Using an Interval Type-2 Fuzzy Neural Network and Tool Chips for Flank Wear Prediction

CHENG-JIAN LIN, (Senior Member, IEEE), JYUN-YU JHANG, SHAO-HSIEN CHEN, AND KUU-YOUNG YOUNG, (Senior Member, IEEE)

1Department of Computer Science and Information Engineering, National Chin-Yi University of Technology, Taichung City 41170, Taiwan
2College of Intelligence, National Taichung University of Science and Technology, Taichung City 404348, Taiwan
3Institute of Electrical and Control Engineering, National Chiao Tung University, Hsinchu City 30010, Taiwan
4Department of Mechanical Engineering, National Chin-Yi University of Technology, Taichung City 41170, Taiwan

Corresponding author: Cheng-Jian Lin (cjlin@ncut.edu.tw)

This work was supported by the Ministry of Science and Technology of the Republic of China, under Grant MOST 108-2221-E-167-026.

ABSTRACT The precision of part machining is influenced by the tool life. Tools gradually wear out during the cutting process, which reduces the machining accuracy. Many studies have used machining parameters and sensor signals to predict flank wear; however, these methods have many limitations related to sensor installation, which is not only time-consuming and costly but also impractical in industry. This paper proposes an interval type-2 fuzzy neural network (IT2FNN) based on the dynamic-group cooperative differential evolution algorithm for flank wear prediction. Moreover, the Taguchi method is used to design cutting experiments for collecting experimental data and reducing the number of experiments. The CIE-xy color chromaticity values, spindle speed, feed per tooth, cutting depth, and cutting time are used as inputs of the IT2FNN, and the output is the flank wear value. The experimental results indicate that the proposed method can effectively predict flank wear with higher efficiency than other algorithms.

INDEX TERMS Flank wear, chip surface, color calibration, interval type-2 fuzzy neural network, differential evolution.

I. INTRODUCTION

Tool life prediction is one of the most important research areas in the machinery industry. When flank wear occurs, the accuracy of the machined product decreases, which results in an increase in the production cost. Therefore, many scholars have proposed methods for improving flank wear and for wear prediction. To reduce flank wear, Debath et al. [1] proposed ANOVA of the surface roughness and flank wear. The feed rate and flow rate of the cutting fluid contribute 34.3% and 33.1% of the surface roughness of the workpiece, respectively. The cutting speed and depth of cut contribute 10% and 20% of the surface roughness, respectively. These two parameters are the main factors affecting flank wear. Moreover, the feed rate has the least contribution to flank wear. Bar-Hen and Etsion [2] studied the effect of the coating thickness and substrate roughness on the flank wear. The flank wear was measured using speed tests with a fixed cutting distance. The aforementioned authors observed a trend of decreasing wear with increasing coating thickness or substrate roughness. Thus, a suitable coating thickness can be selected according to the substrate roughness measured prior to coating. Birmingham et al. [3] using laser-assisted milling for studying the wear of stainless steel. Compared with conventional room-temperature machining, which is conducted under low- and high-feed milling, laser-assisted milling reduced the flank wear rates by up to 50% and the cutting force by up to 33%. The experimental results indicated that laser-assisted milling is effective in prolonging tool life.

Some scholars have established flank wear prediction models by observing the chip characteristics or tool states. Ning et al. [4] analyzed the chip color during high-speed ball-nose end milling to determine the cutting temperature. Their results indicated that the higher the cutting speed and feed rate, the darker is the color of the chip, which indicates that a higher extent of oxidation leads to a higher temperature. In addition, the optimum cutting speed is not the highest possible speed because at high temperatures, the flank wear increases and different chip colors are observed. Bhuiyan et al. [5] presented a new technique for monitoring the effect of chip formation on the tool state. The authors collected signals from an acoustic emission (AE)
sensor. The raw AE signal data indicated that the flank wear and plastic deformation increased with a high cutting speed, feed rate, and depth of cut. Thus, flank wear measurement is strongly influenced by the cutting condition and chip formation has a strong effect on the tool life. Mikołajczyk et al. [6] presented a model for the automatic prediction of tool life in turning operations. In this model, cutting-edge wear parameters obtained through image processing are used as inputs for an artificial neural network. The results of Mikołajczyk et al. indicated that the combination of image processing and ANN modeling is appropriate for the low-cost estimation of tool life in turning operations. Jain and Raj [7] developed a model for predicting the surface roughness of a workpiece by using adaptive neuro-fuzzy inference system (ANFIS) modeling. The predicted surface roughness can be used for tool life management. The ANFIS is used to extract the features of tool states. The input parameters are the feed speed, depth of cut, and cutting force, and the output is the surface roughness. If the surface roughness is smaller than a predefined threshold, the tool is in a good state; otherwise, the tool life has been completed and the tool should be replaced. The results of Jain and Raj indicated that the average error of the ANFIS model was 7.38%.

