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with article entitled "A Review of Response Surface Methodology Approach in Achieving Multi-Response Setup Optimisation in The Machining Proces"

Authored by : Yohanes Tri Joko Wibowo, Nurhadi Siswanto, M. Suef

at The 2nd International Conference On Engineering and Management in Industrial System (ICOEMIS) 2022 organized by Industrial Engineering Department, Faculty of Engineering, Universitas Brawijaya in Malang, 5th October 2022

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HEAD OF INDUSTRIAL ENGINEERING DEPARTMENT
FACULTY OF ENGINEERING UNIVERSITAS BRAWIJAYA

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A REVIEW OF RESPONSE SURFACE METHODOLOGY APPROACH IN ACHIEVING MULTI-RESPONSE SETUP OPTIMISATION IN THE MACHINING PROCESS

by Yohanes Tri Joko Wibowo

Submission date: 08-Sep-2022 08:38AM (UTC-0400)
Submission ID: 1895066632
File name: Full_Paper_ICOEMIS_Yohanes_Tri_Joko_Wibowo_Rev_NS.pdf (559.07K)
Word count: 6300
Character count: 31100

A REVIEW OF RESPONSE SURFACE METHODOLOGY APPROACH IN ACHIEVING MULTI-RESPONSE SETUP OPTIMISATION IN THE MACHINING PROCESS

Yohanes T. Wibowo[1,2], Nurhadi Siswanto[1], M. Suef[1]
Department of Industrial and Systems Engineering, Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia[1]
Department of Mechanical Industry Engineering, Astra Polytechnic, Jakarta, Indonesia[2]

Abstract *A process machining cost is constructed on many factors. All aspects potentially raise the additional charges resulting from not achieving dimension or the lack of surface roughness due to tool wear level are avoided. The accuracy of parameters determines the effectiveness of the machining process. However, these parameters are sensitive, so the different machines may not provide the same performance. The specific machining parameters become less suitable for others. This experimental approach is proposed to obtain the parameter used on other machines without reducing the performance. This multi-response study used a response surface methodology by selecting the material removal area, feed rate, spindle speed, and the number of repetitions as input have a dominant influence on the tool wear and the dimension deviation. A comprehensive range with the specified target is obtained by applying different weights. Testing on 11 units of machines from 3 other countries provides the same performance.*

Keywords*: machining parameter, multi response optimisation, tool wear, dimension deviation*

1. Introduction

Quality is one of the fundamental and essential factors in the production process. Quality connects the voice of business with the voice of the customer (1). Quality generally relates the company with other actors to support business activities in the manufacturing world. To help the manufacturing process, companies need industrial machines to carry out the machining process and make products according to customer needs. It takes customers who need and buy the product to make a profit. It clearly explains the relationship between industry, customers, and machining processes. In summary, a good machining process that meets quality standards and requires a short processing time must be achieved. In the machining process, many topics are ready to use for discussion. By reviewing the process actors, quality standards, the processing time required, and the interaction between these things, fulfilling the factors according to the objectives can be better fulfilled. The modeling study consists of these factors.

Objectives in manufacturing companies are quality, cost, and delivery. They are the components of products and services (2). Along with the times, the objective is defined as quality, speed, and cost as a project management triangle.

Then narrowed again as an economic purpose consisting of survival, profit, and earning (3). In a more operative word, quality is described as short processing time, good results that meet technical demands, and low costs. The industry should understand customer tends to purchase quality products at timely and appropriate prices. In simple words, the industry must provide competitive advantages. Therefore, real-life problem solutions often aim to find less expensive, more effective ways of production and another trade of technical requests without compromising or even sacrificing product quality. In the machining world, many things support the achievement of economic purpose. By matching technical standards and minimizing the dimension deviation in the machining process, industrial existence can be maintained. The level of cutting tool wear is also a different matter but supports the achievement of dimension deviation. This industrial objective can be taken through the stages of the optimization process.

Optimization of the machining process through research models has been widely carried out. The optimization process used Various approach techniques. They will keep being used in line with

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Paper Accepted : ....
Paper Published : ....

e-ISSN XXXX-6025
DOI 10.XXXXX

the more advanced equipment, the more multiple tools and machines, and the development of technology. Milling machines that have been numerically controlled are industrial machines widely used as optimization objects. The consideration of Milling machines is due to their low energy efficiency (4) and high population (5,6). Milling machines' general efficiency is around 14.8% (5). Taking this into account, the optimization of milling machines in the machining process in the manufacturing world is an urgent matter to be addressed immediately (7,8).

