

# Integrated machining error compensation method using OMM data and modified PNN algorithm

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## Abstract

This paper presents an integrated machining error compensation method based on polynomial neural network (PNN) approach and inspection database of on-machine-measurement (OMM) system. To improve the accuracy of the OMM system, geometric errors of the CNC machining center and probing errors are compensated. Machining error distributions of a specimen workpiece are measured to obtain error compensation parameters. To efficiently analyze the machining errors, two machining error parameters,  $W_{err}$  and  $D_{err}$ , are defined. Subsequently, these parameters can be modeled using the PNN approach, which is used to determine machining errors for the considered cutting conditions. Consequently, by using an iterative algorithm, tool path can be corrected to effectively reduce machining errors in the end-milling process. Required programs are developed using Ch language, and modified termination method are applied to reduce computation times. Experiments are carried out to validate the approaches proposed in this paper. The proposed integrated machining error compensation method can be effectively implemented in a real machining situation, producing much fewer errors.

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**Keywords:** Machining error compensation; On-machine measurement; Polynomial neural network; CAD/CAM/CAI integration

## 1. Introduction

Nowadays, with the developments of the CAD/CAM system, end-milling processes are very popular in the field of manufacturing industries. However, there exist some undesirable disturbance factors in the actual machining processes, which are not integrated in current CAD/CAM systems. Among these disturbance factors, the tool deflection problem can directly affect machined surface quality as well as productivity. It is especially difficult to avoid excessive machining errors when slender-type tool is used for manufacturing dies containing complex-sculptured surfaces. Hence, the tool deflection problem must be

treated to obtain an accurate surface form with respect to the designed form obtained from the CAD/CAM systems.

Many researches have been carried out on the compensation of machining errors. The approaches presented in these researches consist of controlling the cutting forces during machining process so that they do not exceed preset forces [13,14]. In contrast to these approaches, Watanabe and Iwai [16] proposed shifting tool position in real time. To implement this approach in real time, measurement instruments (e.g. dynamometer, sensor, amplifier etc.) must be used and thus, machining becomes expensive. Moreover, controlling the cutting forces cannot precisely compensate surface errors and increases machining time. On the other hand, off-line-type error compensation approaches have been proposed [10–12]. These approaches consist of correcting tool paths based on machined surface prediction before the actual milling process. To correct the tool paths, a series of simulations are needed to model the

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cutting forces, to calculate tool deflection, and to predict machined surface shapes. In this case, the simulation errors produced in each step can accumulate and become an important disturbance factor of accurate error compensation. Although these approaches have been improved by various methods, the compensation process has become more complicated. Lo and Hsiao [13] proposed an off-line error compensation approach based on inspection process, which can improve the drawbacks of the other methods. In their method, machining process is executed first using a nominal tool path, and surface errors are measured on the coordinate measuring machine (CMM). Subsequent machining processes are executed with the corrected tool path symmetrically shifted by as much as the measured errors. These series of processes are repeated until the machining errors disappear appropriately. In fact, this approach allows the error compensation process to be effectively implemented for repeated parts, as mentioned in the study, but this approach too has its drawbacks.

To improve such problems, on-machine-measurement (OMM) system has recently received much interest as a new inspection process technique. With the OMM system, inspection process can be carried out directly on the same CNC machining center by exchanging only the cutting tool for measuring probes. In this case, both CAD and CAM databases have to be simultaneously considered to constitute the inspection database because manufacturing and inspection processes can be performed on the same CNC machining center.

This study proposes an efficient machining error compensation method for flat-end milling process based on polynomial neural network (PNN) trained using OMM inspection data, a method which allows outstanding reduction of machining errors without unnecessary repeated processes and expensive costs. From the OMM inspection results, two characterized machining error parameters are defined to simply represent complex machined surface shapes. These parameters can be modeled using the PNN algorithm that describes the direct relationships between given machining conditions and the characterized machining error parameters. To correct a given tool path, an iterative computational approach is proposed, which repeatedly shifts the tool positions to reduce the machining errors. Required programs are developed using C language, and a modified termination method is applied to reduce computation times. Required experiments are carried out to validate the performance of the proposed machining error compensation methodology.

## 2. Machining error compensation methodology

Generally, there is a complicated distribution of machining errors on machined surfaces. It is difficult to functionally obtain a global trend of error distributions because of the non-linearity of the machined surface shapes. In this research, an efficient machining error distribution prediction method is used. Two characterized

machining error parameters are defined so that the amount of machining error can be described without having to model the machined shape exactly. To determine these parameters, OMM inspection data are obtained from the machined surface using a touch-type probe. Since the accuracy of the OMM data generally depends on that of the machining center used, the errors of the CNC machining center and probe must be compensated to improve measurement accuracy. Modified PNN algorithm is applied to define the relationship between measured surface shapes and the characterized machining error parameters. Then, error compensated tool paths are calculated using the proposed iterative method.

### 2.1. Proposed machining error compensation concept

Non-linearity of machined surfaces generally originates from the dynamic behaviors of the cutting tool during machining process. Such non-linearity cannot be easily predicted because the machining process is too complicated to be analyzed computationally. Nevertheless, various approaches have been applied for machining error prediction. The majority of these approaches depend on mechanical modeling of the machining process under various conditions. These modeling techniques employ a large experimental database to account for the wide range of machining conditions. Therefore, these techniques may make the error prediction process unnecessarily complicated.