Fuzzy neural networks (FNN) have been widely used to solve classification [8], [9], prediction [10], [11], and control problems [12], [13]. The FNN introduces the human-understandable structure-like knowledge into neural network (NN). The FNN possesses advantages of both fuzzy logic (FL) and NN, where FL provides human reasoning mechanism and NN enhances the adaptive ability and non-linear approximation ability. FNN allows automation design of fuzzy rules and combines learning of numerical data as well as expert knowledge expressed. Hence, the FNN can solve the shortcomings of traditional fuzzy systems that rely on expert knowledge and experience to design membership functions. In a real environment, the signal data collected by sensors are affected by noise, which causes input signal uncertainty. To improve noise tolerance, Kumar [14] used the interval type-2 fuzzy set (IT2FS) to solve uncertain problems. Compared with Type-1 fuzzy set (T1FS), the footprint of uncertainty (FOU) of IT2FS provided more uncertainties range to cover the input/output domains with fewer fuzzy sets. These make IT2FS more adaptive and realized complex input-output relationships which cannot be achieved by T1FS. The use of IT2FS allows the design of flexible network with enhanced robustness. However, the computational complexity of the aforementioned methods is high. This study referred to the method of Castillo [15] to reduce the computational complexity of interval type-2 fuzzy systems.

The backpropagation (BP) algorithm [16], [17] is used to update the parameters of a fuzzy neural network. The advantage of the BP algorithm is its fast convergence ability; however, BP might cause the system to fall into local optimal solutions. Hence, evolutionary algorithms, such as differential evolution (DE) [18]–[20], particle swarm optimization (PSO) [21], and artificial bee colony [22], have been proposed to search for global optimal solutions. DE algorithms have the advantages of a simple structure, low computational complexity, and low parameter setting requirements. The disadvantages of traditional DE algorithms are that they fall into the local optimal solution easily. Therefore, this study introduces a new evolutionary concept for improving the efficiency of DE algorithms. The proposed method is named the dynamic-group cooperative DE (DGCDE) algorithm and is used to update the parameters of an interval type-2 fuzzy neural network (IT2FNN).

In traditional flank wear prediction methods, machining parameters, cutting forces, current values, and vibration signals are used as inputs. Although these methods can predict flank wear, they do not accurately reflect the condition of the tool. Therefore, in this study, the chip color was used as an input parameter for obtaining accurate flank wear prediction results. Tool chips exhibit different colors with different degrees of flank wear. An industrial camera was used to capture the chip CIE-xy chromaticity values. An IT2FNN based on the DGCDE was then used to predict the flank wear. The chromaticity coordinate values and cutting time were the inputs of the network, and the flank wear value was the output. Finally, a flank wear prediction model was established and its accuracy was verified through experimental results.

**II. FLANK WEAR PREDICTION FRAMEWORK**

The proposed flank wear prediction framework comprises three stages: the cutting experiment, chip feature extraction, and flank wear prediction. The procedure for flank wear prediction is displayed in Fig. 1. In the cutting experiment stage, the Taguchi method is adopted to design cutting parameters. Compared with the trial and error method and full-factor method, the Taguchi method can effectively reduce the number of experiments, time, and cost. Therefore, many scholars have applied the Taguchi method in various fields [2], [23]. After the cutting experiment, the training data related to the flank wear, cutting time, and chip color are collected.

![FIGURE 1. Proposed flank wear prediction framework.](image-url)
To extract chip features, CIE-xy color chromaticity values are obtained for all the chip images captured by industrial cameras in the chip feature extraction stage. An IT2FNN is used in the flank wear prediction stage. The inputs of the IT2FNN are the spindle speed, feed per tooth, cutting depth, cutting time, and CIE-xy color chromaticity values. The output of the network is the flank wear value. Additional details regarding the aforementioned three stages are presented in the subsequent text.

**A. EXPERIMENTAL EQUIPMENT**

An Extron SU-85 computer numerical control (CNC) machine, S50C carbon steel, Chain-Headway MAS-3232-150L-2T tool holder, APKT160408PDER-M02 RM4130 milling insert, and Wenham industrial camera were the experimental equipment used in this study. The Extron SU-85 CNC was used for performing cutting experiments and obtaining a tool chip. The CNC machine specifications are presented in Table 1. The Wenham industrial camera, which contains a color CMOS sensor and has a resolution of 1920 × 1080 pixels (1080p/30 fps), was used to capture images of the chip and measure the flank wear of milling insert.

**TABLE 1. Specifications of the Extron SU-85 CNC machine.**

|                                | 860mm/540mm/630mm |
|--------------------------------|-------------------|
| Travel X/Y/Z                   | 930mm×500mm       |
| Table size                     | 15000rpm          |
| Max spindle speed              | 400 kg            |

**B. CHIP FEATURE EXTRACTION**

Images of the chip were collected using an industrial camera during the cutting experiments. To obtain accurate chip image features and remove unnecessary information around the image, an area of 300 × 300 pixels in the center of the image was selected for analyzing the chip features. The area selected for analyzing the chip features is displayed in Fig. 2. As shown in Fig. 2, two material chips that cutting by using different flank wear inserts present different colors.

In a real environment, the chip images captured by an industrial camera are affected by light sources, color temperature, and brightness, which results in color differences. Therefore, the color calibration method is used to obtain accurate chip image features. The flow of the color calibration process is illustrated in Fig. 3.