Both companies and experts always carry through to achieve this goal using mathematical and statistical optimization techniques. In previous studies, several optimization methods used were empirical studies, meta-heuristics methods, response surface methodology, and other methods. In research, the model setup is specific, so the research results are also specific. The implication is that implementing optimization results is not generally so that positive research results greet the public less through their contributions. The higher variation of the machine and the narrowness of the research object create gaps that impact the need to redo the optimization process for each type of CNC milling machine. This activity will undoubtedly lead to research inefficiency because the broadness of science does not develop. In a situation like this, it is necessary to conduct a study that can carry out an optimization process that can accommodate variations in the types and capabilities of machines in a manufacturing process.

A known statistical and mathematical technique used to be employed for modeling and optimizing experimental design is Response Surface Methodology (RSM) (9). It is very sophisticated in optimization tools since it takes only a tiny amount of experimentation. Besides, it can model and optimize the data. Usually, the researchers use this tool in an experimental laboratory to find the optimum yield or reaction. However, RSM can also be used in engineering applications, management studies (10), and simulation optimization of the multi-line of production (11). Some studies also have used RSM in cutting parameter variation-based machine optimization. Still, it will be reviewed in the next chapter of this article how perfect the RSM as a statistical and mathematical tool modeling to optimize machine process problems in a multi response and multi machines nowadays.

In the following section, RSM will be explained in machine optimization research and how important it is. Also, there would be a numerical experiment using case studies of how response surface modeling should be used in the machine optimization scope. Considering how the different machine responses come from both of the same and different ones in a specific cutting parameter is a probabilistic problem that will lead us to why RSM in machine optimization research is an interesting topic to be reviewed.

Streams on Optimisation

The related research in the manufacturing industry optimization is divided into three streams with different focuses. The first stream is machining optimization through the machining variable variation approach to get the optimal point in the machining process. The second stream is research that uses specific optimization methods, such as mathematical methods for single or multi-objectives. At the same time, the third group focuses on general cutting tool condition variables and typical cutting tool wear. Although there are three streams, researchers often switch streams in each publication. In general, the stream is not visible, but it is clearly visible in research publications. One commonality that becomes the red line of the three streams is that all optimization research has an objectivity that revolves around fulfilling quality, reducing costs, or reducing time.

The first stream begins with research that shows a relationship between variations in machining parameters and power consumption, and the level of wear and tear of cutting tools or the service life of cutting tools (12). Further publications on parameter optimization using the response surface methodology stated that machining parameters are essential things that have been neglected (13). Extending the research, the experimentation suggested that setting the spindle speed can reduce energy costs (14) in the CNC turning machining process (15). The online monitoring system model was first introduced in an empirical study that pays attention to the objective function of surface roughness (15). The monitoring system is confirmed in his research (16). Cutting parameters stated that changes in spindle speed affect energy consumption (17), which continued that process planning

e-ISSN XXXX-6025
DOI 10.XXXXX

and machining parameters affect operational costs (18). This is in line with what the researcher stated in his writing that the variation of parameters affects the machining results or product quality on various machines (19). In another study, the Nelder-Mead technique was used through various parameters for the optimization process (20). The researchers can also apply the management of cutting parameters for optimization processes to milling machines in general and micro milling in particular (21). The summary above summarizes the first stream in the engine optimization process.

In his research, a process of minimizing machining time was carried out to reduce energy consumption in milling machines using the genetic algorithm optimization method (22). The researchers adopted this model for another machine, namely the turning machine (23). Research on the cutting tool's life found that it is influenced and connected to tool wear (24). The energy consumption prediction model is introduced (25). In a follow-up study related to the energy consumption of the x-axis motor, the resulting state that the surface roughness was affected by the machining parameters (26). The simulated annealing optimization method is used to minimize energy consumption (27). The subsequent research raises the topic of cutting tool wear as one of the factors that affect energy consumption (21,28), power consumption efficiency, tool wear (21,29), and machining models in other processes (30). These are studies in the second stream group.