For obtaining an overall machining error prediction without analyzing all the machining process parameters (e.g. cutting forces, tool deflection amount, tool run out, chattering etc.), a direct relationship between the machining conditions and the machining errors would be sufficient. Using the OMM system, machining error distributions can be directly obtained from machined surfaces of a specimen workpiece at specified machining conditions. In fact, the purpose of this study is not to obtain the exact shape of the machined surface, but to reduce the global machining errors by comparing them with the tolerance criteria. To effectively compare the machining errors with the tolerance criteria, a reference machining error must be chosen. Two characteristic parameters are defined, corresponding to two extreme errors, to represent the overall machining error trend. Then, a direct relationship between machining conditions and these characteristic parameters are obtained. This relationship cannot be easily modeled by an analytic approach due to the complicated nature of the machining process; thus, a PNN model is used. The PNN is trained based on the acquired OMM inspection database and corresponding machining conditions. Then, using the trained PNN model, the characteristic parameters can be predicted. To correct the tool path for machining error reduction, an iterative algorithm is proposed. The process carries out repeated comparisons between the predicted characteristic parameters and the imposed tolerance to correct the tool positions until the machining errors are

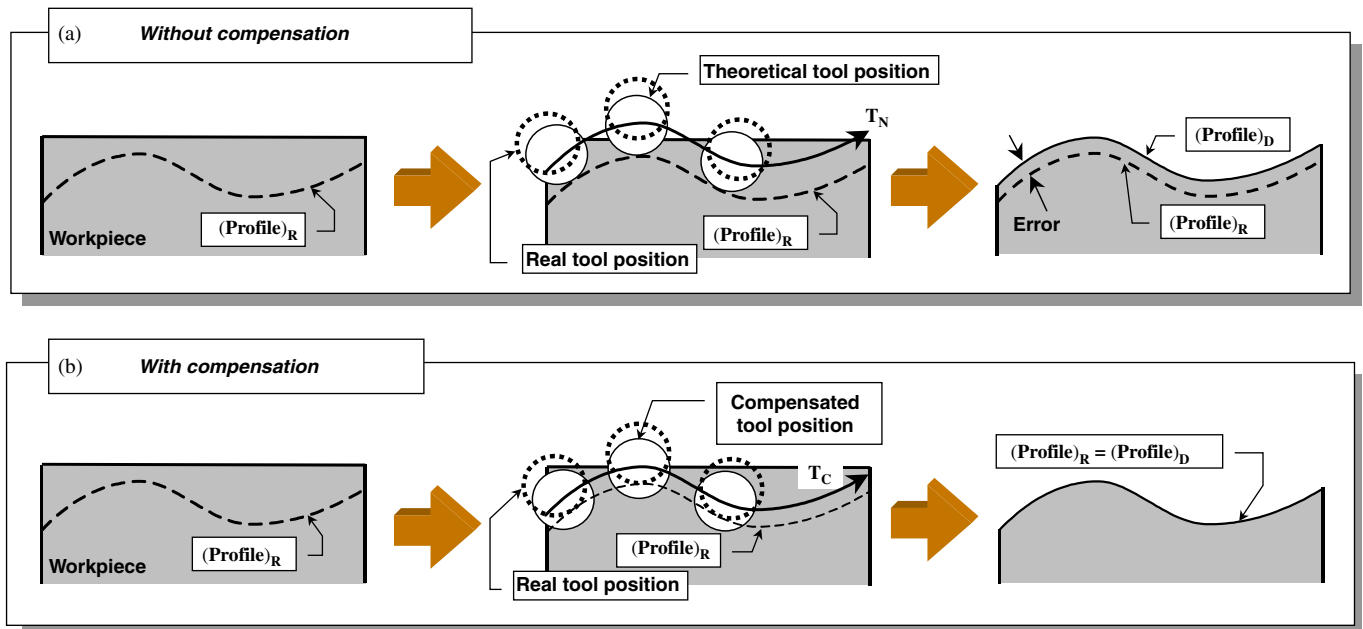


Fig. 1. Basic concept for the proposed machining error compensation.

reduced to a desired level. Fig. 1 shows the basic concept of the proposed machining error compensation method. Fig. 2 illustrates a global process of the proposed approach employed in this study.

## 2.2. Application of OMM system for compensation

Fig. 3 illustrates the basic concept of OMM system. The OMM system makes it possible to perform inspection processes directly on the same CNC machining center by exchanging only a cutting tool for a measuring probe. In this case, both CAD and CAM databases have to be simultaneously considered to construct an inspection database because manufacturing and inspection processes are performed on the same CNC machining center.

The inspection accuracy of the OMM system mainly depends on two error sources: (1) geometric error terms of a machine, and (2) probing errors varying according to probe types. Such errors, measured at the tool tip, are due to dimensional and form errors of its kinematic linkage system, and angular and positional misalignments between each movements. An OMM system can be established by exchanging a cutting tool for a measuring probe, but this exchange can cause an inspection error at the probe. Furthermore, when using a touch-type probe, probing errors, called “pre-travel variation”, must be considered because it is one of the major sources of probing inaccuracy [6]. Using a certificate sphere, it is possible to model pre-travel variation according to the probe-approaching direction, stylus length, and probe diameter, etc. A step-by-step volumetric error analysis using a closed-loop configuration of multi-axis machine tools [5] is applied to improve the inspection process planning of the OMM

system as well as to improve the accurate machining process.

## 2.3. Characterization of machining error parameters

Generally, machined surface shapes are not the same as the deflected tool shapes. Under same cutting conditions, cutting forces vary according to rotational position of the tool; therefore, the amount of tool deflection also varies according to the tool angular position. Therefore, machined surface shapes are generated differently than the deflected tool shapes. The surface errors are not uniformly distributed on the machined surface. Hence, it is necessary to characterize the errors in order to compare them with the given tolerance criteria. In the machined surface prediction process for error compensation according to tolerance criteria, two extreme errors can be taken into account as predominant factors, regardless of surface morphology. In this case, error interval and deviation amount rather than precise surface shape must be considered. First, “maximal error  $E_{\max}$ ” and “minimal error  $E_{\min}$ ” are defined to quantitatively analyze machining error distributions.

