Optimization Cutting Parameters on Turning Process to Increasing Surface Roughness Quality SKT4 Material with Taguchi Method

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Abstract*—In this paper, Taguchi Method is used to identify the optimal combination of turning parameters to minimize surface roughness quality. Turning experiments are carried out following to Taguchi Orthogonal Array L27 (3^4) for the data input and various combinations of four parameters: Cutting speed, feeding, depth of cut and nose radius. The combination of parameters done with experiment on turning machine with the output is Roughness Average (Ra). The Results of the experiment were analyzed with Backpropagation Neural Network to determine the pattern of the relationship between process parameters and response, while Genetic Algorithm method was used for parameter optimization. Combination of the recommended parameters, are cutting speed 131.62 m/min, feeding 0.04 mm/rev, depth of cut 0.3 mm and nose radius is 0.39. As a result, the optimization process can achieve 301.03% from previous experiment. With the result of surface roughness is 1.5 µm.

***Keywords*—Turning process, Roughness Average, Taguchi Method, Backpropagation Neural Network, Genetic Algorithm**

I. Introduction

One of popular process in industry is turning process. Material is removed from the surface of a rotating cylindrical workpiece when a single cutting tool is engaged. The cutting process can be achieve because cutting tool material more harder than the workpiece material, and the cutting tool has a several angles and geometry to make the cutting process is efficient. Cutting action involves shear deformation of work material to form a chip, and as chip is removed, the new surfaces can be exposed [1]. There are several factor on turning process for affected in quality of product, the factor are: Cutting Speed, feeding, cutting tool geometry, cutting tool material, machine condition [2]. Figure 1 Shown working principle of turning process.

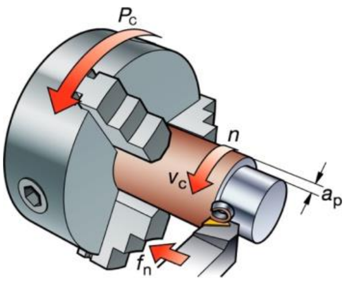

Fig. 1. Basic principle of turning process

As the cutting tool engages the workpiece, the material directly ahead of the tool is sheared and deformed under tremendous pressure. The deformed material then seeks to relieve its stressed condition by fracturing and flowing into the space above the tool in the form of a chip [3]. With Taguchi method and Annova, feed rate can contribute 33.70% for minimum of roughness average on material aluminium alloy [4]. Athreya and Venkatesh on their experimental to cutting mild steel material on turning machine with three factor combinations: cutting speed, depth of cut, and feed rate. The result is cutting speed contribute 58, 49% for minimum surface roughness value [5].

In second semester 2020, Astra Manufacturing Polytechnic need to produce some part namely Guide pin for mould base. The guide pin material is JIS SKT4. Fig. 2 shown guide pin for mould base.

Fig. 2. Guide pin for mold base

The cutting process are done with several combination of parameter:

Cutting tool material	: ISO 6 Carbide
Cutting speed	: 120 m/min
Feeding	: 0.3 mm/rev
Nose radius	: 0.2 mm

Table 1 shown the measuring value from the cutting process from guide pin JIS SKT4.

TABLE I
MEASURING REPORT FROM GUIDE PIN

NO	DIM	TOL	PART NUMBER						
			1	2	3	4	5	6	7
1	Ø 20	±0.1	20.04	0.86	0.86	0.85	20.10	0.86	20.06
2	Ø 34	h6/±0.016	33.962	33.951	33.958	33.955	34.010	33.992	33.980
3	Ø 25	0.1, -0.2	24.86	24.90	24.86	24.84	24.76	24.90	24.82
4	Ø 23	±0.1	23.10	23.04	23.08	0.98	0.98	0.98	0.98
5	140	±0.2	139.82	139.90	139.86	139.92	139.98	139.96	139.96
6	90	±0.15	89.86	89.90	89.96	89.96	90.02	89.94	90,1
7	30	±0.1	29.96	30.02	30.02	29.98	29.90	29.96	29.98
8	5	0, -0.1	05.00		0.23	0.23	0.23	0.23	0.23
9	N6-N7	0.8-1.6 µm	3.64	4.23	5.58	3.76	4.33	5.14	4.97

As shown on Table 1, all surface quality of product is out from surface roughness standard. The roughness tolerance is affected for Ø 34 - h6 (±0.016).