In stream 3, in research related to tool wear, it is stated that energy, tools wear, and costs are interrelated (24). The role of tool wear is explained (29), which strengthens the opinion that tools wear and cutting parameters are essential to carry out optimization (21). The tool wear level is one thing that needs to be monitored (28) so that it can access data to a higher level seamlessly on micro milling(21). Finally, in this study, the RSM method was used to show the contribution of parameters that affect tool wear and dimension deviation. The cutting parameters are material removal rate, feed rate, spindle speed, and repetition, as well as the relationship between the variables on tool wear and dimension deviation.

2. Response Surface Methodology

RSM is a widely used combined technique of statistical and mathematical to build, develop, and optimize a process. The design of experimental techniques is employed to improve the quality. The applications are to design and formulate experimental design (9). Thanks to the RSM technique with its requirement of the minimum number of experiments. RSM has an application to see affected variables in single or multiple characteristics of the responses. RSM has three variables: independent, response, and categorical. Response variables are the performance value of a variable that can sometimes be called the dependent variable. Independent variables are a subject of a control parameter within an experiment. The categorical variable is also a variable that contains values indicating membership in one of several possible categories. In practice, categorical variables must be handled separately by comparing our best-operating conditions concerning the quantitative variables across different combinations of the categorical ones.

RSM began from designing until the optimization phase of the experiment. RSM assumes that the independent variables are not correlated and have a significant value to the response, so it still needs other statistical tools to analyze the model. Analysis of variance was used to find if the model is significant to the data. The correlation regression test was used to see if the model has a correlation and determination value. RSM has two kinds of design experiments often used by the researcher, Box-Behnken Design (BBD) and Central Composite Design (CCD). Box-Behnken Design (BBD) is formed from three-level design efficiency that was designed from an imperfect block design. Box-Behnken Design doesn't have an embedded factorial design. It also doesn't have an extreme point. CCD is the evolution of sequential experiments from two-level factorial.

2.1 Multi-Response Optimisation

In real-life cases, there is more than one response that the industry must optimize simultaneously. They should reduce the cost while product quality keeps improving or even better. Then the decision they are making is more difficult when conflicting conditions exist. For this reason, multi-response optimization is an essential perfect tool to study. Problems in multi-response forms have more than one response to a given situation. This study optimized a manufacturing problem with five responses by applying RSM and two objective functions or performance. Optimization of

e-ISSN XXXX-6025
DOI 10.XXXXX

all responses simultaneously is possible by combining them into a single objective function, which basically represents the relationship of all responses that are to be optimized (31).

2.2 Variable on Machining Process

The specimen material used in this study was C45 with a size of 200mm x 150mm x 60mm, which was processed using a CNC milling machine. The researchers chose this material because it is widely used for general industrial needs. For material homogeneity reasons, the material hardness of each specimen was measured using the Mitutoyo Hardness Testing Machine, Wizhard HR-522 series. The unit used in the measurement results is Rockwell hardness (HRc). The cutting tools used are end mill cutters with the TAPR300R-2020-160 series, namely, end mill cutters with a diameter of 20mm. This cutting tool has 2 Kyocera brand carbide inserts with the APMT1135PDER-KZ-A series. A new carbide insert is also used in every dry-cutting milling machining process carried out on a new specimen. The measuring instrument used to measure the wear of the cutting tools is Laser Control with the Micro Compact NT series. In contrast, the measuring device for measuring the dimensions of the specimen is the Coordinate Measuring Machine (CMM) Brand Brown & Sharpe Global Performance 5.5.5. The CNC milling machines used are Makino brand machines with the KE-55 (KE) series made in China, Makino series S33 (SE) made in Singapore, and Brother (BR) made in Japan, as shown in figure 1.

Figure 1. The Machines: Makino KE-55, Makino S-33 dan Brother.

The cutting parameter levels used in experiments are shown in Table 1.

Table 1. Variables on The Experiment

No	Cutting Parameter	Unit	Level
1	Removal Area	mm^2	0.3 – 2.7
2	Feedrate	mm/min	300 - 1100
3	Spindle Speed	rpm	3000 - 5000
4	Repetition	times	9 - 33
5	Machine		KE-55, S-33, Brother

3. Analysis

The following chapters will analyze numerical experiments, experimental results, and a discussion of these experiments. The results and discussion will describe and explain further the answers to this research problem and the discussion around it. It also contains the value of the data processing results that leads to the analysis, which is enriched by discussion into conclusions.

3.1 Experiment Result

Measurements are made on each specimen that has passed the machining process using specific cutting parameters. In each specimen machining process, a new cutting tool is used, which has never been used before. The cutting parameters used in the experiment and the responses that appear are shown in Table 2.

