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Adaptive Neuro-Fuzzy Control Methods for Milling Operations in Manufacturing Systems

Y. S. Tarng
National Taiwan University of Science and Technology

N. T. Hua
National Taiwan University of Science and Technology

G. J. Huang
National Taiwan University of Science and Technology

In this chapter, an adaptive neuro-fuzzy control system is developed and then applied to control milling processes with non-linear and time-varying cutting characteristics. First, a neuro-fuzzy logic controller is employed to obtain a constant milling force under varying cutting conditions. To obtain optimal control performance, a learning algorithm is used to tune the weights of the fuzzy rules. It is shown that the developed neuro-fuzzy logic controller can achieve an automatic adjustment of feed rate to optimize the production rate with a constant cutting force in milling operations.

6.1 Introduction

Increasing the productivity of machine tools is a principal concern for the manufacturing industry. In recent years, computer numerical control (CNC) has made great progress to increasing the productivity of machine tools [1]. However, a common drawback for CNC technology is that the selection of cutting parameters in the numerical control program is not straightforward, depending greatly upon the well-experienced programmers. To avoid the occurrence of a broken tool, poor surface accuracy, or varying cutting conditions, conservative cutting parameters are usually chosen in the whole machining cycle so as to reduce the productivity of CNC machine tools. Therefore, the use of an adaptive control system for adapting the cutting parameters to the cutting conditions is required [2]. However, machining processes contain complicated, non-linear, and time-varying characteristics due to the interaction of the dynamics of the chip-removal process, the structural dynamics of the machine tool, and the dynamics of the machine tool driver. Hence, the design of the adaptive controller in machining operations with high control performance is a difficult task even using various forms of modern adaptive control algorithms [3-6].

During the past decades, fuzzy control has been proven to be a powerful tool for dealing with complicated, non-linear, and time-varying systems [7]. This is because the fuzzy control action is based directly on the linguistic rules acquired from the knowledge of experts and expressed mathematically through the theory of fuzzy sets [8]. As a result, the fuzzy control can simulate the control action that a human expert would take when controlling the given process. The fuzzy control has also been applied to the control of milling operations [9]. However, there are some drawbacks to the approach using the fuzzy control. First, the fuzzy control design has relied on a priori knowledge of human experts and, thus, the controller performance is dependent on the quality of this expertise. Second, a reliable linguistic rule for the controlled process may not always be obtainable. Third, some significant process changes may be outside the operator's experience and the design procedure appears to be limited by the elucidation of the heuristic rules. Furthermore, evaluation and tuning of the fuzzy logic controller are typically done by a time-consuming trial and error manner. To solve these problems, an adaptive neuro-fuzzy logic controller has been proposed in this study. The adaptive neuro-fuzzy controller has a learning algorithm and is capable of modifying linguistic rules based on an evaluation of the system performance [10]. As a result, the proposed controller can start from an empty linguistic rule base. The modification of linguistic rules is achieved by assigning a credit to the control action based on the present control performance. Milling processes with varying depths of cut [11] are the controlled plant used in this study. It is shown that an optimal neuro-fuzzy logic controller can be obtained by a learning process to achieve an on-line adjustment of feed rate in milling operations with a constant cutting force.

In the following sections, an overview of the adaptive control of milling operations using the adaptive neuro-fuzzy control is described first. A milling process model used as the controlled plant is described next. Then, the development of the adaptive neuro-fuzzy control in milling operation with a constant cutting force is described. Finally, computer simulation and experimental verification of the adaptive neuro-fuzzy control system in milling operations are shown.

6.2 Adaptive Control System for Milling Operations

Basically, the use of an adaptive control system with a constant cutting force in milling operations is to achieve an automatic on-line adjustment of feed rate for optimizing the production rate. Usually, during the milling process, the radial or axial depth of cut increases; correspondingly, the cutting force increases also or even exceeds the preset constant cutting force. It is expected that the control system senses this increase and immediately generates a smaller feed rate to avoid tool breakage. On the other hand, as the radial or axial depth of cut decreases, the cutting force will decrease below the preset constant cutting force. Under this condition, the control system senses this decrease and automatically generates a larger feed rate to maintain the preset constant cutting force with a higher cutting efficiency.

