Application of intelligent modeling methods to enhance the effectiveness of nanofluid / micro lubrication in microdeep drilling holes machining

Wei-tai HUANG* and Jian-ting CHEN*
* Department of Mechanical Engineering, National Pingtung University of Science and Technology
1, Shuefu Road, Neipu, Pingtung 91201, TAIWAN.
E-mail: weitai@mail.npust.edu.tw

Received: 21 July 2020; Revised: 1 September 2020; Accepted: 7 October 2020

Abstract
This research aims to provide a novel nanofluid / minimal lubrication (MQL) technology for 7075-T6 aluminum alloy microdeep drilling. This technology will extend the life of tools used for precision machining. A parameter combination meeting the optimal quality-related objectives was obtained, and a predictive model was developed. Because microdrilling force and torque were two quality-related objectives, this study adopted Taguchi’s robust design, used machining parameters (i.e., nanofluid weight percentage concentration, spindle speed, feed rate, nozzle distance, nozzle angle, MQL flow, air compression, and pecking depth), and performed grey relational analyses to obtain the parameter combination generating the optimal microdrilling force and torque. Subsequently, this study used a neural network and conducted Taguchi grey relational analyses (where Taguchi orthogonal tables were used as the experimental basis and the experimental data from grey relational analyses were used as training examples) to develop a highly accurate microdrilling predictive model. The parameter combination for generating the optimal microdrilling force and torque predicted differed from those of the experiment results by only 0.44% and 1.24%.

Keywords: Micro-deep drilling, Nanofluid, Minimal quantity lubrication (MQL), Grey relation analysis, Artificial neural network (ANN), Back-propagation neutral network, Predictive model

1. Introduction

Micromachining is a widely researched advanced manufacturing technology that has led to microelectromechanical systems, lithography electroforming micromolding, and micromachines. Microelectromechanical systems and lithography electroforming micromolding machining are hindered by problems such as the need to use expensive equipment, material limitations (only silicon-based materials can be used), and degrees of processing freedom required (2D or 2.5D). However, micromachining is used in components and products because of the demand for materials (e.g., metals, nonmetals, and advanced engineering plastics) and complex surfaces (3D). Micromachining is divided into traditional and nontraditional micromachining. Traditional micromachining includes turning, milling, drilling, grinding, and planning, whereas nontraditional micromachining includes electric discharge machining, ultrasonic machining, and laser beam machining. Among microdrilling methods, mechanical microdrilling involves short drilling time, low costs, and favorable roundness, verticality, and surface roughness by Franco-Gasca A.L.A. et al. (2006). Afazova S.M., et al. (2013) proposed a new method, spindle-peak-frequency (SPF) for determining stable microdrilling. The experimental results show that the SPF method can achieve a higher holes length-to-width ratio for micro-drills. Eiji KONDO., et al. (2012) research results indicate that the thrust force caused by tool wear during peck micro-drilling is related to the height of the burr occurring at the outlet of the drilled hole and the pre-failure phase of micro-drills. Nevertheless, many problems remain unsolved in current microdrilling operations, including unstable tool life and difficulty in deburring.

In micromachining, sudden tool breakage during the machining process frequently occurs because tool life is
difficult to predict. Such breakage results in problems such as product defects and process delays. To reduce tool wear and thereby tool replacement time and costs (which lower productivity), wet cutting machining methods that use cutting fluids have become widely used begin from Milton C Shaw (2005). Cutting fluids feature advantages such as lubricating and cooling machining areas, removing shavings, elevating the surface accuracy of machining surfaces, reducing cutting force, and extending tool service lives by Graham T. Smith (1989). However, using cutting fluids in large numbers endangers human health and creates pollution data from DHHS (NIOSH) Publication, No. 98-116. Therefore, to use the advantages of cutting fluids while meeting regulations in environmental protection and labor health acts, cutting methods that utilize minimum quantity lubrication (MQL) have been introduced by Huang W.T. et al. (2016).

MQL involves using high-pressure air to atomize and mix small amounts of cutting fluids before spraying them uniformly (using a nozzle) on tool cutting locations for lubrication. In recent years, MQL-related research has confirmed the effects of MQL on reducing tool wear, increasing surface accuracy, and lowering the cutting force for traditional micromachining operations such as turning, milling, drilling, grinding, and cutting.

Jie Xu et al. (2017) drilled cast iron, S45C, SUS304, and Ti alloy. Using results to compare different lubrication methods of dry, air cooling, and MQL. The experimental results show that the use of MQL lubrication can make tool life is greatly lengthened, and can be friction is suppressed. Heinemann R. et al. (2006) shows the results of deep-hole drilling using MQL have shown that tool life can effectively extend. Huang W.T. et al. (2018) pointed research results using nanofluid/ultrasonic Atomization MQL for grinding hardened mold steel show that it can effectively reduce the grinding force and improve the surface quality of the grinding workpiece. Zhang Y. et al. (2016) used nanofluids for MQL grinding of Ni-based alloy. This result confirms that MoS₂-CNT nanofluid MQL could improve machining precision and surface quality. Huang W.T. et al. (2020) using nanofluid/ultrasonic atomization MQL in a micromilling process research results show that it can effectively reduce micro-milling forces and reduce workpiece burr formation. These effects are more pronounced than those observed from using a considerable amount of wet cutting machining. Therefore, using MQL over traditional wet cutting machining is an increasing trend.

Microdeep drilling is generally defined as a microrodilling operation involving a depth of feed (L) to drill bit diameter (D) ratio (L/D) greater than 10. In this study, L/D = 13 (i.e., the depth of feed and drill bit diameter were 2.6 and 0.2 mm, respectively). Because microdeep drilling is performed at deep drilling lengths and under blind hole conditions, when the drilling depth is more than 2 or 3 times the drill bit diameter, created shavings make it difficult or impossible for cutting fluids to reach the tip of the microdrill by Heinemann K.R. (2004). This greatly reduces the lubrication effects that, along with long drilling depth, results in the heat generated from cutting per unit of time being large and shavings and heat being unable to be expelled on time. During drilling operations, the MQL method outperforms traditional wet lubrication methods in thermal stability and lubrication ability by Said Z. et al. (2019). Heinemann R., et al. (2006) asserted that MQL can be used in microdeep drilling and that between continuously and not continuously supplying MQL, the latter shortens tool life considerably. MQL also substantially lowers the drilling force from that used in dry drilling. Nam S.J. et al. (2011) performed microdrilling experiments on aluminum by using nanocutting fluids of varying concentrations and discovered that adding appropriate amounts of nanofluids can help reduce microdrilling force, extend microdrilling tool life, and reduce burr formations. As previously mentioned, MQL can be used for microdrilling, and nanofluids can be used in MQL during microdrilling operations. Many studies have investigated using nanofluid/MQL in machining and compared their advantages and disadvantages with machining that uses other materials; however, scant studies have explored the use of nanofluid/MQL in microdeep drilling and the influence of lubrication method–related parameters.

This study examined optimal parameters in microdrilling. Taguchi methods are the most widely used robust design methods in process parameter planning because they reveal the effects of various combinations of parameters on the relevant single-mass characteristic. Huang W.T. et al. (2016) used robust design methods to optimize the experimental parameter design in the nanofluid/MQL in micro-drilling process.

However, in actual practice, machining processes often need to optimize multiple quality-related objectives, and methods that can meet such objectives remain to be developed. Some researchers have also tried to solve problems with multiple quality characteristics through grey Relation analysis. Gray theory was first established by Dr. Deng in 1982, and can provide solutions for systems with uncertain models or incomplete information by Deng J. (1989). It avoids the inherent shortcomings of conventional statistical methods, and only requires limited data to estimate the behavior of uncertain systems. It also provides effective solutions to uncertain, multi-input, and discrete data problems. The main function of gray relational analysis is to indicate the degree of correlation between two sequences by measuring the
distance using a discrete measurement method. Tzenga C.J et al. (2009) using the Taguchi method and Grey relational analysis to optimize the multiple quality target experimental process of CNC turning operation parameters for SKD11.

