Tool wear prediction using a hybrid of tool chip image and evolutionary fuzzy neural network

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Abstract
This paper proposes an evolutionary fuzzy neural network (EFNN) for tool wear prediction. Material chips are affected by the cutting conditions during the cutting process. Different tool wear statuses cause material chips to have different colors; thus, the color of a material chip can be a crucial factor in tool wear prediction. In this study, the cutting time and International Commission on Illumination (CIE) xy value were used as the input of the proposed EFNN, and the output was the predicted degree of tool wear. The experimental results indicate that the proposed EFNN with the dynamic group cooperative particle swarm optimization (PSO) algorithm resulted in a smaller mean absolute percentage error (2.83%) than did the backpropagation neural network (9.72%), PSO (7.42%), quantum-based PSO (8.59%), and cooperative PSO (4.09%) algorithms.

Keywords Tool wear · Chip surface · Color calibration · Evolutionary fuzzy neural network · Particle swarm optimization

1 Introduction

Tool life prediction is one of the most crucial tasks in the machinery industry. Tool wear affects the accuracy of fabricated products, and high tool wear results in a higher product defect rate and product cost. Many researchers have attempted to improve the accuracy of tool wear prediction [1, 2]. Numerous studies have predicted tool wear by investigating the parameters of the cutting, down-milling, and up-milling processes as well as measuring the cutting force and sensor signals from machines [3, 4]. Using signals acquired from sensors is an indirect method for predicting tool wear. Reflecting the real cutting situation by using this method is difficult [5, 6]. Moreover, the measurement of the sensor must pass the force flow line. Different signal values are obtained when using sensors to measure cutting tools made of different materials. Therefore, tool wear prediction models developed on the basis of these signals can only be applied to one type of tool. Instead of using sensor signals, material chips can be used for tool wear prediction. These chips are directly affected by the cutting force, tool shape, and heat during the cutting process [7, 8]. During this process, the cutting tool directly contacts the cut material; thus, material chips are more reflective of the current cutting situation than are measured sensor signals. Therefore, the present study used chip surface color for determining the temperature in the cutting procedure and the current cutting status to enhance the accuracy of tool wear prediction.

Neural networks (NNs) have been widely used to develop models for solving prediction problems [9]. Erkan et al. adopted an artificial NN (ANN) [10] to accurately predict the damage factor in the cutting of glass-fiber-reinforced plastic. In addition, they used analysis of variance [11] to determine the parameter with the strongest influence on the damage factor. The results clearly revealed that the feed rate is the most influential parameter affecting the damage factor. Kara et al. established a prediction model by using ANNs [12]. The inputs of this model include cutting speed, cutting tool, workpiece, depth of cut, and feed rate. The output of the aforementioned model is surface roughness. The results of Kara et al. indicated that the 5-14-1 network architecture had the optimal performance. Özgören et al. developed an ANN to predict the torque and power values obtained with a beta-type Stirling engine [13]. Experiments indicated that the aforementioned...
The advantages of NNs are their simple structure, high training speed, and lack of requirement of complicated mathematical models. NNs tend to exhibit black-box behavior that is not understandable by humans. Fuzzy neural networks (FNNs) combine fuzzy logic and NNs and have been used in various applications [14]. In contrast to NNs, FNNs apply fuzzy logic to mimic human reasoning and natural language expression [15–17]. Fuzzy logic adopts linguistic information to model reasoning processes by using qualitative aspects of human knowledge without using precise quantitative measures [18, 19]. Therefore, fuzzy logic is similar to human experience and practice in the description and interpretation of information. By using the concept of membership degrees, FNNs can manage inaccuracy and uncertainty problems [20, 21]. Chungchoo and Saini [22] proposed an online FNN model for the estimation and classification of flank and crater wear. To improve the accuracy of tool wear prediction, they used the AE_{max}, skew, force, and kurtosis values of force bands as network inputs. The results of the aforementioned authors indicated that their proposed method of tool wear estimation could achieve high accuracy. Li et al. [23] presented an FNN for predicting tool life in dry milling operations. This FNN integrates a fuzzy logic inference into an NN structure and is essentially a multilayered fuzzy-rule-based NN. Fuzzy rules increase the prediction accuracy and speed up the learning process of networks. FNNs have higher prediction accuracy than do backpropagation (BP) NNs (BPNNs), radial basis function networks, and multiregression models. The uncertainties caused by the cutting fluid, environmental conditions, and material properties affect the reliability of tool wear prediction. Zhang et al. [24] designed a type-2 fuzzy basis function network for tool wear monitoring. The network can estimate the uncertainty bounds associated with tool wear measurement. The results of Zhang et al. indicated that their tool wear model had higher accuracy and robustness than other methods.