In reality the definition, such as that for the larger or smaller feed rate, contains a certain degree of uncertainty and vagueness. Furthermore, machining processes contain highly non-linear, time-varying and complex characteristics. Therefore, designing the adaptive control system for machining operations is a challenging task. It has been shown that the adaptive neuro-fuzzy control not only has the better potential for controlling non-linear, time-varying, and complex system, but also is a very effective tool for dealing with an uncertain and vague system [12]. Therefore, an adaptive neuro-fuzzy control system has been proposed and developed for the control of milling operations in the present study.

6.3 Adaptive Neuro-Fuzzy Control of Milling Operations

The overall block diagram of the adaptive neuro-fuzzy control system in milling operations is shown in Fig. 6.1. It is shown that the measured cutting force F_c is compared with the reference cutting force F_r from which the error of the cutting force E and the change of the cutting force CF are obtained. These two signals, E and CF, are then sent into the neuro-fuzzy logic controller for generating the change of the feed rate ΔU. In addition, these two signals are also used to tune the structure of the neuro-fuzzy logic controller for improving the control performance in milling operations. The feed rate U is calculated based on the change of the feed rate ΔU. Therefore, an integral control action is generated to eliminate the steady state force error and then the measured cutting force F_c is equal to the reference cutting force F_r. However, the feed rate U must be constrained to a finite value to prevent an excessive cutting force breaking the cutting tool. Therefore, the maximum feed rate U_{max} is used if the feed rate U is greater than U_{max}. The determined feed rate, which is called the command feed rate $U_{com,}$ is sent directly to the machine tool driver system for producing the real feed rate V_f. The cutting tool then proceeds with the real feed rate V_f to cut a workpiece and to generate the measured cutting force F_c again. Hence, an on-line adjustment of feed rate to maintain the constant measured cutting force F_r under varying cutting conditions, can be achieved based on this control system.

Milling Controlled Process

For the machine tool driver shown in Fig. 6.1, the transfer function between the command feed rate U_{com}, and the real feed rate V_f can be expressed as:

$$\frac{V_f(s)}{U_{com}(s)} = \frac{K_n}{(s/\omega_n)^2 + 2\zeta(s/\omega_n) + 1} \tag{6.1}$$

where K_n is the gain of the servo; ω_n is the natural frequency of the servo; ζ is the damping ratio of the servo; and s is the variable of the Laplace transform.

The feed per tooth f_t in the milling process can be expressed as:

$$f_t = \frac{V_f}{Nm} \tag{6.2}$$

where m is the number of teeth and N is the spindle speed (rpm).

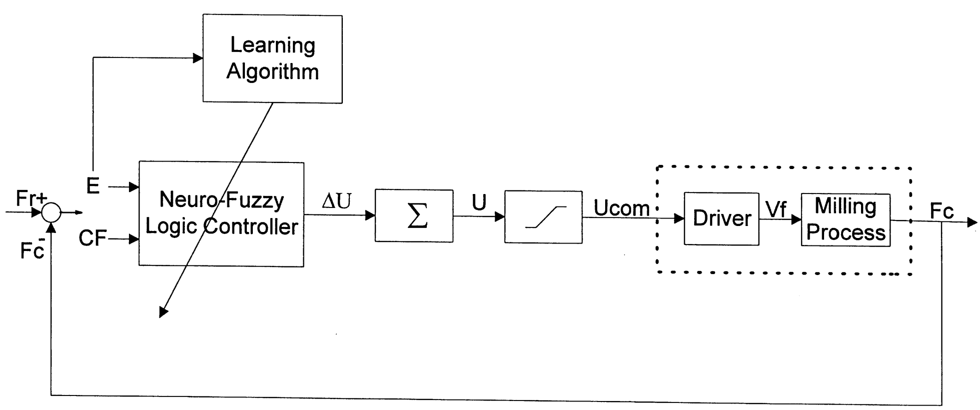

FIGURE 6.1 Block diagram of the adaptive neuro-fuzzy control system in milling operations.