The color calibration model was evaluated according to the color difference units of the US National Bureau of Standards (NBS) [24]. Different levels of color difference represent different degrees of flank wear. To calculate the color difference, the RGB color space must be converted to the CIELAB color space. In this study, the CIELAB color space and regression algorithm were used to establish a color calibration model. The color value table of ColorChecker is provided in [25]. The one-dimensional (1D) look-up table (LUT) of the ColorChecker was used to obtain the adjusted RGB color values (R′, G′, and B′) for the images captured by the industrial camera. The color calibration model was then established using the regression algorithm, defined as in (1), shown at the bottom of the next page, where $L^*, a^*, b^*$ is the standard CIELAB color value in ColorChecker; $R', G', B'$ is the RGB color value adjusted according to the 1D LUT; and $a$, $b$, and $c$ are the color calibration parameters. After the color calibration model was established, the accuracy of the model was evaluated according to the NBS units. The color difference $\Delta E_{ab}^*$ 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 $L_1^*a_1^*b_1^*$ is the standard CIELAB color value in ColorChecker and $L_2^*a_2^*b_2^*$ is the CIELAB color value calibrated by the color calibration model. The $\Delta E_{ab}^*$ value was converted into the NBS unit by using the following equation:

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

The NBS unit is divided into six levels, which are presented in Table 2. If the NBS unit of the color calibration model is $>1.5$, the calibrated color is insufficiently accurate and the color calibration model should be re-established; otherwise, the color calibration model is appropriate.

In the color calibration model, the output of the chip image is the CIELAB color space and the correlated color temperature is 5000 K (D50). The most commonly used standard light source is artificial daylight, which has a correlated color
Flow of the color temperature conversion process.

**FIGURE 4.** Flow of the color temperature conversion process.

First, the CIE LAB color space is converted to the CIEXYZD50 color space (tristimulus values) by using the following equations:

If \( L^* > 7.9996 \),

\[
X_{D50} = 96.42 \times \left( \frac{a^*}{500} + \frac{L^* + 16}{116} \right),
\]
\[
Y_{D50} = 100 \times \left( \frac{L^* + 16}{116} \right), \quad \text{and}
\]
\[
Z_{D50} = 82.49 \times \left( \frac{L^* + 16}{116} - \frac{b^*}{200} \right) \tag{4}
\]

Otherwise,

\[
X_{D50} = \frac{96.42}{7.787} \times \left( \frac{a^*}{500} + \frac{L^*}{116} \right),
\]
\[
Y_{D50} = \frac{903.292}{7.787}, \quad \text{and}
\]
\[
Z_{D50} = \frac{82.49}{7.787} \times \left( \frac{L^*}{116} - \frac{b^*}{200} \right) \tag{5}
\]

In (4) and (5), \( L^*a^*b^* \) is the CIELAB color value and \( XYZ_{D50} \) is the CIEXYZ color value for a color temperature of 5000 K. The D50 color temperature is converted to the D65 color temperature by using the following equation:

\[
[X_{D65}Y_{D65}Z_{D65}] = [X_{D50}Y_{D50}Z_{D50}] \times \begin{bmatrix}
0.9556 & -0.284 & 0.0124 \\
-0.0232 & 1.0101 & -0.0206 \\
0.0633 & 0.0211 & 1.3306
\end{bmatrix} \tag{6}
\]

Finally, the chip feature is obtained by converting CIEXYZD65 into the CIE-xy color space by using the following equation:

\[
x = \frac{X_{D65}}{X_{D65} + Y_{D65} + Z_{D65}}, \quad y = \frac{Y_{D65}}{X_{D65} + Y_{D65} + Z_{D65}} \tag{7}
\]

### III. PROPOSED IT2FNN FOR FLANK WEAR PREDICTION

The proposed IT2FNN is described in this section. A DGCDE algorithm is also proposed for updating the network parameters without falling into local optima, which is a limitation of traditional DE algorithms.

#### A. PROPOSED IT2FNN

The structure of the proposed IT2FNN is described in this section. The IT2FNN can be divided into five layers, namely an input layer, a membership function layer, a firing layer, a consequent layer, and an output layer. Fig. 5 displays the structure of the proposed IT2FNN, and the if–then rule can be expressed as follows:

\[
\text{Rule}_j: \quad \text{If } x_i \text{ is } A_{ij} \text{ and } x_2 \text{ is } A_{2j} \ldots \text{ and } x_n \text{ is } A_{nj}, \quad \text{then } y_j = w_0 + \sum_{i=1}^{n} w_{ij}x_i
\]

where \( x_i (i = 1, 2, \ldots, n) \) is the input, \( A_{ij} \) represents the interval type-2 fuzzy sets \( (i = 1, 2, \ldots, n; j = 1, 2, \ldots, R) \), where \( R \) represents the rule number, and \( w_0 + \sum_{i=1}^{n} w_{ij}x_i \) is a Takagi–Sugeno–Kang-type linear function in the consequent layer.

The detailed operation of each layer of the IT2FNN is described in the following text.
The center-of-gravity method is then used to obtain the crisp set. The center-of-gravity method is described as follows:

\[
\begin{align*}
u^{(4)} &= \frac{\sum_{j=1}^{R} w_j^{(3)} (w_j x_0 + \sum_{i=1}^{n} w_j x_i)}{\sum_{j=1}^{R} w_j^{(3)}}, \\
\pi^{(4)} &= \frac{\sum_{j=1}^{R} w_j^{(3)} (w_j x_0 + \sum_{i=1}^{n} w_j x_i)}{2}
\end{align*}
\]  

**B. PARAMETER LEARNING BASED ON THE DGCDE ALGORITHM**

This section introduces the proposed DGCDE algorithm for updating the network parameters. Traditional DE algorithms use an individual for evolution. In the cooperative method, \( P \) individuals are split into \( N \) 1D subvectors for evolution. Fig. 6 illustrates the differences between the traditional and cooperative evolution methods.

