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Intelligent Machining System Based on CNC Controller Parameter Selection and Optimization

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ABSTRACT This paper introduces an intelligent machining system (IMS) using an adaptive-network-based fuzzy inference system (ANFIS) predictor and the particle swarm optimization (PSO) algorithm with a hybrid objective function. The proposed IMS provides suitable machining parameters for the users, to satisfy different machining requirements such as accuracy, surface smoothness, and speed. First, the key computer numerical control parameters are selected, and the actual trajectories under different machining parameters obtained by linear scales are collected. These data are analyzed to obtain the machining time, contouring error, and tracking error, corresponding to the speed, milling accuracy, and surface smoothness, respectively. Second, a data-driven approach using ANFIS is established to obtain the corresponding relationship model between the machining parameters and three aforementioned performance indices. Subsequently, to establish the IMS, we combine the trained ANFIS model and establish a hybrid objective function optimization problem solved by PSO algorithm according the specific requirement of the user. Finally, the performance and effectiveness of the proposed machining system is demonstrated by experimental practical machining.

INDEX TERMS Machine tools, machining parameters, ANFIS, PSO, optimization.

I. INTRODUCTION

Recently, in the context of Industry 4.0, manufacturing systems are being updated to an intelligent level [1], [2]. The Internet of Things (IoT) and a cyber physical system (CPS) are the key enablers for the next-generation advanced manufacturing systems [3], [4]. At present, computer numerical control (CNC) machining tools are widely used in the industry, making the operation of machine tools convenient. Smooth surface finish and high dimensional precision are some of the requirements of product quality. However, these factors depend on highly skilled operators owing to the specific requirements of different machines and the numerous parameters of the CNC controller. For instance, manufacturers demand a highly-efficient and high-quality CNC machine to reduce defective product rates. This is the reason machining capabilities are extremely important for machine tools [5], [6]. Manufacturers are also concerned about the machining speed, milling accuracy, and smooth surface serving as the machining performance indices. Each product has different machining requirements during the manufacturing processes, and the machining parameter selection of the controllers of the machine tools significantly affect the performance indices. Therefore, in this study, CNC machining parameters are provided by the proposed intelligent machining system (IMS) to achieve the required product quality.

There are several studies on optimizing machining operations [7]–[15]. Literature [7], [8] introduce a virtual CNC system to implement high-speed contouring applications. Chou introduced the concept of a machining expert system [9]. For obtaining accurate surface roughness or machining accuracy prediction, data-driven and neural-fuzzy approaches were presented in [10]–[15]. In addition, an optimization method to minimize surface roughness using an artificial neural network and genetic algorithm was proposed in [16]. To optimize CNC machining parameters, the particle swarm optimization (PSO) algorithm was implemented [17], [18]. In addition, several articles focus on interpolation methods for motion

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control to achieve a high accuracy [19]–[22]. However, the optimization of CNC parameters for simultaneously achieving accuracy, surface smoothness, and speed, is less common. Herein, a hybrid-objective function is designed according to the requirement of the user and then the optimal solution is obtained by PSO.

In this paper, we propose an intelligent system for the selection of CNC machining parameters and optimization of three machining performance indices. This system adopts the techniques of an adaptive-network-based fuzzy inference system (ANFIS) model [23], a hybrid objective function, and the PSO algorithm [24]. The ANFIS plays the role of a surrogate model and we adopt PSO to solve the hybrid-objective function to optimize the machining parameters. In machine tools applications, a surrogate model is used when the outcome of interest cannot be easily directly measured; therefore, a model of the outcome is used instead. In addition, the weighting vectors of the hybrid objective function are selected by the specific requirements of the user according to the product quality. Figure 1 shows the concept of the proposed IMS with one touch operation. Each product has different machining requirements during its manufacturing process, and the main concerns are the machining speed, work piece accuracy, and surface smoothness. However, the adjustment of CNC machining parameters for the three performance indices is not a simple procedure, owing to the fact that the performance indices contradict each other. Therefore, the different performance indices must have their own appropriate CNC machining parameters set. Thus, we here develop an IMS to solve this problem; it can provide the optimum machining parameters for the users according to the product index performance requirements. Finally, the results of practical machining are presented to illustrate the efficiency of the proposed parameter selection system.