The maximal error  $E_{\max}$  is the largest algebraic error on the milled surface with respect to a given coordinate on the desired profile. If this error leads to an undercut with respect to the desired profile,  $E_{\max}$  has positive values; but, if it leads to an overcut,  $E_{\max}$  has negative values. Similarly, the minimal error  $E_{\min}$  is the smallest algebraic error on the milled surface with respect to a given coordinate on the desired profile. If this error leads to an undercut with respect to the desired profile,  $E_{\min}$  has positive values; but, if it leads to an overcut,  $E_{\min}$  has negative values.

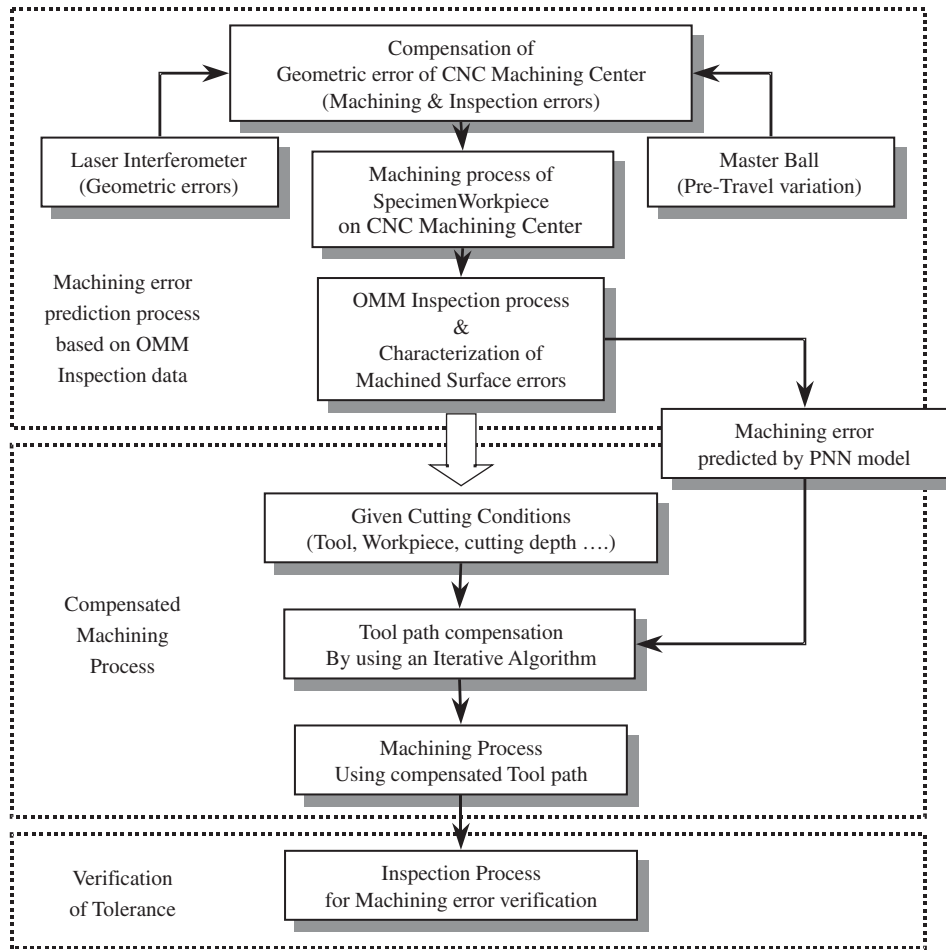


Fig. 2. A schematic diagram of the proposed method.

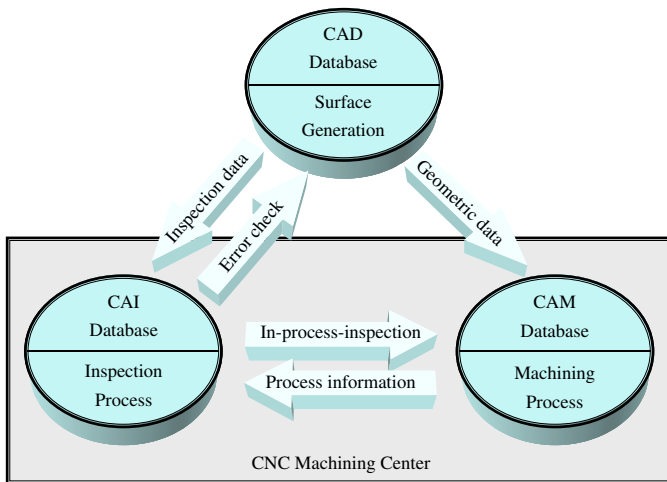


Fig. 3. OMM inspection data feedback for machining error compensation.

Based on these two extreme errors  $E_{max}$  and  $E_{min}$ , the “Error zone” is defined to characterize the distributed surface errors as shown in Fig. 4(a). Under the deflection effects, this error zone deviates from reference profile. To analyze the error zone, two characterized parameters:

“width of error zone  $W_{err}$ ” and “deviation amount of error zone  $D_{err}$ ”. Although these parameters cannot represent all geometrical information of the machined surface form, they can, however, make it possible to effectively analyze the tool-deflection effect on the machined surfaces because it is not necessary to recognize exact surface shapes to compare with the tolerance criteria. These characteristic parameters are derived as follows:

$$W_{err} = \frac{E_{max} + E_{min}}{2} \quad \text{and} \quad D_{err} = E_{min} + \frac{W_{err}}{2}. \quad (1)$$

