Multi-objective Optimization Using BPNN-PSO in the Face Milling Process of AISI 1045

Satrio Darma Utama(✉), Arif Wahjudi, Mohammad Khoirul Effendi, Bobby O. P. Soepangkat, Mazwan, and Ridhani Anita Fajardini

Mechanical Engineering Department, Sepuluh Nopember Institute of Technology, Surabaya 60111, Indonesia
rio.darma18@gmail.com

Abstract. An experiment was carried out in the face milling process of AISI 1045 material to determine the levels of the process parameters that could minimize cutting force (CF) and surface roughness (SR) and also maximize material removal rate (MRR) simultaneously. A Taguchi orthogonal array L_9 was selected for this experiment. The experiment was randomized and replicated twice. The face milling process parameters varied cutting speed (V_c), feeding speed (V_f), and depth of cut (a). The optimization was performed using a combination of backpropagation neural network (BPNN) and particle swarm optimization (PSO) methods. The resulting network architecture configuration has 3 input layers and 3 output layers, with 5 hidden layers where each layer contains 5 neurons. The optimization result shows that the minimum CF and SR and the maximum MRR could be obtained simultaneously using the cutting speed of 308 m/min, feeding speed of 145 mm/min, and depth of cut of 1.5 mm.

Keywords: optimization · BPNN-PSO · face milling

1 Introduction

The milling process is one of the most commonly applied metal-cutting processes since it can be used to produce a high-quality product in a reasonable time but with a high surface quality [1]. Today's manufacturing industry continues to strive to improve efficiency in the machining processes. To achieve high efficiency in the machining processes, one must use less power, have good workmanship, and be time-efficient. If these three things can be accomplished in the machining process, it will increase productivity and reduce costs in the production process. Some responses, such as cutting force, material removal rate, and surface roughness, can influence the quality of the product.

Measurement of the cutting force during the machining process shows that the cutting force affects the material removal rate, tool geometry, product quality, cutting temperature, power consumption, tool wear, and chip formation [2]. The material removal rate of the milling process plays a significant role because it affects productivity, energy consumption, cutting force, tool life, and the cost and production process [3, 4]. In addition to cutting force and material removal rate, surface roughness has a vital role in the

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machining process because surface roughness has a role in measuring the surface quality of the machine; in machining, surface roughness is required to be as low as possible [5]. Surface roughness affects fatigue, wear, friction properties, and machine surface resistance. Therefore surface roughness must be controlled during the machining process [3].

Determining effective process parameters during the machining process must be considered to produce a quality product. And also, selecting the correct process parameters will be able to affect the capacity, time, and production cost [6]. Determining the correct level of machining parameters is usually conducted based on work experience or machining manuals, but this method produces parameters that are not optimal. Another way to select machining parameters is to conduct trial and error experiments, but this purely non-technical experiment takes a long time and costs a lot [7].

Conventional optimization approaches are also used to optimize machining parameters using Taguchi techniques, factorial techniques, and response surface methodology. The new trend of optimization is The application soft computing [5]. Backpropagation neural network (BPNN) is the most popular technique for developing a prediction model. One of the optimization techniques currently used by researchers is particle swarm optimization (PSO). This technique quickly achieves the best answer in the population in each iteration because it is based on the swarm intelligence technique. PSO can solve multi-objective problems to choose the optimal process parameters [8]. Optimization using PSO has been carried out over the last decade in various fields, including manufacturing processes. Comparisons have been made with several other optimization methods in the milling process. PSO is better for finding optimization solutions from several techniques, such as ABC, SA, GA, and Taguchi [9].

Lin et al. [10] perform optimization using the PSO method in the milling process to obtain optimal process parameters for cutting. In another study, Mishra et al. [11] apply optimization based on multi-objective particle swarm optimization with ANN modeling and get higher productivity and stable cutting conditions. Similar studies were conducted by Tien et al. [12], and the optimization results showed that they reduced power consumption by 10.49% and increased surface quality and tool life. The use of BPNN-PSO method is also used in several machining processes. Narcahyo et al. [13] use BPNN-PSO in the carbon fiber-reinforced polymer drilling process. The PSO optimization results simultaneously minimize delamination at the inlet and outlet holes during the CFRP drilling process.