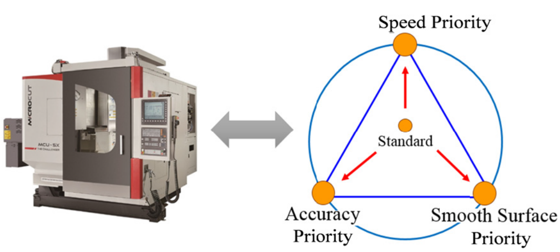


FIGURE 1. Illustration of the machining performance indices.

The remainder of this paper is as follows. Section II introduces the preliminaries including the machining parameters, machining performance index, and used machine tool specification. The major contribution of this paper, the IMS using ANFIS and PSO, is introduced in Section III. The experimental validation is presented to demonstrate the performance and effectiveness of our approach. Finally, the conclusion is given.

II. PRELIMINARIES

Herein, we introduce the preliminaries including the machining parameters, performance indices, and used machine tool specification.

A. CNC MACHINING PARAMETERS

Machining a product that adheres to certain requirements might be a difficult procedure depending on several factors. These factors are related to the mechanical components of the CNC or the control of its motion axes [9], [25]–[28]. The CNC controllers are fundamental for the performance owing to the fact that CNC machining capabilities are directly related to the parameter settings of milling. This study considers three main performance indices: the milling accuracy, surface smoothness, and machining speed.

Each CNC controller provides several parameters whose definitions might vary from manufacturer to manufacturer; these parameters influence the resulting product quality. Hence, it is crucial to select and tune the main parameters to achieve the desired performance indices. These machining parameters are jerk, acceleration, federate, jerk of corner, and centripetal acceleration. This because most CNC controllers are based on the jerk control to generate the tool paths following an order jerk, acceleration/deceleration, velocity, and position [13], [28]. Table 1 lists the definitions of the selected machining parameters. Accord to the selected parameters, the tool paths are generated by interpolation [20]–[22], [27]. The function of an interpolator is to generate the reference axis commands and a smooth velocity variation based on the kinematic profiles of the tool path. These sequences of the reference axis commands are fed to the servo loop of the feed drive system of each motion axis. The main goal while planning the tool paths is to maintain a smooth velocity transition during the high-speed machining process. CNC machining parameters affect the trajectory and velocity planning during the interpolation process. Thus, the selection of machining parameters is an extremely important factor for achieving good performance indices.

TABLE 1. Definition of CNC controller parameters.

Parameters	Definition
J_{max} [m/ s^3]	maximum permissible jerk
A_{max} [m/ s^2]	maximum permissible acceleration
F_{max} [mm/min]	maximum permissible feed rate
$J_{c,max}$ [m/ s^3]	maximum permissible jerk at corners or tangential transitions
$A_{r,max}$ [m/ s^2]	maximum radial acceleration on circles and curved paths

In this study, there are five key CNC machining parameters (J_{max}, A_{max}, F_{max}, $J_{c,max}$, and $A_{r,max}$) that affect the milling accuracy, surface smoothness, and machining speed. Parameters (J_{max}, A_{max}, and F_{max}) control the profile planning of the jerk, acceleration, and velocity, respectively. The virtual controller software of TNC640 by HEIDENHAIN was used to simulate the parameter adjustment of J_{max}, A_{max}, and F_{max} and observe the variations in the commanded curve [29], [30]. Following several simulations and experiments, we have the following results.

1) The planning of the jerk profile is limited by the parameter J_{max}, and the planning of the acceleration is indirectly affected.
2) The acceleration profile is limited by the parameter A_{max}, and the planning of the jerk is also indirectly affected.
3) $J_{c,max}$ predominantly controls the jerk and affects the velocity at the corner of the tool path.
4) $J_{c,max}$ significantly affects the jerk of the corner, and indirectly affects the planning of the velocity profile.
5) $A_{r,max}$ controls the velocity along the circular and curved paths; the velocity can be calculated according to the formula of centripetal acceleration ($V = \sqrt{A \times R}$), where V is the tangential velocity of the circle, A is the centripetal acceleration, and R is the radius of the circle.

More detailed descriptions can be found in [31].

B. MACHINING PERFORMANCE INDICES

The quality of finished products is defined by how close the finished product adheres to the specification. The generally used performance indice are machining accuracy and surface smoothness (or surface roughness). Another considered factor is the machining speed; it is inversely proportional to the accuracy and surface smoothness. As mentioned above, the values of the performance indices are affected by the selected CNC machining parameters. The experimental data are collected by linear scales to calculate the contouring error, tracking error, and machining time. The trending effects of each machining parameter on the milling accuracy, surface smoothness, and machining speed are obtained after analyzing these data. The illustration of our approach is shown in Fig. 2; a detailed description will be introduced in Section III.