Generally, the given machining tolerance zone is decided by two surfaces enveloping the spheres of diameter  $W_{tol}$ , while the centers of the spheres are located on a desired surface. According to circumstances, this desired surface is not coincidental with the reference surface of the tolerance. The machined surfaces have to be in close vicinity to the desired surface to meet the tolerance. Similarly, to represent the tolerance parameters of the characterized surface error parameters  $W_{err}$  and  $D_{err}$ , “width of tolerance criteria  $W_{tol}$ ” and “deviation of tolerance criteria  $D_{tol}$ ” are defined. Here,  $W_{tol}$  represents the diameter of the sphere defining the tolerances as mentioned and  $D_{tol}$  represents the distance between the desired surface and the reference

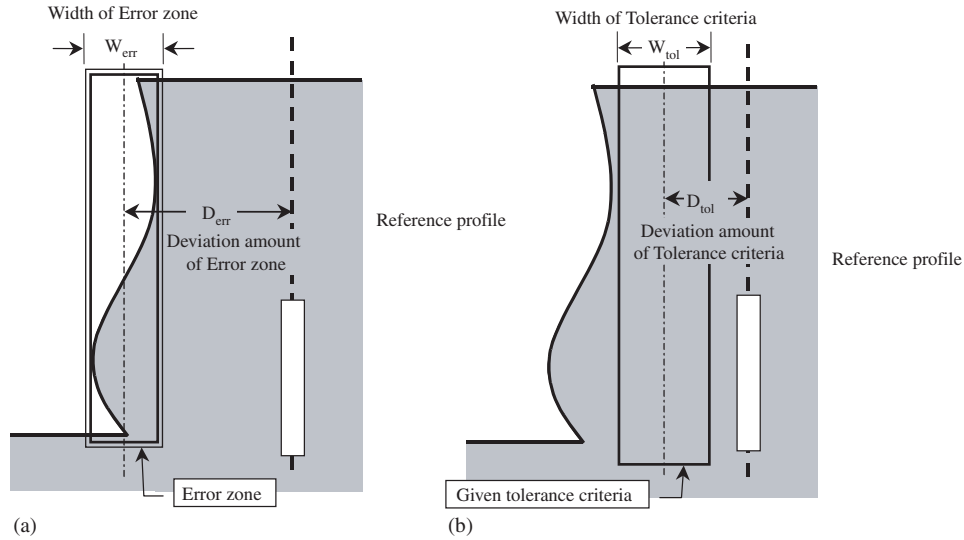


Fig. 4. Characteristic parameters of surface error and tolerance. (a) Error zone characterization; (b) Tolerance criteria characterization.

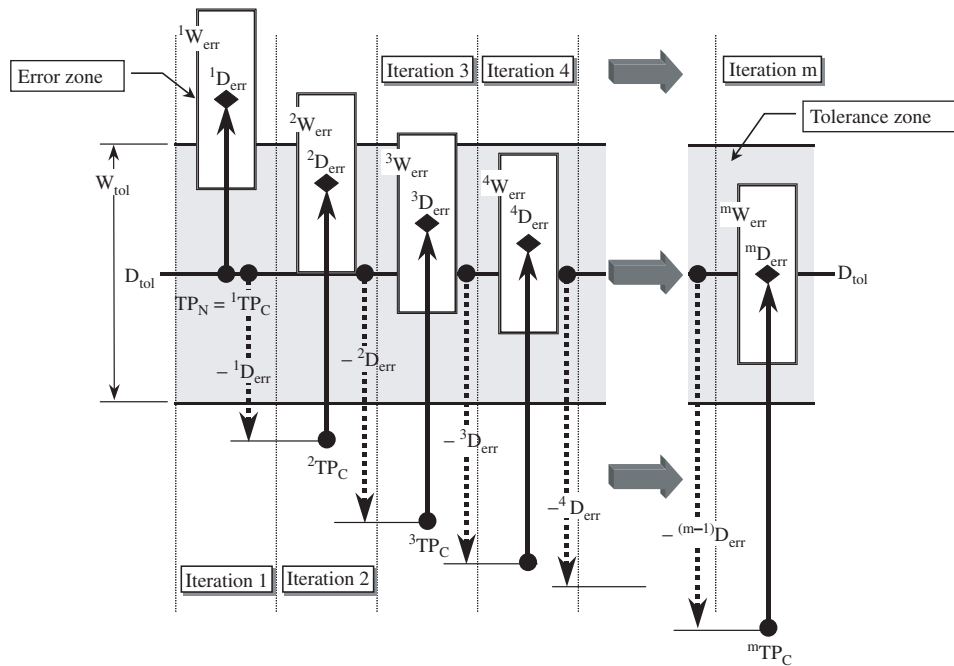


Fig. 5. Iterative procedures for tool position correction.

surface. Fig. 4 shows these parameters from a sectional view. Therefore, comparing only these parameters, it is possible to check whether the machined surface can meet the given tolerance.

2.4. Tool path correction methodology

When correcting a tool path based on the effects of the estimated machining error, the cutting conditions are changed compared to the previous conditions along the nominal tool path. That is, the changed cutting conditions induce changes on the machining errors, which affect the

initial estimate. Such things will be repeated until the changes of the error effects and the cutting conditions mutually decrease, and then, reach a state of balance. In this paper, an improved compensation process is proposed through a computational procedure, which consists of comparing the characterized machining error parameters with the tolerance to correct the tool path iteratively. Since this proposed approach is carried out only in the computational procedure before real machining processes, repetitive machining and inspection processes are not required even if the desired surface forms are changed. The tool path correction methodology is presented in Fig. 5.