The current study focuses on determining the levels of the milling process parameter on AISI 1045 steel to obtain minimal cutting force, surface roughness, and maximum material removal rate. The backpropagation neural network method is used for modeling, while multi-objective optimization is performed using PSO.

2 Experimental Design

2.1 Tools and Materials

The workpiece material used in this experiment is AISI 1045 carbon steel, with a length of 100 mm, a width of 32 mm, and a thickness of 30 mm. This experiment was carried out on a Hartford S-Vertical milling machine plus 10, using a carbide insert KYOCERA

Table 1. Experimental parameters and levels

Process Parameters	Unit	Level 1	Level 2	Level 3
Cutting speed (Vc)	m/min	118	193	308
Feeding speed(Vf)	mm/min	42	98	230
Depth of cut (a)	mm	0.5	1	1.5

type SEKT 1204AFEN-S. The response variables measured were CF, MRR, and SR. CF was measured using a Kistler-type 9272 dynamometer. MRR is obtained by using Eq. 1, while the measurement of SR was carried out using Mitutoyo Surftest SJ 310.

$$MRR = \frac{Wi - Wf}{\rho s.tc} mm^3/second \tag{1}$$

where:

wi = initial weight of material before cutting (g)
wf = weight of final material after cutting (g)
ρs = density of material (g/mm^3)
tc = cutting time (seconds).

2.2 Design of Experiment

This study utilized Taguchi orthogonal array L_9 as the design experiment. The experiments were replicated twice for each combination of parameters. The experimental design uses three parameters, and each parameter has three levels. The experimental parameters are shown in Table 1, and the experimental results are shown in Table 2.

3 Multi-response Optimization Using BPNN-PSO

3.1 Backpropagation Neural Network

Rumelhart et al. developed one of the best models of artificial neural networks, namely backpropagation [14]. BPNN consists of three parts, i.e., the input layer, the hidden layer, and the output layer. In general, the steps of BPNN modeling are the normalization of data, the determination of network architecture, and the implementation of training, testing, and validation.

Data normalization changes a data value into a value between −1 and 1. This normalization was performed by using Eq. 2.

$$P_n = \frac{2(p - \min(p))}{(\max(p) - \min(p))} - 1 \tag{2}$$

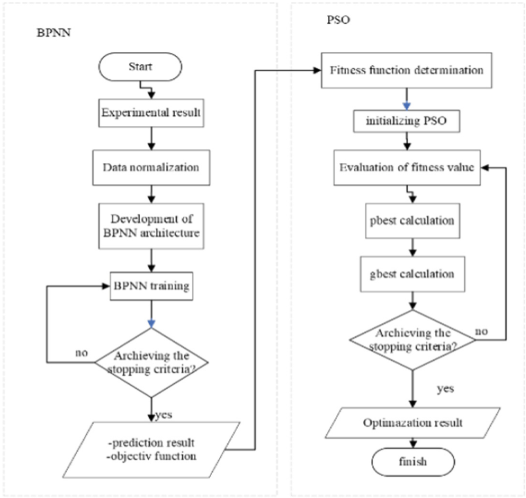

Fig. 1. Flow diagram

where:

p = process and response parameters data from the experiment

P_n = process and response parameters data which have interval values between −1 to 1 and unitless.

In the next step, the trial and error method is utilized to find the architecture of the BPNN network based on the smallest mean square error (MSE) value. The design criteria for determining the BPNN architecture using the trial and error method are as follows:

- Number of neuron in the hidden layer is from 1 to 10.
- Number of hidden layer from 1 to 10.
- Activation function using tansig and logsig for hidden layers.
- Activation function using purelin and logsig for hidden layers
- Training function using trainlm.
- Maximum 1000 epoch.

After that, determine the training, testing, and validation data for the BPNN model. The percentage of data used for training, testing, and validation is 70%, 15%, and 15%, respectively. The BPNN results with the smallest MSE are then stored for optimization. Further, the BPNN model results are compared with experimental results to verify the error value, which is calculated using Eq. 3.

$$\text{Error} = \frac{Exp - BPNN}{Exp} \times 100\% \tag{3}$$

where:

Exp = experimental or observed response value

BPNN = predicted value from BPNN.