Haiyan WANG et al. (2020) proposed that the accurate prediction of cutting force is significant for understanding the cutting process. He used linear and nonlinear cutting force models to create a reliable prediction of cutting force model under different cutting parameters. Many researchers develop new models in cutting parameters by using neural network technology. Some researchers have used traditional methods such as statistical regression and response surface methods to model cutting parameters. However, these methods cannot overcome the nonlinear relationship between cutting conditions and output response. The artificial neural network (ANN) model can solve complex nonlinear problems through large-scale parallelization, thereby solving these problems encountered in the processing process. An artificial neural network is a computing network capable of simulating biological nerve central neurons by Quintana G. et al. (2011). Kulisz M., et al. (2019) shown that using an artificial neural network to predict surface roughness of high speed milling. The investigated machining processes were modeled through statistical artificial neural networks in the milling and brushing cutting process. The artificial neural networks were shown to perform well as a tool for the prediction of Mg alloy surface roughness parameters and the maximum height of the profile (Rz) after milling and brushing.

Thus, this study combined Taguchi’s robust design and grey relational analysis to meet multiple quality-related objectives. In addition, if machining results can be predicted using machining parameters before actual machining operations, overall machining processes can improve. Through establishing a predictive model and obtaining a small amount of experimental data, parameters can be used to predict machining results and save considerable trial and error time and machining costs. The structure of this research is as follows. First, Taguchi's robust design determined the combination of parameters that produced the best microdrilling force and the best microdrilling torque. Subsequently, a gray relational analysis was performed to determine the parameter combination that determined the optimal microdrilling force and torque. Later, the nanofluid / MQL was used for microdeep drilling experiments, and a prediction model of microdrilling force and torque was developed. Finally, compare the different lubrication conditions for microdrilling force, microdrilling torque, tool wear, microdrill Burr quality, and cutting temperature.

2. Experimental Set-Up and Procedures

Section 2.1 is to introduce the relevant research equipment and configuration used in this institute. Section 2.2 is to use Taguchi’s robust process design method with microdrilling force and microdrilling torque as the target to find the optimal process parameters. Section 2.3 is gray relational analysis combined with Taguchi's robust process design method to find process parameters with multiple quality characteristics. Section 2.4 is the prediction model of the optimized process parameters for microdrilling deep holes machining, to predict the processing results of the processing parameters. Section 2.5 is a comparison of microdrilling deep holes machining under different lubrication conditions. The overall experimental process architecture is shown in Fig 1.
2.1 Experimental setup

For the experiments, an LK Machinery Corp TC-510 was used as the machining equipment, and a static pressure high spindle with a maximum rotational speed of 80,000 rpm was used as the spindle. The x-, y-, and z-axis machining strokes were 510, 420, and 350 mm, respectively. The microdrilling force and torque were measured using the dynamometer Kistler 9257B along the $F_x$-, $F_y$-, and $F_z$-axes, and the signals were amplified using the eight-channel amplifier Kistler 5070A, after which the data were collected and sent to a personal computer using a DAQ board USB-4716 for data analysis. The microdrilling and tool tip temperature were measured using the infrared camera FLIR A320. The overall layout of the microdrilling equipment is displayed in Fig.2, and the MQL system used was the Bluebe9722B (Accu-Lube; Fig. 3). Nanofluids atomized using high-pressure air were sprayed between microdrills and workpieces. In this study, a type of vegetable oil was used, and nanodiamonds with varying weight percentage concentrations were added. Nanodiamond particle properties are listed in Table 1. During the experiments, microdrills (DIXI 1135) with a diameter of 200 μm were used. Related microdrilling parameters are presented in Table 2. The 7075-T6 aluminum alloys used as the workpiece materials were 52 mm long, 52 mm wide, and 10 mm thick.

| Table 1 | Chemical properties of diamond particles |
|---------|------------------------------------------|
| Thermal Expansivity | 0.8(10^-6 K) |
| Bulk Weight(g/cm3) | 3.2 ~ 3.45 (g/cm3) |
| Density(g/cm3) | 3.0~3.5 (g/cm3) |
| Heat Conductance | 298K-2000,77K-17500(W/m·K) |
| Thermal Conductivity | 900~2000(W/m·k) |
| Young’s Modulus(Gpa) | 90~100(Gpa) |
### Table 2  Experimental condition

|                      |                  |                  |
|----------------------|------------------|------------------|
| **Workpiece**        | Material         | 7075-T6          |
|                      | Area             | 52×52mm²         |
| **Micro Drill**      | Type             | DIXI 1135        |
|                      | Drill Diameter   | 200μm            |
|                      | Flute Length     | 3mm              |
| **Coolant**          |                  | Dry, MQL, Nanofluid/MQL |
| **Spindle Speed**    |                  | 40,000rpm, 50,000rpm, 60,000rpm |
| **Feed Rate**        |                  | 5μm/rev, 7μm/rev, 10μm/rev |
| **Drilling Depth**   |                  | 2.60mm           |

---

Fig. 2. (a) Spindle and dynamometer system configuration diagram. (b) Micro-tool and nozzle location. (c) Infrared thermography (FLIR A320) to measure microdrilling temperature
2.2 Taguchi’s Robust Design

For Taguchi’s robust design, quality-related objectives minimized microdrilling force and torque. Small force and torque levels led to favorable results. Therefore, the objective was “achieving the lowest micro-drilling force and torque,” and different machining parameter combinations were tested to determine the one generating the highest S/N (Signal-to-noise ratio) value. The quality characteristics selected in this experiment are micro-drilling force and microdrilling torque. The microdrilling force is the measurement of the force in the vertical direction of the Z-axis during microdrilling, and the microdrilling torque is the measurement of the torque force in the X-Y-axis direction during microdrilling. It can simultaneously observe and record the changes of X, Y, Z-axis during microdrilling. In the microdrilling process, once the effective lubrication is not possible, cutting clogging may occur. The microdrilling force and microdrilling torque may exceed the tolerable limit of the micro drills and cause fracture. Microdrilling force and microdrilling torque are often used as characteristic quality indicators in related microdrilling research. The number of experimental factors and levels are detailed below. For the experiments, $L_{18}(2^{17})$ orthogonal tables were used, and the control factors included nanodiamond weight percentage concentration, spindle speed, feed rate, MQL flow, air compression, pecking depth, and the nozzle distance and angle. All these control factors were allocated three levels except for nanodiamond weight percentage concentration, which was allocated two levels. Different control factors were implemented in the experiments to identify the optimal nanofluid/MQL machining parameters. The nozzle angle was the angle between the nozzle and workpiece, and the nozzle distance was the distance between the nozzle and location where the microdrilling tool and workpiece met. Table 3 lists the factors and their number of levels.
Table 3  Design parameters and level

| Factors                      | 1  | 2     | 3     |
|------------------------------|----|-------|-------|
| A · NanoDiamond (wt%)        | 1  | 2     |       |
| B · Spindle Speed (rpm)      | 40,000 | 50,000 | 60,000 |
| C · Feed Rate (μm/rev)       | 5  | 7     | 10    |
| D · Distance of Nozzle (mm)  | 20 | 30    | 40    |
| E · MQL Flow (ml/h)          | 20 | 30    | 40    |
| F · Air Compression (Bar)    | 3  | 4     | 5     |
| G · Pecking Depth (mm)       | 0.04 | 0.05  | 0.06  |
| H · Angle of Nozzle (°)      | 30 | 45    | 60    |

2.3 Grey Relational Analysis (GRA)

This study contained multiple quality-related objectives (a common requirement in actual practice), and the Taguchi method can only be used to meet one quality-related objective. To identify a parameter combination that meets the objectives optimally, this study combined grey relational analysis and Taguchi’s robust design to determine the machining parameters that generate the least microdrilling force and torque. Grey relational analyses were performed on the S/N ratios of microdrilling force and torque (obtained using Taguchi’s robust design) to identify optimal machining parameters.