The aforementioned methods use the BP algorithm, which employs the gradient descent technique to minimize the error function for adjusting network parameters. The BP algorithm has rapid convergence ability; however, it can become trapped in a locally optimal solution. To overcome the drawbacks of the BP algorithm, evolutionary algorithms have been developed to obtain the global optimal solution and solve parameter optimization problems. Evolutionary algorithms include the genetic algorithm [25], ant colony optimization [26], differential evolution [27], the whale optimization algorithm [28], the artificial bee colony algorithm [29], and particle swarm optimization (PSO) [30–32]. PSO has been widely applied in various fields. It has a simple structure, few parameters to set, and superior problem-solving ability. However, the conventional PSO algorithm has unstable convergence and can be easily trapped in a locally optimal solution. To overcome these shortcomings, this study used a new evolutionary concept to improve the performance of PSO.

The aim of this study was to develop a framework for effective and accurate prediction of tool wear. Therefore, this paper proposes an evolutionary FNN (EFNN) for establishing a tool wear prediction model. The contributions of this study are as follows: (1) using chip chromaticity coordinates as a feature vector for predicting the tool wear value; (2) proposing an EFNN to establish a tool wear prediction model; and (3) designing a dynamic group cooperative PSO (DGCPSO) algorithm, which combines the concepts of dynamic groups and cooperation to optimize the network parameters. The rest of this paper is organized as follows. Section 2 introduces the machining principle. Section 3 describes the experimental equipment, materials, and proposed method. Section 4 presents the experimental results. Finally, Sect. 5 presents the conclusions of this study and recommendations for future studies.

2 Machining principle

2.1 Tool wear theory

During the cutting process, the cutting tool rubs against the workpiece and generates excessive heat. As the cutting continues, dents appear on the blade. This phenomenon is called mechanical wear [33, 34]. When the blade of the cutting tool becomes deformed, the cutting resistance and temperature increase, resulting in rapid wearing of the tool and in turn causing the tool to lose its cutting ability [35, 36]. The degree of tool deterioration determines the end of useful tool life. The International Standards Organization (ISO) standard for tool life evaluation (ISO-8688-1 1994) was adopted to estimate tool life in this study. The ISO standard recommends the replacement of a cutting tool if the uniform wear of the flank surface reaches 0.3 mm or the uneven wear reaches 0.6 mm. Taylor’s tool life equation is used to represent the relationship between the tool life and cutting velocity [37, 38]. This equation can be expressed as follows:

\[ VT^n = C \]

where \( V \) represents the cutting velocity (m/min), \( T \) denotes the tool life (min), \( n \) is a constant that depends on the tool material, and \( C \) is a constant. During the machining process, machining parameters are considered in the tool life formula. The detailed tool life formula with machining parameters (feed per tooth and depth of cut) can be expressed as follows:

\[ VT^n f^\alpha d^\beta = C \]

where \( f \) is the feed per tooth (mm/tooth), \( d \) is the depth of the cut (mm), and \( \alpha \) and \( \beta \) are exponential constants.
2.2 Colors of machining chips

During the cutting process, the high-speed rotating tool rubs against the workpiece and generates heat. The high-temperature chips cut from the workpiece are rapidly cooled in air, which causes the production of oxide films of various surface colors [39–41]. Different chip colors correspond to different cutting temperatures. During the cutting process, the chip color changes in the following order: yellow → brown → purple → blue → blue-green.

3 Experimental equipment and materials

This section describes the specifications of the machine tool employed, the workpiece material, the cutting tool, and the industrial camera used.

3.1 Machine tool specification

In this study, experimental data were collected using the five-axis EXTRON SU-85 computer numerical control (CNC) machining center (Yih Chuan Machinery Industry Co., Ltd.). This machine is displayed in Fig. 1, and its specifications are presented in Table 1.

3.2 Workpiece material

The workpiece material used in this study was 2316MOD stainless steel with a size of 136.5 × 73 mm². This material has a martensitic crystal structure and is widely applied in plastic injection molding, extrusion molding, and forging process molding. The aforementioned workpiece is displayed in Fig. 2, and the mechanical properties of 2316MOD stainless steel are presented in Table 2.

3.3 Cutting tool

The R217.69-3232.0-18-3AN tool holder and XOMX180631TR-ME13 F40M disposable blades (SECO tools) were adopted in this study. The aforementioned tool holder and blades are displayed in Figs. 3 and 4, respectively, whereas their specifications are presented in Tables 3 and 4.

