Establishment of the optimal predictive model of die steel SKD11 micromilling via nanofluid (graphene) / ultrasonic atomizing minimum quantity lubrication

W T Huang* and L Y Chen

Department of Mechanical Engineering, National Pingtung University of Science and Technology, 1, Shuefu Road, Neipu, Pingtung 912301, Taiwan
*Email: weitai@g4e.npust.edu.tw

Abstract. This study is mainly utilized nanofluid (graphene) and ultrasonic atomization system to process SKD11 mold steel in micromilling to improve the quality of processed products, find the optimal quality characteristics, and construct an accurate prediction model. In this study, Taguchi's robust design is adopted. The $L_{18}(2^{1} \times 3^{7})$ orthogonal table is used to find the optimal parameter combinations for each quality characteristic, and the micromilling force and micromilling temperature are used as characteristic indicators. The control variables are the average thickness of nanographene, weight percent concentration, ultrasonic atomization amount, spindle speed, feed rate, air pressure, nozzle angle, nozzle distance. Also, a back propagation neural network (BPNN) is used to predict the micromilling processing mode. Taguchi method is used to optimize the hyper parameters in the neural network to improve the accuracy of the prediction model, reduce the input of the number of training samples, and then build a neural network prediction model that can accurately predict the quality characteristics of micromilling force and micromilling temperature. The prediction results show that the milling force parameter value error between the micromilling force model prediction and the single target optimization is 0.55%. The error between the micromilling temperature model prediction and the single-target optimization of the micromilling temperature value is 5.90%.

1. Introduction

With the rapid development of the manufacturing industry and improved product quality, the development of precision and miniaturization is increasing, and micromachining has become the current trend. In the past, micromilling processing was mainly based on dry cutting. Because dry cutting would cause unsatisfactory heat dissipation in the processing area, it was easy to cause unstable tool life, poor workpiece machining accuracy, and poor product surface quality, which can be improved using cutting fluid. Although traditional cutting fluid can alleviate these problems, the high frictional heat accumulation cannot be eliminated during processing, but it is cooled after processing. The effect of lubrication and cooling is not great, and it takes time to dispose of waste cutting fluid. Cost becomes a big expense. More importantly, its waste liquid recycling and environmental protection and the original loss of cutting fluid pump energy [1-3]. Therefore, a new lubrication method is Minimum Quantity Lubrication (MQL). MQL is a minimal amount of cutting fluid mixed with a large amount of high-pressure air and sprayed directly to the cutting area to achieve the purpose of cooling and lubrication. This method can reduce the amount of cutting fluid used, reduce heat and tool wear, and extend the cutting tools' service life. To further improve the lubricating performance of MQL, this study added nanoparticles to the MQL working fluid and produced a suspension stable suspension as nanofluid. The
nanoparticle selected in this study is Graphene. Graphene is the thinnest and strongest new nanomaterial with extremely high electrical conductivity and thermal conductivity [4]. It also assists in using a self-designed ultrasonic atomizing minimum quantity lubrication system, which uses ultrasonic to generate cavitation, atomizes the cutting fluid, and disperses the agglomeration of nanoparticles, and effectively increases the lubrication and cooling effect, which helps to improve the micro Milling performance. This research's goal is the most important machining performance index in micromilling processing, namely the micromilling force and micromilling temperature. The Taguchi method used in the experiment is a powerful statistical method for experiment design. Orthogonal array (OA) can effectively analyze many design variables' experimental data through a few experiments. As a result of OA is a partial factorial matrix, it ensures the balance of comparative factors or the interaction of factors at any level [5-6]. In the predictive model building part, these two goals are not simple linear problems, so they cannot Using simple rules to predict the results. The backward pass neural network has a good ability to solve nonlinear problems. Therefore, this study uses a back propagation neural network and the Levenberg-Marquardt algorithm to establish the micromilling force and micromilling temperature prediction model.

