Optimization of finishing parameters for magnetic compound fluid finishing (MCFF) of copper alloy

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Abstract
As an advanced finishing technology, magnetic compound fluid finishing (MCFF) is considered capable of achieving damage-free finishing of low-hardness materials such as copper alloys with appropriate finishing parameters. However, ignoring the influence of the material removal amount on the dimensional accuracy while optimizing finishing parameters may result in excessive material removal and a reduction in the workpiece’s dimensional accuracy. Thus, a novel finishing parameter optimization method considering dimensional accuracy is proposed in this paper. Firstly, the MCFF experiments are planned and carried out for modeling. Secondly, an MCFF model is established based on the integrated learning theory. The established model, with a prediction layer and a fusion layer, is a multi-layer neural network fusion model which can accurately predict the polished surface quality and material removal amount. Thirdly, the finishing parameters are optimized by the multi-objective particle swarm optimization algorithm, taking the effect of material removal on dimensional accuracy into account. Finally, the model’s prediction accuracy and the superiority of the optimized parameters are verified through experiments. The results demonstrate that the developed model can predict the finishing effect correctly, and a workpiece with high-quality polished surfaces and high dimensional accuracy can be obtained with the optimized finishing parameters.

Keywords Magnetic compound fluid finishing · Neural network · Dimensional accuracy · Finishing parameters · Surface roughness

1 Introduction
Copper and copper alloys with high-quality surfaces are widely used in mems, integrated circuits, lasers, aerospace, and other industries due to their advantages of high thermal, electrical conductivity, high reflectivity, and lightweight [1]. Therefore, the finishing of copper and copper alloys has attracted a lot of attention from researchers. Although conventional mechanical finishing, electrochemical polishing (ECP), and chemo-mechanical polishing (CMP) can be used for finishing copper alloys, there are several disadvantages associated with these processes. Abrasive particles will leave scratches on copper alloys’ surfaces due to the high normal force of conventional mechanical finishing, resulting in a poor polished surface [2]. And harmful gases are generated during the CMP process [3]. In order to overcome the disadvantages of conventional finishing technologies, many advanced finishing technologies have been applied in the finishing of copper and copper alloys. Among various finishing technologies, magnetic field-assisted finishing (MFAF) is considered the most advantageous technology for obtaining a high-quality copper surface without damage [2].

MFAF is a type of superfinishing process, which includes abrasive flow finishing (AFF), magnetic float finishing (MFF), magnetorheological finishing (MRF), magnetic compound fluid finishing (MCFF), ball end magnetorheological finishing (BEMRF), and magnetic abrasive finishing (MAF) [4–7]. And MFAF is regarded as the optimal method for achieving high-quality finishing without damage owed to the tiny controlled finishing force (1 × 10⁻⁴ mN) [6, 8]. Additionally, the material removal amount (MRA) caused by MFAF is less than other finishing technologies, significantly reducing the effect of finishing on dimensional accuracy. It is worth emphasizing that the magnetic grinding brush formed during MFAF is readily deformed and conforms to the contour of the workpiece surface, making it suitable for finishing 3D free-form surfaces and microstructured surfaces [9].
However, numerous investigations have shown that the finishing effect of MFAF is highly reliant on the preparation of finishing liquid and the selection of finishing parameters. To improve the quality of polished surface, extensive studies on the preparation of finishing liquid, the optimization, and selection of finishing parameters have been done. For preparing the finishing liquid, Sidpara et al. studied the effect of the concentration of carbonyl iron particles (CIPs) and abrasives on the final surface roughness (Ra) and material removal rate (MRR). The results indicate that Ra decreases and MRR increases with the increase in CIP concentration, and Ra increases and MRR decreases with the increase in abrasive particle concentration. Finally, the minimized Ra and maximized MRR were obtained with optimized parameters [11]. Kum et al. demonstrated theoretically and experimentally that the abrasive-to-carbonyl-iron volumetric ratio substantially influences the MRR, with the greatest MRR attained at a volumetric ratio of 0.259 [12]. Niranjan et al. investigated the impact of each component’s volume fraction in the finishing liquid on the finishing effect. The optimal finishing liquid ratio was determined via comparison and optimization, and the Ra was decreased by almost 80% [13]. Guo et al. compared the finishing performance of larger-sized alumina and smaller-sized zirconia and pointed out that superior surface quality can be obtained with smaller-sized zirconia [14].

Numerous investigations have revealed that the finishing effect is significantly affected by the type of carrier medium, the type of abrasive particles, the proportion and size of each component, etc. The preparation of the optimal finishing liquid varies according to the finishing material. Thus, preparing the optimal finishing liquid for the current condition is necessary [15, 16]. Additionally, the magnetic compound fluid (MCF), which is produced by combining magnetic fluid (MF) and magnetorheological fluid (MRF), exhibits superior finishing performance than MF and MRF [17]. Therefore, MCF is a fantastic method for achieving high-quality polishing copper and copper alloys.