Each subvector aims to solve a 1D optimization problem. If 30 vectors with 50 dimensions are evolved using the cooperative method, then each vector has 30 \( \times \) 50 = 1500 combinations in each generation. This method can effectively improve the convergence speed; however, it requires a high computing time and easily falls into a suboptimal solution. To enhance the searching ability for the global optimal solution and to reduce the computing time, a DGCDE algorithm that combines the cooperative and dynamic-group methods is proposed. First, each individual is grouped using a dynamic-group algorithm and leader individuals are selected from the group. Only the leader individuals of the group are subsequently evolved using the cooperative method. The proposed DGCDE algorithm can reduce the computational complexity and avoid falling into a suboptimal solution. The flow of the proposed DGCDE algorithm is displayed in Fig. 7.

The detailed learning process is described in the following text.

**Phase I: Initializing the individuals**

All IT2FNN parameters are coded into an individual. Then, the initial value of individual \( X_{P,N} \) is randomly generated in the range \([0, 1] \), where \( P \) is the \( P \)th individual and \( N \) represents the \( N \)th dimension.

**Phase II: Ranking and grouping**

As displayed in Fig. 8, the individuals are ranked in descending order according to their fitness values and the group number is set as 0.

First, the individual with the highest fitness value is set as the leader of the new group for which the group number is updated to 1. Second, the group threshold is calculated to
group ungrouped individuals. The group threshold consists of the fitness and distance thresholds. These threshold values are determined automatically by using the following equations:

$$Fit_{th}(k) = \sum_{i=1}^{P} |Fit(L_k) - Fit(X_i)|$$  \hspace{1cm} (15)$$

and

$$Dis_{th}(k) = \frac{\sum_{i=1}^{P} \sum_{j=1}^{N} (L_{k,j} - X_{i,j})^2}{NG}$$  \hspace{1cm} (16)$$

where $P$ and $N$ are the encoded dimension and total number of individuals, respectively; $Fit(L_k)$ is the fitness value of the $k$th group leader; $L_{k,j}$ represents the $k$th group leader in the $j$th dimension; and $NG$ represents the total number of ungrouped individuals. Finally, the fitness value and the distance value between ungrouped and leader individuals are calculated to determine whether individuals belong to a group. The equations for the aforementioned two parameters are given as follows:

$$G_{fit}(i) = |Fit(L_k) - Fit(X_i)|$$  \hspace{1cm} (17)$$

$$G_{dis}(i) = \sum_{j=1}^{N} \sqrt{(L_{k,j} - X_{i,j})^2}$$  \hspace{1cm} (18)$$

If $G_{fit}(i)$ and $G_{dis}(i)$ are less than $Fit_{th}(k)$ and $Dis_{th}(k)$, respectively, the individual is similar to the leader. Therefore, the group number of the individual is updated to $k$.

**Phase III: Evolution process**

The evolution process of individuals is divided into traditional evolution and cooperative evolution. To reduce the computation time, only leader individuals are selected to be updated using the cooperative evolution method. The aforementioned two evolution methods are introduced in detail in the following text.

1) **TRADITIONAL EVOLUTION METHOD**

The individual evolutionary method of the DE algorithm involves mutation, recombination, and selection. To overcome the drawbacks of traditional DE algorithms, this paper proposes a new mutation method. The trial vector is mutated by adopting a random leader and two random difference
vectors to increase the searchability in the solution space. The equation of the proposed method is as follows:

\[
V_i = X_{rL} + F \cdot (X_{r1} - X_{r2})
\]  

(19)

where \(V_i = [v_{i,1}, \ldots, v_{i,j}]\) is a mutated trial vector; \(X_{rL}\) is a random leader; \(F\) is the mutation weight factor, whose value is set as 0.5; and \(X_{r1}\) and \(X_{r2}\) are randomly selected individuals. A new trial vector is generated by crossing the target and mutation vectors in the recombination operation. This process is expressed using the following equations:

\[
u_{i,j} = \begin{cases} v_{i,j}, & \text{if } \text{rand}_j \leq CR \\ x_{i,j}, & \text{otherwise} \end{cases}
\]

(20)

\[U_i = [u_{i,1}, \ldots, u_{i,j}]\]

(21)

where \(\text{rand}_j\) is a random value between 0 to 1, \(CR\) is the crossover rate, and \(U_i\) is the new trial vector. In the selection step, the trial vectors are evaluated according to their fitness values to select the next generation of target vectors. This operation is expressed as follows:

\[X_i = \begin{cases} U_i, & \text{if } \text{Fit}(U_i) > \text{Fit}(X_i) \\ X_i, & \text{otherwise} \end{cases}
\]

(22)

2) COOPERATIVE EVOLUTION METHOD

The leader individuals are split into \(N\) 1D subvectors. Each subvector selects the best 1D individual. However, each subvector only represents a single dimension of the solution. Its fitness value cannot be evaluated. To calculate the fitness values of all the leader individuals in the subvector, the leader individual with the highest fitness value is set as a context vector. Until the \(N\)th element of the context vector is replaced by each subvector of the \(P\)th individual, the other elements of the context vector continue to have constant values. After the aforementioned process, the best leader individual \(L_{\text{best}}\) can be obtained. All the leader individuals are mutated with reference to \(L_{\text{best}}\) according to the following equation:

\[
V_i = L_{\text{best}} + F \cdot (X_{r1} - X_{r2})
\]

(23)

where \(V_i\) is a mutated trial vector; \(F\) is the mutation weight factor whose value is set as 0.5; and \(X_{r1}\) and \(X_{r2}\) are randomly selected individuals. The recombination and selection operations in the cooperative evolution method are the same as those in the traditional evolution method.