The relevant research results are summarized as follows. Zheng et al. [7] applied micro-lubrication to micromilling Ti-6Al-4V titanium alloy and studied the titanium alloy's micromilling mechanism and compared and analyzed the tool wear, tool life, and cutting vibration under (MQL) and dry cutting conditions, Surface finish, and burr formation. Experimental results show that MQL will significantly increase tool life and reduce material adhesion in micromilling. Kilickap et al. [8] used the Levenberg-Marquardt network for ANN training to predict the effect of different cutting parameters such as cutting speed, feed rate, and depth of cut on cutting force, surface roughness, and tool wear when milling Ti-6242S alloy. It is found that the values obtained by the ANN prediction model and RSM are very close. Erry et al. [9] used back-propagation neural network modeling to predict the cutting temperature when milling H-13 hardened steel. The results showed a high correlation between the predicted temperature and the observed temperature, indicating the validity of the model. Jong et al. [10] used the Taguchi orthogonal method to optimize the neural network's hyperparameters. They built a neural network model that can predict CAE with a backward pass neural network. It is found that the number of neurons in the hidden layer, the number of training times, and the learning rate can be optimized by the Taguchi method, and suitable hyperparameters can be quickly found to improve the prediction accuracy accurately. Mathi et al. [11] used the Levenberg-Marquardt algorithm to predict composite materials' wear rate, compare RMS and BPNN, and found that the Artificial Neural Network (ANN) model has higher modeling capabilities than the RSM model. Huang and Chen [12] used a minimal lubrication (MQL) technology for 7075-T6 aluminum alloy microdeep drilling. Used a neural network and conducted Taguchi grey relational analyses to develop a highly accurate microdrilling predictive model, combination for generating the optimal microdrilling force and torque predicted differed from those of the experiment results by only 0.44% and 1.24%.

This research aims to study the use of nanofluid (graphene)/ultrasonic atomization micro-lubrication in micromilling processing of SKD11 mold steel, and the ultrasonic atomization system can effectively disperse the nanoparticles in the nanofluid and increase the nanoparticle lubrication Benefit, and use the Taguchi method to plan the parameters to find the best combination of the two quality targets, micromilling force, and micromilling temperature. This part is actually to find the optimization of the research process parameters. The data collected by the Taguchi method experiment is combined with the use of back propagation neural network (BPNN) to establish a micromilling prediction model, and the Taguchi method is used to optimize the relevant hyperparameter settings of the prediction model before the prediction model is established to improve the prediction model Accuracy. This part is to find the optimization of BPNN hyperparameter setting. It can provide the basis and reference for parameter selection in related industries before micromilling processing, reducing the uncertainty of process quality.

2. Experiment

2.1. Experiment setting
In the experiment, the material is SKD 11 die steel, with a length of 50mm, a width of 50mm, and a thickness of 15mm. The micromilling machine used is the L.K. Machinery Corp TC-510 central processing machine, which has a maximum three-axis machining stroke of 510mmx420mmx350mm, is equipped with a static airspeed increasing spindle with a maximum speed of 80,000rpm for micromilling processing. The tool used is a DIXI 7242 two-edged micro end mill with a diameter of 300μm. To measure the micromilling force, use the Kistler9257B three-dimensional direction dynamic meter, connect the Kistler5070A eight-channel amplifier to amplify the signal, and then transfer the data to the computer through the DAQ Board (AdvantechUSB-4716) data acquisition card to capture the measurement results. The part for measuring the micromilling temperature is measured with an infrared thermal imager (FLIRA320), set at a distance of 1 meter from the processing area and taken at an angle of 30°. The experimental setup is shown in Figure 1 and Figure 2.

![Figure 1. Experimental setup.](image1)

![Figure 2. Experimental setup.](image2)

2.2. Ultrasonic atomizing MQL system

Due to the nanoparticles' small size effect, the Vander Waals force is generated between the nanoparticles, which causes the agglomeration of the nanoparticles in the fluid. Therefore, in this study, the ultrasonic atomization micro-lubrication system was used to convert the nanofluid Use ultrasonic cavitation for dispersion. Using this ultrasonic drive module to apply a DC voltage to the electrodes of the piezoelectric ceramic sheet (PZT), the piezoelectric ceramic sheet (PZT), which produces the piezoelectric inverse effect, generates high-frequency vibration in the thickness direction to transmit the vibration energy. Given the nanofluid, based on ultrasonic waves' cavitation principle and characteristics, a high-intensity shock wave is generated on the nanofluid's surface to atomize the nanofluid into microscopic particles. The overall structure of the equipment is shown in Figure 3.