Appropriate finishing parameters are necessary for producing high-quality polished surfaces. Therefore, further research is being conducted on the optimization and selection of finishing parameters. Guo et al. demonstrated the rotational speed of the magnet has relatively little effect on the finishing process, while the MCF carrier rotational speed and machining gap significantly affect the finishing process [18]. Alam et al. analyzed the influence of magnetic field intensity on the effect of MRF and pointed out that a high magnetic field promotes faster material removal. Additionally, a high-precision Ra prediction model was developed based on theoretical research [7]. In accordance with fluid mechanics and Preston Equation, the influences of various finishing parameters (including magnetic poles, rotational speeds of workpieces, finishing disk, and the machining gap) on finishing pressure were investigated by Pan et al. Furthermore, a MRR model based on multiple regression was established. After 5 h of finishing with the optimum finishing parameters, the Ra of the single-crystal silicon was decreased from 0.48 μm to 2.4 nm [19]. Sidpara et al. developed a prediction model for MRR and Ra using polynomial fitting. The modeling process accounted for four independent variables: the volume percentage of CIPs and abrasive particles, the carrier wheel rotational speed, and the initial Ra. An excellent finishing effect was obtained by optimizing the finishing parameters [11]. To obtain appropriate finishing parameters, Jiao et al. studied the impact of machining gap and rotational speed on the finishing effect of optical glass. According to this research, finishing with a smaller machining gap and higher rotational speed results in a superior surface and a higher MRR [6]. Mosavat et al. simulated the MAF process with Smoothed Particle Hydrodynamics and analyzed the effects of abrasive particles size, machining gap, and rotational speed on roughness and MRA. A damage-less surface with high quality was obtained with the appropriate finishing parameters [20]. Fan et al. developed a magnetic field-assisted finishing tool for titanium alloy finishing and built an experimental platform to investigate the impact of finishing parameters on finishing quality. The research indicates that the final finishing quality is determined by the abrasive grain size, the machining gap, the feed rate, and the spindle speed. The titanium alloy Ra was reduced from 1.121 μm to 46 nm with the optimized finishing parameters [21].

Most of the research discussed above has focused on silicon wafers, glass, titanium alloys, and other high-hardness materials. In contrast, research on the finishing of low-hardness materials is relatively scarce. In fact, MFAF is also capable of achieving high-quality finishing on low-hardness materials. Some scholars have recently researched obtaining high-quality copper surfaces by MFAF. Kala et al. studied the process of ultrasonic-assisted MRF of copper alloy. They discussed the influence of voltage on the electromagnet, rotational speed, mesh size, and pulse on time of ultrasonic vibration on Ra [22, 23]. Khan et al. conducted an in-depth study on the preparation of the finishing liquid in order to achieve high-quality finishing of copper alloys using BEMRF. Each component’s impact on the finishing effect was investigated, and the optimal finishing liquid was produced. Ra of the copper alloy was reduced to 38 nm by using the optimized finishing liquid [2, 24]. More et al. investigated the effect of finishing parameters on Ra during magnetorheological finishing of copper alloys and developed a Ra prediction model [25].

While extensive research on MFAF has been conducted, the effect of finishing parameters on dimensional accuracy is seldom addressed during parameter optimization, resulting in excessive material removal and a reduction in dimensional accuracy. For instance, Pan et al. neglected the effect of material removal on the dimensional accuracy of single-crystal silicon while optimizing the finishing parameters. Although super-smooth uniform surfaces with
a roughness of 2.4 nm were acquired, the sample thickness was decreased by nearly 39 µm, which would significantly decrease the dimensional accuracy [19].

However, compared to high-hardness materials such as silicon, there is more material removal in the finishing of copper. If the dimensional accuracy is not considered while optimizing the finishing parameters for copper, the dimensional accuracy may decrease more obviously. Therefore, taking the influence of the MRA on dimensional accuracy into consideration is necessary.

To achieve copper alloys with high-quality polished surface and high dimensional accuracy through the MCFF technology, a prediction model indicating Ra and MRA was developed using a fusion neural network model, and the finishing parameters were optimized, taking into account the effect of material removal on dimensional accuracy. This paper is organized as follows: in Sect. 2, the MCFF experiment is designed and executed to obtain the finishing data for modeling; in Sect. 3, a high-precision multi-neural network fusion model (MNNFM) based on the integrated learning theory is established, which is used to accurately predict the polished surface quality and MRA. In Sect. 4, considering the effect of MRA on the dimensional accuracy, the finishing parameters are optimized by the multi-objective particle swarm optimization (MOPSO) algorithm. Conclusions are drawn in Sect. 5.

### 2 Details of the experimental setup

#### 2.1 Preparation of MCF

The MCFF was selected for high-quality copper alloy finishing based on prior research. The MCF is composed of magnetizable particles (CIPs, etc.), carrier medium (silicone oil, mineral oil, etc.), abrasive particles (diamond abrasives, silicon carbide, aluminum oxide, cerium oxide, etc.), and additives (α-fiber, etc.). According to reference [2], the MCF appropriate for the copper alloys was prepared through experiments. In the prepared MCF, MRF-250 is used as the carrier liquid, and CIPs are used as magnetic particles because of their spherical form, high permeability, and high purity. The abrasive particles adopted are cerium oxide, which is the most commonly used material in high-quality finishing. Additionally, a trace of cellulose was added to improve the viscosity of MCF and prevent solid particles from precipitating, improving finishing efficiency. The composition ratio of MCF acceptable for copper alloy was determined in pre-experiment. Firstly, various MCFs with different composition ratios were prepared and used to finish copper alloy samples. Afterwards, the optimal component ratio was determined by using response surface methodology. The optimal composition ratio of the prepared MCF is shown in Table 1. It is worth noting that the selected abrasive particles are spherical, not typical abrasive particles with sharp angles. Moreover, the abrasive particles and CIPs are the same size to provide a superior finishing effect [11, 26].