The chip thickness h on each cutting edge, varying not only by the rotation position of the cutting edge but also by the cutter run-out, can be expressed as:

$$h = \begin{cases} f_t \sin\theta_i + (r_i - r_{r-1}) + h_i & \text{if } f_t \sin\theta_i + r_i > r_{i-1} \\ 0 & \text{if } f_t \sin\theta_i + r_i \leq r_{i-1} \end{cases} \tag{6.3}$$

where θ_i is the rotation angle of the i-th cutting edge, r_i is the radius of the i-th cutting edge, and h_i is the over-cut chip thickness for the i-th cutting edge, which can be expressed as:

$$h_i = \sum_{j=1}^{k} f_t \sin\theta_i + r_{i-j} - r_{i-j-1} \quad \text{until } f_t \sin\theta_i + r_{i-k} - r_{i-k-1} > 0 \tag{6.4}$$

The tangential force and the corresponding radial force acting on the cutting edge can be expressed as:

$$F_t = k_s b h \tag{6.5}$$

$$F_r = k_r F_t \tag{6.6}$$

where b is the axial depth of cut and k_r is the ratio of the tangential force and radial force.

The cutting forces acting on the cutting edge in the X and Y directions can be obtained by decomposing the tangential force F_t and radial force F_r into the X and Y directions:

$$F_x(\theta_i) = F_t \cos\theta_i + F_r \sin\theta_i \tag{6.7}$$

$$F_x(\theta_i) = -F_t \sin\theta_i + F_r \cos\theta_i \tag{6.8}$$

Then, the cutting forces in the X and Y directions with multiple cutting edges can be expressed as:

$$F_X = \sum_{i=1}^{m} \delta(i) F_x(\theta_i) \tag{6.9}$$

$$F_Y = \sum_{i=1}^{m} \delta(i) F_y(\theta_i) \tag{6.10}$$

and

$$\delta(i) = \begin{cases} 1 & \text{if } \theta_s \leq \theta_i \leq \theta_e \\ 0 & \text{otherwise} \end{cases} \tag{6.11}$$

where m is the number of teeth on the cutter, θ_s is the start angle of cut, and θ_e is the exit angle of cut.

Basically, the start angle of cut θ_s and the exit angle of cut θ_e are a function of the radial depth of cut and the geometry of workpiece. Finally, the resultant cutting force F_c can be expressed as:

$$F_c = (F_X^2 + F_Y^2)^{1/2} \tag{6.12}$$

From Eqs. (6.1) through (6.12), it can be seen that the transfer function of the controlled process between the resultant cutting force F and the command feed rate U_{com} contains complicated, non-linear, and time-varying characteristics. The change of cutting parameters such as axial depth of cut b, spindle speed N, and radial depth of cut varies the open-loop gain of the controlled process. Since the performance of the control system (Fig. 6.1) is characterized by the open-loop gain of the controlled process, any variation in these parameters will directly affect the control system response and might even cause instability. Therefore, the use of the neuro-fuzzy logic controller for improving control performance under variations of these cutting parameters will be discussed next.

Neuro-Fuzzy Logic Controller

The neuro-fuzzy logic controller developed in this study is composed of a number of fully interconnected nodes and well organized into four layers (i.e., input layer, membership layer, rule layer, and output layer). Nodes on the first layer are used to receive and normalize the physical inputs of the controller by the scaling factors. The normalized physical inputs are then fuzzified by the membership functions in the second layer. Next, the third layer performs a fuzzy reasoning on control rules to generate an inference output on each rule. Each inference output has its corresponding weight in the output layer. Finally, the weighted inference outputs are summed to produce the output of the controller. The structure of the two-input-one-output neuro-fuzzy control system used in milling operations is shown in Fig. 6.2. In the following, the function of the neuro-fuzzy logic controller is described as follows.

