Application of a neural network for improving the quality of five-axis machining

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Abstract: As many operating parameters are involved in five-axis machining and significantly affect the machining results, use of either an analytical method or an experimental method can only solve the problem to a degree. Therefore, a concept for developing a database system using a neural network as the inference mechanism for the purpose of improving the quality of five-axis machining was addressed in this research. A database system was constructed on the basis of the VERICUT cutting simulation and experimental data from previous literature. The simulation data were put into an intelligent database for automatic generation of the suitable tool inclination angle for each cutting point on the machined surface. The tool inclination angle was the dominating factor for improving the surface quality in five-axis machining. The inclination angle was further entered into a post-processor to modify the cutter location file and to generate the numerical control (NC) program file for practical machining. The input data used in the database required for this system are basic operating parameters, quality requirements and the geometry of the designed sculptured surface. In this research, an intelligent database system for ball mills was successfully established for five-axis machining.

Keywords: five-axis, machining, neural network

1 INTRODUCTION

There are many advantages of using five-axis machining technology for three-dimensional free surface cutting. Owing to the interaction between complicated geometry modelling of the three-dimensional free surface and the five degrees of freedom (DOF) of the five-axis machining system, comprehensive understanding of five-axis machining for improving the cut quality or cut efficiency is still lacking. Some commercial software may help to reduce the complex procedure between the design step and practical machining, but the engineer is still required to input many important operating parameters before obtaining a useable numerical control (NC) program. These operating parameters usually significantly affect the cut quality (surface roughness, dimension accuracy) in practical application. The skilled engineer and many test trials that are usually required to obtain a good quality cut are both costly and time consuming. The development of an intelligent knowledge database system for five-axis machining that improves cut quality and cutting efficiency is obviously needed.

The main purpose of this research is to investigate the feasibility of using a neural network algorithm intelligently to select one of the operating parameters (inclination angle) of five-axis machining. By inputting some of the basic operating parameters, cut quality requirements and geometry information of the designed three-dimensional free surface, the developed system can generate a set of ideal yaw angles and tilt angles that may significantly improve the cut quality [1]. The generated data can be further entered into a post-processor to obtain a cutter location file. The conceptual design of the system developed in this research is shown in Fig. 1. A neural network algorithm was adopted as the inference mechanism of the intelligent database in Fig. 1. The output of the neural network is the yaw angle and tilt angle of the cutter. A popular and simple method for three-dimensional free sculptured surface five-axis machining using a ball-mill assumes that the normal direction of the surface coincides with the orientation of the ball-mill and that the cutter location on the surface is the contact point of the ball-mill during machining. The cutter location can be represented using the orientation and location of the cutter (see Fig. 2). The
mathematical representation \([2, 3]\) can be shown as

\[
L = (M_Q T, M_K T)
\]

where

\[
M_Q T = [C_{XT}, C_{YT}, C_{ZT}]^T
\]

\[
M_K T = [N_{XT}, N_{YT}, N_{ZT}]^T
\]

In the above equations, \(L = (M_Q T, M_K T)\) represents cutter orientation and location, \(M_K T\) represents the components of cutter orientation (normal direction) related to each axis of the workpiece coordinate \((X_M, Y_M, Z_M)\) and \(M_Q T\) represents the components of cutter location (cut position of free surface) related to each axis of the workpiece coordinate. The advantage of the method discussed in the above section is that the cutter is always normal to the cutting surface. However, this assumes a static cutting situation with low cutting efficiency (zero cutting speed) at the ball tip, which causes poor quality of surface finish. An interference cutting condition is easily encountered with complicated free surface cutting using this method \([2, 3]\). Using the cutter edge as the cutting point was then adopted for improving cutting efficiency. Vickers and Quan \([4]\) reported that the surface cut quality can be improved by yawing and tilting the angle of the ball-mill cutter. Their experimental results also showed that, as the inclination angle of the cutting tool decreases, the required number of tool paths decreases. The volume removal rate is increased and the tool life is increased. Similar research performed by Töenischhoff and Hernandez-Camacho \([5]\) discussed the effects of yaw angle and tilt angle on the manufacturability of five-axis die surface machining. An analytical solution of cusp height based on yaw angle and tilt angle was derived by Choi \textit{et al.} \([6]\). The path interval was used as the indicated factor for optimizing the yaw and tilt angle.