Figure 1a shows the state of the prepared MCF under the action of a magnetic field. CIPs and cerium oxide are organized in the direction of the lines of magnetic induction by the action of the magnetic field, forming a large number of complex chain structures [27]. These chain structures are collectively called Flexible Magnetic Abrasive Brush (FMAB) [28]. During the finishing process, FMAB rotates with the MCF carrier and applies normal force (magnetic pressure and hydrodynamic pressure) and shear force on the surface of the workpiece (as shown in Fig. 1b). The finishing force can be controlled by adjusting the intensity of the magnetic field and finishing parameters. The abrasive particle produced indentation on the surface of the copper workpiece due to normal magnetic force. The cross section of the indented region of the abrasive particle corresponds

| Constituents | MRF-250 | CIPs | Cerium oxide | α-cellulose |
|--------------|---------|------|--------------|-------------|
| Content      | 51 wt%  | 38.7 wt% | 7 wt%       | 3.3 wt%     |
| Role         | Carrier liquid | Magnetic particles | Abrasive particles | Additives |

![Fig. 1 a Status of MCF under the action of a magnetic field b Interaction of MCF and workpiece](image-url)
to the profile of the penetrated portion. The removal of material in the form of chips occurs when the penetrated abrasive particle is rotated over the workpiece surface. It should be noted that the removal mechanism occurs only when the reaction force \( F_{R5} \) on the projected region of indent abrasive is lesser than the shear force \( F_\gamma \) exerted by the stiffened MCFF as shown in Fig. 1b).

### 2.2 Experimental platform

The experiment was carried out on the self-built MCF finishing experimental platform (as shown in Fig. 2a). The finishing head has degrees of freedom in the X and Z directions, and the processing platform has degrees of freedom in the Y direction. The finishing head is hollow, with a biased permanent magnet placed within (as shown in Fig. 2b). The permanent magnet rotates in the opposite direction to the finishing head, forming a dynamic magnetic field. Under the action of the magnetic field, the MCF will be adsorbed on the bottom of the finishing head. When the MCF rotates with the finishing head, the surface of the workpiece will be polished by the formed FMAB.

### 2.3 Key finishing parameter determination and experimental design

Taking all parameters into consideration while developing a machining model is time-consuming and unnecessary. Therefore, preliminary experiments were conducted based on previous research results to determine the key finishing parameters (KFPs), which have the most significant influence on the finishing effect and need to be optimized. Finally, the abrasive particles size \( s \), machining gap \( h \), MCF carrier rotational speed \( n \), and finishing time \( t \) were selected as KFPs. The remaining parameters were fixed to their appropriate values. For example, the function of the rotational magnetic is to provide a dynamic magnetic field whose state has a negligible effect on the finishing effect. Therefore, the magnet rotates in the opposite direction of the MCF carrier, and the speed is maintained at 100 rpm.

Each machining parameter’s range should be determined based on the actual machining situation. The amount of MCF involved in polishing is too small, and the polishing effect is not obvious when the machining gap is tiny. The MCF is far from the workpiece, and effective finishing cannot be achieved when the machining gap is too large. As a result, the range of machining gap was limited to 1 to 2 mm. Similarly, slow MCF carrier rotational speed produces an insignificant polishing effect, but quicker rotational speed causes the MCF to be thrown out from the MCF carrier due to centrifugal force. Hence, the MCF carrier rotational speed was regulated to between 200 and 1000 rpm. The polishing effect is also unsatisfactory when the polishing time is too short, and it is not reasonable when the time is too long, so the time was limited to 30 to 150 min. Each KFP was divided into five levels. The machining gap, MCF carrier rotational speed, and finishing time were uniformly distributed. The abrasive particle size cannot be uniformly distributed since it can only be selected according to the existing sizes. The sizes of abrasive particles are 4000 #, 5000 #, 8000 #, 10,000 #, and 12,500 #. The corresponding abrasive particles diameters are 3.4 μm, 2.6 μm, 1.6 μm, 1.3 μm, 1 μm, respectively. The level setting of each KFP is shown in Table 2.