The measured resultant cutting force F_c is compared with a reference cutting force F_r and converted into two controller inputs, the cutting force error E and the cutting force change CF, that is:

$$E(i) = F_r - F_c(i) \tag{6.13}$$

$$CF(i) = F_c(i) - F_c(i-1) \tag{6.14}$$

where i is the index of time increment for sampling the cutting force.

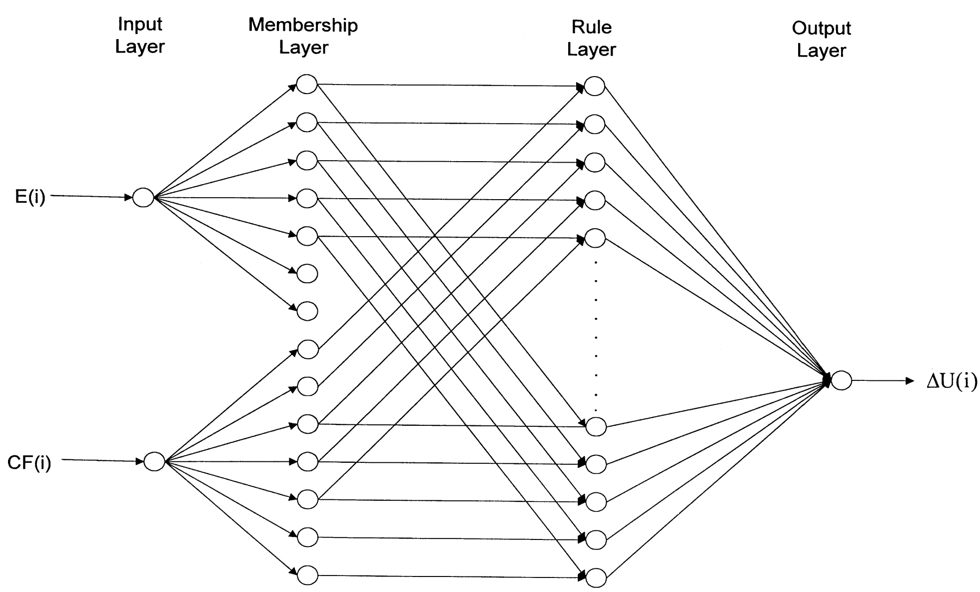

FIGURE 6.2 Structure of the two-input-one-output neuro-fuzzy logic controller.

Therefore, there are two nodes in the input layer of the controller. The two inputs are normalized in the closed interval $[-1, 1]$ by multiplying the corresponding scaling factors, *GE* and *GCF*, that is:

$$e(i) = GE\ E(i) \tag{6.15}$$

$$cf(i) = GCF\ CF(i) \tag{6.16}$$

where $e(i)$ and $cf(i)$ are the two normalized inputs.

The normalized inputs are then mapped into suitable linguistic values by using the membership function of the fuzzy sets. A simple triangular shape of the membership function for grading the membership of the class from members to non-members is used in this study. The triangular membership function $\mu_A(x)$for a linguistic (fuzzy) set A where $-b \le x \le b$ is defined as:

$$\mu_A(x) = \begin{cases} \dfrac{x+b}{a+b} & -b \le x \le a \\ \dfrac{x-b}{a-b} & a \le x \le b \end{cases} \tag{6.17}$$