(1) Grey Relational Generating Operation

This study analyzed S/N ratios obtained using different parameter combinations. Because large S/N ratios result in good results, the Larger-the-Better equation was adopted (1):

\[
x^n_i(k) = \frac{x_0^{(0)(k)} - \min_{\text{all}}[x_i^{(0)(k)}]}{\max_{\text{all}}[x_i^{(0)(k)}] - \min_{\text{all}}[x_i^{(0)(k)}]}
\]

(1)

The grey relational generating operation process normalizes data according to actual situations without distorting the data. Generating operations reduces the randomness of data, improves their regularity, and reveals hidden data. Data produced from grey relational generating operations range from 0 to 1.

(2) Grey Relational Coefficient

An identification coefficient (ζ) of 0.5 was used to calculate the grey relational coefficient (2):

\[
\gamma(x_i(k), x_j(k)) = \frac{\Delta_{\text{min}} + \zeta \Delta_{\text{max}}}{\Delta_0(k) + \zeta \Delta_{\text{max}}}
\]

(2)

where \(\gamma(x_i(k), x_j(k))\) is the relational coefficient, \(\Delta_{\text{max}}\) is the maximum difference, \(\Delta_{\text{min}}\) is the minimum difference, and \(\Delta_0(k)\) is the sequence difference between parent series \(x_0(k)\) and subseries \(x_i(k)\) in their corresponding locations.

(3) Grey Relational Grade

The grey relational grade is obtained by averaging the obtained grey relational coefficients, that is, obtaining the average of the relational coefficient of each subseries (3). The grey relational grade works better when it is close to 1.

\[
\gamma(x_i, x_j) = \frac{1}{n} \sum_{k=1}^{n} \gamma(x_i(k), x_j(k))
\]

(3)
(4) Grey Relational Ordinal

Grey relational grade is the degree of correlation between the reference sequence and compared sequence. Thus, the grey relational grade was ranked from highest to lowest to determine the pros and cons of each machining operation.

2.4 Artificial Neural Network (ANN)

This study adopted the MATLAB neural network module to build a back-propagation network model predicting microdrilling force and torque qualities during microdeep drilling. (as shown in Fig. 4) A back-propagation network solves complex nonlinear relationships between input values and corresponding output values. Its structure, which contains an input layer, hidden layer, and output layer, is based on Taguchi robust design analyses. Each neuron of the input layer is connected to each neuron of the hidden layer through weights and biases. The same happens between each hidden neuron and each neuron of the output layer. The accuracy and efficiency of the network depend on various parameters, such as hidden nodes, activation functions, training algorithm parameters, and characteristics (such as normalization and generalization). The number of hidden layers and the number of neurons in the hidden layer play an important role in the performance of ANN. Too few neurons used in the hidden layer will lead to insufficient fitting, which means that the network cannot provide a good approximation. Conversely, using too many neurons in the hidden layer will cause overfitting problems and an abnormal increase in training time. In this study, the neurons in the input layer were the eight control factors in Taguchi’s robust design analyses: nanofluid weight percentage concentration, spindle speed, feed rate, nozzle distance, nozzle angle, MQL flow, air compression, and pecking depth. The neurons in the output layer were quality-related objectives: microdrilling force and torque qualities. Initialize the weights and deviations of the network to a small random value to avoid immediate saturation of the activation function. In this research, there are eight input layers and two output layers, which are more complex nonlinear problems. Therefore, it is better to select two layers for the hidden layer than a single layer for training. In Learning Function, the kinetic energy weight and deviation value correction is mainly based on the law of slope descent. In the Training Function, the weight value and the deviation value are updated according to the kinetic energy slope rule. The maximum training number was seventy thousand times. It can achieve effective convergence. The neural network trained 18 sets of experimental data to predict the parameters used to meet one and multiple quality-related objectives. Subsequently, experiments were performed to verify prediction accuracy. Then, the predicted errors of root mean square (ERMS) in network tests were compared, and the network engaged in repeated learning until the ERMS converged into desired values. Finally, errors from the network tests were used as the basis of assessment, in which small errors closer to the predicted values than to the target values resulted in good network prediction accuracy. Throughout this research, the data set is divided into two sets, one for training and another for validation. The ERMS equation used in the network tests are as follows (4):

\[ E_{\text{RMS}} = \sqrt{\frac{1}{m n} \sum_{p=1}^{m} \sum_{j=1}^{n} (T_{jp} - Y_{jp})^2} \]  

where \( T_{jp} \) is the target value, \( Y_{jp} \) is the value predicted by the network, \( m \) is the number of test samples, and \( n \) is the number of output functions.
2.5 Comparing for Different Lubrication Methods

In this experiment, optimal machining parameters obtained from Taguchi grey relational analyses were used. The tools and experimental methods adopted were identical to those adopted in previous experiments. The differences in microdrilling force, microdrilling torque, tool wear, microdrill burr quality, and cutting temperature among lubrication methods (i.e., dry cutting, MQL, and nanofluid/MQL) were compared.

3. Results and discussions

3.1 Machining Parameters (Based on Taguchi’s Robust Design) Generating Optimal Microdrilling Force and Torque

3.1.1 Machining Parameters Generating the Optimal Microdrilling Force

For the 18 experiments, Taguchi $L_{18}(2^1 \times 3^7)$ orthogonal tables were used. The microdrilling force for the experiments were measured, after which their S/N ratios were calculated (Table 4). In each of the 18 experiments, 120 holes were continuously microdeep drilling, and the microdrilling force was measured and recorded by the dynamometer. The calculation method uses the average of the measured values for every 20 holes, so there are finally 6 sets of average values in the total average microdrilling force value as the experimental Sample (as shown in Table 5). The S/N ratios of each control factor at different levels were calculated to produce the S/N factor response table (Table 6) and response graph (Fig.5). The table and figure indicate that the effects of the factors on microdrilling force, listed in descending order, were nanofluid weight percentage concentration, feed rate, pecking depth, nozzle distance, nozzle angle, spindle speed, MQL flow, and air compression. The optimal parameter combination was A2 B3 C1 D2 E3 F3 G1 H2, which signified a nanofluid weight percentage concentration of 2 wt% (A2), spindle speed of 60,000 rpm (B3), feed rate of 5 μm/rev (C1), nozzle distance of 30 mm (D2), MQL flow of 40 mL/min (E3), air compression of 5 bar (F3), pecking of 0.04 mm (G1), and MQL nozzle angle of 45° (H2). This nanofluid/MQL parameter combination produced the optimal microdrilling force for microdeep drilling.

Fig. 4. BPN architecture diagram
### Table 4  The experiment of microdrilling force results

| No. | A  | B   | C   | D   | E   | F  | G  | H              | The data of experiments | S/N Ratio |
|-----|----|-----|-----|-----|-----|----|----|-----------------|--------------------------|-----------|
| 1   | 1  | 40000 | 5   | 20  | 20  | 3  | 0.04 | 30              | 1.314                     | -2.37     |
| 2   | 1  | 40000 | 7   | 30  | 30  | 4  | 0.05 | 45              | 1.356                     | -2.65     |
| 3   | 1  | 40000 | 10  | 40  | 40  | 5  | 0.06 | 60              | 1.402                     | -2.94     |
| 4   | 1  | 50000 | 5   | 20  | 30  | 4  | 0.06 | 60              | 1.362                     | -2.68     |
| 5   | 1  | 50000 | 7   | 30  | 40  | 5  | 0.04 | 30              | 1.324                     | -2.44     |
| 6   | 1  | 50000 | 10  | 40  | 20  | 3  | 0.05 | 45              | 1.414                     | -3.01     |
| 7   | 1  | 60000 | 5   | 30  | 20  | 5  | 0.05 | 60              | 1.338                     | -2.53     |
| 8   | 1  | 60000 | 7   | 40  | 30  | 3  | 0.06 | 30              | 1.404                     | -2.93     |
| 9   | 1  | 60000 | 10  | 20  | 40  | 4  | 0.04 | 45              | 1.325                     | -2.44     |
| 10  | 2  | 40000 | 5   | 40  | 40  | 4  | 0.05 | 30              | 1.284                     | -2.17     |
| 11  | 2  | 40000 | 7   | 20  | 20  | 5  | 0.06 | 45              | 1.314                     | -2.37     |
| 12  | 2  | 40000 | 10  | 30  | 30  | 3  | 0.04 | 60              | 1.291                     | -2.22     |
| 13  | 2  | 50000 | 5   | 30  | 40  | 3  | 0.06 | 45              | 1.237                     | -1.85     |
| 14  | 2  | 50000 | 7   | 40  | 20  | 4  | 0.04 | 60              | 1.299                     | -2.27     |
| 15  | 2  | 50000 | 10  | 20  | 30  | 5  | 0.05 | 30              | 1.307                     | -2.33     |
| 16  | 2  | 60000 | 5   | 40  | 30  | 5  | 0.04 | 45              | 1.216                     | -1.70     |
| 17  | 2  | 60000 | 7   | 20  | 40  | 3  | 0.05 | 60              | 1.284                     | -2.17     |
| 18  | 2  | 60000 | 10  | 30  | 20  | 4  | 0.06 | 30              | 1.285                     | -2.18     |
## Table 5  Microdrilling force measurement average sampling value table