### 2.4 Design and development of experiments

Copper alloys (H62) with a fixed size (50 mm × 50 mm × 1 mm) were used as the experimental samples. Because all copper samples were cut from the same copper sample and have the same original surface quality, the influence of the initial surface quality on the polish quality may be disregarded. Due to the difficulty of quantifying the samples’ dimensional accuracy, MRA was utilized to indicate the reduction in dimensional accuracy. The larger the MRA, the more pronounced the influence of polishing on dimensional precision.
The experiments were designed with Design-Expert software, taking the abrasive particles size, machining gap, and MCF carrier rotational speed into account, and 20 sets of experimental parameter combinations were constructed and acquired. To improve the modeling accuracy, the experimental parameter combinations were intentionally increased in the sparse region of the parameter distribution, expanded to 30 groups, and extended in the temporal dimension, resulting in the acquisition of 150 sets of experimental data. Ra and MRA were measured every 30 min in the actual experiment. Ra was measured with the TR200 surface roughness instrument, and the MRA was measured with high precision electronic analysis balance. Eight spots on each sample surface were assessed, and the average value was used to determine the final Ra of the sample surface. Some experimental data are shown in Table 3.

### 3 Modeling and validation

#### 3.1 Establishment of machining model

The accuracy of the machining model has a significant impact on the optimization of finishing parameters. In machining and manufacturing, theoretical modeling and mathematical fitting are standard modeling methods. However, it is difficult to obtain a sufficiently accurate prediction model through theoretical modeling because of the complicated formation mechanism of MCFF. Additionally, it is challenging to achieve high prediction accuracy using single mathematical fitting methods, such as response surface and polynomial fitting. Therefore, an MNNFM with higher prediction accuracy was built in this research. By fusing the predictions from several models, the fusion model can minimize prediction variance and provide more accurate forecasts than a single model. The process is known as ensemble learning.

As shown in Fig. 3, the established MNNFM comprises two layers: a prediction layer and a fusion layer.

In the prediction layer, five kinds of neural network models with excellent prediction performance selected from different neural network models are used to predict Ra and MRA. Each neural network model is an independent predictor with four inputs and two outputs. Four inputs represent the four finishing parameters that need to be optimized, and two outputs represent Ra and MRA, respectively. The structural parameters of each neural network are shown in Table 4. The obtained experimental data were randomly divided into two parts in training the model, with 70% of the dataset employed to train the developed model and 30% used to validate the developed model’s generalization capacity. Finally, the coefficient of determination \( R^2 \) was adopted to evaluate the predictive performance of neural network models, and larger \( R^2 \) indicate that the models are more predictive [29]. The coefficient of determination can be calculated by Eq. (1).

\[
R^2 = \frac{\sum (\hat{y} - \bar{y})^2}{\sum (y - \bar{y})^2}
\]  

where \( y \) is the actual value, \( \bar{y} \) is the average of the actual values, and \( \hat{y} \) is the predicted value of the model.

The fusion layer function is to obtain more accurate prediction results based on the output of each neural network in the prediction layer. The commonly used model fusion strategies contain average fusion, weighted fusion, and model stacking. While average fusion and weighted

| No | s (μm) | h (mm) | n (rpm) | t (min) |
|----|-------|-------|-------|-------|
|    |       |       |       | 30    | 60    | 90    | 120   | 150   |
| 1  | 3.4   | 2     | 200   | Ra (μm) | 0.082 | 0.073 | 0.063 | 0.054 | 0.045 |
|    |       |       |       | MRA (g) | 0.0353 | 0.0522 | 0.0853 | 0.1875 | 0.2701 |
| 2  | 2.6   | 1.5   | 600   | Ra (μm) | 0.065 | 0.048 | 0.041 | 0.039 | 0.038 |
|    |       |       |       | MRA (g) | 0.0558 | 0.1162 | 0.1806 | 0.2289 | 0.2680 |
| ...| ...   | ...   | ...   | ...    | ...   | ...   | ...   | ...   | ...   |
| 29 | 1     | 2     | 600   | Ra (μm) | 0.092 | 0.080 | 0.071 | 0.061 | 0.054 |
|    |       |       |       | MRA (g) | 0.0376 | 0.0536 | 0.0670 | 0.0849 | 0.1546 |
| 30 | 2.6   | 1     | 600   | Ra (μm) | 0.056 | 0.042 | 0.035 | 0.032 | 0.033 |
|    |       |       |       | MRA (g) | 0.0893 | 0.1709 | 0.2473 | 0.2824 | 0.2988 |
fusion are straightforward to calculate, the fusion effect is unsatisfactory. Adopting D-S evidence theory to fuse the multiple neural networks has also been reported, but it is used for classification [30]. Model stacking is a widely used technique in machine learning to improve models’ performance. The fundamental principle behind model stacking is to use predictions from the previous level of machine learning models as input variables for models on the subsequent level [31]. Although model stacking incurs a higher computational cost, it is guaranteed to be accurate. Consequently, the model stacking strategy was utilized to fuse the outputs of the five neural networks shown in Table 4. To obtain the fused Ra and MRA, another neural network is used as the model fusioner, and the output of the prediction layer is used as the input.

3.2 Verification of model prediction performance

On the one hand, the predictive performance of the developed MNNFM was evaluated using the $R^2$, and the obtained $R^2$ was 0.989, which is higher than the $R^2$ of all the models in Table 3. On the other hand, further validation tests were added to validate the models’ predictive performance and quantitatively compare them to the single model. Therefore, ten sets of finishing parameters are randomly created within the feasible area, and the developed MNNFM was utilized to predict Ra and MRA. Simultaneously, the prediction results of five neural networks were recorded for comparison. Finally, the verification experiments were conducted to validate the model’s prediction performance. The results are illustrated in Table 5 and Fig. 4.