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DOI 10.XXXXX

Tabel 2. Experiment Result

No	Removal Area (mm^3)	Feedrate (mm/min)	Spindle Speed (rpm)	Number of Repetition	Machine	Tools Wear (mm)	Dimension Deviation (mm)
1	1,5	220	2900	21	BR	0,005	0,007
2	2,7	120	3200	33	KE	0,011	0,012
3	1,5	320	2900	21	BR	0,003	0,005
4	0,3	120	2620	9	SE	0,004	0,005
5	0,3	120	2620	33	KE	0,012	0,015
6	1,5	220	2900	21	BR	0,005	0,006
7	0,3	320	2620	33	BR	0,006	0,008
8	0,3	120	2620	9	BR	0,004	0,004
9	2,7	120	2620	9	BR	0,005	0,006
10	2,7	320	2620	9	BR	0,002	0,003
11	1,5	220	2900	21	BR	0,004	0,007
12	2,7	220	2900	21	KE	0,005	0,009
13	1,5	320	2900	21	BR	0,002	0,002
14	2,7	320	2620	9	KE	0,003	0,005
15	1,5	220	2900	21	BR	0,005	0,009
16	1,5	220	2900	21	KE	0,005	0,007
17	2,7	320	3200	33	KE	0,005	0,010
18	1,5	220	2900	21	BR	0,004	0,005
19	1,5	220	2900	33	SE	0,009	0,018
20	1,5	220	3200	21	SE	0,004	0,006
21	1,5	220	2900	21	KE	0,005	0,006
22	1,5	220	2900	21	KE	0,005	0,009
23	0,3	120	2620	33	BR	0,013	0,025
24	2,7	320	3200	9	KE	0,002	0,003
25	1,5	220	2900	21	SE	0,005	0,006
26	2,7	120	2620	33	BR	0,012	0,020
27	2,7	220	2900	21	SE	0,004	0,004
28	0,3	120	2620	9	KE	0,004	0,005
29	2,7	120	2620	33	SE	0,013	0,025
30	1,5	220	2900	21	SE	0,003	0,006
31	0,3	320	3200	33	BR	0,005	0,009
32	2,7	320	2620	9	SE	0,003	0,006
33	1,5	220	2900	21	SE	0,004	0,006
34	2,7	120	3200	33	BR	0,014	0,024
35	1,5	220	3200	21	BR	0,003	0,004

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DOI 10.XXXXX

36	1,5	220	2900	33	KE	0,009	0,010
37	2,7	320	2620	33	KE	0,005	0,009
38	0,3	320	2620	33	SE	0,004	0,006
39	2,7	220	2900	21	KE	0,004	0,004
40	0,3	320	2620	9	SE	0,002	0,004
41	2,7	320	3200	33	SE	0,004	0,007
42	2,7	120	3200	9	KE	0,004	0,004
43	1,5	220	3200	21	KE	0,005	0,010
44	1,5	220	3200	21	SE	0,005	0,009
45	1,5	320	2900	21	SE	0,003	0,004
46	1,5	220	2900	21	SE	0,005	0,008
47	2,7	120	3200	33	SE	0,014	0,019
48	1,5	220	2900	21	KE	0,005	0,005
49	2,7	120	3200	9	SE	0,004	0,005
50	0,3	320	2620	9	BR	0,002	0,003
51	1,5	220	2900	33	BR	0,009	0,015
52	0,3	320	3200	9	KE	0,002	0,003
53	1,5	320	2900	21	SE	0,003	0,005
54	2,7	220	2900	21	BR	0,004	0,005
55	2,7	320	2620	33	BR	0,004	0,008
56	0,3	320	3200	33	KE	0,005	0,006
57	2,7	320	2620	33	SE	0,005	0,008
58	1,5	220	2900	21	KE	0,004	0,004
59	2,7	220	2900	21	BR	0,004	0,005
60	0,3	320	2620	33	KE	0,005	0,008
61	0,3	320	3200	9	SE	0,002	0,003
62	2,7	320	3200	9	BR	0,002	0,003
63	1,5	220	2900	33	BR	0,009	0,013
64	1,5	220	2900	21	BR	0,004	0,004
65	2,7	320	3200	9	SE	0,002	0,003
66	1,5	220	2900	21	SE	0,004	0,005
67	0,3	320	3200	9	BR	0,002	0,003
68	1,5	320	2900	21	KE	0,004	0,005
69	2,7	120	2620	9	SE	0,003	0,004
70	1,5	220	2900	21	BR	0,004	0,005
71	0,3	120	3200	9	SE	0,003	0,004
72	0,3	120	3200	9	KE	0,003	0,004
73	1,5	220	2900	21	SE	0,004	0,008
74	0,3	120	3200	33	BR	0,012	0,013