3.4 Industrial camera

Images of material chips were captured using a full-HD 1080p industrial camera from Wenham Company. This camera contains a WH-SDI500 charge-coupled device, which includes a 1X–8X shutter, an automatic white balance, and an 84–560X magnifier. Material chip images were acquired under an ML-66 light-emitting diode light source, and tool wear values were calculated using the camera software. Figure 5 presents an image of the industrial camera used. As depicted in Fig. 5, the cutting chip was placed at the center of the platform, and its image was then obtained at an appropriate magnification.

Table 1 Specifications of the adopted machining tool (EXTRON SU-85)

| Parameter                                      | Specification       |
|-----------------------------------------------|---------------------|
| X-axis/Y-axis/Z-axis travel (mm)              | 860/540/630         |
| X-axis/Y-axis/Z-axis rapid feed rate (m/min)  | 30/30/240           |
| Spindle speed (rpm)                           | 15,000              |
| Table size (m²)                               | 930 × 500           |
| Table load capacity (kg)                      | 400                 |
| Machine weight (kg)                           | 6400                |

Fig. 1 Five-axis machining tool (EXTRON SU-85) that was employed

Fig. 2 Workpiece made of 2316MOD stainless steel
4 Framework of the EFNN-based tool wear prediction method

The prediction framework consists of three phases: data collection, chip feature extraction, and EFNN model establishment. Figure 6 illustrates a flowchart of the proposed tool wear prediction framework. In the first phase, CNC machining parameters are selected for the cutting experiment, and experimental data are collected. In the second phase, material chip images collected by the industrial camera are calibrated using a color calibration model to obtain more accurate chip images. Subsequently, the calibrated chip images are converted into CIE $xy$ chromaticity values to extract chip features. In the third stage, a data-driven approach and EFNN are used to establish a tool wear prediction model. The training scheme of the EFNN uses the proposed DGCPSO algorithm, which overcomes the drawback of the conventional PSO algorithm to increase the prediction accuracy. Details regarding the aforementioned phases are presented in the following text.

4.1 Data collection

A cutting experiment involving three trials was performed using the Extron SU-85 CNC machine. In each trial, the cutting process was executed seven times. In each cutting process, 10 material chip images and the corresponding tool wear value were obtained. Thus, 210 training images were collected in the cutting experiment. The testing data comprised the image data obtained in a selected experimental trial (i.e., 70 images). The dataset can be found in [42]. The CNC machining parameters of the cutting experiment are presented in Table 5. The machining parameters were selected in accordance with the recommendations of the tool manufacturer. The cutting speed, feed per tooth, depth of cut, and width of cut were set as 500 m/min, 0.1, 20 mm, and 1 mm, respectively.

4.2 Feature extraction for the material chips

After the cutting experiment, chip images were obtained using the industrial camera. A full image ($1920 \times 1080$) of the chip

| Coefficient of thermal expansion ($10^{-6}$/K) | Thermal conductivity (W/mK) | Young’s modulus (kN/mm$^2$) | Tensile strength (N/mm$^2$) | Brinell hardness (HB) |
|---------------------------------------------|-----------------------------|-----------------------------|-----------------------------|------------------------|
| 10                                         | 23                          | 215                         | 1350                        | 265–310                |

Fig. 3 SECO tool holder

Fig. 4 SECO disposable blades
contained the chip edge, which was unnecessary information. A total of 300 × 300 pixels at the center of the full image were selected as the chip feature images. A chip feature image is displayed in Fig. 7.

In real environments, brightness, light sources, and color temperature affect the quality of chip images and cause color differences in them. Scholars have used regression algorithms to construct color calibration models and have evaluated the performance of these models on the basis of color differences [43–45]. Because color temperature cannot be calculated in the RGB color space, a regression model is used to convert the RGB color space into the CIELAB color space. This study used a regression algorithm to establish a color calibration model. This model is based on the US National Bureau of Standards (NBS) color difference unit and was used to calibrate chip feature images [46]. The NBS unit can be divided into six levels, as presented in Table 6. The calibrated color is sufficiently accurate if the NBS unit of a color calibration model is less than 1.5; otherwise, the color calibration model should be re-established. A flowchart indicating the process of constructing the color calibration model used in this study is displayed in Fig. 8.