Table 5 and Fig. 4 illustrate that the prediction results of MNNFM are closer to the experimental results than the prediction results of a single model, and the prediction errors are within ±10%, which means that the prediction accuracy of MNNFM is higher than any single model. While a single model may outperform MNNFM at particular points, the model should be evaluated holistically rather than at particular points. Additionally, a single model may have a high prediction deviation at particular points, while MNNFM provides excellent prediction performance at all points and reduces the possibility of large prediction deviations. MNNFM has the capacity to compensate for a single model’s prediction mistakes, which may explain why MNNFM has superior prediction performance. For instance, for the third and fifth sets of finishing parameters in Table 5, the MRAs predicted by the first neural network model are considerably higher than the experimental values. On the contrary, the third neural network model’s prediction results are considerably lower than the experimental values. More significant prediction errors may occur when a single model is adopted, resulting in an inability to evaluate the finishing parameters accurately. When the fusion model is employed, better prediction accuracy is possible. As shown in Fig. 4b, the MNNFM prediction results for the third and fifth sets of finishing parameters are more consistent with the experimental values. Increased prediction accuracy will aid in accurately evaluating the finishing parameters throughout the optimization process, obtaining the most optimum finishing parameters.

The $R^2$ of the established MNNFM is 0.989, which is considerably higher than other single models. Additionally, the MNNFM prediction error percentages for Ra and MRA are within 10%, which is considered acceptable in this research. In general, the developed MNNFM performs well in terms of forecast accuracy, and its prediction outputs may accurately represent the actual processing effect. Therefore, the

Table 4 The parameters of prediction layer neural network

| Net | Number of hidden layers | Number of nodes | Training algorithm | Activation function | $R^2$ |
|-----|------------------------|-----------------|--------------------|---------------------|-------|
| 1   | 1                      | 10              | Elastic BP algorithm | Tanh                | 0.923 |
| 2   | 1                      | 8               | Polak-Ribiers conjugate gradient algorithm | Sigmoid            | 0.935 |
| 3   | 1                      | 9               | Powell-Beale conjugate gradient algorithm | Identity           | 0.925 |
| 4   | 1                      | 8               | BFGS Quasi newton method | Identity           | 0.907 |
| 5   | 1                      | 10              | Levenberg–Marquardt algorithm | Sigmoid            | 0.949 |
subsequent parameter optimization and the analysis of the finishing process are based on the established MNNFM.

4 Optimization of finishing parameters

4.1 Process of parameter optimization

It is unavoidable that material removal may affect the workpiece’s dimension accuracy. However, the decrease of the workpiece’s dimension accuracy caused by excessive material removal is unacceptable. For instance, the MRA obtained is about 0.3 g when the thirties set of finishing parameters in Table 3 is adopted. Based on the surface dimensions of the sample (L 50 mm, W 50 mm) and the density of copper H62 (8.43 g/cm³), it is estimated that the thickness of the sample will decrease by about 14 μ. It is unacceptable in high-precision workpieces. Therefore, it is necessary to consider both Ra and MRA during the optimization of finishing parameters.

In the case of optimizing finishing parameters while taking the effect of MRA on dimensional accuracy into account, the mathematical model is represented by Eq. (2). There are two optimization objectives: minimizing Ra and minimizing MRA. Additionally, the range of each finishing parameter should be limited to the range specified in Table 2.

\[
\begin{align*}
  f_1 : & \min Ra = F_1(s, h, n, t) \\
  f_2 : & \min MRA = F_2(s, h, n, t) \\
  s.t. & \\
  & s \in [1, 1.3, 1.6, 2.6, 3.4] \\
  & 1 \leq h \leq 2 \\
  & 200 \leq n \leq 1000 \\
  & 30 \leq t \leq 150
\end{align*}
\]

Fig. 4 Verification of MNNFM a Ra b MRA
$N$ randomly generated particles (finishing parameters), where each particle has position and velocity properties. In this study, the position and velocity of each particle are four dimensions, respectively representing the four finishing parameters.

\[
\begin{align*}
\mathbf{x}_i &= \{w_i, h_i, n_i, t_i\} \\
\mathbf{v}_i &= \{v_{w_i}, v_{h_i}, v_{n_i}, v_{t_i}\}
\end{align*}
\]

represent position and velocity of particle \(i = 1, \ldots, N\) at iteration \(t = 1, \ldots, t_{\text{max}}\), respectively. The initial position and velocity are random values within the acceptable range.

Then, each particle is evaluated based on the established MNNFM. Particle \(i\) will be determined to be a non-dominated optimal solution and stored in an external repository (REP) if there is no other particle in the entire population that has a better surface and less MRA than particle \(i\). At each iteration of the MOPSO, the obtained non-dominant solutions are compared one by one to the solutions in REP. If the new solution is dominated by any member of REP, the new solution will be discarded; otherwise, the new solution will be added to REP. If there are any solutions in the REP dominated by the new solution, the former will be discarded. When the number of solutions in REP exceeds the limit, an adaptive grid is required to remove excess solutions. The target space is divided into several small regions. If there are multiple solutions in a region, some redundant solutions in the region will be randomly discarded. This allows the final goal to have well-distributed non-dominant solutions [32].