Until 1994, NC programmers were still required to input yaw angle before machining. This is very inconvenient and difficult for users, especially when machining a
complicated sculptured surface. An investigation optimizing and dynamically adapting the cutter inclination angle during five-axis milling of a sculptured surface was then undertaken by Kruth and Klewais [1]. The variations in cusp height, surface precision, surface roughness and machining cost with respect to yaw angle and tilt angle with different kinds of tools were investigated in their work.

The application of neural network technology has expanded rapidly in the past decade and become widely accepted by industry. It simulates the transfer mechanism of human neurons and is very useful for the simulation of non-linear systems [7, 8]. As five-axis machining is a very complicated machining process, it is not only very difficult to obtain a complete database but also the data will be very complicated and too numerous to use traditional database building methods. Neural network technology may overcome the difficulties of non-linearity and large quantity of data. The neural network with a back-propagation algorithm is adopted in this research for generating the optimized operating parameters of the five-axis machining process.

2 BASIC THEORY

To derive the cutter location using the inclination angle concept, the transfer matrix, $\mathbf{L}_T$, between the cutter coordinate system $(X_T, Y_T, Z_T)$ and the local coordinate system $(X_L, Y_L, Z_L)$ was first identified. The coordinate system of a ball-mill with inclination angles $\alpha$ and $\lambda$ is shown in Fig. 2. The three orthogonal unit vectors of the local coordinate system are $X_L$, $Y_L$ and $Z_L$: $X_L$ is the unit tangent vector, $n$, along the $v$ curve ($u$ = constant) of the sculptured surface; $Y_L$ is the unit normal vector, $t$, of the cutting point on the sculptured surface; $Z_L$ is defined as $f = n \times t$. Based on the workpiece coordinate, $f$, $n$, $t$ and $C_L$ can be further represented as $f = (f_X, f_Y, f_Z)$, $n = (n_X, n_Y, n_Z)$, $t = (t_X, t_Y, t_Z)$ and $C_L = (C_{LX}, C_{LY}, C_{LZ})$ (see Fig. 2). In Fig. 2, the cutter moves along the tangential direction of the $v$ curve and rotates by angles $\omega$ and $\lambda$ is relation to the $X_L$ and $Y_L$ axes respectively. Here, $\omega$ is the yaw angle and $\lambda$ is the tilt angle. The cutting point was set at $\beta = \pi/2 - \alpha$ in Fig. 2. Then, $A_T$, the transfer matrix between the cutter coordinate system and the local coordinate system with ball-mills, can be obtained as

![Fig. 2 Schematic diagram showing the coordinate system of ball-mill with inclination angles $\omega$ and $\lambda$](image-url)
follows:

\[ \mathbf{A}_T = \text{rot}(\mathbf{Y}_L, -\omega) \text{rot}(\mathbf{Z}_L, -\lambda) \text{trans}(-r \cos \alpha, r \sin \alpha, 0) \]

\[ = \begin{bmatrix} 
\cos \omega \cos \lambda & \cos \omega \sin \lambda & -\sin \omega & q_X \\
-\sin \lambda & \cos \lambda & 0 & q_Y \\
\sin \omega \cos \lambda & \sin \omega \sin \lambda & \cos \omega & q_Z \\
0 & 0 & 0 & 1 
\end{bmatrix} \]

(4)

where \( r \) is the diameter of the cutter and \( q_X, q_Y, q_Z \) can be further described as

\[ q_X = -r \cos \omega \cos \lambda \cos \alpha + r \cos \omega \sin \lambda \sin \alpha \]  

(5)

\[ q_Y = r \sin \omega \cos \alpha + r \cos \lambda \sin \alpha \]  