In the membership layer, seven linguistic sets are defined as follows: NB - negative big; NM - negative medium; NS - negative small; ZE - zero; PB - positive big; PM - positive medium; PS - positive small. Figure 6.3 shows the shapes of seven linguistic sets for the two normalized inputs. As discussed before, each normalized input is mapped into seven linguistic sets; therefore, the membership layer has fourteen nodes due to the two normalized inputs (Fig. 6.2). As to the rule layer, 49 (7×7) linguistic rules are constructed because seven linguistic sets of the normalized input e are fully interconnected with seven linguistic sets of the normalized input *cf*. It also means that 49 nodes are available in the rule layer. Let the j-th linguistic (fuzzy) control rule be described as follows:

$$\text{if } e \text{ is } A_j \text{ and } cf \text{ is } B_j \text{ then } z \text{ is } C_j.$$

By taking the product compositional operation [7], the fuzzy reasoning of the control rule yields an inference output. Suppose $e = e_o$ and $cf = cf_o$ are the two normalized inputs at time i. The membership function for the j-th rule can be expressed as:

$$\mu_{c_j}(i) = (\mu_{A_j}(x_o) \cdot \mu_{B_j}(y_o)) \tag{6.18}$$

The inference output $\mu_{c_j}(i)$ has its corresponding weight $w_j(i)$ in the output layer. The weighted inference output is equal to the product of the inference output $\mu_{c_j}(i)$ and its corresponding weight $w_j(i)$.

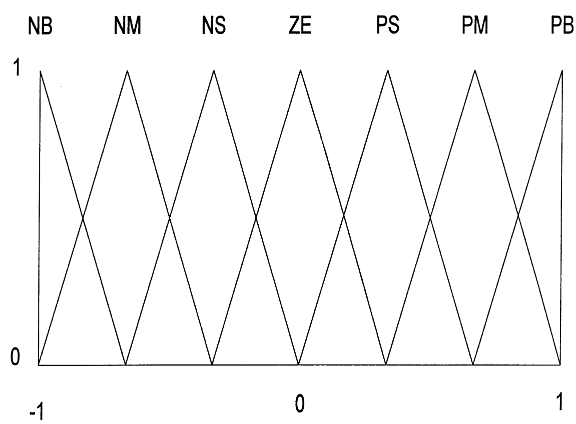

FIGURE 6.3 Shapes of the seven linguistic sets.

The weighted inference outputs are summed to produce the output value of defuzzification $\Delta u(i)$, that can be expressed as:

$$\Delta u(i) = \sum_{j=1}^{n} \mu_{c_j}(i) w_j(i) \tag{6.19}$$

where n is the total number of fuzzy rules in the rule layer.

The output value of defuzzification $\Delta u(i)$, multiplied by the output scaling factor of the controller GU results in the change of feed rate $\Delta U(i)$, that is:

$$\Delta U(i) = GU\Delta u(i) \tag{6.20}$$

Finally, the feed rate U can then be expressed as:

$$U(i) = U(i-1) + \Delta U(i) \tag{6.21}$$

Learning Algorithm for the Neuro-Fuzzy Logic Controller

It is known that the use of the developed neuro-fuzzy logic controller in milling operations is to achieve an on-line adjustment of feed rate with a constant cutting force. To reach the constant cutting force F_r as soon as possible, the cutting force error E and the cutting force change CF must quickly approach zero. Therefore, a performance index that is a function of the normalized force error $e(i)$ and the normalized force error change $cf(i)$ during cutting must be minimized. The performance index PI can be defined as:

$$PI = \frac{1}{2}\sum_{i=1}^{k} (e(i)^2 + \rho \cdot cf(i)^2) \tag{6.22}$$

where k is the total number of sampling data and ρ is a weighting factor.

The negative gradient of the performance index for the optimal control performance [13] can be expressed as:

$$-|\nabla PI| = (-|e(i)| - |cf(i)|) \tag{6.23}$$

To simplify the learning process, only the weight connected with the maximum inference output is adjusted. A change of weight for the j-th rule with the maximum inference output μ; *(i)*can be expressed as:

$$\Delta w_j(i) = \eta(-|\nabla PI|)\begin{bmatrix} e(i) \\ cf(i) \end{bmatrix} \tag{6.24}$$

where η is the learning rate.

