Minimization of thrust force and surface roughness during MQL coolant drilling on tool steel using BPNN-ACO

Rachmadi Norcahyo, Iqbal Faishal Rokhmad, Muslim Mahardika, Bobby Oeddy Pramoedyo Soepangkat, Fathi Robbany
Mechanical and Industrial Engineering Department, Gadjah Mada University, Jl. Grafika No. 2, 55281, Daerah Istimewa Yogyakarta, Indonesia
Email: rachmadinorcahyo@ugm.ac.id

Abstract. The excessive thrust force that generated during the minimum quantity lubrication (MQL) drilling process of tool steel can lower the hole surface quality. Hence, it is necessary to properly choose the combination of machining variables to minimize thrust force (TF) and hole surface roughness (HSR) simultaneously. This study underlines the modelling and minimizing the thrust force and hole surface roughness developed during MQL drilling process by integrating a backpropagation neural network (BPNN) method and ant colony optimization (ACO). The varied drilling parameters were type of drill bit, drill point angle, feeding speed, and cutting speed. The optimum BPNN architecture could be obtained by using 4-20-2 network architecture with tansig activation function.

The optimum MQL drilling parameters that can minimize TF and HSR simultaneously were HSS M2 drill bit, 107° of drill point angle, 0.045 mm/rev of feeding speed and 36 m/min of cutting speed.

Keywords: ACO, BPNN, hole surface roughness, thrust force, optimization

1. Introduction
Nowadays, sustainable manufacturing and clean production are becoming quite popular in the manufacturing industry. This trend was driven by environmental and economic issues that demand a cleaner industry. The manufacturing industries contribute 29% of industrial pollution. This due to most of the electrical energy needed in the manufacturing process that comes from fossil fuel. Furthermore, the usage of chemical and petroleum-based coolant may lead to some problems such as harm of environment and health issue to machine operator due to daily exposure of coolants. Hence the usage of these type of coolant must be changed to the more sustainable solution. Hence, a new idea should be introduced to establish a relationship between conventional flood coolants and dry machining then minimum quantity lubrication is the solution [1-3].

Minimum quantity lubrication (MQL) is formed as a spray of coolants. These coolants applied at 10–100 ml/h of flow rate and assisted by air jet is used to fulfil the need of cooling. Mahalil et al [4] found that when compared to the dry condition, MQL technique can reduce the thrust force and surface roughness during burnishing process on SS 400 carbon steel. MQL have been guaranteed by some research to increase efficiency at machining. This method can provide less coolant waste, which is beneficial for the environment. The implementation of MQL in manufacturing industry will become more frequent, so optimization is needed to find ideal parameters that result in increasing
the quality of production. Otherwise, most of the product will come into rejection site because the quality of the product does not meet the minimum quality requirements [5-7].

Drilling is the most common process in machining. in some industries that contributes about 40% from total machining process [8]. Therefore, critical parameters need to be well defined and increase to increase the production value. In current years, some researcher uses critical parameters such as surface finish parameters (surface roughness) and cutting force to evaluate machinability. Sarikaya et al. [9] found that the most contributing factor to surface roughness is cutting speed. They also done an optimization experiment with Taguchi’s S/N analysis which result in the relation between cutting speed and surface roughness. Motorcu et al. [10] found surface roughness parameter is rising when the larger feed rate is applied. These Authors also using a larger drill bit angle which results in worse surface roughness.

Good and accurate method is needed to achieve good results in optimization. In these past several years, the development of mathematical models has been brought success to find ideal parameters in machining. Some researchers used an artificial neural network (ANN) that can deliver excellent results in optimization parameters [11, 12]. Karthikeyan et al. [13] researched electric discharge machining (WEDM) on Inconel 750 by using a combination of artificial neural network and particle swarm optimization (ANN-PSO) to minimize the surface finish and increase the material removal rate as a result. Sarikaya et al. [14] investigated parameters such as flow rate effect to surface roughness using the Taguchi-Grey Relational Analysis method in lathe machine to cut alloy Haynes 25. Anarghya et al. [15] found response surface methodology (RSM) and multi-layered perceptron neural network (MLPNN) can give the best result in optimizing torque and Thrust force while drilling of aramid composite. Solati et al. [16] use a genetic algorithm (GA) integrated with the ANN model to shape optimum parameters in laser drilling. Singh et al. Optimized surface roughness and precision of hole diameter in the drilling of EN-31 alloy steel and find good results using Taguchi-Grey Relational Analysis [17].

Many researchers proved that a combination of ANN and other optimization techniques can provide great results. Hence, ANN can be described as a guaranteed method to find ideals parameters. Meanwhile, no research has been conducted to predict TF and HSR using a combination of backpropagation neural network and ant colony optimization. In this study, a backpropagation

![Diagram](image-url)
neural network was employed to mimicking the MQL drilling operations. Moreover, ant colony optimization will be utilized to minimize the TF and HSR simultaneously by finding the best combination of the type of drill bit, drill point angle, feeding speed, cutting speed.