In the optimization process of MOPSO, each particle continually updates its velocity and position by Eqs. (3) and (4). \(p_i\) represents the best position of each particle; \(p_g\) represents the position of the best population leader. Additionally, the location of the best particle can not be found directly. Instead, the crowding of the solutions in the REP will be calculated, and the solutions with lower crowding are more likely to be selected as the best population leader.

\[
\begin{align*}
\mathbf{v}_{i+1} &= w_{i} \mathbf{v}_{i} + c_1 r_1 \left( p_i - \mathbf{x}_i \right) + c_2 r_2 \left( p_g - \mathbf{x}_i \right) \\
\mathbf{x}_{i+1} &= \mathbf{x}_i + \mathbf{v}_{i+1}
\end{align*}
\]

where \(r_1\) and \(r_2\) are uniformly distributed random numbers between 0 and 1, and \(c_1\) and \(c_2\) are learning factors; \(w\) represents the inertial weight coefficient and controls the tradeoff between the global and local history, which is calculated by Eq. (5):

\[
w = \frac{w_{\text{max}} - t(w_{\text{max}} - w_{\text{min}})}{t_{\text{max}}}
\]

The number of non-dominated optimal solutions that can be stored in REP can be adjusted according to actual needs. The REP can store up to 50 sets of non-dominated optimal solutions in this research. This means that 50 sets of excellent finishing parameters will be obtained after finishing, which are the results of balancing Ra and MRA. Table 6 shows part of the non-dominated solutions recorded in REP. The complete non-dominated solutions are shown in the Appendix. The finishing parameters in the Appendix can provide a high-quality surface and minimize material removal, ensuring dimensional accuracy.

### 4.2 Discussion of optimization results

By analyzing the non-dominated optimal solutions recorded in REP, it can be found that: (1) When the high-quality
When a polished surface is required, the finishing parameters adopted have a larger abrasive particles size, smaller machining gap, faster MCF carrier rotational speed, and longer finishing time; (2) When the quality requirement for the polished surface is not strict, the finishing parameters used have a medium size, larger machining gap, lower MCF carrier rotational speed, and shorter finishing time. In order to explore the reasons, the influences of the finishing parameters on Ra and MRA were studied, and the obtained results are shown in Fig. 6.

As shown in Fig. 6, the finishing time is the most influential parameter on Ra and MRA, followed by machining gap and abrasive particles size. With the increase of time, Ra shows a decreasing trend. Further, it can be found that the rate of decline decreased as time passed. The reason behind this is that the initial material surface is rough and contains many readily removed micro bulges, resulting in a rapid decrease in Ra. In the later stage, the material surface becomes smooth. While removing the micro-protrudes, the abrasive particles will also break the smooth surface, resulting in a slower decreasing rate of Ra. Therefore, when the required surface quality of the workpiece is high, long-time finishing is difficult to avoid. However, it is not prudent to raise the finishing time blindly. After the workpiece’s surface quality reaches a certain point, increasing the finishing time improves the workpiece’s surface quality slightly while increasing the time cost and material removal significantly. Thus, when the required surface quality is not crucial, the machining time can be reduced and the machining efficiency is enhanced by optimizing other machining parameters.

The machining gap significantly impacts the finishing effect since it alters the finishing force. The smaller the machining gap, the greater the finishing force. With a smaller working gap, the magnet is closer to the workpiece’s surface, the magnetic cluster produced is more stable, exerting more pressure on the workpiece’s surface. Additionally, the amount of MCF flowing through the machining gap per unit time is constant when the MCF carrier speed is determined. A reduced machining gap increases hydrodynamic pressure on the workpiece’s surface, resulting in increased finishing force. As shown in Fig. 6a, the workpiece’s surface quality declines as the machining gap grows. This is because the tiny shear is insufficient to remove the material, and more elastic deformation occurs on the material’s surface, making

| No | $a$ (μm) | $h$ (mm) | $n$ (rpm) | $t$ (min) | Ra (μm) | MRA (g) |
|----|---------|---------|---------|----------|---------|---------|
| 1  | 3.4     | 1       | 1000    | 150      | 0.0304  | 0.2753  |
| 2  | 3.4     | 1       | 860     | 131      | 0.0314  | 0.2546  |
| ...| ...     | ...     | ...     | ...      | ...     | ...     |
| 49 | 1.6     | 2       | 200     | 36       | 0.0714  | 0.0312  |
| 50 | 1.3     | 2       | 200     | 30       | 0.0807  | 0.0272  |

![Fig. 6](https://example.com/fig6.png) **a** Effect of KFPs on Ra. **b** Effect of KFPs on MRA
it difficult to improve the workpiece’s surface quality. The increased shear force will remove material effectively and improve the workpiece’s surface quality. Therefore, a smaller machining gap will be selected to get a high-quality polished surface. However, smaller machining gaps also mean more significant material removal. A larger machining gap was selected when the quality of the polished surface was not demanding.