### Table 4

| Symbol | Property                  | XOMX180631TR-ME13 F40M |
|--------|---------------------------|-------------------------|
| EA     | Blade clearance angle (°) | 15                      |
| RA     | Blade bevel (°)           | 30                      |
| l      | Blade length (mm)         | 16.5                    |
| d      | Blade width (mm)          | 11.2                    |
| s      | Blade thickness (mm)      | 6.35                    |

Fig. 5  Industrial camera used in this study

Fig. 6  Flowchart of the proposed tool wear prediction framework
the standard CIELAB color value in ColorChecker, and
$L^* \Delta L^*$ difference was calculated using the following equation:

$$L_2^* a_2^* b_2^* =$$

$$\begin{bmatrix}
L_1^* a_1^* b_1^* \\
L_2^* a_2^* b_2^* \\
\vdots \\
L_{24}^* a_{24}^* b_{24}^*
\end{bmatrix} =$$

$$\begin{bmatrix}
1 & R_1 & G_1 & B_1 & R\hat{1} & G\hat{1} & B\hat{1} & R_2 & G_2 & B_2 & R\hat{2} & G\hat{2} & B\hat{2} & 1 \\
1 & R_2 & G_2 & B_2 & R\hat{2} & G\hat{2} & B\hat{2} & 1 & R_3 & G_3 & B_3 & R\hat{3} & G\hat{3} & B\hat{3} & 1 \\
1 & R_3 & G_3 & B_3 & R\hat{3} & G\hat{3} & B\hat{3} & 1 & R_4 & G_4 & B_4 & R\hat{4} & G\hat{4} & B\hat{4} & 1
\end{bmatrix} \times$$ (1)

where $L^* a^* b^*$ is the standard CIELAB color value in ColorChecker; $R\hat{G}\hat{B}$ is the RGB color value adjusted by the 1D LUT; and $a$, $b$, and $c$ are the color calibration parameters. After establishment of the color calibration model, the color difference was calculated using the following equation:

$$\Delta E_{ab}^* = \sqrt{(L_2^* - L_1^*)^2 + (a_2^* - a_1^*)^2 + (b_2^* - b_1^*)^2}$$ (2)

where $\Delta E_{ab}^*$ represents the color difference, $L_1^* a_1^* b_1^*$ denotes the standard CIELAB color value in ColorChecker, and $L_2^* a_2^* b_2^*$ is the CIELAB color value calibrated using the color calibration model. The parameter $\Delta E_{ab}^*$ was converted into the NBS unit to evaluate whether the color calibration model was sufficiently accurate.

$$\text{NBS unit} = \Delta E_{ab}^* \times 0.92$$ (3)

In this study, the CIE $xy$ chromaticity coordinate was used as a feature vector of the chip images. The advantage of the CIE $xy$ chromaticity coordinate is that it specifies the magnitude-independent hue and purity of a color. A color can be specified uniquely by its $xy$ chromaticity coordinate. The color calibration model could output chip images in the CIELAB color space. However, the correlated color

![Image](image-url)

**Fig. 7** Chip feature image
temperature of CIELAB is 5000 K (D50), which is different from the most common color temperature of artificial daylight 6500 K (D65). The color temperature had to be changed before conversion from the RGB color space to the CIE \( \text{xy} \) color space. The color conversion process is illustrated in Fig. 9.

Calibrated chip images were converted into the CIEXYZD50 color space (tristimulus values) by using the following equations:

\[
\begin{align*}
X_{D50} &= 96.42 \times \left( \frac{a^*}{500} + \frac{L^* + 16}{116} \right)^3, \\
Y_{D50} &= 100 \times \left( \frac{L^* + 16}{116} \right)^3, \\
Z_{D50} &= 87.69 \times \left( \frac{L^* + 16}{116} - \frac{b^*}{200} \right)^3, \\
\end{align*}
\]

else

\[
\begin{align*}
X_{D50} &= 0.000787 \times \left( \frac{a^*}{500} + \frac{L^*}{116} \right), \\
Y_{D50} &= \frac{a^*}{903.329} Z_{D50} = 87.69 \times \left( \frac{L^*}{116} - \frac{b^*}{200} \right)^3, \\
\end{align*}
\]

where \( L^*a^*b^* \) is the CIELAB color value and \( XYZ_{D50} \) is the CIEXYZ color value for a color temperature of 5000 K. The color temperature D50 was converted into D65 by using the following equation:

\[
[X_{D65} Y_{D65} Z_{D65}] = [X_{D50} Y_{D50} Z_{D50}] \begin{bmatrix} 0.9556 & -0.0284 & 0.0124 \\ -0.0232 & 1.0101 & -0.0206 \\ 0.0633 & 0.0211 & 1.3306 \end{bmatrix}
\]

The calibrated image of a chip was obtained by converting the CIEXYZD65 color space into the CIE \( \text{xy} \) color space by using the following equation:

\[
CIE_x = \frac{X_{D65}}{X_{D65} + Y_{D65} + Z_{D65}} \quad CIE_y = \frac{Y_{D65}}{X_{D65} + Y_{D65} + Z_{D65}}
\]

Finally, each pixel of the image was summed and averaged to determine the chromaticity:

\[
x = \frac{\sum_i^n CIE_x_i}{n} \quad y = \frac{\sum_i^n CIE_y_i}{n}
\]

where \( n \) is the total number of image pixels.