The new weight $w_j(i)^{\text{new}}$ corresponding to the maximum inference output $\mu_j(i)$ can then be expressed as:

$$w_j(i)^{\text{new}} = w_j(i)^{\text{old}} + \Delta w_j(i) \tag{6.25}$$

6.4 Computer Simulation and Experimental Verification

Computer Simulation

In the simulation, a 12 mm diameter HSS end mill with four flutes, rotating 400 rpm, machining 6061 aluminum blocks ($k_s = 1500$ N/mm^2, $k_r = 0.6$) was used. The reference force of 300 N and the maximum feed rate U_{max} of 75 mm/min were selected in the control loop (Fig. 6.1). The peak resultant cutting force in a revolution is the criterion to be controlled in the adaptive neuro-fuzzy control system. The scaling factors of the controller, $GE = 0.0033$, $GCF = 0.0017$, $GU = 0.1$, were chosen, respectively. Since this control system is a sampled-data system, the machine tool driver [Eq. (6.1)] needs to be identified by using Z-transform.

The cut geometry with the changes of the axial depth of cut in milling operations is shown in Fig. 6.4. Figure 6.5 shows the variation of the *PI* value with the number of learning (cutting) cycles. The weighting factor $\rho = 6$ and the learning rate $\eta = 0.25$ were used in the learning process. It can be seen that the *PI* value decreases as the number of learning cycles increases. The initial learning convergence of the *PI* value is very fast, followed by a period of slower convergence to the minimum value. Hence, it can be clearly shown that control performance of the milling process becomes better and better through the learning process.

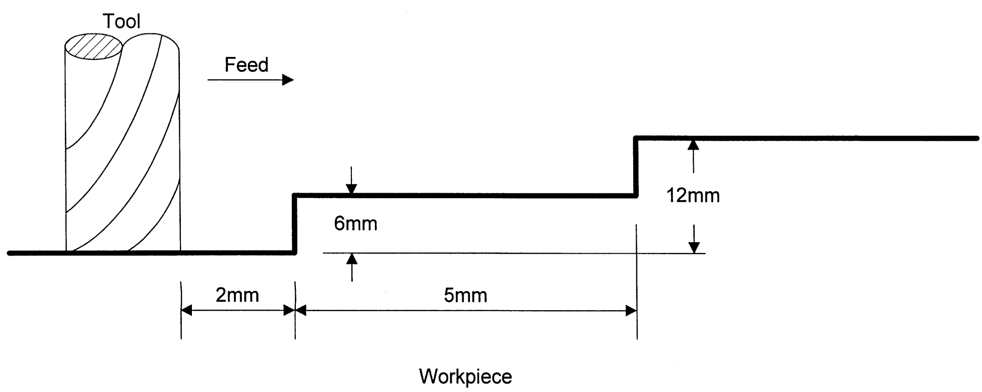

FIGURE 6.4 Cut geometry with the changes of the axial depth of cut.

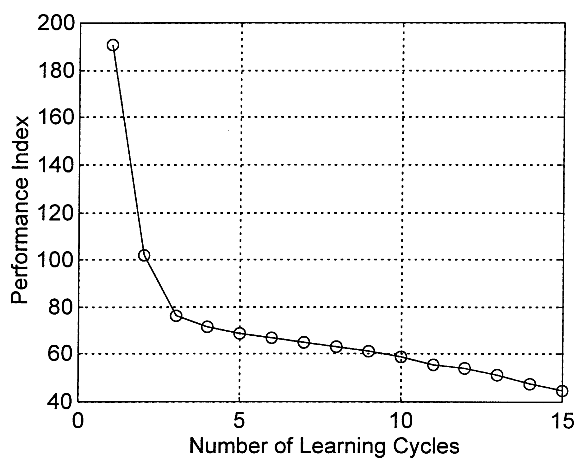

FIGURE 6.5 Effect of the *PI* value on the learning cycle.

