Multi-objective Optimization of Turning Process Steel SKD 11 Using BPNN-Artificial Bee Colony (ABC) Method

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Abstract. In the turning process, the force is a constraint factor that must be considered because a large cutting force will generally result in a high surface roughness value. Therefore, selecting suitable parameters for the turning process is necessary to minimize surface roughness (SR), cutting force (F_c), and feeding force (F_f) and increase the tool's life (TL). This study uses a combination method of backpropagation neural network (BPNN) and artificial bee colony (ABC) to obtain the level of turning process parameters that produce maximum TL and minimum SR, F_c, and F_f. The material utilized in the turning process is SKD 11. This study used the L9 orthogonal array from the Taguchi experimentation design. The optimum parameters of optimization results using the ABC method are cutting speed 288.910 (m/min), depth of cut 0.5 (mm), feed rate 0.094 (mm/rev), and tool nose radius 0.931 (mm). Furthermore, the results of response prediction with BPNN compared to the average confirmation experiment produced errors below 5% which means that the BPNN-ABC method succeeded in optimizing and predicting multi-objective responses in this study.

Keywords: BPNN-ABC · Turning · Surface Roughness · Cutting Force · Feeding Force · Tool's Life

1 Introduction

The final quality of the workpiece is very important to note, one of which is surface roughness. Surface roughness is affected by machining parameters such as cutting speed, feed rate, and tool nose radius [1]. The results of research conducted by Bhise and Jogi also stated that cutting speed and feed rate significantly affected surface roughness [2]. In addition to surface roughness, the force generated during the machining process is also important. In the turning process, three forces are generated during the machining process, namely, cutting force, feeding force, and radial force [3]. Research conducted by Mutyalu et al. showed that the feed rate and depth of cut affected the cutting force [4]. In addition to SR and cutting forces, tool life is also an important aspect to consider. Tools with a high service life can optimize the production process and reduce costs in

T. P. Syawitri et al. (Eds.): MEST 2022, AER 222, pp. 520–529, 2023.
https://doi.org/10.2991/978-94-6463-134-0_49

the turning process. Feed rate and cutting speed are factors that significantly influence tool life [5, 6].

The selection of the levels of the machining parameters with multiple objectives using experimentation is considered time-consuming, tedious, and costly. Hence, researchers have utilized metaheuristics or soft computing techniques to perform modeling and machining parameter optimization. Artificial neural network (ANN) has attained so much attention for modeling complicated nonlinear systems and predicting the responses. Multi-objective optimization using soft computing techniques can usually be accomplished by using, for example, genetic algorithm (GA), simulated annealing (SA), particle swarm optimization (PSO), firefly algorithm (FA), artificial bee colony (ABC), and ant colony optimization (ACO).

BPNN is one of the artificial neural network (ANN) that is often used to predict the response of the machining processes. The model from BPNN with a small error can predict the response well [7, 8]. Numerous research studies related to the application of BPNN have been carried out in various fields, especially in the machining processes. BPNN is commonly used to develop a model for predicting response parameters. The combination of this technique with a metaheuristic method is quite often used for optimizing response parameters. ABC is one of the metaheuristic methods that is often utilized for optimization [9, 10]. ABC is a swarm-based optimization method that simulates the behavior of honey bees while foraging. This optimization method was first introduced in 2005 by Karaboga and Basturk [11]. This study aimed to obtain optimal process parameters that maximize tool life and minimize surface roughness, cutting force, and feeding force simultaneously using the BPNN-ABC combination method.

2 Research Methodology

2.1 Backpropagation Neural Network Modeling

BPNN was first introduced by Rumelhart et al. in 1985 [12]. BPNN model is considered the most effective technique in modeling for various cases. The first step in modeling is to normalize the data of process parameters and response measurements with limits of −1 and 1. Normalization can be calculated using Eq. 1 [13].

$$D_n = \frac{2\left(D_{Exp} - min\left(D_{Exp}\right)\right)}{\left(max\left(D_{Exp}\right) - min\left(D_{Exp}\right)\right)} - 1 \tag{1}$$

where:

D_n = Data normalization results of process parameters and experimental response.

D_{Exp} = Data of process and response parameters from the experiment.

BPNN consists of 3 layers, namely, the input layer, hidden layer, and output layer, and each layer has neurons that are interconnected between each layer. The input layer is the process parameters, and the output layer is the response parameters. The number of hidden layers and the number of neurons in the hidden layer are determined using BPNN parameters used in the trial and error method are as follows: the trial and error method to obtain the minimum mean square error (MSE) value.

- Number of inputs 4.
- Number of outputs 4.
- Number of hidden layers 1 to 5.
- The number of neurons in each hidden layer is 1 to 10.
- Activation functions using logsig and tansig.
- Training function using trainlm.
- Maximum 1000 epochs.