When a nominal tool path is being generated in a CAM system, cutter location (CL)-point data are determined to prevent the interpolation errors between the CL-points from exceeding the given tolerance. If the initial shape of the workpiece between consecutive CL-points does not maintain the same form, the cutting tool will encounter a varied depth of cut while passing these CL-points. First, the nominal tool path has to be divided into an appropriate number of tool positions to take into account the depth of cut transitions. For each divided tool position, we apply an iterative procedure to search for the corrected tool position. This procedure is depicted in Fig. 5. Here,  $\text{TP}_N$  represents a divided tool position from a nominal tool path, and  ${}^i\text{TP}_C$  represent a corrected tool position at  $i$ th iteration. For each  $i$ th iteration, we compute values of  ${}^i\mathbf{W}_{\text{err}}$  and  ${}^i\mathbf{D}_{\text{err}}$  with respect to  ${}^i\mathbf{R}_D$  (radial depth of cut) corresponding to the corrected tool position  ${}^i\text{TP}_C$  by using the PNN model trained on the basis of the OMM inspection data. The corrected tool position  ${}^i\text{TP}_C$  is repetitively corrected by a previously computed value of  ${}^i\mathbf{D}_{\text{err}}$  until  ${}^i\mathbf{D}_{\text{err}}$  should be coincidental with  $\mathbf{D}_{\text{tol}}$ . Finally, it is possible to reach a  $m$ th iteration, where  ${}^m\mathbf{D}_{\text{err}}$ , computed at the tool position  ${}^m\text{TP}_C$  corrected by  ${}^{-(m-1)}\mathbf{D}_{\text{err}}$ , would be coincidental with  $\mathbf{D}_{\text{tol}}$ . This algorithmic will be applied into all the divided tool positions until we obtain all the corrected tool positions. Finally, a set of the corrected tool positions becomes a corrected tool path.

As mentioned, this tool path correction methodology is carried out in a computational process. According to circumstances,  ${}^m\mathbf{W}_{\text{err}}$  can be larger than  $\mathbf{W}_{\text{tol}}$  after finishing the tool position correction if a narrow tolerance is imposed on the desired surface. Since this case could be checked by using our tool path correction methodology, it is possible to avoid unnecessary tool path correction with respect to the tolerance. In other words, the computational tool path correction process allows us to find out tolerance criteria, which can be fulfilled in the given machining conditions.

### 3. Modified PNN algorithm application

#### 3.1. Polynomial neural network

The relationship between the tool deflection effects and the machining errors cannot be simply defined because the machining process includes a certain non-linearity. One of the approaches along the systematic design of nonlinear relationships is PNN, often referred to as group method of data handling (GMDH), which consists of a multi-layered perceptron-type network [8,9]. In this study, it is tried to model the nonlinear relationships between the characterized machining error parameters ( $\mathbf{W}_{\text{err}}$  and  $\mathbf{D}_{\text{err}}$ ) and the machining conditions by using the PNN approach.

The PNN algorithm [9] can be represented as a set of neurons whose different pairs in each layer are connected through a quadratic polynomial to produce new neurons in the next layer. Such representation can be used in modeling

to map inputs to outputs. The formal definition of the identification problem is to find an approximate function  $\hat{f}$  that can be used instead of the actual one,  $f$ , to predict output  $\hat{y}$  for a given input vector  $\mathbf{X} = (x_1, x_2, x_3, \dots, x_n)$  as close as possible to the actual output  $y$ . Therefore, multi-input-single-output data pairs for given  $M$  observations can be represented as follows:

$$y = f(x_{i1}, x_{i2}, x_{i3}, \dots, x_{in}) \quad \text{where } i = 1, 2, 3, \dots, M. \quad (2)$$

It is now possible to train a PNN to predict the output values  $\hat{y}_i$  for any given input vector  $\mathbf{X} = (x_{i1}, x_{i2}, x_{i3}, \dots, x_{in})$ , that is

$$\hat{y}_i = \hat{f}(x_{i1}, x_{i2}, x_{i3}, \dots, x_{in}) \quad \text{where } i = 1, 2, 3, \dots, M. \quad (3)$$

It is necessary now to determine a PNN so that the square of the difference between the actual output and the predicted one is minimized as follows:

$$\sum_{i=1}^M \{ \hat{f}(x_{i1}, x_{i2}, x_{i3}, \dots, x_{in}) - y_i \}^2 \rightarrow \min. \quad (4)$$

General connection between input and output variables can be expressed by a complicated polynomial form as follows:

$$y = a_0 + \sum_{i=1}^n a_i x_i + \sum_{i=1}^n \sum_{j=1}^n a_{ij} x_i x_j + \sum_{i=1}^n \sum_{j=1}^n \sum_{k=1}^n a_{ijk} x_i x_j x_k + \dots \quad (5)$$

This is known as the Ivakhnenko polynomial [8]. However, for most of the applications, the quadratic form of only two variables is used to predict output  $y$  as follows:

$$\hat{y} = G(x_i, x_j) = a_0 + a_1 x_i + a_2 x_j + a_3 x_i x_j + a_4 x_i^2 + a_5 x_j^2. \quad (6)$$

The coefficients  $a_i$  in Eq. (5) are calculated using regression techniques so that the difference between the actual output,  $y$ , and the calculated one,  $\hat{y}$ , for each pair of  $(x_i, x_j)$  as input variables is minimized. Indeed, a tree of polynomials is constructed using the quadratic form given in Eq. (6), whose coefficients are obtained in a least-squares sense. In this way, the coefficients of each quadratic function  $G_i$  are obtained to optimally fit the output in the whole set of input-output data pairs; that is,

$$r^2 = \frac{\sum_{i=1}^M (y_i - \hat{y})^2}{\sum_{i=1}^M y_i^2}. \quad (7)$$

In the basic form of the PNN, all the possibilities of two independent variables out of a total of  $n$  input variables are taken to construct the regression polynomial in the

form of Eq. (6) that best fits the dependent observations  $\{y_i, i = 1, 2, \dots, M\}$  in a least-squares sense.