The learning process was terminated after 15 cutting cycles because the improvement rate of the *PI* value became insignificant. After the learning process is completed, the weights in the output layer are no longer changed and the neuro-fuzzy logic controller is ready to be applied for machining tests.

Experimental Results and Discussion

To verify the adaptive neuro-fuzzy logic controller, cutting tests with the same cutting conditions as mentioned before were performed on the CNC machining center. The cutting force signal was obtained from a dynamometer (Kistler 9255B) mounted under the workpiece and the feed rate signal was directly measured and extracted from the CNC controller. Both signals were recorded on a PC-486 through a data acquisition board (DT2828).

Figure 6.6 shows the measured feed rate and measured cutting force during machining of the cut geometry with the changes of the axial depth of cut. As shown in Fig. 6.4, the end mill starts 2.0 mm from the workpiece. Since the end mill has not entered the workpiece, the maximum feed rate should be used in order to save the machining time (Fig. 6.6(a)). Once the cutting tool starts to engage the workpiece with the axial depth of cut of 6 mm, a sudden overshoot of the cutting force is generated (Fig. 6.6(b)). The cutting tool is quickly slowed down to prevent the excessive cutting force breaking the cutting tool. After the cutting force returns to the level of the reference force F_r, the cutting tool proceeds at a constant feed rate. A similar cutting phenomenon is also shown in the change of the depth of cut from 6 mm to 12 mm.

A more complicated pocket workpiece with a spiral-out tool path (Fig. 6.7) was used in the experiments. In this pocket machining, the radial depth of cut varies not only by way of different traveling paths but also by different positions of a path [14]. Figure 6.8(a) shows the cutting force and machining time using the constant feed rate generated by a commercialized CAD/CAM system. The use of the constant feed rate generated by the CAD/CAM system is the most common approach in the industry. Figure 6.8(b) shows the cutting force and machining time using the adaptive feed rate generated by the adaptive neuro-fuzzy controller. It is shown that machining time saved is about 23% through this approach.

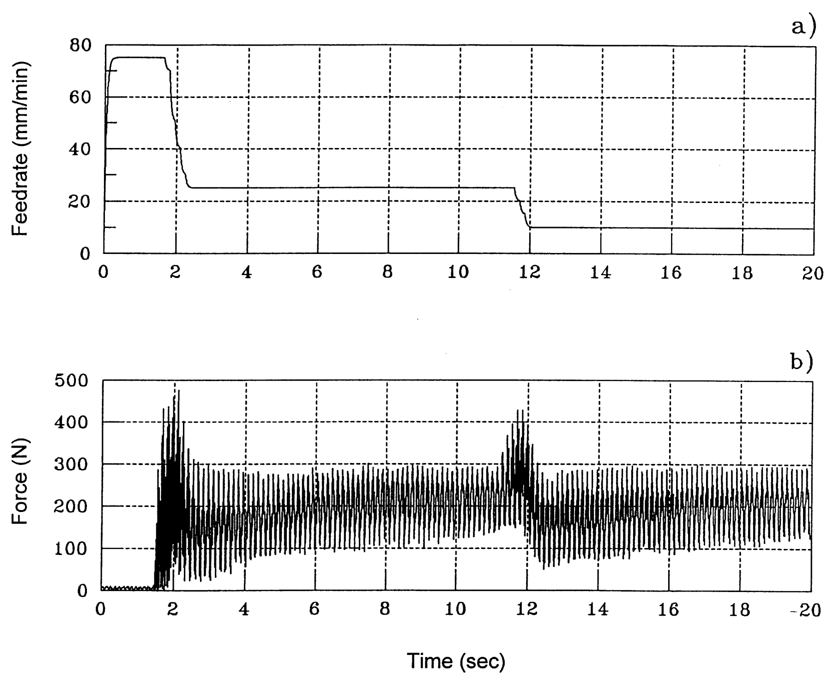

FIGURE 6.6 Experimental results with the changes of the axial depth of cut: (a) measured feed rate; (b) measured cutting force (reference force = 300 N; spindle speed = 400 rpm).