Phase IV: Evaluation of the solution and checking the terminal condition

The fitness values of all individuals are evaluated to determine the best solution. Then, the terminal condition is checked. If the terminal condition is satisfied, the learning process is terminated; otherwise, the algorithm goes back to phase 2. The pseudocode of DGCDE is as shown in Fig. 9.

IV. EXPERIMENTAL RESULTS

The experimental results are presented in this section. Section IV-A outlines the collection and analysis of the cutting data when using the Taguchi method. It also describes the relationship between the cutting factors and flank wear. Section IV-B presents the flank wear prediction results obtained using the proposed IT2FNN. It also presents a comparison of the results obtained with the proposed method and different evolutionary algorithms.

A. COLLECTION AND ANALYSIS OF THE CUTTING DATA

In the cutting experiment, S50C carbon steel with size of \(155 \times 150 \times 100\) mm\(^3\) was provided as the experimental material. The advantages of carbon steel are efficiently malleable, extremely tough, and highly affordable. The chemical compositions and mechanical properties of carbon steel are shown in Table 3-4. The specifications of tool holder (MAS-3232-150L-2T) and milling insert (APKT160408PDER-M02 RM4130) are respectively shown in Fig. 10 and Table 5-6.

| C   | Mn   | P   | S   | Si   |
|-----|------|-----|-----|------|
| 0.47-0.53 | 0.60-0.90 | 0.030 | 0.035 | 0.15-0.35 |
To avoid excessive abrasion of milling insert in cutting experiment flank wear under different cutting conditions must be considered. This study is based on the ISO-8688-1/1994 standard for testing and analysis which uniform wear is 0.3 mm and non-uniform wear is 0.6 mm (tool life criterion). An industrial camera was adopted to measure the flank wear of milling insert. As displayed in Fig. 11, the maximum flank wear ($V_B^{\text{max}}$) was acquired as wear value.

Because full-factor experiments are costly and time-consuming, the Taguchi method was adopted to collect the training data. Three critical factors that affect flank wear, namely the spindle speed, feed per tooth, and cutting depth, were considered in the cutting experiment. Each factor was assigned three levels, as presented in Table 7. Therefore, a three-level orthogonal array (OA), $L_9(3^4)$, was used to design the cutting experiment, where $L_9(3^4)$ represents the use of four factors with three levels each in nine experiments.

Nine trials of the cutting experiment were performed with the Extron SU-85 CNC machine. In each experimental trial, the cutting process was executed ten times. Moreover, ten chip images were collected in each cutting process. Thus, 900 training data points (images) were collected in the nine experimental trials. Table 8 presents the results of the cutting experiment.
The flank wear value and signal-to-noise ratio (SNR), which are useful indicators of the cutting performance, were obtained in the Taguchi experiment. In this study, a small SNR ratio was selected as the objective function. The SNR ($\delta$) in the $i$th experiment is calculated as follows:

$$\delta_i = -10 \log_{10} \frac{\sum_{i=1}^{n} (\gamma_i^2)}{n}$$  \hspace{1cm} (24)

where $\gamma_i$ represents the flank wear value in the $i$th experiment and $n$ denotes the number of samples.
FIGURE 14. Prediction results obtained with various algorithms for testing dataset 2.

The SNR response (Table 9) was acquired from the $L_9$ OA. The $\delta$ values and ranks in the table indicate which factors significantly influenced the results. A higher rank indicates that a factor has a greater influence on the results. Fig. 12 indicates that the flank wear was most influenced by the feed per tooth, followed by the cutting depth and spindle speed.

The analysis of variance (ANOVA) method was then employed to estimate the percentage contribution (PC)
FIGURE 15. Prediction results obtained with various algorithm for testing dataset 3.

of process factors on the cutting experiment data from the Taguchi method. The ANOVA method can quantify the effect of various input factors affecting machining. The PC of each factor is calculated as follows:

\[ DF = K_A - 1 \]  \hspace{1cm} (25)

\[ SS_A = \sum_{i=1}^{K_A} \left( \frac{A^2_i}{\mu_{A_i}} \right) - \frac{T^2}{N} \]  \hspace{1cm} (26)

\[ SS_T = \sum_{i=1}^{K_A} y^2_i - \frac{T^2}{N} \]  \hspace{1cm} (27)

\[ SS_E = SS_T - (SS_A + SS_B + \ldots) \]  \hspace{1cm} (28)
TABLE 9. SNR response.

| Level | A     | B     | C     |
|-------|-------|-------|-------|
| 1     | 17.55 | 13.66 | 19.20 |
| 2     | 17.90 | 18.64 | 17.23 |
| 3     | 17.94 | 21.09 | 16.97 |
| Delta | 0.39  | 7.43  | 2.23  |
| Rank  | 3     | 1     | 2     |

\[ MS_A = \frac{SS_A}{DF} \quad (29) \]
\[ MS_E = \frac{SS_E}{DF} \quad (30) \]
\[ F_A = \frac{MS_A}{MS_E} \quad (31) \]
\[ PC = \frac{SS_A}{SS_T} \times 100\% \quad (32) \]

where \( DF \) is degrees of freedom; \( K_A \) is number of levels of factor \( A \); \( SS_A \) is the sum of squares of factor \( A \); \( A_i \) is the summation of all observations of level \( i \) of factor \( A \); \( n_A_i \) is the number of all observations at level \( i \) of factor \( A \); \( T \) denotes the summation of all observations; \( N \) is the total number of experiments; \( SS_E \) is error sum of squares; \( MS_A \) is the variance of the factor; \( MS_E \) is mean square error; and \( F_A \) represents the \( F \) ratio of factor \( A \).