### 4.3 EFNN prediction model

This section introduces the proposed EFNN model for tool wear prediction. The proposed EFNN has many advantages over a conventional NN. First, the EFNN combines fuzzy logic and a functional-link NN to prevent overfitting. Second, the EFNN can reasonably eliminate noise from the internal rules through appropriate fuzzy treatment. Third, the EFNN can approximate a nonlinear function. The proposed EFNN model is divided into two parts: the EFNN architecture and DGCPSO learning algorithm. Figure 10 shows the block diagram of the proposed tool wear prediction model. Through feature extraction, the CIE \( \text{xy} \) chromaticity value of a chip is obtained. This value and the cutting time are input to the proposed EFNN to determine the tool wear value.

#### 4.3.1 Evolutionary fuzzy neural network

Figure 11 displays the architecture of the proposed EFNN, which comprises an input layer, a membership function layer,
The firing number, \( \omega_u \) an upper boundary function is expressed as follows:

\[
\text{THEN} \quad \text{IF } x_1 \text{ is } A_{ij} \text{ and } x_2 \text{ is } A_{2j} \ldots \text{and } x_i \text{ is } A_{ij} \text{ THEN } y_j = \sum_{k=1}^{M} \omega_{kj} \varphi_k = \omega_{1j} \varphi_1 + \omega_{2j} \varphi_2 + \cdots + \omega_{Mj} \varphi_M
\]

where \( x_i \) represents the input, \( y_j \) is the output, \( A_{ij} \) represents the interval type-2 fuzzy set, \( j = 1, 2, \ldots, R \) represents the rule number, \( \omega_{kj} \) is the link weight, \( \varphi_k \) represents the basis trigonometric function, and \( M \) is the number of basis functions.

In layer 2 of the EFNN, each interval type-2 fuzzy set \( (A_{ij}) \) uses a Gaussian primary membership function with a mean uncertainty of \([m_{ij1}, m_{ij2}]\) and a standard deviation of \( \sigma_{ij} \). This function is expressed as follows:

\[
u_{ij}^{(2)} = \exp\left( -\frac{(u_{ij}^{(1)} - m_{ij})^2}{\sigma_{ij}^2} \right) \equiv N\left(m_{ij}, \sigma_{ij}; u_{ij}^{(1)} \right), \quad m_{ij} \in [m_{ij1}, \ m_{ij2}] \quad (9)
\]

where \( m_{ij} \) and \( \sigma_{ij} \) are the mean and standard deviation, respectively. The type-2 Gaussian membership function consists of an upper boundary \( u_{ij}^{(2)} \) and a lower boundary \( u_{ij}^{(2)} \), which are expressed as follows:

\[
u_{ij}^{(2)} = \begin{cases} 
N\left( m_{ij}^{(1)}, \sigma_{ij}; u_{ij}^{(1)} \right), & \text{if } u_{ij}^{(1)} < m_{ij}^{(1)} \\
1, & \text{if } m_{ij}^{(1)} \leq u_{ij}^{(1)} \leq m_{ij}^{(2)} \\
N\left( m_{ij}^{(2)}, \sigma_{ij}; u_{ij}^{(1)} \right), & \text{if } u_{ij}^{(1)} > m_{ij}^{(2)}
\end{cases}

\]

\[
u_{ij}^{(2)} = \begin{cases} 
N\left( m_{ij}^{(1)}, \sigma_{ij}; u_{ij}^{(1)} \right), & \text{if } u_{ij}^{(1)} \leq \frac{m_{ij}^{(1)} + m_{ij}^{(2)}}{2} \\
N\left( m_{ij}^{(1)}, \sigma_{ij}; u_{ij}^{(1)} \right), & \text{if } u_{ij}^{(1)} > \frac{m_{ij}^{(1)} + m_{ij}^{(2)}}{2}
\end{cases}
\]

\[
u_{ij}^{(2)} = \begin{cases} 
N\left( m_{ij}^{(1)}, \sigma_{ij}; u_{ij}^{(1)} \right), & \text{if } u_{ij}^{(1)} \leq \frac{m_{ij}^{(1)} + m_{ij}^{(2)}}{2} \\
N\left( m_{ij}^{(1)}, \sigma_{ij}; u_{ij}^{(1)} \right), & \text{if } u_{ij}^{(1)} > \frac{m_{ij}^{(1)} + m_{ij}^{(2)}}{2}
\end{cases}
\]