![Figure 3. Ultrasonic atomizing MQL system.](image3)
2.3. Experimental design for optimization of micromilling process quality

The quality characteristics of the optimized process in this experiment are micromilling force and micromilling temperature. It is expected that the smaller the value of micromilling force and micromilling temperature, the better, so the quality characteristics are defined as static small-looking characteristics, smaller-the-better signal-to-noise (S/N) ratios, which was expressed as (1), use the orthogonal table $L_{18}(2^{7} \times 3^{7})$ to find the design parameters of micromilling force and micromilling temperature. The control factor is the average thickness of nanographene and nanometer Rice particle weight percent concentration, spindle speed, feed rate, nozzle distance, ultrasonic atomization amount, air pressure, nozzle angle. This experiment's fixed parameters are axial cutting depth 100 μm, cutting length 100 mm, orthogonal table $L_{18}(2^{7} \times 3^{7})$. The configuration is shown in Table 1.

$$S/N = -10 \log \left[ \frac{1}{n} \sum_{i=0}^{n} y_i^2 \right]$$

(1)

$n$: Instances observed in each experimental combination
$y_i$: The $i$-th datum in the experimental combination

2.4. Neural network hyperparameter setting.

The micromilling process is a complicated manufacturing process that involves many considerations. Simple linear methods and rules cannot be used to make accurate process quality predictions. But for the BPNN with multiple hidden layers, it does have good results in nonlinear calculation and prediction. Therefore, in this study, BPNN is used to predict the micromilling process's quality characteristics (micromilling force and micromilling temperature). When using BPNN, the Taguchi method will optimize the hyperparameters of the neural network to improve the prediction accuracy. Use the Matlab nntool module to build a BPNN $L_{9}(3^{4})$ hyperparameter model and use the two single-target $L_{18}$ experimental data introduced in the previous paragraph as training data. The prediction target value calculates the Mean Square Error (MSE) between the experimental result data and the predicted value. The calculation method is as (2) to find a single quality characteristic hyperparameter combination. When the MSE is closer to zero, the prediction result is closer to the true value and accurate, so the quality characteristic is defined as the static low-looking characteristic. It is hoped that an accurate prediction model of the micromilling process can be established. The control hyperparameter factors are the training Epochs (maximum number of cycles), Hidden Layer 1 (Neurons), Hidden Layer 2 (Neurons), Mu (initial value of momentum)). The control factors and levels of the orthogonal table are shown in Table 2.

$$MSE = \frac{1}{m} \sum_{i=1}^{m} (y_i - \hat{y}_i)^2$$

(2)

$m$: The number of units.
$y_i$: The estimated value.
$\hat{y}_i$: The actual value.
$MSE$: The expected value of the error square.

| Table 1. Design parameters and level. |
|--------------------------------------|
| **Factor**                          | **Level** |
| A  | Graphene average flake Thickness (nm) | 8 | 60 |
| B  | Density of Nanofluid (wt%) | 0.25 | 0.5 | 1.0 |
| C  | Spindle Speed (rpm) | 45000 | 55000 | 65000 |
| D  | Feed Rate (μm/rev) | 0.5 | 0.75 | 1.0 |
| E  | Nozzle Distance (mm) | 20 | 30 | 40 |
| F  | Amount of Atomization (ml/h) | 15 | 25 | 35 |
| G  | Air Pressure (bar) | 1 | 2 | 3 |
| H  | Nozzle angle (°) | 30 | 45 | 60 |
3. Results and discussions

3.1. Experimental results of micromilling process quality optimization
The S/N values of micromilling force and micromilling temperature measured by $L_{18}(2^4 \times 3^3)$ orthogonal table for micromilling processing are shown in Table 3. Table 4 is the micromilling force S/N factor response table, and Table 5 is the micromilling temperature S/N factor response table. We can know the degree of influence of each control factor on the micromilling force and micromilling pin temperature from the factor response table. The optimized parameter combination of micromilling force is A2B2C2D2E2F1G1H3; the optimized parameter combination of micromilling temperature is A1B1C1D2E2F2G1H1. Table 6 and Table 7 are the experimental results of the confirmation experiment. After the confirmation experiment, the best parameter combination micromilling force is 25.39N, and the micromilling temperature is 105.72°C.