The percentages of data used for training, testing, and validation are 70%, 15%, and 15%, respectively [14]. The Levenberg-Marquardt (LM) algorithm is used for training because of the convergence speed compared to other training methods [15]. BPNN prediction results are compared with experimental results by calculating the error value using Eq. 2 [16]. The obtained BPNN model and objective function are saved and will be used for optimization of the response parameters.

$$Error = \frac{D_{Exp} - BPNN}{D_{Exp}} \times 100\% \tag{2}$$

2.2 Artificial Bee Colony (ABC) Optimization Method

The ABC optimization method is used as a multi-objective optimization method to determine the correct level of the turning process parameters. ABC optimization method initiated by food search performance by an employed bee. As soon as a nectarized place has been found, the employed bee will dance (signal), so the onlooker bee can harvest the nectar. Then the onlooker bee will determine the good food sources to harvest, leave the source exhausted, and turn into a scout bee. The scout bee task is finding new, randomly generated sources in the search room, where the bee will forget the previous less nectar position information until the best food source position is found [17]. The steps for using the BPNN-ABC method are shown in Fig. 1.

2.3 Tools and Materials

The working material chosen for this study is SKD 11 steel with hardness ranging from 60–62 HRC. The material is a round bar with a diameter of 50 mm and a length of 50 mm. The cutting tool used in this study was a CNMG-type KORLOY Cermet Carbide insert tool. The tool holder used is the PCLNR 2020 K12 type, with a length of 100 mm and an angle of Kr of 90°. This research was conducted using a lathe model DY-410X000G made by Ann Yang Machinery Co. Ltd. (Taiwan). The SR value was measured using the Mitutoyo Surftest SJ-301, and the cutting forces were measured using the Kistler type 9272 dynamometer.

2.4 Experiment Design

This study used the L9 orthogonal array from the Taguchi experimentation design. The process parameters used are shown in Table 1. The response measured is SR, F_c, F_f, and TL. These responses will be used as targets for BPNN training (Table 2).

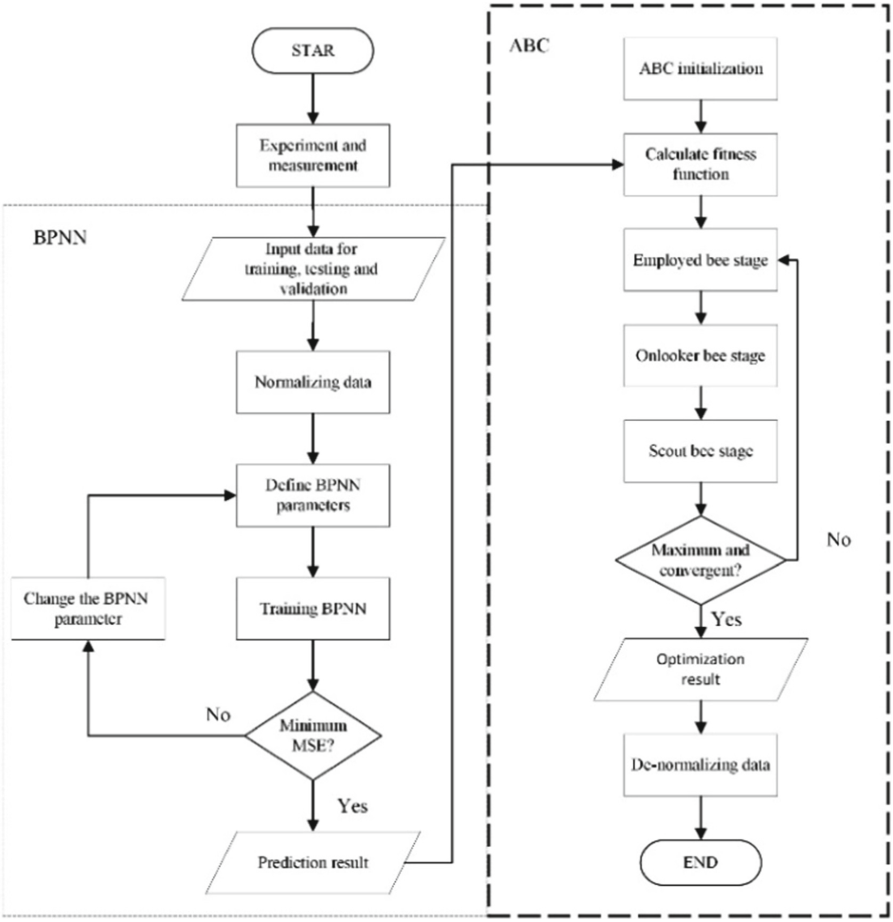

Fig. 1. Flowchart

Table 1. Process Parameters

	Parameters	Unit	Level		
			1	2	3
A	Cutting speed (V)	m/min	144	196	314
B	Depth of cut (a)	mm	0.5	0.75	1.0
C	Feed rate (f)	mm/rev	0.05	0.10	0.15
D	Tool nose radius (r)	mm	0.4	0.8	1.2