As shown in Fig. 6a, b, smaller MRA and larger Ra are obtained when the abrasive particles and CIPs are small in size. A potential explanation for this phenomenon is that the shear and normal force increase as the abrasive particle size when the CIPs and abrasive particles are the same sizes [33], and the lack of shear and normal forces leads to poor polishing efficiency when the abrasive particles and CIPs are small. When medium-sized abrasive particles and CIPs are used, shear and normal forces are enhanced, allowing for high-efficiency polishing. This results in a higher MRA and a lower Ra. However, with a constant percentage of abrasive particle mass, the number of abrasive particles involved in polishing decreases as the size of the abrasive particles increases. Therefore, increasing the size of abrasive particles and CIPs does not result in a constant rise in polishing efficiency. On the contrary, when the abrasive particles are too large, the polishing efficiency decreases instead, leading to a decrease in MRA and an increase in Ra. Therefore, Ra tends to decrease and then increase with increasing abrasive particles size, whereas MRA tends to increase and then decrease. For the above reasons, when high-quality surfaces are required, the optimal abrasive particle size should be 2.6 μm, disregarding dimensional accuracy, and the optimized abrasive particle size is 3.4 μm when the dimensional accuracy is taken into consideration. This is mainly because the increase in Ra is not apparent, while the decrease in MRA is apparent when the abrasive particle size increases from 2.6 to 3.4 μm. When surface quality requirements are not strict, abrasive particles are typically 1.6 μm in size, which can strike a balance between surface quality and dimensional accuracy.

The MCF carrier rotational speed effect on Ra and MRA is insignificant. When the MCF carrier rotational speed is increased, the speed of the abrasive particles and the force produced by the abrasive particle rise as well. In general, Ra decreases as the speed rises, whereas MRA increases. However, when the speed is excessive, Ra exhibits an insignificant upward trend, and MRA exhibits a significant downward trend. This phenomenon may be caused by the increase of the centrifugal force of the abrasive particles due to the excessive speed, which increases the probability of the abrasive particles escaping from the FMAB and reduces the finishing efficiency. As a result, a large MCF carrier rotational speed is required when the surface quality requirements are high. When the surface quality requirements are not strict, a low speed may satisfy the requirements and reduce MRA.

The above part discusses the distribution of the non-dominant optimal solutions derived via an investigation of the effect of finishing parameters on Ra and MRA. The following part will illustrate the superiority of the non-dominated optimal solutions discovered through comparison.

Ra and MRA corresponding to the non-dominated optimal solutions are offered in Fig. 7. In addition, the results of the previous experiment are also shown in Fig. 7. It can be found that the optimized Ra and MRA tend to the lower-left corner, which means that the workpiece with high-quality, low MRA, and high dimensional accuracy can be obtained using the optimized finishing parameters. For instance, to obtain polished surfaces with Ra less than 0.05 μm, the Ra obtained using the optimal finishing parameters in the
previous experiment is 0.0493 μm, and the MRA is 0.1942 g (Point A in Fig. 7). When the finishing parameters are selected from the non-dominant solutions, the obtained Ra is 0.0482 μm, but the MRA is only 0.0747 g (Point B in Fig. 7). The MRA is reduced by about 61.54%. In addition, the finishing time is reduced from 90 to 62 min, and finishing efficiency is improved. Assuming that the material is uniformly removed, the thickness reduction of the workpiece decreases from 9.215 to 3.544 μm. This means that the dimensional accuracy is improved by 61.54% with the optimized finishing parameters.

To compare the optimization results of finishing parameters with considering dimensional accuracy and without considering dimensional accuracy, the particle swarm optimization algorithm was employed to optimize the finishing parameters without considering dimensional accuracy. The obtained iteration process and finishing parameters are shown in Fig. 8. The Ra obtained by using the finishing parameters in Fig. 8 is 0.0303 μm, and the MRA is 0.2982 g (Point C in Fig. 7). However, the smallest Ra that can be obtained using the finishing parameters optimized considering the dimensional accuracy is 0.0306 μm, which is almost the same as the Ra obtained without considering the dimensional accuracy, and the obtained MRA is reduced to 0.2625 g (Point D in Fig. 7). The amount of material removed was decreased by 11.97%. This demonstrates that even when a highly polished surface is requested, the proposed optimization algorithm may successfully decrease MRA, maintaining the workpiece’s dimension accuracy.

Additionally, the improvement of the workpiece’s dimensional accuracy will be more apparent when the demands for the workpiece’s surface quality are not strict. Under the condition that the workpiece with Ra less than 0.0400 μm can meet the requirements of use, the polished surface with Ra of 0.0398 μm can be obtained by using the finishing parameters in the non-dominant optimal solution, and the corresponding MRA is 0.1414 g (Point E in Fig. 7). Suppose the optimized finishing parameters without considering dimensional accuracy are adopted. In that case, the quality of the polished surface exceeds the need, resulting in an increase in MRA and a reduction in the workpiece’s dimensional accuracy. MRA will be decreased by 52.58% using the optimized finishing parameters considering dimensional accuracy, which means that the workpiece’s dimensional accuracy will be improved by 52.58%. Additionally, the machining time will be decreased from 150 to 90 min, which means a significant increase in machining efficiency.