II. RESEARCH METHODS

A. Research Flow

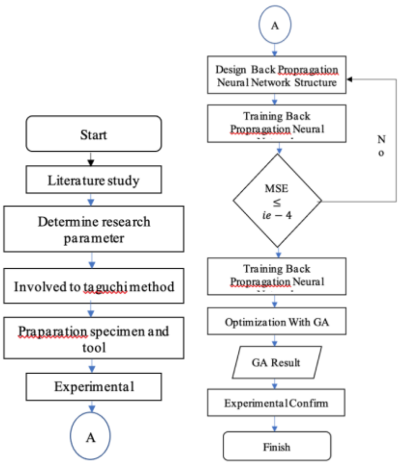

Fig. 3. Research flow from optimization cutting parameters

Referring to Fig. 3, the data is carried out from specification of cutting tool and standard cutting parameter recommendation sheet. From this data, an experimental design was carried out using the Taguchi method with an orthogonal matrix L_{27} (3^4).

B. Data Collection

The experimental is begins with collecting all specification from each part from the workpiece material, cutting tool material, and turning machine. These data are used as a reference for conducting research, because they will affect the results.

- JIS SKT 4 Material

JIS SKT 4 material is hot work steel classification with widely application in manufacturing process. SKT4 material has good hot hardness, usually use to die mold, hot forging die and aluminum forge die. Table 2 shown chemical composition of SKT4 material.

TABLE II
CHEMICAL COMPOSITION OF SKT4 MATERIAL

Spec.	Unit	Value
C	%	0.5 – 0.6
Si	%	0,1 - 0,4
Mn	%	0.15 – 0.35
P	%	0.030
S	%	0.20
Cr	%	1

- Cutting tool

Cutting tool is one of the most effect to cutting process in material removal process machining, cutting tool can achieved the efficiency of process or the process done with fail. In this experimental, ISO 6 cut is used to cut the workpiece. Fig. 4 shown ISO 6 carbide:

Fig. 4. ISO 6 carbide

The specification of ISO 6 describes in Table 3:

TABLE III
ISO 6 SPECIFICATION

Specification	Description
Material	Carbide
Holder dimension	12x12 mm
Rake angle	12°
Clearance angle	8°
Cutting Speed	100-150 m/min

- Turning Machine

This experimental was done with cutting process on turning machine at Astra Manufacturing Polytechnic workshop. Fig. 5 shown Lei Shin universal turning machine for this experimental study.

Fig. 5. Leishin turning machine

Leishin is universal lathe machine which can perform external or internal turning process, drilling, threading, etc. Table 4 shown the specification from the turning machine in this experimental.

TABLE IV
LEISHIN SPECIFICATION

Parameter	**Value**
Type	LA46080B
Maker	Lei Shin
Dimension	560x1100 mm
Motor power	7.5 Kw
Spindle Bore	80 mm
Weight	2100 Kg
Base material	Cast Iron

- Parameters of process

Process parameters are parameters that can be controlled and the value can be determined by the researcher [6]. There are four parameters in this study: cutting speed, feeding, depth of cut and nose radius where each factor varied by three variations. The combination of parameters shown on Table 5.

TABLE V
COMBINATION OF PARAMETERS

No	**Parameter**	**Variation**		
1	Cutting Speed (m/min)	100	125	150
2	Feeding (mm/rev)	0.02	0.03	0.04
3	Depth of Cut (mm)	0.1	0.3	0.5
4	Nose Radius (mm)	0.2	0.4	0.6

- Constant Parameters

The constant parameter is the parameter that is not varied in research. The value of this parameter is maintained throughout the experimental process. As the constant parameter on this research are:

a. Tool rake angle : 12°
b. Tool lead angle : 90°
c. Tool material : Carbide
d. Cutting condition : Dry cutting
e. Material diameter : 20 mm
f. Cutting length : 40 mm

- Degree of Freedom

The experimental design used is the orthogonal array matrix with the L_{27} (3^{13}) design which is defined as the number of experiments twenty-seven times with three levels on thirteen input variables [7]. Table 6 shown degree of freedom.