Table 2. Experimental Design and Results

No.	Machining Parameters				SR (μm)	Fc (N)	Ff (N)	TL (minutes)
	A	B	C	D				
1	144	0.5	0.05	0.4	2.477	14.455	13.249	32.27
2	144	0.75	0.1	0.8	2.436	30.409	17.914	25.73
3	144	1	0.15	1.2	2.327	47.739	22.066	29.98
4	196	0.5	0.1	1.2	2.637	21.054	9.436	25.22
5	196	0.75	0.15	0.4	1.355	37.983	23.582	25.53
6	196	1	0.05	0.8	2.522	26.633	22.778	27.57
7	314	0.5	0.15	0.8	0.924	25.741	11.035	8.88
8	314	0.75	0.05	1.2	4.319	19.241	12.132	8.5
9	314	1	0.1	0.4	1.004	39.294	30.375	4.58

Table 3. BPNN Architecture

Parameters	Surface Roughness	Cutting Force	Feed Force	Tool Life
Activation Function	tansig	tansig	tansig	tansig
Hidden Layers	4	3	5	5
Neurons each Hidden Layer	5	5	4	5

3 Results and Discussion

3.1 BPNN Prediction Results

BPNN has been used to predict the value of the response parameters, namely SR, F_c, F_f, and TL. The measurement data for each response parameter is divided randomly, training, testing, and validation. Table 3 shows the BPNN architecture with the smallest MSE for each response parameter used in this study.

The BPNN prediction results obtained the smallest MSE values of 1.6139e−04 for surface roughness, 1.7784e−04 for cutting force, 7.4704e−05 for feeding force, and 4.6334e−05 for tool life, respectively. Figure 2 Shows the comparison between the target and the BPNN prediction results for each response. The average value of BPNN prediction error for surface roughness is 0.31%, cutting force is 0.29%, feeding force is 0.32%, and tool life is 0.14%, respectively. The average error value for each response is below 5%, meaning the BPNN has predicted all response parameters satisfactorily [18].

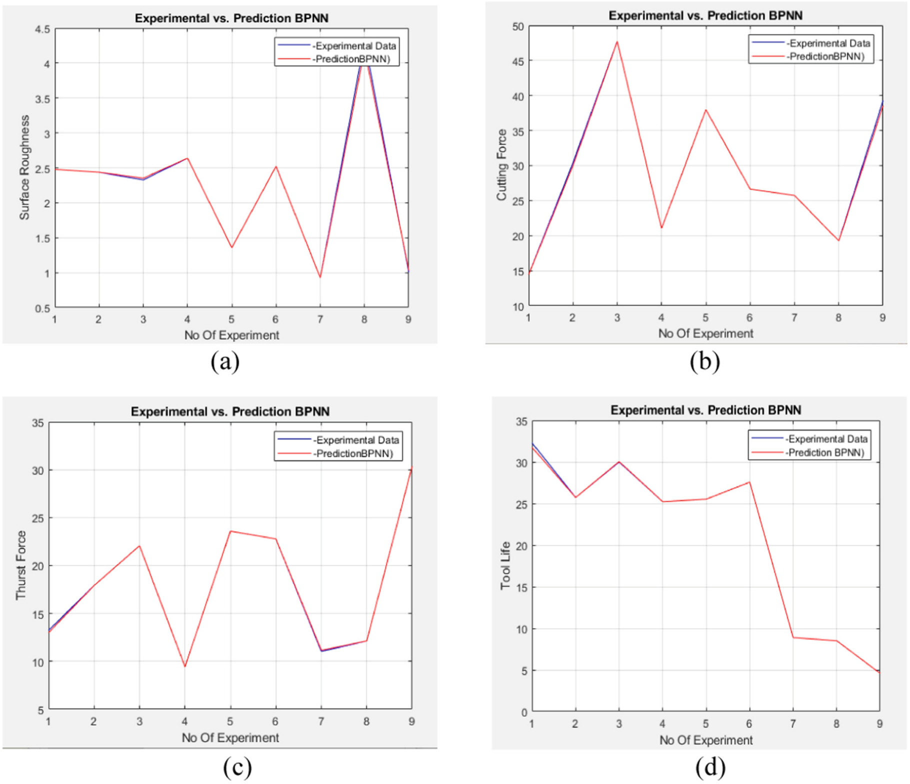

Fig. 2. Comparison of BPNN Predictions with Experiments for (a) SR, (b) F_c, (c) F_f, and (d) TL