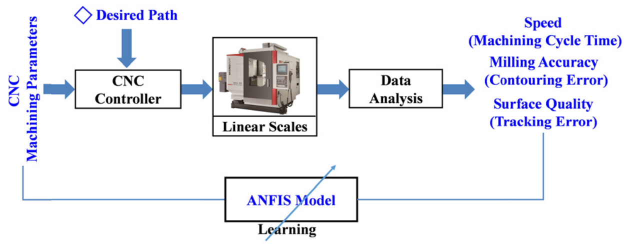
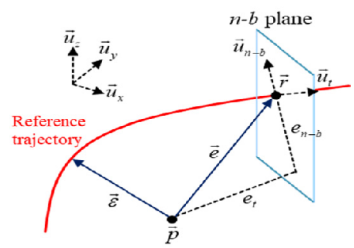


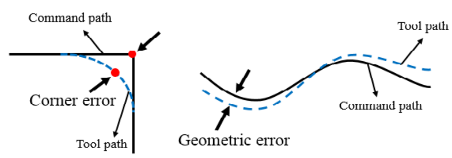
FIGURE 2. Illustration of data collection and training scheme for the intelligent machining system.

1) MILLING ACCURACY

To assess the milling accuracy, the contouring error, including the corner and geometric errors, is used for evaluation, i.e., a large contouring error value corresponds to a low accuracy. The corner error is defined as the shortest distance between the measured tool path and the vertex of the ideal corner path [9], [28]. The geometric error is the distance between the ideal and measured tool paths. Figure 3 illustrates the contouring error. Figure 3(a) illustrates the tracking error $\vec{e}$ and contour error $\vec{\varepsilon}$ where x, y, and z of $\vec{u}$ are the unit vectors, where $\vec{r} = [r_x, r_y, r_z]$ is the reference position, $\vec{p} = [p_x, p_y, p_z]$ is the actual position, and $\vec{r}_{path}$ is the trajectory position. $\vec{e}$ and $\vec{\varepsilon}$ can be illustrated in the t–n–b coordinate frame. The symbols, t, n, and b, of e denote the tangential, normal, and binormal vectors. The corner and geometric errors are presented in Fig. 3(b) [13]. References [13] and [31] report several experiments and simulations of a rhombus path, to observe the effects of the performance indices on adjusting each CNC machining parameter individually. From the experimental results, it can be seen that the contouring error increases when the values of the parameters J_{max}, A_{max}, F_{max}, $J_{c,max}$, and $A_{r,max}$ increase. Therefore, it can be concluded that the milling accuracy decreases with an increase in the values of the five machining parameter.



(a)



(b)

FIGURE 3. Illustration of the contouring error, (a) tracking error and contouring error in the tool paths; (b) corner error and geometric error.

2) SURFACE SMOOTHNESS

Surface smoothness (or surface quality) is the most frequently used index to evaluate the machining quality in terms of surface roughness. It is defined as the fine irregularities produced on a workpiece on using a cutting tool. Fig. 4 shows the illustration of the roughness and waviness on a machining surface [30]. According to the results of [9], [13], [31], the surface smoothness is proportional to the tracking error, $\vec{\varepsilon}$ (as shown in Fig. 3(a)); therefore, herein, we use the tracking error to evaluate the corresponding surface smoothness. As shown in Fig. 3(a), the tracking error is the error between command and actual values.

3) MACHINING SPEED

In the machining process, the machining speed is evaluated by measuring the time for the axes motion, called as the

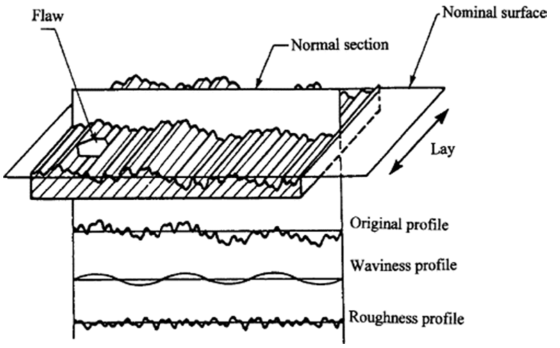


FIGURE 4. Illustration of the roughness and waviness on a surface [32].

cycle time. Different machining times under different CNC parameters are obtained, and the corresponding experimental results are shown in Fig. 5. This shows that the machining time decreases with increasing values of the machining parameters, i.e., the machining speed is proportional to the selected CNC parameters. Therefore, it can be concluded that increasing the machining parameters can enhance the machining speed.