| No. | No.1~20 Holes | No.21~40 Holes | No.41~60 Holes | No.61~80 Holes | No.81~100 Holes | No.101~120 Holes | Total Average |
|-----|---------------|---------------|---------------|---------------|---------------|----------------|---------------|
| 1   | 1.246         | 1.447         | 1.610         | 1.200         | 1.170         | 1.208          | 1.314         |
| 2   | 1.451         | 1.201         | 1.361         | 1.276         | 1.245         | 1.605          | 1.356         |
| 3   | 1.307         | 1.307         | 1.546         | 1.405         | 1.334         | 1.514          | 1.402         |
| 4   | 1.416         | 1.457         | 1.447         | 1.245         | 1.385         | 1.220          | 1.362         |
| 5   | 1.156         | 1.469         | 1.277         | 1.295         | 1.307         | 1.442          | 1.324         |
| 6   | 1.460         | 1.388         | 1.364         | 1.425         | 1.382         | 1.465          | 1.414         |
| 7   | 1.310         | 1.269         | 1.542         | 1.254         | 1.441         | 1.209          | 1.338         |
| 8   | 1.295         | 1.318         | 1.524         | 1.405         | 1.322         | 1.560          | 1.404         |
| 9   | 1.392         | 1.210         | 1.283         | 1.364         | 1.356         | 1.345          | 1.325         |
| 10  | 1.249         | 1.275         | 1.294         | 1.278         | 1.257         | 1.352          | 1.284         |
| 11  | 1.270         | 1.347         | 1.282         | 1.422         | 1.295         | 1.268          | 1.314         |
| 12  | 1.283         | 1.363         | 1.313         | 1.278         | 1.284         | 1.224          | 1.291         |
| 13  | 1.244         | 1.236         | 1.258         | 1.237         | 1.222         | 1.226          | 1.237         |
| 14  | 1.222         | 1.358         | 1.242         | 1.328         | 1.302         | 1.344          | 1.299         |
| 15  | 1.248         | 1.410         | 1.38           | 1.245        | 1.329          | 1.231          | 1.307         |
| 16  | 1.204         | 1.248         | 1.184         | 1.198         | 1.202         | 1.260          | 1.216         |
| 17  | 1.241         | 1.326         | 1.359         | 1.356         | 1.275         | 1.148          | 1.284         |
| 18  | 1.332         | 1.195         | 1.225         | 1.244         | 1.466         | 1.251          | 1.285         |

## Table 6  Factors response table for signal to noise

| Factor | A    | B    | C    | D    | E    | F    | G    | H    |
|--------|------|------|------|------|------|------|------|------|
| Level 1| -2.667 | -2.452 | -2.217 | -2.395 | -2.455 | -2.428 | -2.241 | -2.405 |
| Level 2| -2.139 | -2.429 | -2.474 | -2.309 | -2.420 | -2.399 | -2.475 | -2.336 |
| Level 3| -2.328 | -2.518 | -2.506 | -2.335 | -2.383 | -2.494 | -2.468 |        |
| Effect | 0.528 | 0.124 | 0.301 | 0.196 | 0.121 | 0.045 | 0.253 | 0.132 |
| Rank   | 1    | 6    | 2    | 4    | 7    | 8    | 3    | 5    |
3.1.2 Machining Parameters Generating the Optimal Microdrilling Torque

For the 18 experiments, Taguchi $L_{18}(2^3 \times 3^7)$ orthogonal tables were used. The microdrilling torque for the experiments were measured, after which their S/N ratios were calculated (Table 7). In each of the 18 experiments, 120 holes were continuously microdeep drilling, and the microdrilling torque was measured and recorded by the dynamometer. The calculation method uses the average of the measured values for every 20 holes, so there are finally 6 sets of average values in the total average microdrilling torque value as the sample of the experiment (as shown in Table 8). The S/N ratios of each control factor at different levels were calculated to produce the S/N factor response table (Table 9) and response graph (Fig. 6). The table and figure indicate that the effects of the factors on microdrilling torque, listed in descending order, were nanofluid weight percentage concentration, feed rate, MQL flow, spindle speed, pecking depth, nozzle angle, nozzle distance, and air compression. The optimal parameter combination was A2 B3 C1 D3 E3 F3 G1 H1, which signified a nanofluid weight percentage concentration of 2 wt% (A2), spindle speed of 60,000 rpm (B3), feed rate of 5 μm/rev (C1), nozzle distance of 40 mm (D3), MQL flow of 40 mL/min (E3), air compression of 5 bar (F3), pecking of 0.04 mm (G1), and an MQL nozzle angle of 30° (H1). This nanofluid/MQL parameter combination produced the optimal microdrilling torque for microdeep drilling.

3.2 Machining Parameters (Based on Grey Relational Analyses) Generating the Optimal Microdrilling Force and Torque

In the previous section, Taguchi’s robust design method was used to identify the optimal parameter combinations generating the optimal microdrilling force and torque. However, the parameter combinations for microdrilling force and torque were not identical. Thus, grey relational analyses were combined with Taguchi’s robust design to determine the parameter combination generating the optimal microdrilling force and torque and meet demands for actual practice. First, S/N ratios meeting one quality-related objective were normalized. Large S/N ratios resulted in good results; therefore, the Larger-the-Better equation was adopted (Table 10). A value of 0.5 was set as the identification coefficient ($\zeta$), and the normalized S/N ratios for each quality-related objective were substituted into Eq. (2) to calculate the grey relational coefficients. Subsequently, Eq. (3) was used to obtain grey relational grades and list them in descending order (Table 11). Finally, grey relational analyses were performed to obtain the response values of each factor at different levels to produce a response table (Table 12) and response graph (Fig. 7). The Taguchi method is a robust design approach to using statistical experimental design concepts. An OA enables analysis of numerous design variables with a small number of experiments. But the shortcomings are only limited to the optimization of a single target feature. The actual problem that the industry often faces is that a process usually needs to optimize several targets at the same time, which becomes optimizing the multiple quality target. However, at this time, the robust process design method cannot meet our requirements for optimizing the characteristics of multiple targets. It must be combined with other methods to optimize the multiple quality target. This experiment uses grey relational analyses. The method is characterized by the ability to perform correlation analysis and model construction of the system model for uncertainties, multi-inputs, and discrete data. Since the two targets of this experiment, microdrilling force, and torque, belong to two completely different physical...
quantities, they cannot be compared with each other. It is necessary to convert the microdrilling force and torque value to a value between 0 and 1 through grey relational analyses to compare and analyze each other. Taguchi grey relational analyses revealed that meeting multiple quality-related objectives required that microdrilling and torque be minimized, the optimal parameter combination was A2B3C1D3E3F3G1H2. The available microdrilling force is 1.143 N, and the microdrilling torque is 0.01140 N·m. Compared with the two single-target optimization results, 1.211 N and 0.01091 N·m. Taking into account the two goals at the same time, 5.94% and 4.49% of the quality characteristics of the single goal optimization are lost, respectively. In contrast, the quality characteristics of microdrilling torque loss are less. It can be seen that in grey relational analyses, the weights are more in the goal of microdrilling torque. In the optimal parameter combination of microdrilling torque, there is only one difference in H factors, which is the angle of the nozzle. Adjusting the angle of the nozzle from 30° to 45° can help optimize the multiple quality target at the same time. From Table 12, it can be seen that H factors are the third factor in the ranking.