$$\binom{n}{2} = \frac{n(n-1)}{2}. \quad (8)$$

Eq. (8) represents the number of neurons that will be constructed in the second layer of the feedforward network from the observations  $\{(y_i, x_{ip}, x_{iq}); i = 1, 2, 3, \dots, M\}$  for different  $p, q \in \{1, 2, 3, \dots, M\}$ . In other words, it is now possible to construct  $M$  data triples  $\{(y_i, x_{ip}, x_{iq}); i = 1, 2, 3, \dots, M\}$  from observation using such  $p, q \in \{1, 2, 3, \dots, M\}$  in the following form:

$p, q \in \{1, 2, 3, \dots, M\}$  the form

$$\begin{bmatrix} x_{1p} & x_{1q} & \dots & y_1 \\ x_{2p} & x_{2q} & \dots & y_2 \\ \dots & \dots & \dots & \dots \\ x_{Mp} & x_{Mq} & \dots & y_M \end{bmatrix}. \quad (9)$$

Using the quadratic sub-expression in the form of Eq. (9) for each row of  $M$  data triples, the following matrix equation can be readily obtained as follows:

$$\mathbf{A}\mathbf{a} = \mathbf{Y}, \quad (10)$$

where  $\mathbf{a}$  is the vector of unknown coefficients of the quadratic polynomial in Eq. (6).

$$\begin{aligned} \mathbf{a} &= \{a_0, a_1, a_2, a_3, a_4, a_5\}, \\ \mathbf{Y} &= \{y_1, y_2, y_3, \dots, y_M\}^T. \end{aligned} \quad (11)$$

$\mathbf{Y}$  is the vector of output values from observation, as follows:

$$\mathbf{A} = \begin{bmatrix} 1 & x_{1p} & x_{1q} & x_{1p}x_{1q} & x_{1p}^2 & x_{1q}^2 \\ 1 & x_{2p} & x_{2q} & x_{2p}x_{2q} & x_{2p}^2 & x_{2q}^2 \\ \dots & \dots & \dots & \dots & \dots & \dots \\ 1 & x_{Mp} & x_{Mq} & x_{Mp}x_{Mq} & x_{Mp}^2 & x_{Mq}^2 \end{bmatrix}. \quad (12)$$

The least-squares technique from multiple-regression analysis leads to the solution of the normal equations in the following form:

$$\mathbf{a} = (\mathbf{A}^T \mathbf{A})^{-1} \mathbf{A}^T \mathbf{Y}. \quad (13)$$

This equation determines the vector of the best coefficients of the quadratic Eq. (6) for the whole set of  $M$  data triples. However, such solution obtained directly from normal equations can be susceptible to round off error and, more importantly, to the singularity of these equations.

For a PNN application, the cutting conditions (radial depth of cut, axial depth of cut, feedrate) and  $\mathbf{W}_{\text{err}}$  and  $\mathbf{D}_{\text{err}}$  are taken into account as input–output pair data. The PNN model will be trained by the OMM inspection data on a machined specimen part. After training, the values of  $\mathbf{W}_{\text{err}}$  and  $\mathbf{D}_{\text{err}}$  can be determined for any given cutting conditions. This trained PNN will be used to correct the tool path by an iterative methodology.

Table 1  
Summarized algorithm

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```

iTPC = TPN; % Initialization of the corrected tool position iTPC
For i = 1 to M do
Begin
iRD = f(iTPC); % Calculation of the radial depth of cut iRD with respect
to iTPC
iWerr = PNN model(iRD); % Calculation of iWerr by the PNN model
iDerr = PNN model(iRD); % Calculation of iDerr by the PNN model
If (Dtot - iDerr ≈ 0)
Exit of "For statement";
Else
(i+1)TPC = Dtot - iDerr;
End
    