TABLE VI
DEGREE OF FREEDOM

No	Variable Parameter Process	Number of Level (k)	V_{fl} = (k- 1)
1	Cutting Speed (m/min)	3	2
2	Feeding (mm/rev)	3	2
3	Depth of cut (mm)	3	2
4	Nose radius (mm)	3	2
Total Degree of Freedom (V_{fl})			8

III. RESULTS AND DISCUSSIONS

A. Data Analysis

The experiment was carried out by combining the process parameter variables for cutting process. The process parameters used in this study were cutting speed, feeding, depth of cut and nose radius. From these parameters then combined 27 times the experimental design with 3 times the replication and randomization in each test. Table 7 shown the surface roughness average value from this experimental.

TABLE VII
SURFACE ROUGHNESS VALUE

No	Variable of Process				Response		
	Cutting Speed (m/min)	Depth of cut (mm)	Feeding (mm/rev)	Nose Radius (mm)	Ra 1 (μm)	Ra 2 (μm)	Ra3 (μm)
1	100	0,1	0,02	0,20	2,41	2,62	2,72
2	125	0,3	0,03	0,4	2,48	2,50	2,54
3	150	0,5	0,05	0,6	6,11	6,29	5,88
4	125	0,3	0,05	0,6	1,87	1,82	1,88
5	150	0,5	0,02	0,20	2,50	2,46	2,50
6	100	0,1	0,03	0,4	5,50	5,43	5,62
7	150	0,5	0,03	0,4	1,41	1,45	1,64
8	100	0,1	0,05	0,6	3,42	3,49	3,69
9	125	0,3	0,02	0,20	4,97	4,68	4,72
10	125	0,5	0,03	0,6	1,85	1,76	1,85
11	150	0,1	0,05	0,20	2,45	2,36	2,35
12	100	0,3	0,02	0,4	5,34	5,29	5,33
13	150	0,1	0,02	0,4	2,11	2,32	2,43
14	100	0,3	0,03	0,6	3,34	3,39	3,46
15	125	0,5	0,05	0,20	4,79	4,67	4,77
16	100	0,3	0,05	0,20	2,69	2,82	2,98
17	125	0,5	0,02	0,4	2,50	2,62	2,74
18	150	0,1	0,03	0,6	6,32	6,40	6,61
19	150	0,3	0,05	0,4	1,81	1,79	1,92
20	100	0,5	0,02	0,6	3,62	3,52	3,61
21	125	0,1	0,03	0,20	5,01	5,13	5,20
22	100	0,5	0,03	0,20	1,67	1,72	1,80
23	125	0,1	0,05	0,4	2,03	2,11	2,14
24	150	0,3	0,02	0,6	6,68	6,74	6,83
25	125	0,1	0,02	0,6	1,64	1,70	1,76
26	150	0,3	0,03	0,20	3,59	3,54	3,44
27	100	0,5	0,05	0,4	4,97	5,14	5,30

B. Data processing with Backpropagation Neural Network

- Pre-processing Data

Pre-processing is a form of initialization of experimental data which has different intervals and units into non-dimensional data whose intervals are determined between -1 to 1. This process is carried out on the input parameters and constants, namely as parameter data for the experimental process on the turning machine, with the output value generated from the experimental which is the minimum surface roughness value [8].

- Network Determination

Network determination is significantly influenced by the functions that make up the network, so it is necessary to pay attention to the selection of functions used to simplify and speed up the training process. In this research, the functions used in the Backpropagation Neural Network are limited, namely the activation function and the training function. The signal from the neuron input whether it is up or not is greatly influenced by the activation function. So that the training function is also influenced by whether or not it is appropriate to select the function.