### Table 7 The experiment of microdrilling torque results

| No. | A   | B     | C     | D   | E   | F   | G     | H     | The data of experiments | S/N Ratio |
|-----|-----|-------|-------|-----|-----|-----|-------|-------|--------------------------|-----------|
| 1   | 1   | 40000 | 5     | 20  | 20  | 3   | 0.04  | 30    | 0.0151                   | 36.42     |
| 2   | 1   | 40000 | 7     | 30  | 30  | 4   | 0.05  | 45    | 0.0162                   | 35.81     |
| 3   | 1   | 40000 | 10    | 40  | 40  | 5   | 0.06  | 60    | 0.0164                   | 35.70     |
| 4   | 1   | 50000 | 5     | 20  | 30  | 4   | 0.06  | 60    | 0.0163                   | 35.76     |
| 5   | 1   | 50000 | 7     | 30  | 40  | 5   | 0.04  | 30    | 0.0153                   | 36.31     |
| 6   | 1   | 50000 | 10    | 40  | 20  | 3   | 0.05  | 45    | 0.0184                   | 34.70     |
| 7   | 1   | 60000 | 5     | 30  | 20  | 5   | 0.05  | 60    | 0.0158                   | 36.03     |
| 8   | 1   | 60000 | 7     | 40  | 30  | 3   | 0.06  | 30    | 0.0165                   | 35.65     |
| 9   | 1   | 60000 | 10    | 20  | 40  | 4   | 0.04  | 45    | 0.0155                   | 36.19     |
| 10  | 2   | 40000 | 5     | 40  | 40  | 4   | 0.05  | 30    | 0.0122                   | 38.27     |
| 11  | 2   | 40000 | 7     | 20  | 20  | 5   | 0.06  | 45    | 0.0150                   | 36.48     |
| 12  | 2   | 40000 | 10    | 30  | 30  | 3   | 0.04  | 60    | 0.0145                   | 36.77     |
| 13  | 2   | 50000 | 5     | 30  | 40  | 3   | 0.06  | 45    | 0.0120                   | 38.42     |
| 14  | 2   | 50000 | 7     | 40  | 20  | 4   | 0.04  | 60    | 0.0146                   | 36.71     |
| 15  | 2   | 50000 | 10    | 20  | 30  | 5   | 0.05  | 30    | 0.0148                   | 36.60     |
| 16  | 2   | 60000 | 5     | 40  | 30  | 5   | 0.04  | 45    | 0.0107                   | 39.41     |
| 17  | 2   | 60000 | 7     | 20  | 40  | 3   | 0.05  | 60    | 0.0123                   | 38.20     |
| 18  | 2   | 60000 | 10    | 30  | 20  | 4   | 0.06  | 30    | 0.0137                   | 37.27     |
### Table 8  Microdrilling torque measurement average sampling value table

| No. | No.1~20 Holes | No.21~40 Holes | No.41~60 Holes | No.61~80 Holes | No.81~100 Holes | No.101~120 Holes | Total Average |
|-----|---------------|----------------|----------------|----------------|----------------|------------------|---------------|
|     | Average Value | Microdrilling Torque (N-m) |
| 1   | 0.0160        | 0.0168          | 0.0159         | 0.0136         | 0.0162         | 0.0120           | 0.0151        |
| 2   | 0.0154        | 0.0183          | 0.0127         | 0.0163         | 0.0160         | 0.0187           | 0.0162        |
| 3   | 0.0166        | 0.0158          | 0.0145         | 0.0149         | 0.0139         | 0.0229           | 0.0164        |
| 4   | 0.0157        | 0.0160          | 0.0170         | 0.0165         | 0.0159         | 0.0168           | 0.0163        |
| 5   | 0.0153        | 0.0165          | 0.0156         | 0.0149         | 0.0179         | 0.0114           | 0.0153        |
| 6   | 0.0157        | 0.0201          | 0.0196         | 0.0187         | 0.0198         | 0.0163           | 0.0184        |
| 7   | 0.0171        | 0.0153          | 0.0153         | 0.0136         | 0.0161         | 0.0172           | 0.0158        |
| 8   | 0.0163        | 0.0103          | 0.0146         | 0.0132         | 0.0148         | 0.0131           | 0.0165        |
| 9   | 0.0175        | 0.0135          | 0.0160         | 0.0130         | 0.0175         | 0.0155           | 0.0155        |
| 10  | 0.0129        | 0.0120          | 0.0120         | 0.0118         | 0.0120         | 0.0123           | 0.0122        |
| 11  | 0.0155        | 0.0160          | 0.0148         | 0.0153         | 0.0137         | 0.0149           | 0.0150        |
| 12  | 0.0146        | 0.0145          | 0.0135         | 0.0151         | 0.0150         | 0.0143           | 0.0145        |
| 13  | 0.0123        | 0.0121          | 0.0120         | 0.0117         | 0.0118         | 0.0121           | 0.0120        |
| 14  | 0.0154        | 0.0152          | 0.0149         | 0.0137         | 0.0161         | 0.0125           | 0.0146        |
| 15  | 0.0153        | 0.0146          | 0.0139         | 0.0143         | 0.0155         | 0.0153           | 0.0148        |
| 16  | 0.0093        | 0.0103          | 0.0101         | 0.0114         | 0.0115         | 0.0113           | 0.0107        |
| 17  | 0.0119        | 0.0116          | 0.0121         | 0.0126         | 0.0120         | 0.0136           | 0.0123        |
| 18  | 0.0163        | 0.0103          | 0.0146         | 0.0132         | 0.0148         | 0.0131           | 0.0137        |

### Table 9  Factors response table for signal to noise

| Factor | A  | B  | C  | D  | E  | F  | G  | H  |
|--------|----|----|----|----|----|----|----|----|
| Level 1| 35.84 | 36.58 | 37.38 | 36.61 | 36.27 | 36.69 | 36.97 | 36.84 |
| Level 2| 37.57 | 36.42 | 36.53 | 36.74 | 36.67 | 36.67 | 36.60 | 36.75 |
| Level 3| 37.13 | 36.21 | 36.77 | 37.18 | 36.75 | 36.54 | 36.53 |       |
| Effect | 1.73 | 0.71 | 1.18 | 0.16 | 0.91 | 0.09 | 0.42 | 0.31 |
| Rank   | 1   | 4   | 2   | 7   | 3   | 8   | 5   | 6   |
Table 10  Data preprocessing of each performance characteristic

| Run | Thrust Force | Torque |
|-----|--------------|--------|
| 1   | 0.3754       | 0.3647 |
| 2   | 0.2145       | 0.2349 |
| 3   | 0.0436       | 0.2122 |
| 4   | 0.1915       | 0.2234 |
| 5   | 0.3365       | 0.3403 |
| 6   | 0            | 0      |
| 7   | 0.2829       | 0.281  |
| 8   | 0.0365       | 0.2009 |
| 9   | 0.3329       | 0.3163 |
| 10  | 0.4938       | 0.7581 |
| 11  | 0.3754       | 0.3768 |
| 12  | 0.4655       | 0.4395 |
| 13  | 0.6847       | 0.7884 |
| 14  | 0.4343       | 0.4267 |
| 15  | 0.4025       | 0.4017 |
| 16  | 1            | 1      |
| 17  | 0.4938       | 0.743  |
| 18  | 0.4897       | 0.5442 |