Table 2. Design parameters and level.

| Factor              | Level     |
|---------------------|-----------|
| A Epochs            | 1000      |
| B Hidden Layer 1 (Neurons) | 3  |
| C Hidden Layer 2 (Neurons) | 3  |
| D Mu                | 0.001     |

Table 3. Quality characteristic results for micromilling process quality.

| NO. | A  | B  | C  | D  | E  | F  | G  | Micromilling Force(N) | S/N(dB) | Micromilling Temperature (°C) | S/N(dB) |
|-----|----|----|----|----|----|----|----|-----------------------|---------|--------------------------------|---------|
| 1   | 8  | 0.25 | 45000 | 0.5 | 20 | 15 | 1  | 30                   | 25.59   | -28.160                       | 115.88  |
| 2   | 8  | 0.25 | 55000 | 0.75 | 30 | 25 | 2  | 45                   | 25.58   | -28.157                       | 116.09  |
| 3   | 8  | 0.25 | 65000 | 1   | 40 | 35 | 3  | 60                   | 25.85   | -28.249                       | 133.37  |
| 4   | 8  | 0.5  | 45000 | 0.5 | 30 | 25 | 3  | 60                   | 25.71   | -28.201                       | 112.10  |
| 5   | 8  | 0.5  | 55000 | 0.75 | 40 | 35 | 1  | 60                   | 25.67   | -28.188                       | 111.96  |
| 6   | 8  | 0.5  | 60000 | 1   | 20 | 15 | 2  | 45                   | 25.65   | -28.181                       | 136.15  |
| 7   | 8  | 1    | 45000 | 0.75 | 20 | 35 | 2  | 60                   | 25.71   | -28.203                       | 118.51  |
| 8   | 8  | 1    | 55000 | 1   | 30 | 15 | 3  | 60                   | 25.74   | -28.212                       | 139.80  |
| 9   | 8  | 1    | 65000 | 0.5 | 40 | 25 | 1  | 45                   | 25.73   | -28.209                       | 138.63  |
| 10  | 60 | 0.25 | 45000 | 1   | 40 | 25 | 2  | 30                   | 25.76   | -28.219                       | 124.38  |
| 11  | 60 | 0.25 | 55000 | 0.5 | 20 | 35 | 3  | 45                   | 25.73   | -28.207                       | 144.90  |
| 12  | 60 | 0.25 | 65000 | 0.75 | 30 | 15 | 1  | 60                   | 25.53   | -28.139                       | 124.57  |
| 13  | 60 | 0.5  | 45000 | 0.75 | 40 | 15 | 3  | 45                   | 25.81   | -28.235                       | 147.65  | -43.385                       |
| 14  | 60 | 0.5  | 55000 | 1   | 20 | 25 | 1  | 60                   | 25.55   | -28.149                       | 126.29  | -42.027                       |
| 15  | 60 | 0.5  | 65000 | 0.5 | 30 | 35 | 2  | 30                   | 25.61   | -28.164                       | 134.55  | -42.578                       |
| 16  | 60 | 1    | 45000 | 1   | 30 | 35 | 1  | 45                   | 25.74   | -28.212                       | 150.75  | -43.565                       |
| 17  | 60 | 1    | 55000 | 0.5 | 40 | 15 | 2  | 60                   | 25.74   | -28.212                       | 149.63  | -43.500                       |
| 18  | 60 | 1    | 65000 | 0.75 | 20 | 25 | 3  | 30                   | 25.73   | -28.208                       | 137.80  | -42.785                       |

Table 4. Response table for micromilling cutting force.