2. Research Methodology
In this study, an integration of two method namely backpropagation neural network (BPNN) and ant colony optimization (ACO) has been applied to mimicking the developed thrust force and hole surface roughness throughout MQL drilling process of EMS-45 tool steel. The steps for predicting and minimizing the thrust force (N) and hole surface roughness (µm) can be seen in Figure 1. The EMS-45 tool steel having 20 mm in thickness, 250 mm x 25 mm in length and width, with 29 HRC of Hardness. The drilling procedure were done with different type of drill bit, namely HSS M2 and HSS M35 with 10 mm of diameter. Furthermore, the experiment also conducted by varying the drilling parameters, namely feeding speed (0.04, 0.07 and 0.1 mm/rev), cutting speed (25, 37 and 50 m/min), and drill point angle (102°, 118°, and 134°). The drilling experiment were performed on Hartford S-Plus 10 by using MQL drilling technique. Thrust force measurement were done by utilizing a Kistler 9272 dynamometer. The experiment setups can be seen in Figure 2.

![MQL Drilling Setup](image)
Experiment were carried out according to the Taguchi’s design of experiment. The orthogonal array used for the experiment was $L_{18}$, which accommodating three drilling parameters (feeding speed, cutting speed, and drill point angle) with three different levels and one drilling parameters (type of drill bit) with two different levels. Three replications were done for each Taguchi’s drilling combination to ensure the accuracy of the drilling prediction using BPNN-ACO.

3. Experiment Results and BPNN-ACO Optimization

After performing drilling experiments according to the Taguchi’s design of experiments, measured TF and HSR can be seen in the Table 1. After drilling experiment, the next procedure was determining the best BPNN architecture by optimizing its parameters using ACO. The total data (54) was split into three, where 70%, 15% and 15% were applied for training, testing, and validation, respectively.

| No | Type of drill bit | Drill Point Angle | Feeding Speed (mm/rev) | Cutting Speed (m/min) | Thrust Force (TF) [N] | Hole Surface Roughness (HSR) [µm] |
|----|------------------|-------------------|------------------------|----------------------|---------------------|-------------------------------|
| 1  | HSS M2           | 102               | 0.04                   | 25                   | 712.15              | 4.36                          |
| 2  | HSS M2           | 102               | 0.07                   | 37                   | 1,099.00            | 3.38                          |
| 3  | HSS M2           | 102               | 0.1                    | 50                   | 1,404.50            | 4.25                          |
| 4  | HSS M2           | 118               | 0.04                   | 25                   | 897                 | 3.97                          |
| 5  | HSS M2           | 118               | 0.07                   | 37                   | 1,228.51            | 2.93                          |
| 6  | HSS M2           | 118               | 0.1                    | 50                   | 1,462.50            | 3.68                          |
| 7  | HSS M2           | 134               | 0.04                   | 37                   | 1,012.53            | 2.48                          |
| 8  | HSS M2           | 134               | 0.07                   | 50                   | 1,304.00            | 2.58                          |
| 9  | HSS M2           | 134               | 0.1                    | 25                   | 1,870.00            | 4.51                          |
| 10 | HSS M35          | 102               | 0.04                   | 50                   | 575.8               | 4                            |
| 11 | HSS M35          | 102               | 0.07                   | 25                   | 1,123.00            | 4.6                           |
| 12 | HSS M35          | 102               | 0.1                    | 37                   | 1,431.00            | 4.76                          |
| 13 | HSS M35          | 118               | 0.04                   | 37                   | 864.05              | 4.04                          |
| 14 | HSS M35          | 118               | 0.07                   | 50                   | 1,299.00            | 3.61                          |
| 15 | HSS M35          | 118               | 0.1                    | 25                   | 1,464.24            | 6.01                          |
| 16 | HSS M35          | 134               | 0.04                   | 50                   | 999.5               | 3.24                          |
| 17 | HSS M35          | 134               | 0.07                   | 25                   | 1,333.00            | 3.34                          |
| 18 | HSS M35          | 134               | 0.1                    | 37                   | 1,607.00            | 4.24                          |

The optimum BPNN architecture to predicting the TF and HSR having four neurons on the input layer, twenty neurons on the hidden layer, and two neurons on the output layer (4-20-2), with tansig activation function as shown in the Figure 3. By utilizing this network architecture, the predicting thrust force and hole surface roughness mean square error (MSE) was 0.015715 at epoch 67 as shown in Figure 4. Moreover, Figure 5 shows the comparison between experiment result and prediction value of TF and HSR. By analysing the Figure 5, it may be declared that BPNN-ACO was capable to estimate the TF and HSR during MQL drilling process of EMS-45 tool steel, since the prediction and experimental results were approximately the same.
Figure 4. MSE Calculation of BPNN-ACO Prediction Technique

Figure 5. Comparison among Prediction and Experimental Results by Utilizing BPNN-ACO for (a) Thrust Force and (b) Hole Surface Roughness During MQL Drilling Process of EMS-45
Next steps, to minimize thrust force and hole surface roughness a fitness function must be determined by using BPNN model. Fitness function applied in this study was computed by combining all objective function \[18\] using equation \((1)\), while \(\text{Obj}_{TF}\) and \(\text{Obj}_{HSR}\) were computed using equations \((2)\) and \((3)\).