Fig. 6. Factor Response Graph of S/N
Table 11 Grey relational coefficient and Grey relational grade

| Run | Thrust Force | Torque | GRG   | Rank |
|-----|--------------|--------|-------|------|
| 1   | 0.4932       | 0.4404 | 0.4668| 10   |
| 2   | 0.4091       | 0.3952 | 0.4022| 14   |
| 3   | 0.3464       | 0.3883 | 0.3674| 16   |
| 4   | 0.3994       | 0.3917 | 0.3956| 15   |
| 5   | 0.4699       | 0.4311 | 0.4505| 11   |
| 6   | 0.3333       | 0.3333 | 0.3333| 18   |
| 7   | 0.4411       | 0.4102 | 0.4257| 13   |
| 8   | 0.3442       | 0.3849 | 0.3646| 17   |
| 9   | 0.4679       | 0.4224 | 0.4452| 12   |
| 10  | 0.5812       | 0.6739 | 0.6276|  3   |
| 11  | 0.4932       | 0.4452 | 0.4692|  9   |
| 12  | 0.5575       | 0.4715 | 0.5145|  6   |
| 13  | 0.8157       | 0.7026 | 0.7592|  2   |
| 14  | 0.5334       | 0.4659 | 0.4997|  7   |
| 15  | 0.5109       | 0.4552 | 0.4831|  8   |
| 16  | 1            | 1      | 1     |  1   |
| 17  | 0.5812       | 0.6605 | 0.6209|  4   |
| 18  | 0.5776       | 0.5231 | 0.5504|  5   |

Table 12 Response table for GRG values

| Factor | A | B | C | D | E | F | G | H |
|--------|---|---|---|---|---|---|---|---|
| Level 1| 0.406 | 0.475 | 0.612 | 0.480 | 0.458 | 0.510 | 0.563 | 0.491 |
| Level 2| 0.614 | 0.487 | 0.468 | 0.517 | 0.527 | 0.487 | 0.482 | 0.568 |
| Level 3| 0.568 | 0.449 | 0.532 | 0.545 | 0.533 | 0.484 | 0.471 |    |
| Effect | 0.208 | 0.093 | 0.164 | 0.052 | 0.088 | 0.046 | 0.081 | 0.098 |

Fig. 7. Response graph for mean grey relational grades
3.3 Predictive Model for Microdeep Drilling

In this section, a predictive model built using a back-propagation neural network was developed to predict microdrilling force and torque for microdeep drilling. The 18 sets of experimental data obtained from the Taguchi grey relational analyses were used as training and test samples. The network was trained 70,000 times and producing converging $E_{\text{RMS}}$ results (Fig. 8). In Fig. 8, the red line represents the $E_{\text{RMS}}$ results of the model training process, and the blue line represents the $E_{\text{RMS}}$ results of the model testing process. Model training and model testing $E_{\text{RMS}}$ results before trained 5,000 times have a large error value, and there is no stable situation. After approaching trained 40,000 times, the $E_{\text{RMS}}$ results of Model training and model testing showed stable convergence. Until the trained 70,000 times, the $E_{\text{RMS}}$ results of Model training and model testing reached the minimum value. Microdrilling force and torque predicting and measuring the 18 experiments were plotted into scatter plots (Figs. 9 and 10), where the horizontal and vertical axes signified the target output layer output value ($T_j$) and predicted output layer output value ($Y_j$), respectively. The figures illustrate that all points were located near the diagonals, which indicate favorable learning results, and that parameter combinations could be predicted. Finally, parameter combinations generating the optimal microdrilling force, microdrilling torque, and microdrilling force and torque of multiple quality-related objectives (obtained from Taguchi’s robust design experiments and Taguchi grey relational analyses) were tested, and the results revealed that the parameter combinations predicted were accurate. The predicted parameter combination generating the optimal microdrilling force differed from that of the experiment results by only 0.58%. The predicted parameter combination generating the optimal microdrilling torque differed from that of the experimental results by only 1.39%. Moreover, the predicted parameter combination generating optimal multiple quality-related objectives microdrilling force and torque of differed from those of the experimental results by only 0.44% and 1.24%, respectively (Table 13). While optimizing the process parameters of nanofluid/MQL technology for 7075-T6 aluminum alloy microdeep drilling, this study used a neural network and conducted Taguchi grey relational analyses to develop a highly accurate microdrilling predictive model. The establishment of this predictive model can reduce artificial Uncertainty and does not require complicated mathematical calculations. Compared with traditional methods, the output can more fully meet the requirements of technical engineers and customers. The current industry uses engineers' field experience to practice weights, which brings many uncertainties. The application in the real world can further encourage the transfer of technology based on the neural network to establish a predictive model from academia to industry.

Table 13. Comparisons between predicted optimal parameter combinations and those obtained from experiments

| Optimal objective(s) to be achieved | Optimal parameter combination | Experimental results | Network prediction | Difference |
|------------------------------------|-------------------------------|----------------------|--------------------|------------|
| Microdrilling force                | A2B3C1D2E3F3G1H2             | 1.211 N              | 1.204 N            | 0.58%      |
| Microdrilling torque               | A2B3C1D3E3F3G1H1             | 0.01091 N-m          | 0.01076 N-m        | 1.39%      |
| Multiple quality-related objectives | Microdrilling force | A2B3C1D3E3F3G1H2     | 1.143 N             | 1.148 N     | 0.44%      |
|                                    | Microdrilling torque         | A2B3C1D3E3F3G1H2     | 0.01140 N-m        | 0.01126 N-m | 1.24%      |
Fig. 8. Comparison of model training and model testing $E_{rms}$ results of predictive model

Fig. 9. Predicted values of ANN and regression model for thrust force
3.4 Optimal Parameter Combinations for Different Lubrication Methods

In the comparison of different lubrication methods in this section, three different lubrication methods, dry drilling, MQL and nanofluid/MQL are used for comparison. In the experimental parameters of the three different lubrication methods, the multi-objective optimization process parameters of the experimental results in Section 3.2 are used for comparison experiments. The optimal parameter combination was A2 B3 C1 D3 E3 F3 G1 H2, which signified a nanofluid weight percentage concentration of 2 wt% (A2), spindle speed of 60,000 rpm (B3), feed rate of 5 μm/rev (C1), nozzle distance of 40 mm (D3), MQL flow of 40 mL/min (E3), air compression of 5 bar (F3), pecking of 0.04 mm (G1), and an MQL nozzle angle of 45° (H2). A factor Part of it is nanofluid concentration. Only nanofluid/MQL has this control parameter. In D factors nozzle distance, E factors MQL flow, F factors air compression, H factors MQL nozzle angle, these 4 control parameters are MQL and nanofluid/MQL. Kind of lubrication method used. These two lubrication methods share the same MQL system used was the Bluebe9722B, so these 4 control parameters can have common optimization characteristics. The three control parameters of B factors spindle speed, C factors feed rate, and G factors pecking are generally used in most microdrilling processes. In the experiment, LK Machinery Corp TC-510 was used as the three different lubrication methods. The machining equipment and a static pressure high spindle with a maximum rotational speed of 80,000 rpm were used as the spindle. Therefore, these three control parameters can have common optimization characteristics. The experimental results presented in this section are to compare the difference in the effectiveness of the nanofluid/MQL lubrication method and the dry drilling and MQL lubrication method that does not use nanofluid.

3.4.1 Microdrilling Force and Torque with Different Lubrication Methods

This section explores the effects of different lubrication methods on microdrilling force and torque. Experiments were performed using the optimal parameter combinations obtained in the previous section, and the results between the lubrication methods were compared. To obtain the microdrilling force and torque, the force and torque of every 20 holes were measured and averaged; a total of 120 holes were drilled. Figures 11 and 12 indicate that using MQL and nanofluid/MQL (2 wt%) reduced the microdrilling force and torque. To analyze and compare the effects of the lubrication methods on microdrilling force and torque, the overall microdrilling force and torque obtained from 120 holes were averaged and plotted. When dry drilling was used, drill breakage was observed in the 17th hole. The average microdrilling force and torque for drilling 17 holes were 4.392 N and 0.0461 N-m, respectively. When MQL was used, the average microdrilling force and torque for drilling 120 holes were 2.085 N and 0.0203 N-m, respectively. When nanofluid/MQL was used, the average microdrilling force and torque for drilling 120 holes were 1.143 N and 0.0114 N-m, respectively. The microdrilling force results are displayed in Fig. 13. These results revealed that the use of nanofluid/MQL (2 wt%) most reduced microdrilling force and torque, followed by using MQL and dry drilling, and dry drilling caused the drill bit to break on the 17th hole. This indicated that using MQL and nanofluid/MQL increased the service life of the
microdrills.