The firing strengths \( u_{ij}^{(3)} \) and \( u_{ij}^{(3)} \) of each rule node in layer 3 are computed through the algebraic product operation:

\[
u_{ij}^{(3)} = \prod_{i}^{R} u_{ij}^{(2)} \quad \nu_{ij}^{(3)} = \prod_{i}^{R} u_{ij}^{(2)} \quad (11)
\]

where \( \prod_{i}^{R} u_{ij}^{(2)} \) and \( \prod_{i}^{R} u_{ij}^{(2)} \) represent the firing strengths of the intervals’ upper and lower bounds, respectively. The type-2 fuzzy set is transformed into a type-1 fuzzy set by using the reduction of order method. This method is expressed as follows:

\[
u^{(4)} = \frac{\sum_{j=1}^{R} \nu_{ij}^{(3)}}{\sum_{j=1}^{R} \nu_{ij}^{(3)}} \quad \nu^{(4)} = \frac{\sum_{j=1}^{R} \nu_{ij}^{(3)}}{\sum_{j=1}^{R} \nu_{ij}^{(3)}} \quad (12)
\]

where \( \sum_{k=1}^{M} \omega_{kj} \varphi_k \) is a nonlinear combination of EFNN inputs. The functional expansion is based on basis trigonometric functions and defined as follows:

\[
[\varphi_1; \varphi_2; \cdots; \varphi_M] = [x_1, \sin(\pi x_1), \cos(\pi x_1), \cdots, x_n, \sin(\pi x_n), \cos(\pi x_n)] \quad (13)
\]

where \( M = 3 \times n \), where \( n \) is the number of inputs) is the number of basis functions. After the reduction process, the output is defuzzified by computing the average of \( u^{(4)} \) and \( u^{(4)} \). The crisp value \( y \) is obtained as follows:

\[
y = \frac{u^{(4)} + u^{(4)}}{2} \quad (14)
\]
4.3.2 DGCPSO learning algorithm

The traditional PSO algorithm has the advantages of rapid convergence and simple implementation; however, in the case of complex problems, its precision is insufficient, and it can be easily trapped into a locally optimal solution. A DGCPSO algorithm is proposed to enhance the learning efficiency of the proposed EFNN. In contrast to the traditional evolution method, the cooperative evolution method involves splitting $P$ particles into $N$ subvectors for evolution to solve a 1D optimization problem. Figures 12 and 13 illustrate the differences between the traditional and cooperative evolution methods. The cooperative evolution method can increase the convergence speed; however, it requires a long computing time and can easily fall into a suboptimal solution. To overcome these drawbacks, the dynamic group strategy is used to enhance the ability to search for the global optimal solution. In the DGCPSO algorithm, each particle is grouped according to a dynamic group strategy, and the particle with the highest fitness is selected as the leader. Only the leader particles of each group are evolved using the cooperative method. This strategy reduces the computational complexity of the algorithm and prevents it from falling into a suboptimal solution. A flowchart illustrating the proposed DGCPSO algorithm is displayed in Fig. 14.

All the EFNN parameters are coded into a particle with the uncertainty mean $m_{ij}$, standard deviation $\sigma_{ij}$, and consequence link weight $\omega_{ij}$. The fitness values of all the particles are ranked in descending order, and the initial group number is set as 0 (Fig. 15).

The particle with the highest fitness is set as the leader of the new group, and the group number is updated from 0 to 1.

Then, the distance and fitness thresholds of each ungrouped particle are calculated using the following equations, respectively:

\[
\delta_k = \frac{\sum_{i=1}^{P} \sum_{j=1}^{D} (L_{k,i} - X_{ij})^2}{NG}
\]

\[
\psi_k = \frac{\sum_{i=1}^{P} F(L_k) - F(X_i)}{NG}
\]

where $\delta_k$ and $\psi_k$ represent the distance and fitness thresholds, respectively; $P$ and $N$ are the encoded dimension and total number of particles, respectively; $L_{k,i}$ represents the $k$th group leader with the $i$th dimension; $F(\cdot)$ denotes the fitness function; and $NG$ represents the total number of ungrouped particles. The distance and fitness between the ungrouped and leader particles are calculated as follows:

\[
D_i = \sum_{j=1}^{P} (L_{k,j} - X_{ij})^2
\]

\[
F_i = |F(L_k) - F(X_i)|
\]

A particle is similar to the $g$th group leader if $D_i$ and $F_i$ are less than $\delta_k$ and $\psi_k$, respectively. The group number of this particle is updated to $g$. The grouping process is completed until no ungrouped particles exist. The evolution process is divided into traditional evolution and cooperative evolution. These evolution methods are introduced in detail in the following text.