e-ISSN XXXX-6025
DOI 10.XXXXX

75	0,3	320	3200	33	SE	0,004	0,007
76	1,5	220	3200	21	KE	0,003	0,004
77	1,5	220	2900	21	KE	0,003	0,004
78	1,5	220	2900	33	KE	0,004	0,006
79	0,3	120	3200	33	SE	0,013	0,023
80	2,7	120	2620	9	KE	0,004	0,007
81	2,7	320	3200	33	BR	0,005	0,009
82	1,5	220	3200	21	BR	0,004	0,007
83	2,7	120	2620	33	KE	0,012	0,014
84	1,5	220	2900	21	KE	0,005	0,008
85	1,5	320	2900	21	KE	0,003	0,005
86	0,3	320	2620	9	KE	0,002	0,004
87	0,3	120	2620	33	SE	0,013	0,014
88	0,3	120	3200	9	BR	0,003	0,004
89	1,5	220	2900	21	SE	0,004	0,004
90	2,7	120	3200	9	BR	0,003	0,005
91	2,7	220	2900	21	SE	0,004	0,008
92	0,3	120	3200	33	KE	0,013	0,022
93	1,5	220	2900	33	SE	0,009	0,014

Based on the experimental data and responses in Table 2, a numerical experiment was carried out using RSM. From numerical experiments, information was obtained that the contribution of the feedrate and repetition variables was the dominant one for the tool wear response, both independently and when the two variables interacted—likewise, the dimensional deviation response. The feedrate and repetition variables also contribute dominantly. The results of other numerical experiments are presented in the following table and figure.

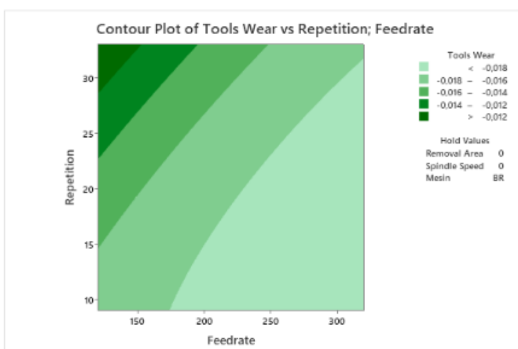

Figure 2. Contour Plot of Tools Wear on Brother Machine

e-ISSN XXXX-6025
DOI 10.XXXXX

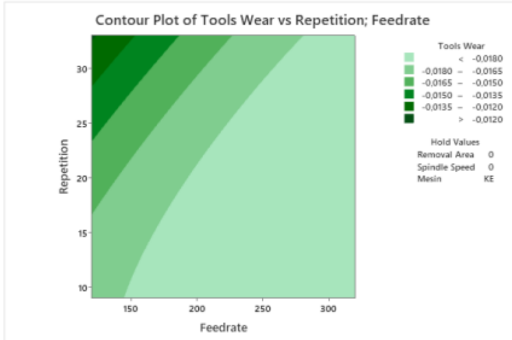

Figure 3. Contour Plot of Tools Wear on Makino KE-55 Machine

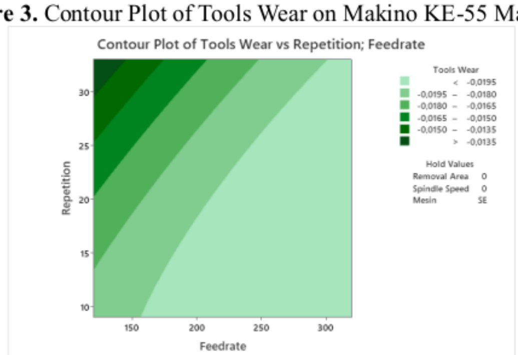

Figure 4. Contour Plot of Tools Wear on Makino S-33 Machine

Figures 2, figure 3, and figure 4 describe the role and value of feedrate and repetition concerning the value of tools wear for each machine. The lighter the color, the less tools wear. Figure 5, it is depicted in a surface the interaction pattern between feedrate, repetition, and tools wear in a 3-dimensional figure. Figures 5, 6, and 7 explain the interaction between variables related to response tools wear and dimension deviation on the Brother, Makino S-33, and Makino KE-55 machines.