Table 2. Experimental design and experimental results

Order	**Parameter Level**			**Experiment Results**		
	Vc	Vf	a	CF (N)	SR (μm)	MRR (mm^3/second)
1	1	1	1	41.65	1.51	9.67
				41.99	1.64	9.61
2	1	2	2	168.54	1.61	45.31
				158.87	1.60	45.45
3	1	3	3	359.90	1.85	156.37
				361.85	1.67	163.70
4	2	1	2	91.55	1.19	20.03
				92.46	1.23	20.06
5	2	2	3	191.52	1.15	67.73
				190.68	1.16	68.14
6	2	3	1	100.40	1.24	52.45
				100.61	1.29	52.18
7	3	1	3	106.89	0.73	29.76
				113.75	0.73	29.72
8	3	2	1	68.19	0.80	22.05
				66.32	0.86	24.33
9	3	3	2	159.10	0.96	105.85
				183.48	0.93	107.58

3.2 Partial Swarm Optimization (PSO)

PSO adjust the behavior of certain animals in their ecosystem, such as flocks of birds or fish, where they do not have a leader to guide them to get food, so they scatter randomly to find a place to eat. When one particle or a bird sees a short or correct path to a food source, the rest of the flock can follow the course instantly, even if their position is quite far from the group [13].

Each particle will be evaluated using the fitness value obtained from the fitness function. The best value for each particle in all iterations is called Pbest, and the best fitness value for all particles in all iterations in the search space is called Gbest [14].

This study obtained the fitness function by combining the three objective functions for each response from the BPNN prediction results. The objective function of each response can be used in Eq. 4. The transfer tangent function (sigmoid hyperbolic tangent) is used for the activation function. The steps for using BPNN-PSO are shown in Fig. 1.

$$\mathrm{Obj} = ((\sum_{j=1}^{12} Vab.\left(\left(\frac{2}{1+e^{-2p}}\right)-1\right) + \mathrm{v0_b})) \tag{4}$$

Table 3. BPNN Modelling Result

Response	Neurons	Hidden Layers	Activation Function	MSE
CF	5	5	Tansig	0.0066
SR	5	5	Tansig	0.0056
MRR	5	5	Tansig	0.00030579

where:
Obj = response from the experiment
A = number of neurons in the hidden layers
B = number of process responses
v0 = value of bias from hidden layer to output layer
p = value of activation for each neuron in the hidden layer.

4 Results and Discussion

4.1 BPNN Modeling Results

Based on the BPNN modeling results with the smallest MSE, 5 hidden layers are obtained, and each layer has 5 neurons. Trainlim is used as a training function. CF, SR, and MMR have MSE values of 0.0066, 0.0056, and 0.00030579, respectively, shown in Table 3. BPNN modeling results are also compared with experimental results, as shown in Table 4, where the error value is less than 5%. Hence, it can be said that the BPNN modeling results are satisfactory because they resemble experimental results.

4.2 PSO Optimization Result

The objective function of each BPNN response is used as a fitness function in PSO optimization. The fitness function is shown in Eq. 5.

$$\text{Max fitness function} = \text{Obj}_1 - \left(\text{Obj}_2 + \text{Obj}_3\right) \tag{5}$$

where:
Obj_1 = Material remoal rate
Obj_3 = cutting force
Obj_2 = surface roughness.

The combination of milling parameters obtained from PSO optimization is shown in Table 5. The optimum face milling parameters are a cutting speed of 308 m/min, a feeding speed of 145 mm/min, and a depth of cut of 1.5 mm. It can minimize CF and SR and increase the MRR simultaneously. Response prediction using a combination of optimized face milling parameters can produce CF of 111.275 N, SR of 0.733 µm, and 105.953 mm^3/second for the MMR.