(6)

\[ q_Z = -r \sin \omega \cos \lambda \cos \alpha + r \cos \omega \sin \lambda \sin \alpha \]  

(7)

Therefore, the transfer matrix, \( \mathbf{M}_T \), between the cutter coordinate system and the workpiece coordinate system was obtained as

\[ \mathbf{M}_T = \mathbf{M}_l \mathbf{A}_T \]

\[ = \begin{bmatrix} f_X & n_X & t_X & C_{LY} \\
f_Y & n_Y & t_Y & C_{LY} \\
f_Z & n_Z & t_Z & C_{LZ} \end{bmatrix} \times \begin{bmatrix} \cos \omega \cos \lambda & \cos \omega \sin \lambda & -\sin \omega & q_X \\
-\sin \lambda & \cos \lambda & 0 & q_Y \\
\sin \omega \cos \lambda & \sin \omega \sin \lambda & \cos \omega & q_Z \\
0 & 0 & 0 & 1 \end{bmatrix} \]

\[ = \begin{bmatrix} K_X & ? & Q_X \\
K_Y & ? & Q_Y \\
K_Z & ? & Q_Z \\
0 & 0 & 0 & 1 \end{bmatrix} \]

(8)

In the above equation, \( K_X, K_Y, K_Z \) and \( Q_X, Q_Y, Q_Z \) can be obtained as follows:

\[ K_X = f_X \cos \omega \sin \lambda + n_X \cos \lambda + t_X \sin \omega \sin \lambda \]  

(9)

\[ K_Y = f_Y \cos \omega \sin \lambda + n_Y \cos \lambda + t_Y \sin \omega \sin \lambda \]  

(10)

\[ K_Z = f_Z \cos \omega \sin \lambda + n_Z \cos \lambda + t_Z \sin \omega \sin \lambda \]  

(11)

\[ Q_X = f_X q_X + n_X q_Y + t_X q_Z + C_{LY} \]  

(12)

\[ Q_Y = f_Y q_X + n_Y q_Y + t_Y q_Z + C_{LY} \]  

(13)

\[ Q_Z = f_Z q_X + n_Z q_Y + t_Z q_Z + C_{LZ} \]  

(14)

where \([K_X, K_Y, K_Z, 0]^T\) shows the relative components of each axis between the cutter coordinate system and the workpiece coordinate system, and \([Q_X, Q_Y, Q_Z, 1]^T\) shows the axial components of the original point of the cutter coordinate system relative to the workpiece coordinate system. The cutter location of the ball-mill in this study was then defined as \( L = (Q, K) \). In the above discussion, the cutter location file \( L = (Q, K) \) can be obtained from equations (9) to (14) with the yaw angle and tilt angle given. Different yaw angle and tilt angles have different cutter location files. It is obvious that a different yaw angle and tilt angle will produce a different machining quality. The mathematical analysis method is one way to obtain an optimized yaw angle and tilt angle. However, with the five-axis machining process, a mathematical analysis method is very complicated and involves many operating parameters. Therefore, this research applies an algorithm automatically to generate yaw angle and tilt angle using a back-propagation neural network calculation.

3 NEURAL NETWORK

The basic architecture of the back-propagation neural network includes an input layer, hidden layers and an output layer [7]. A layer is defined as a group of parallel neurons without any interaction between them. In this research, the total layers of the neural network were set as a minimum of three layers and a maximum of five layers. The two main calculations generally included in a neural network are forward calculation and backward calculation. The first weight matrix was randomly generated and applied to the forward calculation. The calculation was executed layer by layer until the output layer. The differences between the output results and the expected values were used in the backward calculation procedure for calculating the weight matrix. The forward calculation and the backward calculation were repeated until the differences between output values and expected values were smaller than an allowable value. As hypertangent functions have the advantages of easy convergence and high stability during the training process, a hypertangent function was used as the action function in this research [7]. In the forward calculation, the input \( X_i \) was multiplied by the weight value \( W_{ij} \) to obtain a total net value. Using the action function, the output value of each layer was obtained from the total net value. The set of each parallel input parameter was called a pattern. Both forward and backward calculations are very essential for the training process. However, the details of the forward calculation will not be discussed here. A delta rule (gradient descent algorithm) is used to reduce the cost function and approach the right weight value \( W_{ij} \) in the backward calculation. The definition of cost function is based on the least mean square error, which is

\[ E = \{e_1, e_2, e_3, \ldots, e_j, \ldots, e_q\} \].