The above study demonstrates that the finishing parameters obtained by the proposed finishing parameter optimization method may minimize material removal and enhance the workpiece’s dimensional accuracy while obtaining a high-quality polished surface.

4.3 Validation of optimization results

To validate the optimization results, validation experiments were done on both optimization results without considering MRA and the optimization results with considering MRA. Each group of experiments was repeated three times. Figure 9 shows the comparison between the experimental results and the predicted results. It can be found that the predicted results are close to the experimental results.
Table 7 shows the mean value of the three experimental values and the deviation between the predicted and experimental results. It can be found that the prediction errors of the optimized finishing parameters are less than 10%, demonstrating that the suggested MNNFM accurately represents the real processing effect and has an outstanding prediction accuracy. The proposed modeling method and finishing parameter optimization method are demonstrated to play an excellent role in the MCF finishing process. The proposed multi-objective optimization method can significantly decrease the roughness of the polished surface while maintaining dimensional accuracy.

The Keyence VHX-5000 series ultra-depth depth three-dimensional microscope system was used to observe the surface morphology of copper alloy. Figure 10f shows the surface morphology of the unpolished copper alloy, which has a roughness of 0.184 μm. It can be found that there are obvious stripes on the surface of the workpiece, which is due to the fact that the copper alloy used has been processed by the drawing process, resulting in regular stripes on the surface. The stripes were largely eliminated in the polishing example using both group A and group B processing parameters, but considerable fine traces remained. Additionally, the polished surface quality achieved with optimal group B parameters was nearly identical to that obtained with group A parameters but with less material removal and a shorter processing time. The residual texture becomes finer, and the surface finish is further improved when polished with group E parameters. Excellent polishing results were achieved with both group C and group D parameters. The original texture on the workpiece’s surface is almost completely removed, producing a smooth microscopic surface. It is noteworthy that none of the polished surfaces is scratched, illustrating the exceptional quality and damage-free polishing that can be accomplished when copper alloys are polished with MCF.

![Fig. 10 Surface morphologies with different polishing effects](image-url)
5 Conclusion

The aim of the present research was to determine the optimal finishing parameters for copper alloys in order to obtain the workpieces with a high-quality surface and high dimensional accuracy. The finishing model was established, and the finishing parameters were optimized. The main conclusions are summarized as follows:

- The finishing time has the most significant effect on Ra and MRA, followed by the machining gap and abrasive particle size. In contrast, the MCF carrier rotational speed has a minor impact on Ra and MRA.
- Although a high-quality polished surface usually requires more material removal, the optimum balance between them may be achieved by utilizing the optimum finishing parameters obtained by the proposed method.
- In pursuing the highest quality polished surface, a slight sacrifice of finishing quality may bring a considerable increase in dimensional accuracy by using optimized finishing parameters.
- In the case of low finishing quality requirements, taking the effect of material removal on dimensional accuracy into consideration when optimizing finishing parameters may significantly improve the workpiece’s dimensional accuracy.

Appendix

Non-dominated optimal solutions recorded in REP.

| No | W (μm) | h (mm) | n (rpm) | t (min) | Ra (μm) | MRA (g) |
|----|--------|--------|---------|---------|---------|---------|
| 1  | 3.4    | 1      | 1000    | 150     | 0.0303  | 0.2625  |
| 2  | 3.4    | 1      | 780     | 142     | 0.0310  | 0.2520  |
| 3  | 3.4    | 1.1    | 660     | 150     | 0.0316  | 0.2626  |
| 4  | 3.4    | 1      | 750     | 132     | 0.0327  | 0.2182  |
| 5  | 3.4    | 1      | 680     | 130     | 0.0331  | 0.2271  |
| 6  | 3.4    | 1.1    | 760     | 119     | 0.0336  | 0.2351  |
| 7  | 3.4    | 1.1    | 710     | 121     | 0.0339  | 0.2278  |
| 8  | 3.4    | 1      | 660     | 104     | 0.0339  | 0.2268  |
| 9  | 3.4    | 1.3    | 840     | 130     | 0.034   | 0.2244  |
| 10 | 3.4    | 1.3    | 510     | 121     | 0.0343  | 0.2117  |
| 11 | 1.6    | 1.2    | 470     | 80      | 0.0351  | 0.1980  |
| 12 | 2.6    | 1.4    | 310     | 103     | 0.0352  | 0.2229  |
| 13 | 1.6    | 1.7    | 200     | 109     | 0.0360  | 0.1989  |
| 14 | 3.4    | 1.2    | 810     | 110     | 0.0360  | 0.2132  |
| 15 | 1.6    | 1.4    | 310     | 85      | 0.0364  | 0.1627  |
| 16 | 1.6    | 1.8    | 430     | 99      | 0.0381  | 0.1662  |
| 17 | 1.6    | 1.7    | 340     | 78      | 0.0383  | 0.1235  |
| 18 | 1.6    | 1.8    | 310     | 72      | 0.0385  | 0.1501  |
| 19 | 1.6    | 1.7    | 200     | 80      | 0.0388  | 0.1427  |

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Declarations

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