C. SPECIFICATIONS OF CNC MACHINE TOOL

In this study, the Microcut-MCU-5X five-axis CNC machine tool was used to collect the experimental data. Figure 6 and Table 2 introduce the used machinery and major specifications, respectively. The type of CNC controller used is HEIDENHAIN TNC640 [30]. HEIDENHAIN TNSCOPE software was used to collect data such as the corresponding position, velocity, acceleration, and jerk for each axis. The sampling time for the data collection is 3 ms, and the feedback of the control system is a closed loop.

TABLE 2. Major specifications of machine tool (Microcut-MCU-5X).

X/Y/Z axes travel [mm]	600/600/500
Rapid traverse X/Y/Z [mm/min]	36000/36000/36000
Maximum speed A/C [rpm]	16.6/90
Spindle speed range [rpm]	12000 (std)/15000 (opt)
Rapid traverse X/Y/Z [mm/min]	36000/36000/36000
Maximum weight on the table [kg]	600
Machine weight [kg]	8000
Type of position control	Full-closed control

The position control loop includes dynamic characteristics such as the resonance of the machine body, stick slip, friction, back-lash, and axial motion, they cause machining errors. It signifies that it is impossible for a machine tool to move perfectly according to the control commands. There will always be a tracking error between the commanded position and actual position. Therefore, in this study, linear scales are used to collect the data as they can provide information about the actual motion characteristics.

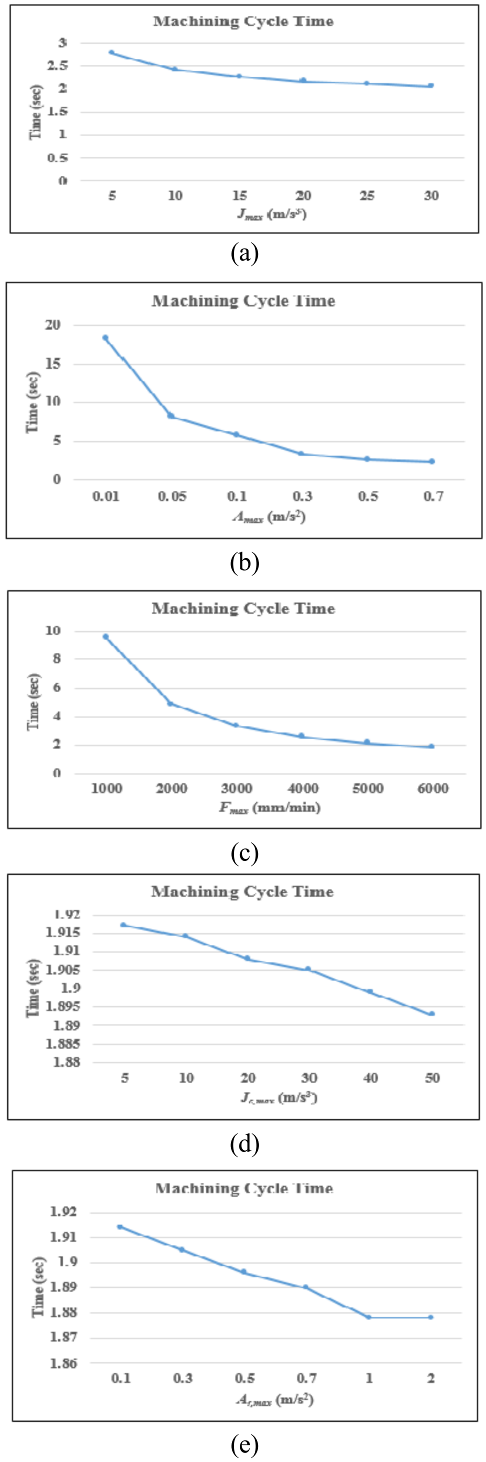


FIGURE 5. Trend of the machining time for variations in each machining parameter, (a) J_{max}; (b) A_{max}; (c) F_{max}; (d) $J_{c,max}$; (e) $A_{r,max}$.