- Number of Neurons on Hidden Layer

The results of the Backpropagation Neural Network training obtained are strongly influenced by the number of neurons and hidden layers used, so it needs to be considered in determining the number [9].

TABLE VIII
NUMBER OF NEURON

No	Number of Neurons
1	2
2	4
3	8
4	9

- Network Initialization

Network formation in Backpropagation Neural Network is done by adding a hidden layer to the network. However, the network needs to be initialized first by adding an activation function and a training function. In this research, the activation function used is the "tansig" function and the "logsig" function, while the training function uses the "trainrp" function [10].

- Initialize Weight and Bias Values

The network formation process is carried out by adding weight and bias values to each network. The process of adding it starts from a small number randomly. However, if the weight and bias values are determined, it can also be done by giving the values directly

- Stopping criterion

The termination criteria consist of several BPNN parameter that can be adjusted before training is carried out [10]

net.trainParam.epochs = 5000, is the maximum number of epochs used in calculating, which is 5000

net.trainParam.time = 3000, is the maximum estimate used in calculating that is 10 seconds.

net.trainParam.goal = 1e-4; is the maximum performance value performed in the calculation, which is 0.001.

net.trainParam.min_grad = 1e-18, is the maximum gradient value used in calculating, which is 0.000000000000000000001

net.trainParam.max_fail = 8, is the maximum number of validation epochs used in performing calculations, which is 10 times [11].

- Percentage of Training Data and Test Data

net.divideParam.TrainRatio = 80/100, the training data used is 65 data [12]

net.divideParam.valRatio = 0/100, the validation data used is 0 data

net.divideParam.testRatio = 20/100, is the testing data used, namely 16 data

- Learning Rate

Learning rate is one of the training parameters on a network that is used to calculate the weight correction value. In principle, the smaller the learning rate value used, the more precise the algorithm will be.

- Network Architecture Forms [13]

TABLE IX
COMBINATION OF ERROR CALCULATION PARAMETERS

No	Hidden Layer	Number of Neurons	Activation Function	Training Function	Max. Epoch	Epoch	Mean Square Error
1	2	7	Tansig	Trainrp	5000	3836	0.00097385
2	2	7	Logsig	Trainrp	5000	2083	0.00097385
3	2	8	Tansig	Trainrp	5000	1918	0.000730501
4	2	8	Logsig	Trainrp	5000	2226	0.000730501

Based on calculations performed using MATLAB, the smallest mean square error value is 0.00073051 in experimental 3. So, the BPNN architecture formation is formed consist of 2 hidden layers, 8 neurons, the activation function is "Tansig" and the training function is "Trainrp". The form of network architecture result from this calculation is shown in Fig. 6.

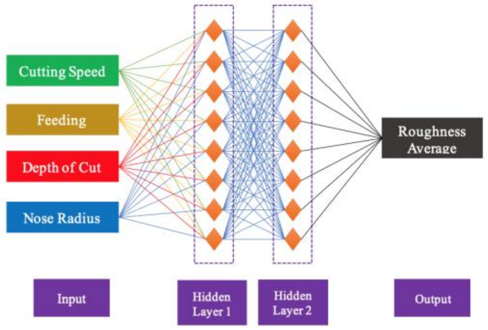

Fig. 6. Architecture of network formation 2-8-8-1

- Backpropagation Neural Network Results

The result obtained from the data training process using BPNN method are data pattern that are formed close to the responds. Fig. 7 shown experimental cutting process data with training data.

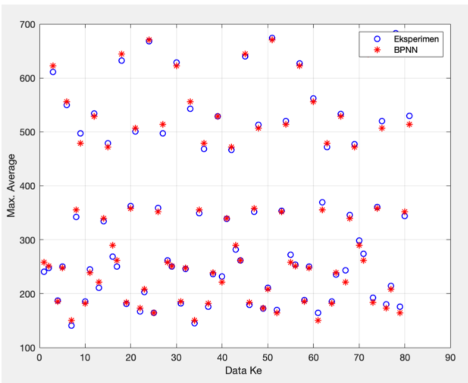

Fig. 7. Experimental vs BPNN

C. *Optimization of Response Parameters Using Genetic Algorithm Method*

The optimization method carried out with the Genetic Algorithm is used to find the optimal parameter composition, so minimum surface roughness value can achieve in product.