In the above
equation [8]

$$e_i = \frac{1}{2} \sum_{ui} (P_i^u - Y_i^u)^2$$

$$= \frac{1}{2} \sum_{ui} \left( P_i^u - g \left[ \sum_j W_{ij} g \left( \sum_k W_{jk} X_k \right) \right] \right)^2$$ (15)

$Y_i$ is the output value of the forward calculation at the $i$th neuron and $P_i$ is the expected value of the output layer at the $i$th neuron. In the training mode, the expected values are the data of yaw angle and tilt angle from the cutting simulation. For the application mode, the expected values are the optimized yaw angle and tilt angle which will be further applied to the calculation of the cutter location file. The matrix adjustment between the output layer and the hidden layer is then obtained as

$$\Delta W_{ij} = -\eta \frac{\partial E}{\partial W_{ij}} = \eta \sum_u (P_i^u - Y_i^u) g(\text{net}_u) O_j^u$$ (16)

where $\eta$ is the learning rate of the network (increasing the learning rate will increase the training speed but also increase the divergence chance), and $g(\text{net}_u)$ is the activation function which is a hyperbolic tangent function.

The adjustment matrix between the input layer and the hidden layer is obtained as

$$\Delta W_{jk} = -\eta \frac{\partial E}{\partial W_{jk}} = \eta \sum_u (P_i^u - Y_i^u) g(\text{net}_j) W_{ij} g(\text{net}_u) X_k^u$$ (17)

The flow chart of the neural network subprogram is shown in Fig. 3. The subprogram is edited and constructed using

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**Fig. 3** Flow chart of the neural network subprogram
C++ language with object-oriented concepts. Yaw angle and tilt angle are the output results of the developed system. It is worth mentioning that a subprogram for curvature analysis of the designed three-dimensional surface is necessary before the neural network calculation can be made. This curvature analysis subprogram was based on C++ language which can accept geometry data from any computer aided design (CAD) software (data generated by a C++ based software, or data with an IGES format). The curvature of any point of interest on a three-dimensional free surface can be obtained from this subprogram. The output of the curvature analysis subprogram was arranged in a special form that can be accepted by the neural network subprogram. Part of the inputs to the neural network subprogram comes from the direct input of the user. A user interactive interface was constructed in this research which can effectively read the input data from the user and preprocess the relative input data into an adequate form for the neural network training process or inference process.

The cutting tool diameter and path interval are two important operating parameters that may significantly affect machining quality. The allowable surface average error and allowable maximum error are two important evaluation indices for surface quality evaluation. Therefore, the read-in data include diameter of cutting tool, path interval, allowable surface average error and allowable maximum surface error. The relative subprograms were loaded and compiled together. Yaw angle and tilt angle can be automatically generated together. Yaw angle and tilt angle can be automatically generated by this system.

4 PARAMETER DESIGN FOR SIMULATION

A suitable range of operation parameters of five-axis machining used for the neural network training calculation is essential for a successful intelligent five-axis machining database system. The diameter of the cutting tool, inclination angle, operating information (path interval) and quality requirements were included in each training pattern. Figure 4 shows the configuration of the neural network used in this study. In the practical machining of a three-dimensional surface, rough machining is usually cut using a 3 or 4 DOF milling

**Fig. 4** Configuration of the neural network
machine first. Only finish machining is considered to be cut on a five-axis machine. Therefore, finish machining (not rough machining) was the main step considered in the following research. The feed rate was then set at 600 mm/min. The angular speed of spindle was set at 1200 r/min. The variation in path interval along the \( v \) direction, \( F_v \), was considered to be 1, 3 and 5 mm with a tool diameter of 10 mm, 1.6, 4.8 and 8 mm with a tool diameter of 16 mm, and 2, 6 and 10 mm with a tool diameter of 20 mm. The yaw angles \( \omega \) and tilt angles \( \lambda \) were set at 0, 10 and 20° [1]. Using the parameters discussed above, the training data file for the neural network may have a total of \( 3 \times 3 \times 4 \times 3 \times 3 = 324 \) arrays.