III. INTELLIGENT MACHINING SYSTEM (IMS)

In industrial applications, the adjustment of the CNC machining parameters for a specific requirement of product quality

FIGURE 6. Five-axis machine tool (Microcut-MCU-5X).

is usually decided based on the experience of an expert. Our goal is to develop an IMS to provide a more effective and convenient procedure for parameters selection. The proposed IMS combines the ANFIS model establishment and a hybrid objective optimization problem by PSO. The weighting vectors of the objective functions are defined by the user-specific requirement. The major contribution of IMS is to help effectively users to optimize and select the best CNC machining parameters for different product requirements. Specifically, users can rapidly vary the parameters according to the machining capability when the manufactures various products. In addition, the users can use the IMS to help them when they do not have any knowledge on how to select the CNC machining parameters.

A. DEVELOPMENT OF IMS

The experimental machinery used is the Microcut-MCU-5X at the National Chung Hsing University (5-axis machine tool) with CNC controller TNC640 (HEIDENHAIN). The corresponding flow chart of the development of the IMS is shown in Fig. 7. There are three stages: relational analysis and data collection, ANFIS model establishment, and optimization. In the first stage, we have selected the parameters (J_{max}, A_{max}, F_{max}, $J_{c,max}$, and $A_{r,max}$), and the relational analysis introduced in Section II. Subsequently, a set of five CNC machining parameters are randomly chosen and then a rhombus path is designed to test and collect the data in actual machine tool. Herein, we collect the position data of the axial movement by the linear scales; the mechanical dynamic characteristics are also included in this information.

Next, the entire collected data are analyzed to obtain the corresponding contour error and tracking error. Subsequently, the ANFIS and data-driven approaches are applied to establish the corresponding relationship model between the CNC machining parameters and the three performance indices. This ANFIS model plays the role of a surrogate model [33]; it can efficiently calculate the machining results for a given set of machining parameters. Several heuristic algorithms were proposed to optimize the weighting vectors [34]–[36]. In this paper, we adopt the ANFIS to obtain the relation between CNC machining parameters and performance indices. Thus, ANFIS is trained by recursive least square and backpropagation algorithm. The corresponding training scheme of ANFIS are presented in Figure 8, the inputs and outputs are

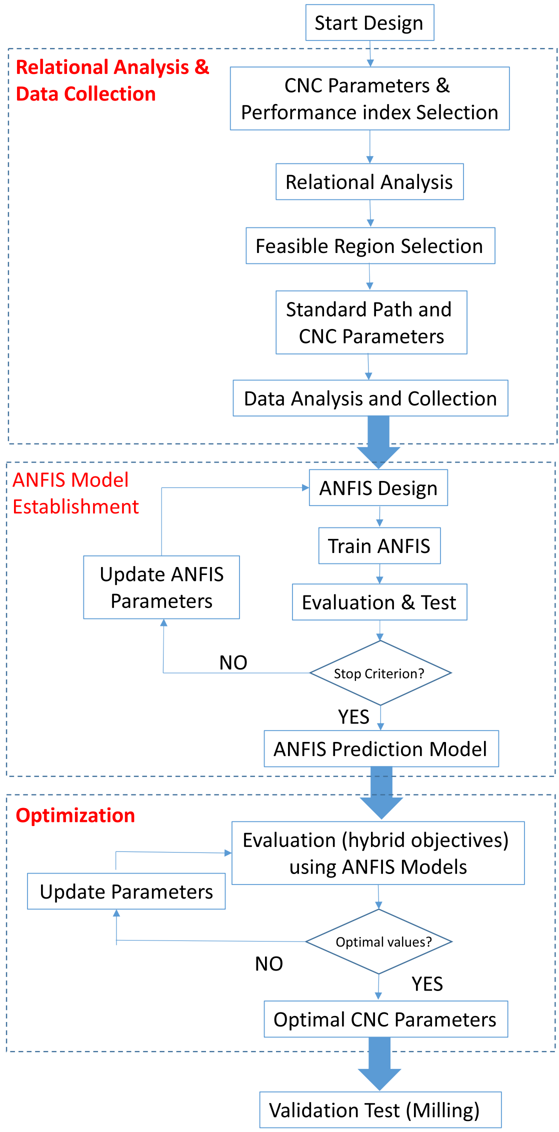


FIGURE 7. Flow chart of developing the proposed IMS.