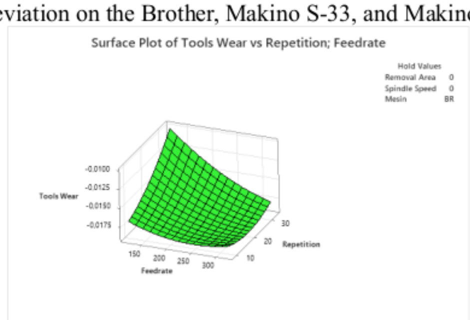

Figure 5. Surface Plot of Tools Wear on Brother Machine

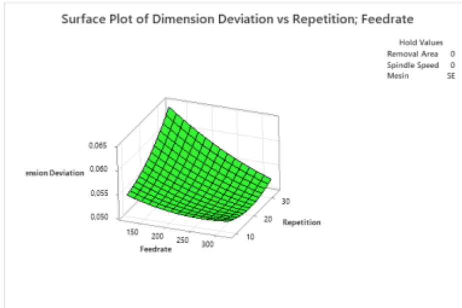

Figure 6. Surface Plot of Dimension Deviation on Makino S-33 Machine

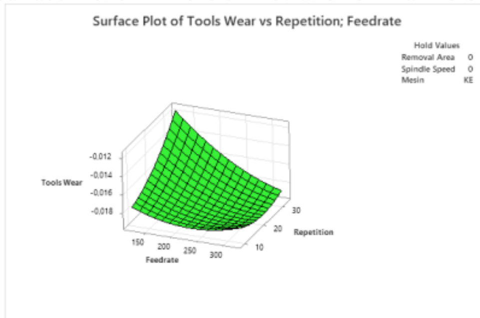

Figure 7. Surface Plot of Tools Wear on Makino KE-55 Machine

The cutting parameter values that provide the optimal solution for the existing conditions are obtained based on the iterations carried out. The existing multi-objectives are based on the response during the machining process. Details and combinations of cutting parameters are shown in Table 3.

Table 3. Optimal Solution for Multi Response Optimisation on Multi Machines

No	Removal Area (mm^3)	Feedrate (mm/min)	Spindle Speed (rpm)	Repetition	Machine	Tools Wear (mm)	Dimension Deviation (mm)
1	0,3	261	3200	9	Brother	0.001	0.001
2	0,3	261	3066	9	Makino KE-55	0.002	0.003
3	0.3	265	2936	9	Makino S-33	0.001	0.001

3.2 Result Validation

In this chapter, the validation process by testing the cutting parameter values is carried out to confirm the response predicted by RSM.

Based on Table 3, the experiment was carried out again using these cutting parameters. The total number of machines used is 11 CNC milling machines with different brands, series, and countries of manufacturers. One specimen was tested on each machine. After the machining process is complete, tools and specimens are measured using the instruments used in the previous experimental process. The responses that appear are recorded and compared with the response values of the predicted results of mathematical experiments, as shown in Table 4. Through this validation process, the prediction performance of the numerical experiment results is seen and tested.

e-ISSN XXXX-6025
DOI 10.XXXXX

Table 4. Result Validation Optimal Solution for Multi Response Optimisation on Multi Machines

Test No	Machine	Predicted Tools Wear	Measured Tools Wear	Predicted Dimension Deviation	Measured Dimension Deviation
1	Brother 1	0.001	0.002	0.000	0.002
2	Brother	0.001	0.003	0.000	0.003
3	Brother	0.001	0.002	0.000	0.003
4	Makino KE-55	0.002	0.003	0.003	0.003
5	Makino KE-55	0.002	0.003	0.003	0.003
6	Makino KE-55	0.002	0.003	0.003	0.004
7	Makino KE-55	0.002	0.002	0.003	0.004
8	Makino S-33	0.001	0.001	0.002	0.002
9	Makino S-33	0.001	0.002	0.002	0.002
10	Makino S-33	0.001	0.001	0.002	0.003
11	Makino S-33	0.001	0.002	0.002	0.002

3.3 Discussion

In the optimization process in this study, RSM used 93 specimens. In this study, variations were made on the removal rate, feed rate, spindle speed, repetition, and machine. The tools wear, and dimension deviation variables are selected for the response variable. The selection of variables is based on previous studies by considering the research results and the existing gaps. By utilizing the RSM technique, information on cutting parameter values is obtained that can provide an optimal solution in the form of lower tool wear and minimal deviation dimensions.