![Graph showing the comparisons of average thrust force microdrilling 120 holes under Dry, MQL and Nanofluid/MQL(2wt%)](image1)

**Fig. 11.** The comparisons of average thrust force microdrilling 120 holes under Dry, MQL and Nanofluid/MQL(2wt%)  

![Graph showing the comparisons of average torque microdrilling 120 holes under Dry, MQL and Nanofluid/MQL(2wt%)](image2)

**Fig. 12.** The comparisons of average torque microdrilling 120 holes under Dry, MQL and Nanofluid/MQL(2wt%)
3.4.2 Effects of Lubrication Methods on Microdrilling Temperature

This section investigates the effects of the three lubrication methods on microdrilling temperature, and the parameter combination remained constant. During drilling processes, tool bellies and workpieces undergo friction and generate heat that increases the temperature of the tools and workpieces. Unfortunately, the tool temperature accelerates tool wear, which results in unfavorable tool surface accuracy. Therefore, effectively reducing tool temperature helps improve tool wear and surface accuracy. In this experiment, to achieve the accuracy and consistency of the experimental data, the microdrill temperatures were measured by continuous microdrill 120 holes at the same time under the three non-lubrication methods. Before the experiment, the microdrilling tool and the microdrilling tool measured by the infrared camera were used. The workpiece materials temperatures are 38.5°C. In this study, when dry drilling was used, the microdrill broke on the 17th hole, and the highest temperature before drill breakage was 136.2°C. When MQL was used, the average temperature for drilling 120 holes was 120.05°C. When nanofluid/MQL was used, the average temperature for drilling 120 holes was 115.47°C. To analyze and compare the effects of lubrication methods on microdrilling temperature, the average overall microdrilling temperature was plotted (Figs. 14 and 15). In this experiment, an infrared camera is used to measure the microdrilling temperatures. The measurement focus of the infrared camera is the sharp point of the microdrilling tool contacting the workpiece. Because this measurement method is an indirect measurement, the actual temperature of the microdrilling temperatures cannot be directly measured. However, it is possible to compare the differences and effectiveness of the three different lubrications in microdrilling temperatures under the same level of conditions. In Fig. 14, it can be observed that in MQL and nanofluid/MQL, the microdrilling temperatures have a simultaneous downward trend when microdrilling to the 60th hole, which is unlikely to occur under normal continuous microdrilling. It speculated that the reason is the spindle rotational speed of the machining equipment used in the experiment is not high enough. Thus it is also equipped with a static pressure high spindle to achieve the spindle speed required by the experimental control factor. The driving power source used by the Static pressure high spindle is the net air pressure as the input, and the exhaust is also required as the output. The position of the exhaust is around the spindle. The static pressure high spindle may interfere with the measured value of the infrared camera during the exhaust process. In Fig. 16 average drilling temperature, it can be observed that the average lubrication method using MQL is 120.05°C, and the average lubrication method using nanofluid/MQL is 115.47°C. Although the difference between the two lubrication methods is only 4.58°C, this measurement method is an indirect measurement that cannot directly measure the actual temperature of the microdrilling temperatures. For example, the microdrilling temperatures obtained by the indirect measurement can be estimated back to the actual microdrilling temperatures. The lubrication method using nanofluid/MQL still has a certain degree of layering that can be reduced the benefits of microdrilling temperatures. According to the figures, using MQL produced lubricating and cooling effects. Because nanofluid/MQL added nanodiamonds to the cutting fluids and utilized the excellent thermophysical properties of nanoparticles, it cooled the
microdrilling temperature more than the other two lubrication methods did. In the experiments, the nanodiamonds featured thermal conductivity as high as 2320 W/mk, which enabled them to quickly lower the temperature and subsequently tool wear.

3.4.3 Effects of Lubrication Methods on Microdrilling Tool Wear

This section examined the effects of three lubrication methods on tool wear. The parameter combination remained constant. Scanning electron microscope (SEM) images of microdrilling tool wear after drilling 120 holes were obtained for the three lubrication methods(Fig. 16). When dry drilling was used, the microdrills broke; thus, no tool wear data could be obtained. From the frame selection in Figure 16, it can be seen that in the use of MQL lubrication, drill wear produces about 50% of a larger area of wear and cracking compared to the original tool. And when using nanofluid/MQL (2 wt %) In the lubrication mode, drill wears only produces about 5~10% slight abrasion compared with the original tool, and it is possible to continue the microdeep drilling processing operation. When MQL and nanofluid/MQL were used, tool wear was primarily observed in the corners. The wear type was cutting edge failure, which occurs at high
temperatures. The microdrill broke during dry drilling may have been because of the high temperature exacerbating cutting edge failure, which reduced the tool sharpness and made drilling difficult and result in breakage. According to the microdrilling temperature measured, using MQL and nanofluid/MQL (2 wt%) reduced the microdrilling temperature and microdrill wear. Adding nanofluids with nanodiamonds and a weight percentage concentration of 2 wt% reduced drilling temperature and drill wear.

3.4.4 Post drilling Hole Quality for the Three Lubrication Methods

This section explored the effects of the three lubrication methods on microdrill burr quality. The parameter combination remained constant. SEM images of the microdrill burr are displayed in Fig. 17. In the three non-lubrication methods, it compared the first hole of the initial microdeep drilling and the final hole. When dry to the 17th hole caused microdrills broke, thus the final hole was the 16th hole. And MQL and nanofluid/MQL (2 wt%) is the 120th hole. According to the figure, when dry drilling was used, large burrs occurred around the holes because the microdrills underwent considerable tool wear, which caused the tools to become blunt. This led to strong friction between the tools and workpieces. In addition, no cutting fluids were in place to remove the burrs (Fig. 17[a]). By contrast, MQL and nanofluid/MQL (2 wt%) effectively reduced shavings in the holes and microdrill burrs because they effectively maintained tool sharpness. Figure 17(b) illustrates the microdrill quality from when MQL was used, and 17(c) presents the microdrill quality when nanofluid/MQL (2wt%) was used. In general, microdrilling shavings and burrs are difficult to remove. However, using MQL and nanofluid/MQL (2 wt%) in microdrilling can reduce burr formation and help shoving removal. From the frame selection in figure 17 (the most massive burr), the comparison of the burr area from the first hole in three different lubrication methods. Microdeep drilling shows that the use of Dry produces 50% more burr area compared to nanofluid/MQL (2 wt%) Compared with nanofluid/MQL (2 wt%), the use of MQL produces 30% more burr area range. In the final hole comparison part, the burrs area range is the same in the three non-lubricated modes because the tool is worn out. Compared with the initial burr area of the first hole, the area of burrs is larger than that of nanofluid/MQL (2 wt%). The area of burrs is more than that of nanofluid/MQL (2 wt%) when using MQL. A 50% burrs area range is produced.

Fig. 16. SEM micrographs of the tool rake face microdrilling 120 holes under (a) Original tool, (b) MQL and (c) Nanofluid/MQL (2wt%)
4. Conclusions

This study developed a predictive model for the parameter combination required to meet quality-related objectives. From the experiments, the following conclusions were made:

1. During the experiments, Taguchi grey relational analyses revealed that meeting multiple quality-related objectives required that microdrilling and torque be minimized. The control factors were nanofluid weight percentage concentration, spindle speed, feed rate, nozzle distance, nozzle angle, MQL flow, air compression, and pecking depth. According to the experiments, the optimal parameter combination was A2B3C1D3E3F3G1H2, which signified a nanofluid weight percentage concentration of 2 wt% (A2), spindle speed of 60,000 rpm (B3), feed rate of 5 μm/rev (C1), nozzle distance of 40 mm (D3), MQL flow of 40 mL/min (E3), air compression of 5 bar (F3), pecking of 0.04 mm (G1), and MQL nozzle angle of 45° (H2). This nanofluid/MQL parameter combination produced the least microdrilling force and torque for microdeep drilling.