| Factor | A     | B     | C     | D     | E     | F     | G     | H     |
|--------|-------|-------|-------|-------|-------|-------|-------|-------|
| Level1 | -28.201 | -28.191 | -28.203 | -28.190 | -28.184 | -28.185 | -28.181 | -28.192 |
| Level2 | -28.190 | -28.185 | -28.188 | -28.188 | -28.179 | -28.190 | -28.191 | -28.212 |
| Level3 | -28.211 | -28.191 | -28.201 | -28.220 | -28.220 | -28.223 | -28.190 |       |
| Effect | 0.00  | 0.02  | 0.02  | 0.02  | 0.04  | 0.01  | 0.04  | 0.01  |
| Rank   | 8     | 3     | 4     | 5     | 2     | 6     | 1     | 7     |
Table 5. Response table for micromilling temperature.

| Factor | A    | B    | C    | D    | E    | F    | G    | H    |
|--------|------|------|------|------|------|------|------|------|
| Level1 | -41.880 | -42.022 | -42.133 | -42.411 | -42.241 | -42.612 | -42.111 | -42.071 |
| Level2 | -42.761 | -42.111 | -42.323 | -41.970 | -42.213 | -41.974 | -42.240 | -42.830 |
| Level3 | -42.853 | -42.553 | -42.621 | -42.520 | -42.393 | -42.631 | -42.079 |
| Effect | 0.88  | 0.83  | 0.45  | 0.62  | 0.31  | 0.64  | 0.53  | 0.76  |
| Rank   | 1     | 2     | 7     | 5     | 8     | 4     | 6     | 3     |

Table 6. Optimization results for micromilling cutting force.

| Factor&Level | Micromilling Cutting Force(N) | S/N(dB) |
|--------------|------------------------------|---------|
| NO.12        | A2B1C3D2E 2F1G1H3            | 25.53   | -28.139 |
| Optimization | A2B2C2D2E 2F1G1H3            | 25.39   | -28.093 |

Table 7. Optimization results for micromilling temperature.

| Factor&Level | Micromilling Temperature(℃) | S/N(dB) |
|--------------|-------------------------------|---------|
| NO.5         | A1B2C2D2E 3F3G1H1            | 111.96  | -40.981 |
| Optimization | A1B1C1D2E 2F2G1H1            | 105.72  | -40.483 |

3.2. Neural network hyperparameter setting experimental results

Before training the BPNN network model, the first thing to do is determine the appropriate network settings hyperparameter. The hyperparameter that the network should select, such as the number of training times, the number of neurons in the first layer of the hidden layer, the number of neurons in the second layer of the hidden layer, and Mu (Initial value of momentum) and other settings. Since network hyperparameter settings have a considerable influence on network prediction errors and convergence results, hyperparameter selection first uses Taguchi L9(3^4) orthogonal table to perform neural network hyperparameter optimization and calculate the predictions of 9 groups of models. The value of MSE value and the MSE value as the target value calculate the S/N value as shown in Table 8. The 9 groups of models' training parameters are the micromilling force and the micromilling temperature is the experimental results of each Taguchi experiment. Table 9 is the micromilling force BPNN hyperparameter optimization S/N factor response table. Table 10 is the micromilling temperature BPNN hyperparameter optimization S/N factor response table. The micromilling force BPNN hyperparameter optimization obtained after the analysis of the response table is A3B3C2D3. The micromilling temperature BPNN hyperparameter optimization is A1B3C1D3. The combination comparison table of micromilling force and micromilling temperature BPNN hyperparameter optimization is shown in Table 11 and Table 12. After confirming the experiment, the optimal network parameter combination micromilling force MSE value is 0.0196, and the micromilling temperature MSE value is 38.949. After optimization, the micromilling force and micromilling temperature are compared with the best group of the original orthogonal table. Increase the MSE value by 0.54% and 6.94%, respectively. From the factor response table, it can also be found that the BPNN hyperparameter optimization affects the micromilling force. The maximum impact factor is set for Mu (initial value of momentum). The initial value of momentum can be obtained from the factor response table in Table 9. The closer the value is to 0.1, the better the effect. Too small initial value of momentum will make the error of MSE value larger. The maximum influencing factor of the micromilling temperature is the number of neurons in the hidden layer's first layer. The experimental results show that the predicted MSE value is the most accurate when the number of neurons in the hidden layer is 10 layers. The factor response table in Table 10 shows that the hidden layer neurons too many or too few numbers will cause the MSE value error to be too large, and the middle level 6 has the best MSE value. It can be seen from the above that in the BPNN hyperparameter optimization, the control factor Mu (initial value of momentum) and the level of the number of neurons in the first layer of the hidden layer have a great influence on the accuracy of the target value MSE.
3.3. Neural network BPNN micromilling process quality test results