Table 4. The comparison between the BPNN modeling result and the experimental results

No	CF			SR			MRR		
	Exp	BPNN	Error	Exp	BPNN	Error	Exp	BPNN	Error
1	41.65	47.71	−14.53	1.51	1.58	−4.64	9.67	9.75	−0,83
2	41.99	47.71	−13.60	1.64	1.58	3.66	9.61	9.75	−1,46
3	168.54	142.68	15.34	1.61	1.60	0.62	45.31	45.3	0,02
4	158.87	142.68	10.18	1.6	1.61	−0.63	45.45	45.3	0,33
5	359.9	359.23	0.18	1.85	1.76	4.86	156.37	160	−2,32
6	361.85	359.23	0.72	1.67	1.76	−5.39	163.7	160	2,26
7	91.55	91.78	−0.25	1.19	1.2	−0.84	20.03	20	0,15
8	92.46	91.78	0.73	1.23	1.2	2.44	20.06	20	0,30
9	191.52	190.03	0.77	1.15	1.56	−35.6	67.73	67.9	−0,25
10	190.68	190.03	0.34	1.16	1.56	−34.4	68.14	67.9	0,35
11	100.40	108.45	−8.01	1.24	1.26	−1,61	52.45	52.2	0,48
12	100.61	108.45	−7.79	1.29	1.26	2.33	52.18	52.2	−0,04
13	106.89	104.42	2.31	0.73	0.73	0.00	29.76	29.7	0,20
14	113.75	104.42	8.20	0.73	0.73	0.00	29.72	29.7	0,07
15	68.19	47.6	30.19	0.8	0.83	−3.75	22.05	23.3	−5,67
16	66.32	47.6	28.22	0.86	0.83	3.49	24.33	23.3	4,23
17	159.1	152.25	4.30	0.96	0.93	3.12	105.85	107	−1,09
18	183.48	152.25	17.02	0.93	0.93	0.00	107.58	107	0,54
Average			4.131	Average		−3.69	Average		−0,274

Table 5. Optimization results and response prediction

Optimum parameter combination			**Response prediction**		
Vc (m/min)	Vf (mm/min)	a (mm)	CF (N)	SR (µm)	MRR (mm^3/sec)
308	145	1.5	111.275	0.733	105.953

4.3 Confirmation Experiment

The confirmation experiment is a verification process of prediction results using BPNN with experimental results using BPNN-PSO process parameters optimization. Confirmation experimental results are shown in Table 6, where 5 replications were carried out, and the average value of the CF was 111.868 N, SR was 0.733(µm), and MRR was 105.735 (mm^3/min). In addition, a test of the similarity of the average value with the value of the BPNN-PSO was carried out using a one-sample T-test method. Based on the one sample T-test, the p-value for each response is 0.278, 0.463, and 0.798, which means

Table 6. Comparison between BPNN-PSO predictions with confirmatory experiments

BPNN-PSO prediction parameters			**BPNN-PSO prediction responses**			**Results of the confirmation experiment**		
Vc (m/min)	*Vf* (mm/min)	*a* (mm)	CF (N)	SR (μm)	MRR (mm^3/min)	CF (N)	SR (μm)	MRR (mm^3/min)
308	145	1.5	111.275	0.733	105.953	113.122	0.728	106.976
						112.276	0.727	103.122
						110.266	0.735	105.771
						111.54	0.739	107.699
						112.14	0.761	105.11
Average						111.868	0.738	105.735
Error (%)						0,53	0,677	−0,206

that statistically, the experimental confirmation results are the same as the BPNN-PSO optimization results.

5 Conclusion

From this study, the conclusions based on the process of experimentation and optimization are as follows:

- The best network architecture to predict the response value in this study is 3 input layers, and 5 hidden layers, each has 5 neurons and 3 output layers. Tansig and purelin is used as the activation function for hidden layers and output layer
- BPNN modeling results compared to experimental results have an error below 5%, this shows that the BPNN modeling is satisfactory because it resembles the experimental results.
- The minimum cutting force, surface roughness and the increase of material removal rate could be obtained simultaneous by using a cutting speed of 308 m/min, a feeding speed of 145 mm/min, and a depth of cut of 1.5 mm.
- The BPNN-based PSO optimization method is acceptable because all the relative errors between predictions and experimental confirmation are less than 5%.

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