Both measured results and calculated results should be considered as indices for evaluating the surface cut quality and can be used as input data for the training calculation. The surface texture on a two-dimensional cross-section is normally used as one of the basic indices for evaluating surface machining quality. The three characteristics of waviness, lay and roughness are necessary for representation of the surface quality of a three-dimensional free surface. Waviness shows the large-scale quality of the cutting surface and is usually affected by deflection or vibration of the machine structure. This large-scale variation in machining quality will not be considered in this study. The lay on the machining surface is mainly generated by the tool path and will be discussed in the next section. The surface roughness is affected by many parameters such as feed rate, spindle speed, tool shape, chattering, etc. The experimental data will be applied for modifying the simulation data. The zigzag method and the pocket method are two popular methods for tool path planning in free surface machining. In these two methods, between any two adjacent tool paths, when the tool is cutting along the \( u \) or \( v \) direction, there exists a convex section of height \( h \) which is usually called the scallop height or cusp height (see Fig. 5). The variation in path interval \( p \) (distance between two adjacent tool paths) will affect the resulting height \( h \). The projection of the ball-mill along the cutting direction is circular. Lin and Koren [9] and Choi et al. [6] derived the relationship of path interval, surface geometry and cusp height with a ball-mill. Using the definition of Fig. 5, the relationship between cusp height and path interval or surface

![Fig. 5 Schematic diagram showing the relationship of the operating parameters for three-dimensional free surface machining](image)
geometry was obtained as follows [6, 9]:

\[ p = \frac{1}{\rho} \sqrt{4(r + \rho)^2(h + \rho)^2 - \left(\rho^2 + 2\rho + (h + \rho)^2\right)^2} \]

\[ h = \begin{cases} \sqrt{\frac{-b - \sqrt{b^2 - 4c}}{2}} - \rho, & \rho > 0 \\ \sqrt{\frac{-b + \sqrt{b^2 - 4c}}{2}} - \rho, & \rho < 0 \end{cases} \]

where \( p \) is the path interval of two adjacent tool paths along the \( v \) direction, \( h \) is the cusp height formed by two adjacent tool paths along the \( v \) direction, \( \rho \) is the radius of curvature of the surface curve along the \( v \) direction, \( r \) is the radius of the ball-mill and \( b \) and \( c \) are defined as

\[ b = \frac{p^2(r + \rho)^2}{R^2} - 4(r + \rho)^2 + 4\rho + 2\rho^2 \]

\[ c = \rho^4 + 4\rho^3 + 4\rho^2 \rho^2 \]

In this research, the calculation of the cusp height using equations (19) to (22) is based on the parameters given in Table 1. The cusp height obtained was considered to be the average error of the machined surface. The average error is one of the important factors for evaluating machining quality. It is worth mentioning that equations (19) to (22) do not account for the effects of inclination angle on the calculation of cusp height. The effects of tool vibration and tool chattering on the accuracy of the NC table will also be encountered in practical machining. Inclusion of all the effects would make the theory very complicated. To simplify the explanation and make the implementation easier, only yaw angle and tilt angle will be considered in this research. For different five-axis machining systems and machining environments, it is suggested that data from practical machining be used and measured by the surface roughness measuring machine. Considering the situation of practical machining, a modification of the theoretical cusp height in equation (20) may then be meaningful.

The experimental results of Kruth and Klewais were used in this research to modify the theoretical cusp height. The experimental results of surface roughness and surface deviation versus ball-mill yaw angle with variation in the tilt angle from 0 to 20° were shown in Fig. 6 [1].