Using the Matlab nntool module to establish BPNN training functions all use the Levenberg-Marquardt algorithm. The BPNN architecture diagram is shown in Figure 4. The micromilling force BPNN hyperparameter is set to the optimized experimental results obtained in Section 3.2. The training times are 2000 times, and the hidden layer is the first. One layer is 6, the second layer is 10, and the initial value of momentum is 0.1. After the BPNN is trained, verified, and tested, according to the Neural network BPNN regression graph shown in Figure 5, the R-value for training is 0.9979, the verification R-value is 0.99997, the test R-value is 0.99998, and the overall R-value is 0.9971. The BPNN hyperparameter setting at the micromilling temperature is the same as the optimized experimental results obtained in section 3.2. The training times are 1000 times, the first hidden layer is 6, the second hidden layer is 3, the initial value of momentum is 0.1, and the hidden layer. The data uses 18 sets of experimental data obtained in Section 3.1. The BPNN system randomly allocates 12 sets for training, 3 sets for verification, and 3 sets for testing. After BPNN is trained, verified, and tested, according to the Neural network BPNN regression graph shown in Figure 6, the R-value for training is 0.9991, the verification R-value is 0.99994, the test R-value is 0.99992, and the overall R-value is 0.9999. From the

Table 8. Quality characteristic results for neural network hyperparameter setting.

| NO. | A  | B  | C  | D   | Micromilling Cutting Force(N) | Micromilling Temperature(℃) Predictive Value | MSE | S/N(dB) |
|-----|----|----|----|-----|-------------------------------|---------------------------------------------|-----|--------|
| 1   | 1000 | 3  | 3  | 0.001 | 25.84                          | 117.23                                    | 0.2031 | 132.599 | 13.844 | -42.450 |
| 2   | 1000 | 10 | 10 | 0.05  | 25.70                          | 126.16                                    | 0.0986 | 417.895 | 20.117 | -52.421 |
| 3   | 1000 | 6  | 6  | 0.1    | 25.53                          | 112.18                                    | 0.0197 | 41.851  | 34.092 | -32.434 |
| 4   | 1500 | 3  | 10 | 0.1    | 25.59                          | 113.33                                    | 0.0415 | 58.0217 | 27.623 | -35.271 |
| 5   | 1500 | 10 | 6  | 0.001 | 25.84                          | 143.45                                    | 0.2103 | 1423.711 | 13.542 | -63.068 |
| 6   | 1500 | 6  | 6  | 0.05   | 25.79                          | 117.27                                    | 0.1662 | 133.425 | 15.586 | -42.504 |
| 7   | 2000 | 3  | 6  | 0.05   | 25.64                          | 127.60                                    | 0.0646 | 478.756 | 23.786 | -53.602 |
| 8   | 2000 | 10 | 3  | 0.1    | 25.54                          | 124.11                                    | 0.0225 | 338.181 | 32.933 | -50.582 |
| 9   | 2000 | 6  | 10 | 0.001 | 25.58                          | 123.57                                    | 0.0397 | 318.736 | 28.019 | -50.068 |

Table 9. Response table for micromilling cutting force neural network hyperparameter setting.