Table 10 shows the ANOVA table, which includes PC. Form Figure 12 and Table 10, it can be observed that the most important factor can be determined by larger difference in the SNR ratio. From the percentage contributions (Table 10), the highest and most significant effect contributing to the flank wear is the feed per tooth (81.62%). The second-highest contribution is the cutting depth (9.67%). A less contribution is the spindle speed (0.39%). Moreover, the error (unknown and uncontrolled factors) of percentage contribution is low which means that no important factors have been omitted in this cutting experiment.

TABLE 10. ANOVA results for cutting experiment.

| Source | DF | SS     | MS     | \( F \) | \( \rho \) | PC (%) |
|--------|----|--------|--------|--------|---------|--------|
| A      | 2  | 0.00011 | 0.00005 | 0.05   | 0.956   | 0.39%  |
| B      | 2  | 0.02446 | 0.01223 | 9.81   | 0.092   | 81.62% |
| C      | 2  | 0.00290 | 0.00145 | 1.16   | 0.462   | 9.67%  |
| Error  | 2  | 0.00249 | 0.00124 | —      | —       | 8.32%  |
| Total  | 8  | 0.02997 | —      | —      | —       | 100.00%|

B. FLANK WEAR PREDICTION RESULTS

To verify the prediction accuracy of the proposed method, testing data parameters that differed from the training data parameters were considered. The cutting parameters were set within the range of the testing data, as presented in Table 11. Three testing data sets with different parameter combinations were selected to test the generalization ability and robustness of the prediction model. We performed a simulation to compare the accuracy of the proposed method with that of other evolutionary algorithms [17]–[21]. The dataset of flank wear is publicly available at [26]. The initial parameter setting of the various algorithms which consists of Number of populations (\( NP \)), Generation (\( G \)), Fuzzy rule (\( R \)), inertia weight (\( \omega \)), acceleration constants (\( C_1 \) and \( C_2 \)), mutation weight (\( F \)), crossover rate (\( CR \)), normal distribution of mean (\( \mu_{CR} \)), location parameter of the Cauchy distribution (\( \mu_F \)), the rate of parameter adaptation (\( c \)), the greediness of the mutation strategy (\( p \)), the constant value (\( \alpha \)) and the probability value (\( \epsilon \)) is presented in Table 12.

| Source | DF | SS     | MS     | \( F \) | \( \rho \) | PC (%) |
|--------|----|--------|--------|--------|---------|--------|
| Spindle speed | 160 | 0.15   | 0.9    |
| Set 1  | 175 | 0.17   | 0.5    |
| Set 2  | 180 | 0.12   | 0.7    |
| Set 3  |     |        |        |        |        |        |

TABLE 11. Cutting parameters for the testing data.

\[ F = \frac{1}{RMSE + 1} \quad (33) \]

and

\[ RMSE = \sqrt{\frac{\sum_{i=1}^{N}(\hat{y}_i - y_i)^2}{N}} \quad (34) \]

The proposed method was also compared with other evolutionary algorithms, such as the BP neural network (BPNN), PSO, DE, JADE, and cooperative co-evolutionary DE (CCDE) algorithms. Figs. 13–15 present comparisons of the results obtained with the different algorithms for testing datasets 1–3, respectively. As displayed in Fig. 13(a),
the BPNN algorithm exhibited suitable accuracy for the first 60 SNRs; however, it performed poorly for the remaining values. Figs. 13(b)–13(e) display the prediction results for each algorithm, which vary considerably. Fig. 14 indicates that except the BPNN algorithm, the predicted results of each algorithm were similar to the desired output. As displayed in Figs. 15(a)–15(e), the prediction results of each algorithm were poor for the dataset 2. Only the proposed DGCDE method provided high-accuracy prediction results for all the data in the three testing datasets.

The detailed comparison of the different algorithms is presented in Table 13. The evaluation results were calculated using the mean absolute percentage error (MAPE). The MAPE is calculated as follows:

\[
MAPE = \frac{100}{n} \sum_{i=1}^{n} \frac{|y_i - \hat{y}_i|}{y_i}
\]  

where \(n\) is the total number of data points, \(y_i\) is the actual parameter value, and \(\hat{y}_i\) is the predicted parameter value. Table 13 indicates that the traditional evolutionary algorithms (PSO and DE) tended to fall into a local optimal solution; thus, some testing results for the PSO and DE algorithms had lower accuracy than the BPNN algorithm. The CCDE algorithm provide accurate prediction results for the three testing datasets; however, it still fell into a suboptimal solution. The proposed DGCDE algorithm uses the dynamic-group mechanism, which can address the drawbacks of traditional evolutionary algorithms and improve the searching ability for the global optimal solution. The prediction results indicate that the proposed method was more accurate than the other algorithms and had the smallest MAPE. Meanwhile, the proposed IT2FNN model is also compared with the T1FNN, as presented in Table 14. As displayed in Table 14, the performance of IT2FNN is superior to T1FNN, while had lower MAPE in the three test data sets. The reason lies in the IT2FS which contains FOU provides a more flexible and more powerful way to deal with fuzzy inference.