2. Among dry drilling, MQL, and nanofluid/MQL, nanofluid/MQL increased cutting fluid thermal conductivity, which effectively reduced the drilling temperature to lower than that of dry drilling (136.2°C vs. 115.47°C, a decrease of 20.73°C). The thermal conductivity of nanofluid/MQL increased because it contains nanodiamonds.

3. For microdrilling force, compared with dry drilling, which had an average microdrilling force of 4.392 N, the nanofluid/MQL method had an average microdrilling force of 1.143 N (a decrease of 3.249 N, an approximately 2.84-fold decrease). Similarly, compared with dry drilling, the nanofluid/MQL method had an average microdrilling torque of 0.0114 N-m (a decrease of 0.0347 N-m, an approximately 3.04-fold decrease). These effectively reduced tool wear and increased microdrill service lives.

4. Using nanofluid/MQL effectively removed burrs around the holes, which substantially enhanced microdrill burr quality because adding nanodiamonds improved nanofluid lubrication, which allowed the microdrill tools to remain sharp and thereby reduced burrs in the surrounding.

5. The $E_{RMS}$ convergence diagram indicates that the predictive model for microdrilling force and torque was accurate. This indicated that users only need to input the machining parameters into the back-propagation network to accurately predict the microdrilling force and torque for microdeep drilling. According to the results, the parameter combination

![Fig. 17. SEM micrographs of the drilled holes, (a) Dry, (b) MQL and (c) Nanofluid/MQL (2wt%)](image-url)
for generating the predicted optimal microdrilling force differed from that of the experiment results by only 0.58%. The parameter combination for generating the predicted optimal microdrilling torque differed from that of the experiment results by only 1.39%, and the multiple quality-related objectives parameter combination for generating the predicted optimal microdrilling force and torque differed from those of the experiment results by only 0.44% and 1.24%, respectively.

Acknowledgements

This work was supported in part by the Ministry of Science and Technology, Taiwan, R.O.C., under Grant Numbers MOST 108-2637-E-020-008, and MOST 109-2221-E-019-MY2. The authors also thank to Researchers Supporting Project number (#NPUST-KMU-109-P009), NPUST-KMU JOINT RESEARCHPROJECT.

References

Afazova S.M., Ronaldoa R., Londsdbaleb D., Zdebskia D., Ratchevas M., Analysis of micro-drilling of glassy ceramic Macor nozzles for scanning droplet systems, Journal of Materials Processing Technology, Vol.213, No.2 (2013), pp.221-228.

Deng J, Introduction to grey system, The Journal of Grey System, Vol.1, No.1 (1989), pp.1–24.

Eiji KONDO, Ryoga KAMO and Hiroshi MURAKAMI, Monitoring of Burr and Pre-failure Phase Caused by Tool Wear in Micro-Drilling Operations Using Thrust Force Signals, Journal of Advanced Mechanical Design, Systems, and Manufacturing, Vol.6, No.6 (2012), DOI:https://doi.org/10.1299/jamdsm.6.885.

Franco-Gasca A.A., Herrera-Ruiza G., Peniche-Veraa R., Romero-Troncosob R. J., Leal-Tafollac W., Sensorless tool failure monitoring system for drilling machines, International Journal of Machine Tools and Manufacture, Vol.46, No.3-4 (2006), pp.381-386.

Graham T. Smith, Advanced machining: the handbook of cutting technology, London, U.K.: Springer. (1989)

Haiyan WANG, Jianyu WANG, Jimming ZHANG, Kexin TAO and Dongxu WU, Identification and analysis of cutting force coefficients in the helical milling process, Journal of Advanced Mechanical Design, Systems, and Manufacturing, Vol.14, No.1 (2020), DOI:10.1299/jamdsm.2020jamdsm0020.

Heinemann R., Hinduja R., Barrow G., Petullib G., Effect of MQL on the tool life of small twist drills in deep-hole drilling, International Journal of Machine Tools and Manufacture, Vol.46, No.1 (2006), pp.1-6.

Heinemann K.R., Improving the performance of small diameter twist drills in deep-hole drilling, University of Manchester, (2004)

Huang W.T., Chou F.I., Tsai J. T., Lin T.W., Chou J.H., Optimal Design of Parameters for the Nanofluid/Ultrasonic Atomization Minimal Quantity Lubrication in a Micromilling Process, IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS, Vol.16, No.8 (2020), pp.5202–5212.

Huang W.T., Liu W.S., Tsai J.T., Chou J.H., Multiple Quality Characteristics of Nanofluid/Ultrasonic Atomization Minimum Quality Lubrication for Grinding Hardened Mold Steel, IEEE TRANSACTIONS ON AUTOMATION SCIENCE AND ENGINEERING, Vol.15, No.3 (2018), pp.1065–1077.

Huang W.T., Wu D.H., Chen J.T., Robust design of using nanofluid/MQL in micro-drilling, The International Journal of Advanced Manufacturing Technology, Vol.85 (2016), pp.2115–2161.

Huang W.T., Wu D.H., Lin S.P., Liu W.S., A combined minimum quantity lubrication and MWCNT cutting fluid approach for SKD 11 end milling, The International Journal of Advanced Manufacturing Technology, Vol.84 (2016), pp.1697–1704.

Jie XU, Keiji YAMADA, Katsuhiko SEKIYA, Ryutaro TANAKA and Yasuo YAMANE., Study of comparing cutting force signal features for dry, air cooling and minimum quantity lubrication (MQL) drilling, Journal of Advanced Mechanical Design, Systems, and Manufacturing, Vol.11, No.2 (2017), DOI:10.1299/jamdsm.2017jamdsm0030.

Kulisz M., Zagórski I., Matuszak J., Klonica M., Properties of the Surface Layer After Trochoidal Milling and Brushing: Experimental Study and Artificial Neural Network Simulation, Applied Sciences, Vol.10, No.75 (2020), pp.1-26.

Milton C Shaw., Metal cutting principles, Vol.2 (2004), New York: Oxford university press.

Nam S.J., Lee P.H., Lee S.W., Experimental characterization of micro-drilling process using nanofluid minimum quantity lubrication, International Journal of Machine Tools and Manufacture, Vol.51, No.7-8 (2011), pp.649-652.

National Institute of Occupational Safety and Health, What you need to know about occupational exposure to metalworking fluids, DHH5 (NIOSH) Publication, (1998), pp.98-116.

Quintana G., Garcia-Romeu M. L., Ciurana J., Surface roughness monitoring application based on artificial neural networks for ball-end milling operations, Journal of Intelligent Manufacturing, Vol.22 (2011), pp.607-617.
Said Z., Gupta M., Hegab H., Arora N., Khan A.M., Jamil M., Bellos E., A comprehensive review on minimum quantity lubrication (MQL) in machining processes using nano-cutting fluids, The International Journal of Advanced Manufacturing Technology, Vol.105 (2019), pp.2057–2086.

Tzenga C.J., Linb Y.H., Yanga Y.K., Jengc M.C., Optimization of turning operations with multiple performance characteristics using the Taguchi method and Grey relational analysis, Journal of Materials Processing Technology, Vol.209, No.6 (2009), pp.2753-2759.

Zhang Y., Li C., Jia D., Li B., Wang Y., Yang M., Hou Y., Zhang X., Experimental study on the effect of nanoparticle concentration on the lubricating property of nanofluids for MQL grinding of Ni-based alloy, Journal of Materials Processing Technology, Vol.232 (2016), pp.100-115.