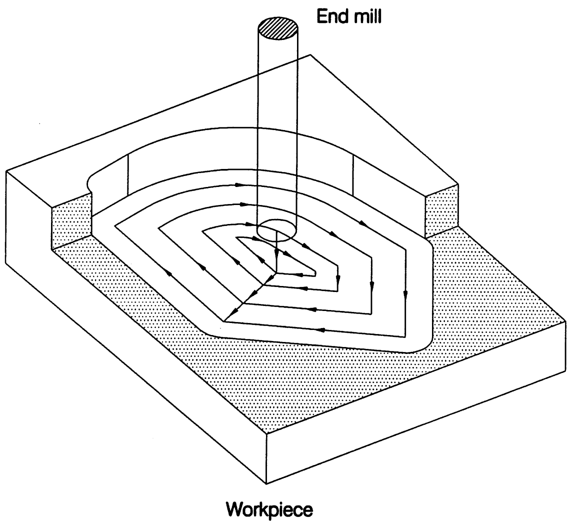

FIGURE 6.7 Pocket machining with a numerical control tool path.

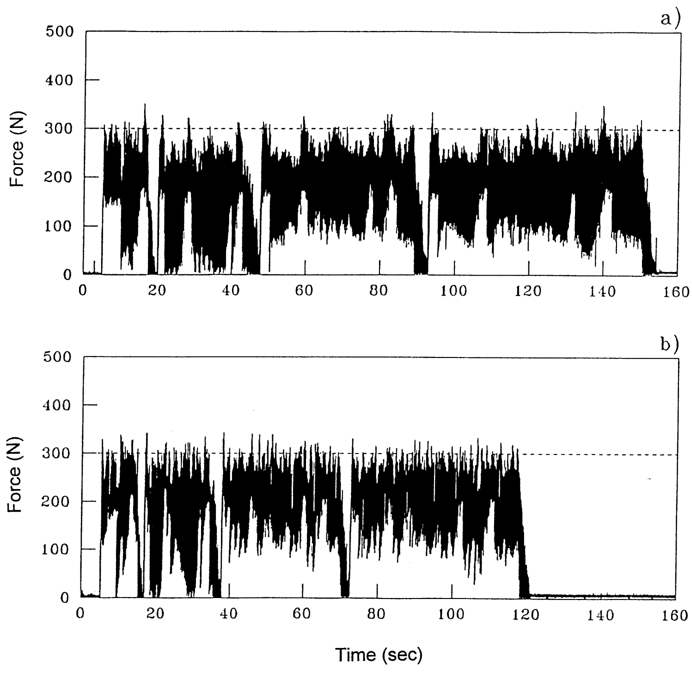

FIGURE 6.8 Measured cutting forces for the pocket machining: (a) without the adaptive neuro-fuzzy control; (b) with the adaptive neuro-fuzzy control (reference force = 300 N; spindle speed = 400 rpm).

6.5 Conclusions

An adaptive neuro-fuzzy control system in milling operations has been described in this paper. The main advantage of this approach is that the control performance of the neuro-fuzzy logic controller can be improved through the learning process. As a result, the proposed adaptive controller starts from an empty rule base and the design cycle time for the neuro-fuzzy control system can be greatly reduced.

Computational simulations and experimental cutting tests have been performed in milling operations to confirm the proposed method. Good control performance of feed rate and cutting force in milling processes have also been shown. Hence, a powerful technique for constructing the adaptive control system in milling operations has been demonstrated in this study.

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