As the amount of experimental data was limited, not all digital values required for the input data in the neural network calculation were included. Therefore, a second-order linear regression method was used to interpolate the experimental results. The regression results were also shown in Fig. 6. The regression results from the experimental data were coupled with the theoretical cusp height in equation (20) to enhance the reality of the surface quality. The coupled result was obtained as follows:

\[ h' = h + f(\lambda) + g(\omega) \]

\[ = h + (1.9174\lambda^2 - 7.6987\lambda + 5) \]

\[ + (-0.2937\omega^2 + 2.4591\omega - 2.085) \]

where \( h' \) is the modified cusp height and the yaw angle, \( \omega \), and tilt angle, \( \lambda \), are in degrees. Now, the modified cusp height, \( h' \), represents the average error of the machined surface and will be included in the input data in the training data file for the simulation calculation of the neural network. Figure 7 shows the variation in the modified average error with a 20 mm ball-mill. The ratio of path interval to tool radius, \( p/r \), the curvature of the sculptured surface, \( \rho \), the yaw angle, \( \omega \), and the tilt angle, \( \lambda \), were included in Fig. 7. In Fig. 7, the modified average error, \( h' \), increased as the \( p/r \) ratio increased. With the same surface curvature, error \( h' \) increased slightly when the yaw angle increased but increased very significantly when the tilt angle increased. For different tool diameters, a similar tendency was also found. This result is reasonable as the error caused by yaw angle is mainly generated in the \( u \) direction. The \( h' \) value obtained by equation (23) or equation (20) only takes into consideration the \( v \) direction. To obtain the
maximum overcut and undercut, a full understanding of the coupled effects of yaw angle and tilt angle on machining error is necessary. Therefore, a machining simulation using VERICUT was performed and is described below.

Using the parameters given in Table 1, the machining simulation was performed by VERICUT simulation software [10]. Both the overcut and undercut were examined using the AUTO-DIFF function [10]. The results of maximum overcut, OC$_{\text{max}}$, and maximum undercut, UC$_{\text{max}}$, were then obtained from the report of cutting simulations. The simulation data of maximum overcut and maximum undercut of each cutting simulation were recorded and used for the training data of neural network calculation in this research.

The OC$_{\text{max}}$ and UC$_{\text{max}}$ values obtained from the AUTO-DIFF checking report were considered as the maximum errors of the machined surface. Figure 8 shows the maximum error of VERICUT cutting.
simulation results with a $\rho = 100$ mm ruled surface. The results of VERICUT cutting simulation show that the maximum error on the free surface is inversely proportional to the tool diameter. Therefore, the larger the tool diameter, the smaller is the cutting error. Also, the maximum error has a similar tendency regardless of the variation in curvature of the three-dimensional free surface.

In Fig. 8, some of the simulation results are irregular. The simulation was repeated several times to examine the irregularity, as irregular data may affect the training results of the neural network. The data irregularity may be due to software floating point calculation error or the singular point on the cutting boundary. However, results of the neural network simulation proved this irregularity to be within the acceptable range.

5 INFERENCE RESULTS AND DISCUSSIONS

The data obtained from the above were applied to the inference mechanism of the knowledge database system for learning purposes. Some pilot studies were designed and performed to examine the learning performance or convergence speed of the neural network with different network parameters. Here, the network parameters include the learning rate, the number of layers and the number of neurons on each layer. The learning rate was substantially decreased from 0.05 to 0.001 during the numerical calculation. The decreasing rate depended on the convergence rate. The noise factor and momentum term were set at 0.01 and 0.001 respectively and fixed through the analysis process. The setting values were obtained from practical experience of the pilot study. Figure 9 shows the convergence speed comparison of three-, four- and five-layer networks with the same training data. In Fig. 9, the training cycle number is shown on the horizontal axis and the error of the last training cycle is shown on the vertical axis. The error of the last cycle in Fig. 9 shows that a three-layer architecture is much less accurate than a four- or five-layer architecture. Several kinds of neuron arrangement for the three-layer network (6–18–2, 6–8–2, 6–4–2) were also designed and tested in the pilot study. The results show that the convergence speed was similar and no significant improvement could be achieved by varying the neuron arrangement for three-layer architecture. Therefore only four- and five-layer architectures were further considered to investigate the inference performance of a neural network in this research.