- **Traditional evolution method**

To overcome the drawbacks of traditional PSO algorithms, this paper proposes a new position update method. In this method, the particles refer to the leader particle $L_k$ in their group rather than their personal best position. The position update formula is as follows:

\[
V_i(n+1) = \omega \times V_i(n) + C_1 \times rand_1 \times (L_k - X_i(n))
\]

\[
+ C_2 \times rand_2 \times (P_{G best} - X_i(n))
\]

\[
X_i(n+1) = X_i(n) + V_i(n+1)
\]
where \( V_i(n) \) is the particle velocity, \( X_i(n) \) is the current position of the particle, \( P_{\text{Gbest}} \) is the global best value of all particles, \( \omega \) is the inertia weight, \( C_1 \) represents the cognitive parameter, \( C_2 \) represents the social parameter, and \( \text{rand}_1 \) and \( \text{rand}_2 \) are random numbers between 0 and 1.

- Cooperative evolution method

The leader particles are divided into \( N \) 1D subvectors. For each subvector, the best 1D particle is selected. Until the \( N \)th element of the \( P_{\text{Gbest}} \) particle is replaced by each subvector of the \( P \)th particle in sequence, the other elements of the \( P_{\text{Gbest}} \) particle remain constant. After the aforementioned process, the new global best particle \( L_{\text{best}} \) is obtained. All the leader particles are updated with reference to \( L_{\text{best}} \) in the following equation:

\[
V_i(n + 1) = \omega \times V_i(n) + C_1 \times \text{rand}_1 \times (P_i - X_i(n)) + C_2 \times \text{rand}_2 \times (L_{\text{best}} - X_i(n)) \tag{21}
\]

\[
X_i(n + 1) = X_i(n) + V_i(n + 1) \tag{22}
\]

where \( P_i \) is the personal best solution of the \( i \)th leader particle.

The Pearson correlation coefficient was used to analyze the relationship between the CIE \( xy \) chromaticity and tool wear values. This coefficient is expressed as follows:

\[
r_{ab} = \frac{\sum_{i=1}^{n} (a_i - \bar{a})(b_i - \bar{b})}{\sqrt{\sum_{i=1}^{n} (a_i - \bar{a})^2} \sqrt{\sum_{i=1}^{n} (b_i - \bar{b})^2}} \tag{23}
\]

where \( n \) is the sample size; \( a_i \) and \( b_i \) represent the \( i \)th sample; and \( a \) and \( b \) denote the sample mean. The higher the value of \( r \), the stronger the positive correlation between two variables.
Table 7 presents the coefficients of correlation between the CIE $xy$ chromaticity and tool wear values. The $r$ values between the $x$ chromaticity and tool wear values and between the $y$ chromaticity and tool wear values were 0.709 and 0.512, respectively, indicating that the $x$ chromaticity had a stronger positive correlation with the tool wear than the $y$ chromaticity did. Although the $y$ chromaticity value had only a moderate positive correlation with the tool wear value, the CIE $xy$ chromaticity was still related to the tool wear value.

### 5.2 Tool wear prediction results

The BP algorithm is the most commonly used algorithm for training ANNs. However, BP has the drawback of falling into a local optimal solution. Some scholars have used evolutionary algorithms to replace the BP method and have compared the effectiveness of BP and evolutionary algorithms [48–50].

Their results indicate that evolutionary algorithms can not only overcome the problems of limited optimization and local convergence but also enhance the prediction accuracy. To demonstrate the effectiveness of the proposed DGCP algorithm, its prediction accuracy was compared with those of the BPNN [9], PSO [30], quantum-based PSO (QPSO) [31], and cooperative PSO (CPSO) [32] algorithms. Table 8 lists the initial parameters of the BPNN, including the number of hidden neurons, learning rate, and activation function.