\[
F_{\text{fitness}} = \text{Obj}_{TF} + \text{Obj}_{HSR}.
\]

\[
\text{Obj}_k = \left(\sum_{k=1}^{2} v_{kj} \left(\frac{2}{1+e^{-2z_j}} - 1\right) + v_{0k}\right),
\]

\[
z_j = \left(\sum_{j=1}^{20} (u_{ji} \cdot x_i)\right) + u_{0j},
\]

with:

- \(\text{Obj}_{TF}\) : Identified as thrust force objective function.
- \(\text{Obj}_{HSR}\) : Identified as hole surface roughness objective function.
- \(\text{Obj}_k\) : Identified as objective function, i.e., thrust force and hole surface roughness.
- \(x_i\) : Normalization value of MQL drilling parameters.
- \(z_j\) : Activation value for each neuron on hidden layer.
- \(i\) : Sign of MQL drilling process parameters, \(i = 1, 2, 3, 4\).
- \(j\) : Sign of neurons on hidden layer, \(j = 1, 2, ..., 20\).
- \(k\) : Sign of MQL drilling response parameters, \(k = 1, 2\).
- \(u_{ji}\) : Weight value for input layer to hidden layer.
- \(u_{0j}\) : Bias value for input layer to hidden layer bias.
- \(v_{kj}\) : Weight value for hidden layer to output layer.
- \(v_{0k}\) : Bias value for hidden layer to output layer.

The applied parameters of ACO in this study were the maximum number of iterations, intensification factor, deviation distance ratio, and the number of ants, in succession were 1000, 0.5 and 1, and 100. The minimum TF and HSR can be obtained by using optimum MQL drilling parameters i.e., HSS M2 drill bit, 107° of drill point angle, 0.045 mm/rev of feeding speed and 36 m/min of cutting speed. The predicted thrust force and hole surface roughness using optimum MQL drilling parameters in succession were 632.07 N and 2.97 µm.

4. Conclusion
The following are the conclusions from this study:
- The optimum BPNN network architecture could be achieved by using four neurons on the input layers, twenty neurons on the hidden layers, and two neurons on output layer with tansig activation function.
- The optimum MQL drilling parameters were HSS M2 drill bit, 107° of drill point angle, 0.045 mm/rev of feeding speed and 36 m/min of cutting speed.
- The minimum thrust force and hole surface roughness using optimum MQL drilling parameters in succession were 632.07 N and 2.97 µm.

5. Acknowledgement
The authors express their gratitude to the Gadjah Mada University for providing research grant number 2403/UN1.P.III/DIT-LIT/PT/2020.

6. Reference list
[1] Zhao G Y, Liu Z Y, He Y, 2017 Cao H J and Guo Y B Energy 133 142-157
[2] Hill E C 1992 Tribology International 25 141-143
[3] Singh G, Aggarwal V, Singh S 2020 Journal of Cleaner Production 271 122185
[4] Mahalil K, Rahim E A, Mohid Z 2019 IOP Conf. Series: Materials Science and Engineering 494 012001
[5] R. Padmini, Krishna P V, Rao G K M 2016 Tribology International 94 490-501
[6] Mia M 2018 Measurement 121 249-260
[7] Yıldırım C V, Kivak T, Sarıkaya M, Şirin S 2020 Journal of Materials Research and Technology 9 2079-2092
[8] Geng D, Liu Y, Shao Z, Lu Z, Cai J, Li X, Jiang X, Zhang D 2019 Composite Structures 216 168-186
[9] Yıldırım Ç V, Kivak T, Sarıkaya M, Erzincanlı F 2017 Arabian Journal for Science and Engineering 42 4667–4681
[10] Motorcu A R, Kuş A, Durgun I 2014 Measurement 58 394-408
[11] Soepangkat B O P, Pramujati P, Effendi M K, Norcahyo R, Mufarrih A M 2019 International Journal of Precision Engineering and Manufacturing 20 593-607.
[12] Soepangkat B O P, Norcahyo R, Pamuji D R, Lusi N 2018 International Review of Mechanical Engineering 12 42-54.
[13] Babu K N, Karthikeyan R, Punitha 2019 A Materials Today: Proceedings 19 501-505
[14] Sarıkaya M and Güllü A 2015 Journal of Cleaner Production 91 347-357,
[15] A. Anarghya, Harshith D N, Rao N, Nayak N S, Gurumurthy B M 2018 Heliyon 4 703
[16] Solati A, Hamedi M, Safarabadi M 2019 Optics & Laser Technology 113 104-115
[17] Singh P K, Kumar K, Saini P 2020 Materials Today: Proceedings 26 2961-2971
[18] Soepangkat B O P, Norcahyo R, Effendi M K, Pramujati M K 2020 Engineering Science and Technology, an International Journal 23 700-713.