.006	20	5
14	0.007	20	5
15	0.004	10	5
16	0.006	10	15
17	0.007	20	5
18	0.008	20	25

Figure 13.
Input data from Minitab 19 and Prediction (delta SR).



Row No.	delta SR	prediction(d...	pressure	time
1	0.007	0.007	10	25
2	0.008	0.007	10	25
3	0.005	0.004	10	5
4	0.008	0.008	20	15
5	0.005	0.004	10	5
6	0.007	0.007	20	5
7	0.010	0.009	20	25
8	0.007	0.008	20	15
9	0.007	0.007	20	5
10	0.009	0.008	20	15
11	0.007	0.007	10	25
12	0.006	0.006	10	15
13	0.008	0.010	20	25
14	0.006	0.007	20	5
15	0.004	0.005	10	5
16	0.006	0.006	10	15
17	0.011	0.009	20	25
18	0.005	0.006	10	15

Figure 14.
Input data from Minitab 19 and Prediction (Delta SR). (Cont.).



Name	Type	Missing	Statistics		
Label delta SR	Real	0	Min 0.004	Max 0.011	Average 0.007
Prediction prediction(delta SR)	Real	0	Min 0.004	Max 0.010	Average 0.007
pressure	Integer	0	Min 10	Max 20	Average 15
time	Integer	0	Min 5	Max 25	Average 15

Attribute	Coefficient	Std. Error	Std. Coefficient	Tolerance	t-Stat	p-Value	Code
pressure	0.000	0.000	0.630	1	5.864	0.000	****
time	0.000	0.000	0.656	1	6.104	0.000	****
(Intercept)	0.002	0.001	?	?	2.225	0.042	**

Figure 15.
Apply model; pressure, time, delta SR, and cross-validation.

Performance Vector; Root mean squared error: 0.001 ± 0.001 (micro average: 0.001 ± 0.000)

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4. Conclusions

The experiment of workpiece polishing mold steel. Steps follow to prepare the workpiece surface, measure initial surface roughness before and after the AFM process, and profile of surface. The result is that pressure is 10 bar, 20 bar consequently and time range 5, 15, and 25 minutes:

Pressure 10 bar; the difference before and after of average SR, trend to decrease. The difference; The difference; is delta 0.006 to 0.011 µm. Pressure 20 bar; the difference before and after of average SR, trend to decrease. The value of before and after of average surface roughness middle and trend to decrease surface roughness value (Ra) from 0.034 to 0.021 µm. More pressure will affect the surface roughness that able to produce a difference in surface roughness that is greater as a result, a smooth surface can be obtained in a faster time and closer to the required surface roughness SR. That increases with the number of cycles and extrusion pressure, whereas it decreases with the increase in abrasive mesh size.

- Statistics Factorial Regression obtained from experimental results It was found that there was a significant difference at 0.05 of the pressure, and time, especially at a pressure of 20 bar and a time of 25 minutes, gave the best results.
- Machine Learning Prediction with the Rapid Miner program to make predictions about expected experiment results from actual experimental results to compare with predictions. To make the selection of various parameters more accurate. Performance Vector; Root mean squared error: 0.001 ± 0.001
- The results of AFM demonstrate its effectiveness in achieving high-quality surface finishes and the overall surface integrity of the workpiece. Surface roughness measurements provide quantitative data on the achieved surface quality and machining efficiency. It is the prototype to drive the abrasive media to achieve finer control of the variables to develop more precision in the subsequent generation development and develop a polishing control system that uses intelligence to work with a sensor system using AI technology. This can be further applied to industrial work for internal and precision processing prospects. This is to provide basic information for further development of the prototype AFM machine for increased efficiency for use in the country and region in the future.

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