3.2 ABC Optimization Results

The parameters ABC used are the number of bee colonies 50, the number of onlookers bees 50, and the maximum iteration 100. The result of BPNN in the form of an objective function is then used as a fitness function in ABC optimization. Because of the three responses, namely surface roughness, cutting force, and feeding force looking for the minimum value while the tool life is looking for the maximum value, the fitness function is [14]:

$$\max f(x) = Obj_4 - (Obj_1 + Obj_2 + Obj_3) \tag{3}$$

where

Obj_1 = objective function of the SR.
Obj_2 = objective function of the F_c.
Obj_3 = objective function of the F_f.
Obj_4 = objective function of the TL.

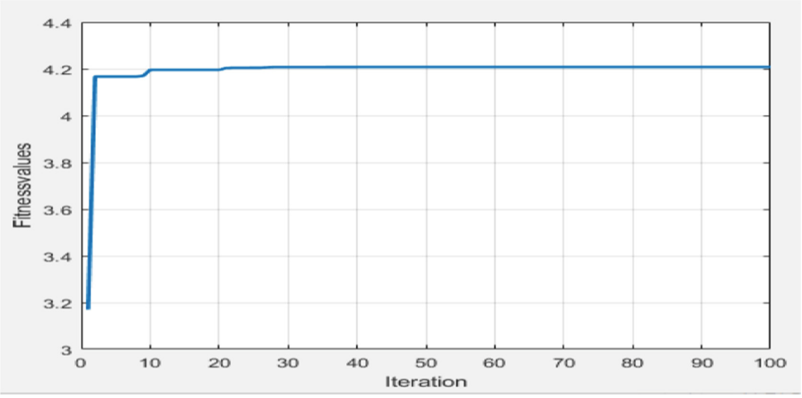

Fig. 3. ABC Iteration

Table 4. Optimum Process Parameters ABC Optimization Results

Process Parameters	Unit	Before Normalization	After Normalization
V	m/min	0.704	288.910
a	mm	−1	0.5
f	mm/rev	−0.081	0.094
r	mm	0.328	0.931

Figure 3 shows an ABC iteration graph with a maximum fitness function, which begins to converge on the 30 iterations. The optimum process parameters of optimization results are shown in Table 4. The BPNN prediction results for optimum process parameters obtained are surface roughness 0.951 µm, cutting force 9.095 N, feeding force 10.233 N, and tool life 31.962 min.

3.3 Confirmation Experiments

A confirmation experiment was conducted to compare the response value of the BPNN prediction results with the experimental results. The process parameters used in the confirmation experiment are the parameters of the optimization results by the ABC method. Confirmation experiments were carried out five times. Table 5 shows the comparison data between BPNN prediction and experiment results.

Table 5. Results Of The Confirmation Experiment And The Prediction

SR (μm)			F_c (N)			F_f (N)			TL (minutes)		
BPNN-ABC	Exp	Error (%)	BPNN-ABC	Exp	Error (%)	BPNN-ABC	Exp	Error (%)	BPNN-ABC	Exp	Error (%)
0.951	0.89	0.17	9.09	9.021	0.42	10.233	11.249	2.34	31.962	30.87	0.37
	0.952			9.409			10.514			31.73	
	0.963			8.97			10.066			32.43	
	1.01			9.054			9.981			32.21	
	0.95			8.83			10.582			31.98	
Average	0.953			9.05			10.47			31.84	

4 Conclusion

The combination of an artificial bee colony (ABC) and back propagation neural network (BPNN) has been shown to be able to maximize TL and minimize SR, F_c, and F_f. The following points are the conclusions drawn from this study:

- The optimal BPNN topology for each response can be achieved by using two hidden layers, three neurons in each hidden layer, and the activation function tansig.
- BPNN has been able to predict the maximum tool life and minimum surface roughness, cutting force, and feed force after proper training because the average error yielded is less than 5%
- The optimum process parameters of optimization
- results using the ABC method are a cutting speed of 288.910 (m/min), depth of cut of 0.5 (mm), feed rate of 0.094 (mm/rev), and tool nose radius of 0.931 (mm).
- The error values of the comparison results between the BPNN prediction response and the confirmation experiment were surface roughness of 0.17%, cutting force of 0.42%, feeding force of 2.34%, and tool life of 0.37%. ABC optimization method that is integrated with BPNN produces compelling results since all of the error value between the prediction and confirmation experiments is shown to be lower than 5%.

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