```

---

### 3.2. Modified PNN algorithm

In general PNN algorithm, errors are compared with the threshold value  $R$  at each node. Node outputs are selected only when the errors are smaller than  $R$ . However, such method can cause increasing number of remaining nodes, as node outputs become closer to the required outputs, and as such, the number of computational procedures can increase. Thus, in this study, the modified algorithm-terminating method [7] is employed, which uses variable (decreasing) threshold values as increasing layers. The following threshold conditions are calculated at each layer to avoid increasing node numbers.

$$R_s = R \text{ MIN}_s + \delta, \quad (14)$$

where  $\delta$  is a predefined value for proper computation.

### 3.3. System implementation using Ch language

In this study, required programs are developed using Ch language, which is developed by Cheng [3,4]. Ch is a general-purpose, block-structured interpretive programming language developed to be especially suitable for research and applications in scientific and system programming. The programmed algorithm is summarized as Table 1.

Also, to integrate the developed PNN program with existing OMM libraries, Ch SDK is used so that C/C++ scripts (Ch scripts) can be interfaced with C/C++ binary libraries. To implement a unified experimental environment, required A/D board library functions are interfaced with the main program using embedded Ch for cutting force variation monitoring. Schematic diagram for such procedure is illustrated in Fig. 6. Fig. 7 shows the implemented machining error compensation system structure based on the above-mentioned concept.

## 4. Experimental work

### 4.1. OMM system calibration

A laser interferometer is used to measure the geometric error components of a three-axis vertical machining center (HiMac-V100, Hyundai). Based on the measured error

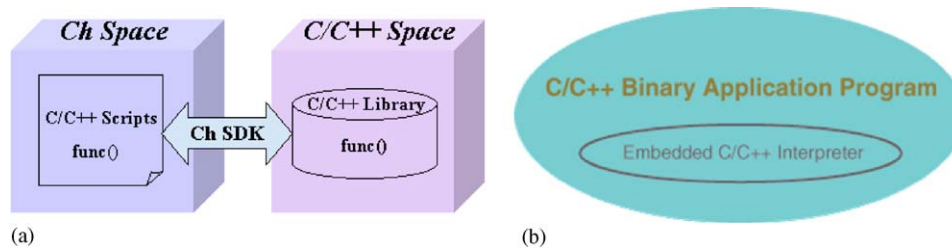


Fig. 6. Diagram for Ch SDK and Embedded Ch. (a) Ch SDK; (b) Embedded ch.

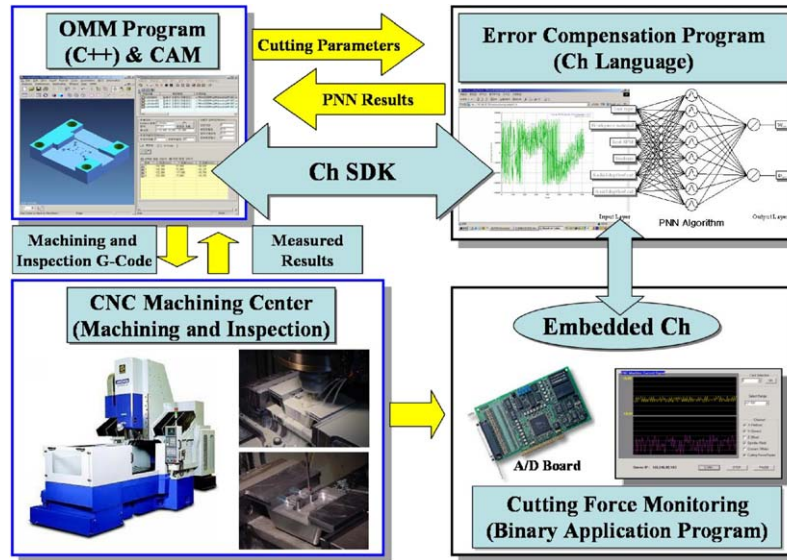


Fig. 7. Developed machining error compensation system structure.

components, the transformation matrices can be determined [5]. Since the transformation matrices are functions of the cutting tool or the probe locations, the geometric errors can be compensated when the CL-points or the probe positions are given. To compensate for the pre-travel variation errors, a certificate sphere, called the “master ball” (Renishaw, 25 mm-diameter), and a touch-type probe (Renishaw, 2 mm-diameter, 80 mm-stylus length) are used to make the probing error map, which depends on tilt and roll angle according to the probe-approaching directions. When using the OMM system on a three-axis machining center, tilt angle varies from  $0^\circ$  to  $90^\circ$ , and roll angle varies from  $0^\circ$  to  $360^\circ$ . In these ranges, the pre-travel variations are measured using a certificate sphere, which can vary according to the tilt angle and the roll angle. When inspecting the machining errors on the OMM system, the pre-travel variations are compensated on the basis of this probing error map. The tilt angle and the roll angle can be determined by the geometric shape of the desired surface corresponding to the CAD data.

#### 4.2. Determination of characterized machining error parameters

Through the geometric error compensation of the machining center and the probing errors, the machining

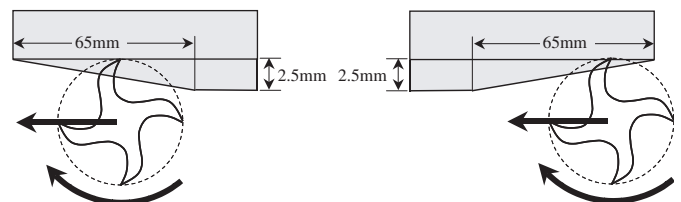


Fig. 8. Machining process of specimen workpieces.