As the tool deteriorates and the tool wear increases, the friction on the surface of tool chip also increases. Due to different frictional forces, the chips produce different colors. The change of the CIE-xy color chromaticity value on each cutting process for three testing data sets is shown in Fig. 16. In this figure, it can be observed that the chromaticity value increases with the increase of cutting time. However, in the test data set 1, the features in the cutting process 3, 7, 9 are not obvious. This leads to poor performance of the prediction model in test set 1. Figure 17 shows the influence of different flank wear values on the chip for three testing data sets. In Fig. 17, when the flank wear value is low in
reduce the defect rate of machined parts. In this paper, a novel framework which employs the chip color as a feature factor was proposed to improve the prediction accuracy. A color calibration model was designed to extract the CIE-xy color chromaticity values of the chip. After that, the CIE-xy color chromaticity values, spindle speed, feed per tooth, cutting depth, and cutting time are used as inputs of the IT2FNN to establish the prediction model. Additionally, the DGCDE was developed to enhance the performance of IT2FNN. The proposed DGCDE combines the cooperative and dynamic-group method to improve the searchability of traditional DE. The experimental results indicated that the proposed DGCDE method effectively predicted flank wear and had a lower average MAPE (6.7%) than other algorithms. Compared to the BPNN and T1FNN model, the average MAPE of IT2FNN (6.7%) is also superior to BPNN (16.1%) and T1FNN (9.54%). In the future work, the temperature factor will be considered to improve the accuracy of the prediction model.

V. CONCLUSION

Flank wear is a key factor that directly affects processing quality and cost. The timely changing of machining tools can

the first experiment, the chip color appears turquoise. As the flank wear value increases, the chip color is changed from blue-green to yellow-green. This indicates that different flank wear values result in different chip colors.

V. REFERENCES

[1] S. Debnath, M. M. Reddy, and Q. S. Yi, “Influence of cutting fluid conditions and cutting parameters on surface roughness and tool wear in turning process using taguchi method,” Measurement, vol. 78, pp. 111–119, Jan. 2016.

[2] M. Bar-Hen and I. Etsion, “Experimental study of the effect of coating thickness and substrate roughness on tool wear during turning,” Tribol. Int., vol. 110, pp. 341–347, Jun. 2017.

[3] M. J. Bermingham, D. Kent, and M. S. Dargusch, “A new understanding of the wear processes during laser assisted milling 17–4 precipitation hardened stainless steel,” Wear, vols. 328–329, pp. 518–530, Apr. 2015.

[4] Y. Ning, M. Rahman, and Y. S. Wong, “Investigation of chip formation in high speed end milling,” J. Mater. Process. Technol., vol. 113, nos. 1–3, pp. 360–367, Jun. 2001.

[5] M. S. H. Bhuiyan, I. A. Choudhury, and Y. N. Nukman, “An innovative approach to monitor the chip formation effect on tool state using acoustic emission in turning,” Int. J. Mach. Tools Manuf., vol. 58, pp. 19–28, Jul. 2012.

[6] T. Mikolajczyk, K. Nowicki, A. Bustillo, and D. Y. Pimenov, “Predicting tool life in turning operations using neural networks and image processing,” Mech. Syst. Signal Process., vol. 104, pp. 503–513, May 2018.

[7] V. Jain and T. Raj, “Tool life management of unmanned production system based on surface roughness by ANFIS,” Int. J. System Assurance Eng. Manage., vol. 8, no. 2, pp. 458–467, Jun. 2017.

[8] Y. Deng, Z. Ren, Y. Kong, F. Bao, and Q. Dai, “A hierarchical fused fuzzy deep neural network for data classification,” IEEE Trans. Fuzzy Syst., vol. 25, no. 4, pp. 1006–1012, Aug. 2017.

[9] M. F. Mohammed and C. P. Lim, “An enhanced fuzzy min-max neural network for pattern classification,” IEEE Trans. Neural Netw. Learn. Syst., vol. 26, no. 3, pp. 417–429, Mar. 2015.

[10] J. Tang, F. Liu, Y. Zou, W. Zhang, and Y. Wang, “An improved fuzzy neural network for traffic speed prediction considering periodic characteristic,” IEEE Trans. Intell. Transp. Syst., vol. 18, no. 9, pp. 2340–2350, Sep. 2017.

[11] M. Han, K. Zhong, T. Qiu, and B. Han, “Interval type-2 fuzzy neural networks for chaotic time series prediction: A concise overview,” IEEE Trans. Cybern., vol. 49, no. 7, pp. 2720–2731, Jul. 2019.

[12] W. He and Y. Dong, “Adaptive fuzzy neural network control for a constrained robot using impedance learning,” IEEE Trans. Neural Netw. Learn. Syst., vol. 29, no. 4, pp. 1174–1186, Apr. 2018.

[13] X. Yu, Y. Fu, P. Li, and Y. Zhang, “Fault-tolerant aircraft control based on self-constructing fuzzy neural networks and multivariable SMC under actuator faults,” IEEE Trans. Fuzzy Syst., vol. 26, no. 4, pp. 2324–2335, Aug. 2018.