The cutting parameter values are tested in actual case machining in the validation stage. The cutting parameter values are tested to see if the optimal solution offered by RSM can provide the optimal solution as a multi-response setup on multi machines. Based on Table 4, the actual value of the tool wear number close to the predicted value can be concluded. Likewise, the actual value of the dimension deviation number is close to the predicted dimension deviation. Based on the actual value close to the predicted value, it can be concluded that the use of RSM for the optimization process has answered the current needs. Another conclusion is that it is true that RSM can be used for process improvement in the engineering field (January). The tools wear rate model using RSM was confirmed at the validation stage, and the data obtained that the most significant deviation of 0.002mm occurred only once. In comparison, the deviation of 0.001 mm occurred seven times, and the remaining three were correct. Likewise, dimension deviation validation provides data that there are two deviations of 0.003mm, one deviation of 0.02mm, three times deviation of 0.001mm, and the remaining five times without any dimension deviation. If we assume that the deviation between prediction and actual is 0.002, then the reproducibility of tools wear is 91% and 82%. The prediction accuracy level for tools wear, and dimension deviation is also in the same number.

With this description, the proposed model convincingly shows a good and satisfactory level of accuracy and reproducibility. In addition, the result shows the cut tool's wear rate is affected by the feed rate, and the number of repetitions is correct. Feed rate and repetition contribute dominantly to tools wear rate and dimension deviation independently and when interacting. The relationship between feed rate and repetition is reciprocal. The greater the number of repetitions, the greater the tools wear. Likewise, with feed rate. The higher the feed rate, the greater the tools wear.

In the real world, the industry has many CNC milling machines with a large variety of brands and machine series. Determining different and specific cutting parameter values for each machine, as shown in Table 3, will cause difficulties and potential for human error in the production team. Considering this, to help the production process team and prevent potential human errors, adjustments are made to the specific cutting parameter values in each machine. With a slight

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adjustment, a uniform cutting parameter value is obtained for all machines with response predictions that are not much different. There are even values that give the same result. Details of adjusted cutting parameters that provide optimal solutions for multi-response setups for multi-machines can be seen in Table 5. The * sign indicates the cutting parameter value offers better performance, and ** indicates the response value is slightly reduced but still in a suitable category. Table 5 shows a summary of all cutting parameter values that provide optimal solutions for multi-response on multi objects or multi machines where all machines have different series and brands.

Tabel 5. Optimal Solution for Multi Response Optimisation on Multi Machines - Adjusted

No	Removal Area (mm^3)	Feedrate (mm/min)	Spindle Speed (rpm)	Repetition	Machine	Tools Wear (mm)	Dimension Deviation (mm)
1	0,3	265	3100	9	Brother	0.001	0.000*
2	0,3	265	3100	9	Makino KE-55	0.002	0.003
3	0.3	265	3100	9	Makino S-33	0.001	0.002**

4. Conclusion

This paper is intended to answer a specific machine optimization model that is only suitable for machine setups with the same machine and setup details. Differences in brands, machine series, and process setups are believed not to be used as optimization objects if they take parameters with different setups. Several previous studies have been described in preliminary research. This machining setup selects the cutting parameters that have a dominant contribution to the machining process. The optimization process uses RSM techniques. In this study, it has been shown that the feed rate variable and the number of repetitions have a dominant contribution to tools wear and dimension deviation, and RSM is an essential and perfect tool for optimizing with multi-response setups on multi objects and optimization model based on multi-response on multi-object has been carried out and validated convincingly. This research has just performed multi-response optimization on multi objects (multi machines). However, this optimization only takes machines made in Asian countries and has not taken machines made in European countries. Therefore, in future work, the researchers must be continued is to find a multi-response optimization model for multi-machines from different countries or continents where the concepts and values of making machines are already much different.

Funding

This research funding was obtained from the Directorate of Research, Technology, and Community Service; Ministry of Education, Culture, Research, and Technology; the Republic of Indonesia, in accordance with the Main Contract for Doctoral Dissertation Research Scheme under Grant Number 084/E5/PG.02.00.PT/2022 and 1409/PKS/ITS/2022.

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* Corresponding author. Email : siswanto@ie.its.ac.id
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