and the inspection errors can be significantly reduced. Therefore, the tool deflection and run-out effects can become predominant factors causing machining errors. First, flat-end milling processes of two specimen workpieces are performed as shown in Fig. 8. Thus, it is possible to check the variations of  $W_{err}$  and  $D_{err}$ . In these machining processes, a flat-end mill with initially machined parts is used. The detail specifications of the cutter and the machining conditions are given in Table 1.

Surface errors, distributed on the machined surfaces, are measured using the OMM system. After  $E_{max}$  and  $E_{min}$  are determined at each position,  $W_{err}$  and  $D_{err}$  can be determined. According to the locations of the measuring points, it is possible to find out the values of the radial depth of cut  $R_D$  corresponding to all  $W_{err}$  and  $D_{err}$ . Based



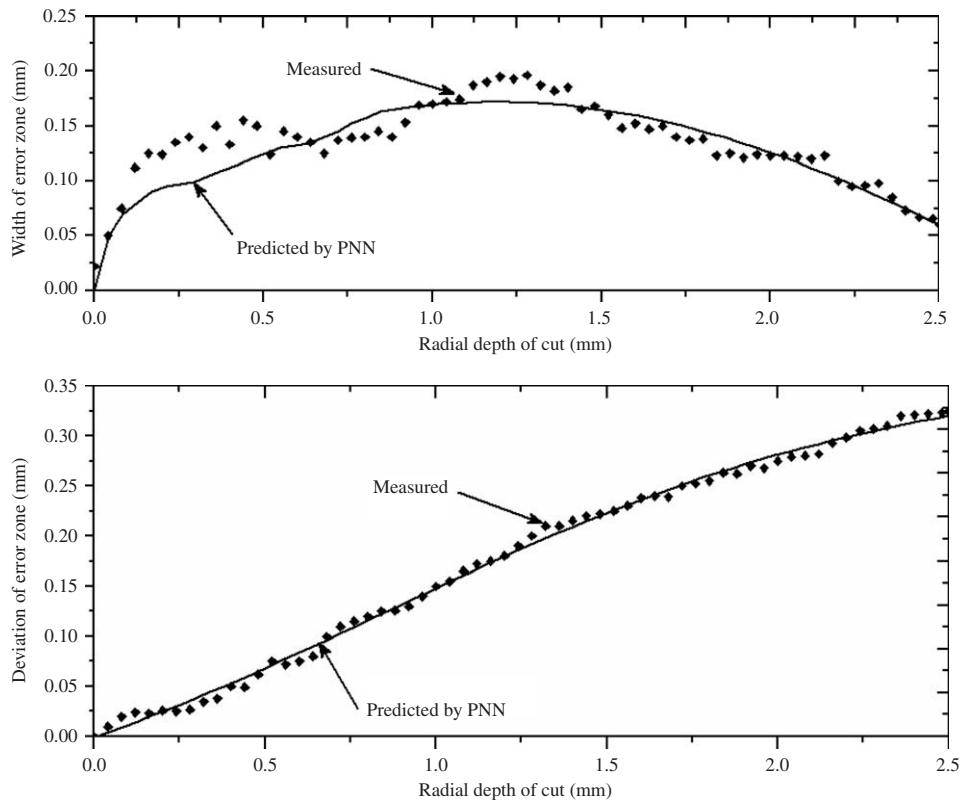


Fig. 9. Characterization of  $W_{err}$  and  $D_{err}$ .

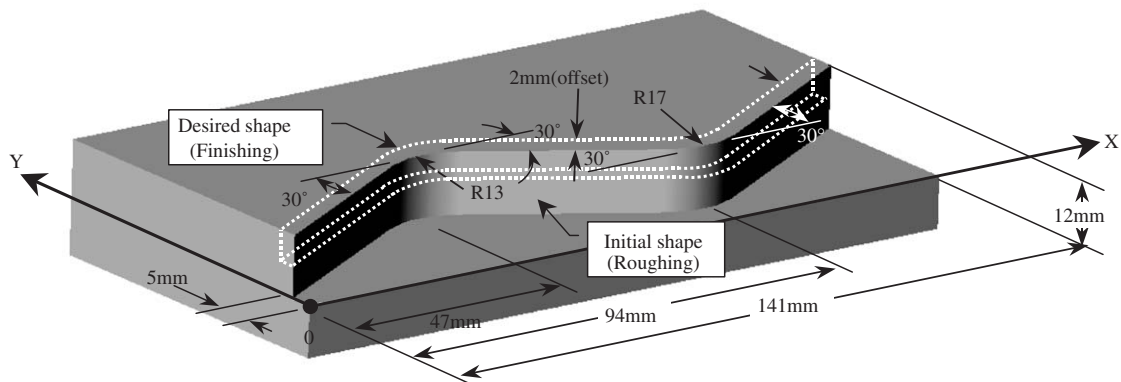


Fig. 10. Desired shape of machined part.

on the inspection data, the PNN model, which relates  $W_{err}$  and  $D_{err}$  to  $R_D$ , can be trained and Fig. 9 shows the values of  $W_{err}$  and  $D_{err}$  measured and predicted by the PNN model with respect to  $R_D$ .

### 4.3. Experimental results

Based on the PNN model trained by the OMM inspection data, it is tried to correct the cutting tool path for a different shape of a machining part. Fig. 10 shows the

Table 2  
Specifications of machining process

Tool		Machining conditions	
Flute part $\phi$	6 mm	Spindle speed	1500 rpm
Cylindrical part $\phi$	8 mm	Feedrate	30 mm/min
Used length	50 mm	Milling mode	Down milling
Flute part length	30 mm	Radial depth	0–2.5 mm
Flute number	4	Axial depth	6 mm (fixed)
Helix angle	30°	Workpiece	Mild steel

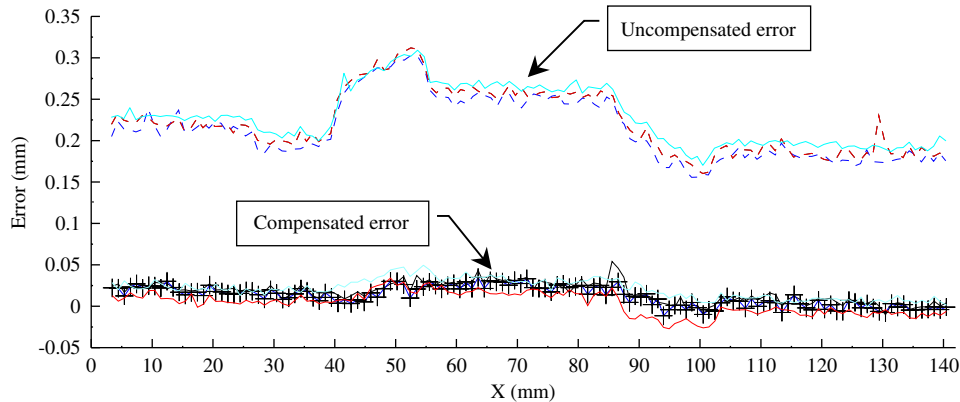


Fig. 11. Compensated machining error distributions.

desired shape for this machining part. This machining operation aims to manufacture an offset surface 2 mm from the roughed surface. The desired shape is a combination of straight lines and arcs. Therefore, the radial depth of cut varies along the tool path despite the 2 mm constant offset. Using the proposed tool path correction methodology, a new tool path is generated to minimize the errors, and two cutting processes are carried out with both uncorrected and corrected tool paths to compare error distributions under the cutting conditions shown in Table 2. Fig. 11 shows uncompensated and compensated surface error distributions. These results show that the compensated errors can be remarkably reduced by about 90 percent compared to uncompensated errors. Such results insist that the proposed machining error compensation method for flat end-milling process can be applied to real precision machining process.

## 5. Conclusions

The main purpose of this study is to implement an agile machining error compensation method for flat-end milling processes based on the PNN trained by the OMM inspection data. Based on the OMM inspection results, a PNN model for machining error prediction process is constructed by using Ch language. Thus, direct relationships between given machining conditions and the machining errors can be described. To correct the tool path for the machining error reduction, an iterative computational approach is applied, which repeatedly shifts the tool positions to reduce the predicted surface errors. In experimental examples, the compensated errors decrease remarkably by about 90 percent compared to uncompensated errors.

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## Further reading

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