| Factor | A  | B  | C  | D   |
|--------|----|----|----|-----|
| Level1 | 22.68 | 21.75 | 20.79 | 18.47 |
| Level2 | 18.92 | 22.20 | 25.25 | 19.83 |
| Level3 | 28.25 | 25.90 | 23.81 | 31.55 |
| Effect | 9.33 | 4.15 | 4.47 | 13.08 |

Table 10. Response table for micromilling temperature neural network hyperparameter setting.

| Factor | A  | B  | C  | D   |
|--------|----|----|----|-----|
| Level1 | -42.44 | -43.77 | -45.18 | -51.86 |
| Level2 | -46.95 | -55.36 | -45.92 | -49.51 |
| Level3 | -51.42 | -41.67 | -49.70 | -39.43 |
| Effect | 8.98 | 13.69 | 4.52 | 12.43 |
| Rank   | 3   | 4   | 2   |

Table 11. Optimization results for micromilling cutting force neural network hyperparameter setting.

| Factor & Level | MSE | S/N(dB) |
|----------------|-----|---------|
| NO.3           | 0.0197 | 34.092  |
| Optimization   | 0.0196 | 34.139  |

Table 12. Optimization results for micromilling temperature neural network hyperparameter setting.

| Factor & Level | MSE | S/N(dB) |
|----------------|-----|---------|
| NO.3           | 41.852 | -32.434 |
| Optimization   | 38.949 | -31.809 |
obtained R-value, it can be known that the Neural network BPNN model has excellent prediction accuracy. Table 13 uses this to establish the Neural network BPNN model to verify the two target optimization prediction values' prediction results and the two target optimization actual experimental data. The results show that the micromilling force and micromilling temperature prediction model has good accuracy, its micromilling force prediction error is 0.55%, and the micromilling temperature prediction error is 5.90%.

Table 13. Optimization experimental result value and BPNN predictive value comparison table.

| Optimization Factor&Level | Experimental Result Value | BPNN Predictive Value | Error Value |
|---------------------------|---------------------------|-----------------------|-------------|
| Micromilling Cutting Force(N) | A2B2C2D2E2F1 G1H3 | 25.39 | 25.53 | 0.55% |
| Micromilling Temperature(℃) | A1B1C1D2E2F2 G1H1 | 105.72 | 111.96 | 5.90% |

Figure 4. BPNN architecture diagram.

4. Conclusion
This research uses nanofluid (graphene)/ultrasonic atomization micro-lubrication to process SKD11 mold steel in micromilling. The ultrasonic atomization system effectively disperses the nanoparticles in
the nanofluid and increases the effectiveness of nanoparticle lubrication. And use the robust design method to plan the parameters, find the best combination of the two quality targets, micromilling force, and micromilling temperature quality characteristics. Simultaneously, the BPNN hyperparameter is optimized by a robust design method, and the optimized BPNN hyperparameter will be used to establish and improve the accuracy of the micromilling processing prediction model. The experimental results of this research are as follows.

1. From the results of the $L_{18}(2^4 \times 3^7)$ robust design experiment, it is known that the optimal parameter combination of micromilling force is $A_2B_2C_2D_2E_2F_1G_1H_3$, and its micromilling force value is 25.39N. The optimal combination of micromilling temperature is $A_1B_1C_2D_2E_2F_1G_1H_1$ and its micromilling temperature. The value is 105.72°C.

2. From the $L_{9}(3^7)$ robust design experiment results, the combination of micromilling force hyperparameter optimization in the BPNN hyperparameter optimization is $A_3B_3C_2D_3$, and its MSE value is 0.0196, which is 0.54% higher than the best group of the original orthogonal table. The maximum influencing factor is set for $\mu$ (initial value of momentum). The closer the initial value of momentum is to 0.1, the better the effect. If the initial value of momentum is too small, the error of MSE value will be larger. The hyperparameter optimization of the micromilling temperature is $A_1B_3C_1D_3$, and its MSE value is 38.949, which is 6.94% higher than the best group of the original orthogonal table. The largest influencing factor is the number of neurons in the first layer of the hidden layer. The predicted MSE value is the most accurate when the number of hidden layer neurons is 10 layers. Too many or too few hidden layer neurons will cause the MSE value error to be too large. In the BPNN hyperparameter optimization, the control factor $\mu$ (initial value of momentum) and the number of neurons in the first layer of the hidden layer greatly influence the accuracy of the target value MSE.