[14] A. Kumar and V. Kumar, “Evolving an interval type-2 fuzzy PID controller for the redundant robotic manipulator,” Expert Syst. Appl., vol. 73, pp. 161–177, May 2017.
C.-J. Lin et al.: Using an Interval Type-2 Fuzzy Neural Network and Tool Chips for Flank Wear Prediction

[15] O. Castillo and P. Melin, “A review on the design and optimization of interval type-2 fuzzy controllers,” *Appl. Soft Comput.*, vol. 12, no. 4, pp. 1267–1278, Apr. 2012.

[16] M. Yaghini, M. M. Khoshraftar, and M. Fallahi, “A hybrid algorithm for artificial neural network training,” *Eng. Appl. Artif. Intell.*, vol. 26, no. 1, pp. 293–301, Jan. 2013.

[17] K. Abbasi, A. Kumar, R. Ranjan, and S. Kumar, “A rainfall prediction model using artificial neural network,” in *Proc. IEEE Control Syst. Grad. Res. Colloq.* (ICSGRC), Jul. 2012, pp. 82–87.

[18] G.-T. Zhang, N. Zhang, and J. Zhang, “Application of differential evolution algorithm for solving discounted 0–1 knapsack problem,” in *Proc. IEEE 2nd Inf. Technol., Netw., Electron. Automat. Control Conf.* (ITNEC), Dec. 2017, pp. 1558–1561.

[19] J. Zhang and A. C. Sanderson, “JADE: Adaptive differential evolution with optional external archive,” *IEEE Trans. Evol. Comput.*, vol. 13, no. 5, pp. 945–958, Oct. 2009.

[20] G. A. Trunfio, “A cooperative coevolutionary differential evolution algorithm with adaptive subcomponents,” *Procedia Comput. Sci.*, vol. 51, no. 1, pp. 834–844, 2015.

[21] B. Borowska, “Nonlinear inertia weight in particle swarm optimization,” in *Proc. 12th Int. Sci. Tech. Conf. Comput. Sci. Inf. Technol.* (CSIT), vol. 1, Sep. 2017, pp. 296–299.

[22] V.-E. Neagoe and C.-E. Neghina, “An artificial bee colony approach for classification of remote sensing imagery,” in *Proc. 10th Int. Conf. Electron., Comput. Artif. Intell.* (ECAI), Jan. 2018, pp. 1–4.

[23] G. Lei, C. Liu, Y. Li, D. Chen, Y. Guo, and J. Zhu, “Robust design optimization of a high-temperature superconducting linear synchronous motor based on taguchi method,” *IEEE Trans. Appl. Supercond.*, vol. 29, no. 2, pp. 1–6, Mar. 2019.

[24] T. Inami, Y. Tanimoto, N. Minami, M. Yamaguchi, and K. Kasai, “Color stability of laboratory glass-fiber-reinforced plastics for esthetic orthodontic wires,” *Korean J. Orthodontics*, vol. 45, no. 3, pp. 130–135, 2015.

[25] D. Pascale, “RGB coordinates of the macbeth colorChecker,” Babel Color Company, Montreal, QC, Canada, Tech. Rep. 36941390, 2006, pp. 1–16.

[26] C. J. Lin, J. Y. Jhang, S. H. Chen, and K. Y. Young. (May 2020). The Flank Wear Dataset. [Online]. Available: https://tinyurl.com/ybv2ef3k

CHENG-JIAN LIN (Senior Member, IEEE) received the B.S. degree in electrical engineering from the Ta Tung Institute of Technology, Taiwan, in 1986, and the M.S. and Ph.D. degrees in electrical and control engineering from National Chiao-Tung University, Taiwan, in 1991 and 1996, respectively. He is currently a Chair Professor with the Computer Science and Information Engineering Department, National Chin-Yi University of Technology, Taichung City, Taiwan. His current research interests are machine learning, pattern recognition, intelligent control, image processing, intelligent manufacturing, and evolutionary robot.

JYUN-YU JHANG received the B.S. and M.S. degrees from the Department of Computer Science and Information Engineering, National Chin-Yi University of Technology, Taichung City, Taiwan, in 2015. He is currently pursuing the Ph.D. degree with the Institute of Electrical and Control Engineering, National Chiao-Tung University, Hsinchu City, Taiwan. His current research interests include fuzzy logic theory, type-2 neural fuzzy systems, evolutionary computation, machine learning, and computer vision and application.

SHAO-HSIEN CHEN received the B.S. degree from the National Chin-Yi University of Technology, Taiwan, in 1992, and the M.S. and Ph.D. degrees from National Chung Cheng University, Taiwan, in 2001 and 2006, respectively. From 2005 to 2009, he was a Research and Development Manager with Ching Hung Machinery & Electric Industrial Company Ltd., and AWEA Machinery & Electric Industrial Company Ltd., Taiwan. Since 2009, he has been an Assistant Professor with the National Chin-Yi University of Technology. His research interests include smart machine tool design and superalloy machining.

KUU-YOUNG YOUNG (Senior Member, IEEE) received the B.S. degree in electrical engineering from National Taiwan University, Taiwan, in 1983, and the M.S. and Ph.D. degrees in electrical engineering from Northwestern University, Evanston, IL, USA, in 1987 and 1990, respectively. He is currently a Professor with the Electrical Engineering Department, National Chiao-Tung University, Hsinchu City, Taiwan. His current research interests are intelligent control, image processing, and robotic control.