- Determination of Process Parameter Boundaries

The limit value in the simulation process parameter is determined by the maximum and minimum values of each process variable as shown in Table 7.

TABLE VII
VARIABLE LIMIT OF GA TESTING PROCESS

Parameter	Limit		Interval
	Maximum	Minimum	
Cutting Speed	150	100	50
Feeding	0.05	0.02	0.03
Depth of cut	0.6	0.2	0.4
Nose radius	0.4	0.2	0.2

- Representation of Each Chromosome

One of the optimization processes in Genetic Algorithm is done by regenerating the chromosomes that were previously available. This regeneration process is carried out by means of crossover and mutation.

- Determination of Fitness Functions

In the Genetic Algorithm method, the process of determining the target is done by positioning the optimal conditions of the parameters themselves, so that the process of placing these conditions becomes a critical point in this analysis

- Determination of the Options Structure

Genetic algorithm options structure consists of several options to solve problems in optimization. The MATLAB "gaoptimset" function is used as an option to perform these calculations. Population size 150, Generation 20, Elite count 50

Pareto fraction : 0.8
Crossover fraction : 0.6
Migration fraction : 0.4
Tol Fun : 1e-9
Selection Process : Roulette Wheel Selection

- Result of Optimization of Genetic Algorithm

Based on these parameter recommendations, the cutting speed are 131.62 m/min, feeding 0.04 mm/rev, depth of cut 0.3 and nose radius is 0.39 mm.

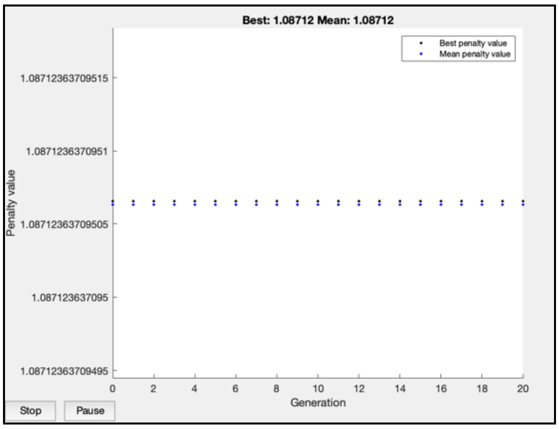

Fig. 8. Best result from genetic algorithm

D. *Confirm Trial*

Experimental confirmation is carried out to ensure the parameters recommended by the Genetic Algorithm are optimal increasing surface quality of guide pin product. Table 12 is shown the composition of the parameters tested.

TABLE XII
OPTIMAL COMPOSITION

Parameter	Value	Result of Simulation
Cutting Speed	131.62	1.50 µm
Feeding	0.04	
Depth of Cut	0.3	
Nose radius	0.39	

The surface roughness average result from cutting process before the experimental is 4.52 µm. And after optimization process, the surface roughness can achieve 1.50 µm. So, this experimental can increasing 301.33% surface roughness average from guide pin product.

IV. CONCLUSIONS AND RECCOMENDATIONS

A. *Conclusions*

The result of this research carried out by optimizing the parameters of cutting process of JIS SKT4 material to increasing of surface roughness average quality or minimalize roughness average value for guide pin JIS SKT4 material surface.

1. Surface roughness value from the product can improve 301.33% from 4.52 µm to 1.52 µm.
2. The optimal combination parameters for cutting process of guide pin JIS SKT4 material are, cutting speed 131.62 m/min, feeding 0.04 mm/rev, depth of cut 0.3 mm and nose radius 0.39 mm.

B. *Recommendations*

Research on guide pin JIS SKT4 surface is need to continue with different cutting tool and machined. And the surface roughness average value from experimental need to compare with theoretical calculation.

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