3. The micromilling force BPNN constructs the prediction model part. It can be known that the training R-value is 0.9979, the verification R-value is 0.99997, the test R-value is 0.99998, and the overall R-value is 0.9971. The difference between the predicted micromilling force and the actual machining value is 0.55%. In the part of the micromilling temperature BPNN construction prediction model, the training R-value is 0.9991, the verification R-value is 0.99994, the test R-value is 0.99992, and the overall R-value is 0.9999. Comparing the micromilling temperature prediction with the actual machining value, the error value is 5.90%.

Acknowledgments

This study was supported in part by the Ministry of Science and Technology, Taiwan, R.O.C., under Grant Numbers MOST 109-2221-E-020-019-MY2. The authors thank the Researchers Supporting Project number (#NPUST-KMU-109-P009), NPUST–KMU JOINT RESEARCH PROJECT.

References

[1] Debnath S, Reddy M M and Yi Q S 2016 Influence of cutting fluid conditions and cutting parameters on surface roughness and tool wear in turning process using Taguchi method. Measur ment, vol 78, 111-119
[2] Chan C Y, Lee W B and Wang H 2013 Enhancement of surface finish using water miscible nano cutting fluid in ultraprecision turning. International Journal of Machine Tools and Manufact ure, vol 73, 62-70
[3] Davoodi B and Tazehkandi A H 2014 Experimental investigation and optimization of cutting parameters in dry and wet machining of aluminum alloy 5083 in order to remove cutting fluid. J urnal of Cleaner Production, vol 68, 234-242
[4] Weinert K, Inasaki I, Sutherland J W and Wakabayashi T 2004 Dry machining and minimum quantity lubrication. Annals of the CIRP, vol 53, 511-537
[5] Huang W T, Wu D H, and Chen J T 2016 Robust design of using nanofluid/MQL in micro-drilling, Int J Adv Manuf Technol, vol 85, 2155-2161
[6] Huang W T, Wu D H, Lin S P and Liu W S 2016 A combined minimum quantity lubrication and MWCNTcutting fluid approach for SKD 11 end milling. Int J Adv Manuf Technol, vol 84, 1697-1704
[7] Zhen X, Liu Z and Chen M 2013 Experimental study on micromilling of Ti6Al4V with minimum quantity lubrication. *International Journal of Nanomanufacturing*, vol 9 nos. 5-6, 570-582

[8] Erol K, Ahmet Ya, Yahya H and Sman Ç 2017 Mathematical Modelling and Optimization of Cutting Force, Tool Wear and Surface Roughness by Using Artificial Neural Network and Response Surface Methodology in Milling of Ti-6242S. *Multidisciplinary Digital Publishing Institute*, vol 7 no 10, 10.3390/app7101064

[9] Erry Y T, Adesta, Muataz H F, Al H, Suprianto M Y and Muhammad R 2012 Prediction of Cutting Temperatures By Using Back Propagation Neural Network Modeling When Cutting Hardened H-13 Steel in CNC End Milling. *Trans Tech Publications Switzerland*, vol 576, 91-94

[10] Jong W R, Huang Y M, Lin Y Z, Chen S C and Chen Y W 2020 Integrating Taguchi method and artificial neural network to explore machine learning of computer aided engineering. *Journal of the Chinese Institute of Engineers*, vol 43, 346-356

[11] Mathi K, Karthikeyan G and Jinu Gowthami T R 2020 Prediction of specific wear rate for LM25/ZrO2 composites using Levenberg–Marquardt backpropagation algorithm. *Journal of Materials Research and Technology*, vol 9, 530-538

[12] Huang W T and Chen J T 2020 Application of intelligent modeling methods to enhance the effectiveness of nanofluid / micro lubrication in micro deep drilling holes machining, *J. Adv. Mech. Des. Syst. Manuf.*, vol 14, (7):01-26. DOI: 10.1299/jamdsm.2020jamdsm000x