For the four-layer network, the example neuron arrangement design was 6–12–10–2. Six neurons were used in the input because there were six parameters used for the training process. The parameters for neural network calculation are summarized in Table 1. The average error in Table 1 was calculated using equation (23) with different parameters. The maximum error in Table 1 was obtained from the AUTO-DIFF function of VERICUT simulation. The two neurons in the output layer represent the yaw angle and tilt angle of the cutter. As discussed in the above sections, yaw angle and tilt angle were the parameters expected to be important for improving the quality of five-axis machining.

For the five-layer network, the example neuron arrangement design was 6–12–10–8–2. A typical training result of the neural network is summarized in
Table 2. In Table 2, the results of the five-layer network show better convergence speed than the four-layer network, with the same allowable error of 0.001. This implies that the neuron arrangement of a five-layer network has better inference performance when representing the non-linear interaction between the input parameters. With the same required allowable error, the required training times are more for a four-layer network than for a five-layer network. The converging condition during the learning procedure is shown in Fig. 10. For the inference performance, both the four- and five-layer networks have a predicted output with an average error lower than 1 per cent (see Table 2).

A very interesting result worth mentioning is that the predicted error of tilt angle in both four- and five-layer networks is lower than 0.2 per cent, which is much better than the predicted error for yaw angle output (see Fig. 11). From the discussion of modified cusp height [average error in equation (23)], the average dimension error increased proportionally with an increase in tilt angle or yaw angle (see Fig. 7). However, the relationship between the maximum error and the inclination angle is highly non-linear (see Fig. 8). For a tool diameter of 10 mm with a path interval of 3 or 5 mm in Fig. 8, the maximum error was very similar for some cases. This may be why the test result of the yaw angle has a slightly larger error. This error did not cause any difficulties in the application of a neural network in the intelligent database system. The allowable error of the neural network calculation can approach less than 1 per cent (even for yaw angle calculation), with very good inference ability. The \(\omega\) and \(\lambda\) angles obtained can be further applied to equations (9) to (14) to obtain a cutter location file to be used for practical machining.

6 SUMMARY

The neural network algorithm was used as an inference mechanism in the system developed in this research for improving the cut quality of five-axis machining. The system developed in this research can intelligently generate improved digital values of yaw angle and tilt angle for five-axis machining. The input data included path interval (operating parameters), dimension average error and maximum error (quality) and curvature at cutting point (geometry of the designed three-dimensional free surface). The results obtained can be entered into the post-processor.

<table>
<thead>
<tr>
<th>Number of layers</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Architecture of network</td>
<td>6–12–10–2</td>
<td>6–12–10–8–2</td>
</tr>
<tr>
<td>Allowable error</td>
<td>0.001</td>
<td>0.001</td>
</tr>
<tr>
<td>Training times when allowable error (%) reached</td>
<td>37 002 ± 5</td>
<td>13 503 ± 5</td>
</tr>
<tr>
<td>Average error when allowable error (%) reached</td>
<td>Yaw angle 0.899</td>
<td>Tilt angle 0.121</td>
</tr>
<tr>
<td></td>
<td>Tilt angle 0.801</td>
<td>Tilt angle 0.098</td>
</tr>
</tbody>
</table>
Fig. 10  Converging condition for four-layer (6–12–10–2) and five-layer (6–12–10–8–2) architecture

Fig. 11  Test results with a five-layer neural network: (a) tilt angle test, (b) yaw angle test
to generate the cutter location file and the NC file for practical machining. The VERICUT cutting simulation is also used in this research to supply part of the simulation data used for the database system verification. The ball-mill database was successfully established in this research. The verification shows the feasibility of using a neural network as the inference mechanism effectively to generate the inclination angle for five-axis machining.

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