Different activation functions result in differing prediction performance. In the accuracy comparison experiment, three activation functions—namely the linear, sigmoid, and tanh functions—were used to evaluate the BPNN. The mean square errors (MSEs) obtained using these functions are presented in Table 9. The BPNN with the linear activation function had the lowest MSE. Therefore, the linear activation function was adopted in this study.
Table 10 lists the initial parameters of the proposed DGCPSO algorithm: the number of particles, inertia weight (w), acceleration constants (C₁ and C₂), number of generations, and number of fuzzy rules. The DGCPSO algorithm was evaluated 10 times to ensure search stability for the solution. During the training process, the reciprocal of [1 + the root MSE (RMSE)] was used as the fitness function. A high fitness value implied a superior solution. The adopted fitness function was defined as follows:

\[ F = \frac{1}{RMSE + 1} \]  

\[ RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (\hat{y}_i - y_i)^2} \]  

where \(\hat{y}_i\) is the predicted output. Figure 17 illustrates the prediction results obtained using different algorithms. The “number of data” axis represents the total number of testing data. In the experimental trial conducted to obtain the testing dataset, the cutting process was executed seven times. Ten material chip images and corresponding tool wear values were collected in each cutting process. Thus, 70 pieces of testing data were obtained. As displayed in Fig. 17a, the BPNN algorithm had high accuracy for the first 40 ratio of testing data but performed poorly for the remaining 30 data pieces. By contrast, the PSO algorithm exhibited high accuracy for the final 30 pieces of testing data. Figure 17c, d shows the oscillating prediction results in each step of the QPSO and CPSO algorithms, respectively. The proposed DGCPSO algorithm uses the dynamic group mechanism to overcome the drawbacks of traditional evolutionary algorithms and improve the algorithm’s ability to search for the global optimal solution. Therefore, as illustrated in Fig. 17e, the proposed DGCPSO algorithm displayed high accuracy for all the testing data. The MAPE of each algorithm is presented in Table 12. The proposed algorithm had the smallest MAPE among the compared algorithms. Figure 18 illustrates the distribution of the tool wear prediction results in the form of boxplots. As indicated by Fig. 18, the proposed DGCPSO algorithm had a smaller distribution of responses than did the other algorithms. Thus, the proposed method is relatively stable in and suitable for tool wear prediction.

6 Conclusion

In the machining process, tool wear directly affects processing quality and cost. Replacing processing tools in time is crucial. This paper proposes a tool wear prediction method based on
material chip chromaticity; the method can replace the indirect method of using captured sensor signals for determining tool wear. The major contributions of this paper are as follows:

- Cutting temperature affects the quality of chip images and the calculated colors of chips. This study developed a color calibration model by using a regression algorithm to reduce the color difference between chip images. The calibrated color difference $\Delta E_{ab}^*$ was less than 1.5.

| Fitness value         | Number of rules | 4   | 5   | 6   |
|-----------------------|-----------------|-----|-----|-----|
| Best fitness value    | 0.988707        | 0.991587 | 0.990425 |
| Worst fitness value   | 0.955493        | 0.964216 | 0.954232 |
| Average fitness value | 0.978293        | 0.982429 | 0.976923 |
| Standard deviation    | 0.010577        | 0.008454 | 0.012037 |

Fig. 17 Prediction results obtained using various algorithms. (a) BPNN, (b) PSO, (c) QPSO, (d) CPSO, (e) DGCPSO
A new EFNN that combines fuzzy logic and a functional-link NN is proposed to establish a tool wear prediction model. In addition, we investigated the performance of this network with different numbers of fuzzy rules. The results indicated that the best fitness value (0.9915) was obtained using five fuzzy rules.

- The proposed DGCPSO algorithm uses a hybrid method that involves a dynamic group strategy and the cooperative concept to avoid being easily trapped into local optima, which occurs with the traditional PSO algorithm. The experimental results indicate that the proposed DGCPSO algorithm has a 4.59% and 5.76% lower MAPE than the traditional PSO and QPSO algorithms.

- In the prediction experiment, the proposed EFNN with the DGCPSO algorithm exhibited the smallest MAPE (2.83%), followed by the BPNN (9.72%), PSO (7.42%), QPSO (8.59%), and CPSO (4.09%) algorithms. Thus, the proposed EFNN has high prediction accuracy and can be used for tool wear prediction.

In future studies, we will use different combinations of machining parameters to establish a tool wear prediction model.
model. Practical application of the proposed system is a major challenge. In the future, we will consider using chips that fly out during the machining process for predicting tool wear.

**Code availability** Not applicable

**Author contribution** Conceptualization, C.-J.L.; methodology, C.-J.L. and J.-Y.J.; software, C.-J.L., J.-Y.J., and S.-H.C.; data curation, J.-Y.J., and S.-H.C.; writing—original draft preparation, C.-J.L. and J.-Y.J.; funding acquisition, C.-J.L. All authors have read and agreed to the published version of the manuscript.

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**Data availability** The author confirms that the data supporting the findings of this study are available within the paper. Available: https://tinyurl.com/flank-wear-dataset

**Declarations**

**Conflict of interest** The authors declare no competing interests.

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