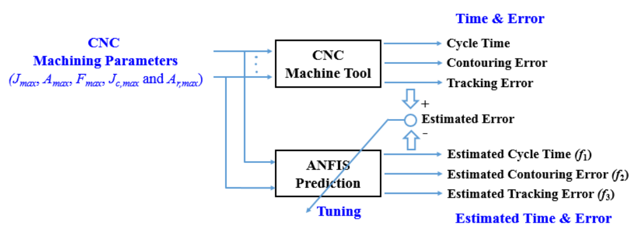


FIGURE 8. Training scheme of ANFIS for CNC machining parameters.

parameters (J_{max}, A_{max}, F_{max}, $J_{c,max}$, and $A_{r,max}$) and (estimated cycle-time f_1, estimated contour error f_2, and estimated tracking error f_3).

Following the above, the PSO algorithm is utilized and combined with the ANFIS model to establish the IMS. The optimization scheme of the CNC machining parameters based on the PSO algorithm is introduced in Figure 9(a).

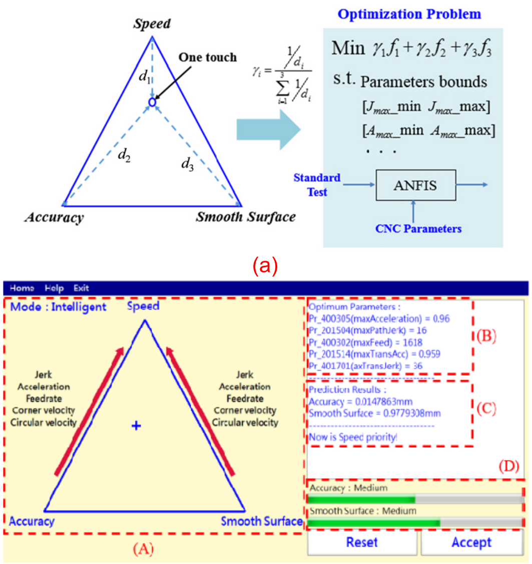


FIGURE 9. IMS illustration, (a) Optimization illustration of hybrid objective function; (b) Operation results of the IMS.

The milling requirement is selected by a triangular design that contains the following information: speed, milling accuracy, and surface smoothness. The corresponding hybrid objective function of the PSO algorithm used in the intelligent system is defined as follows:

$$f(.) = \gamma_1 f_1 + \gamma_2 f_2 + \gamma_3 f_3,$$
$$\gamma_i = \frac{\frac{1}{d_i}}{\frac{1}{d_1} + \frac{1}{d_2} + \frac{1}{d_3}}, \quad i = 1, 2, 3 \tag{1}$$

where d_i is the distance between the target position selected by the user and the three vertices of the triangle. γ_i is inversely proportional to d_i, and it represents the weight of each performance index. The objective functions, $f_1(.)$, $f_2(.)$, and $f_3(.)$, are the estimated machining time (speed), contouring error (milling accuracy), and tracking error (smooth surface), respectively, in which the estimated values are normalized in [0, 1] for optimization. According to the machining requirements, users can select the appropriate target position within the triangular interface. Obviously, $f(.) = f_1$ for speed priority when we select the vertex of speed and $f(.) = f_2$ for accuracy priority when we select the vertex of accuracy. This system can help users to determine the best CNC machining parameters for the different performance indices. The remaining is to solve the optimization problem, herein, we adopt the PSO to treat it, shown in Figure 9(a). The corresponding evaluation (values of objective functions) are obtained by using ANFIS predictors. The optimization problem is formulated as

$$\text{minimize } f(.) = \gamma_1 f_1 + \gamma_2 f_2 + \gamma_3 f_3$$
$$\text{subject to } X = \{x_1, x_2, \ldots, x_N\} \in S,$$
$$S = \{X \in \Re^D \,|\, L_B \le X \le U_B, L_B, U_B \in \Re^D\} \tag{2}$$

where $f(.)$ is the hybrid-objective function, X denotes the tuning parameters (CNC parameters), U_B and L_B are the corresponding upper and lower bound vectors, respectively, and D is the problem dimension, herein $D = 5$. The update laws of PSO is introduced as

$$V(k+1) = wV(k) + c_1\varphi_1[p_{best} - X(k)] + c_2\varphi_2[g_{best} - X(k)] \tag{3}$$
$$X(k+1) = X(k) + V(k+1) \tag{4}$$

where V denotes the velocity (update) for particle X: (J_{max}, A_{max}, F_{max}, $J_{c,max}$, and $A_{r,max}$), w is the inertia weight, $c_1, c_2 > 0$, and ϕ_1, ϕ_2 are random numbers between [0, 1], p_{best} is the best solution of the current particle, and g_{best} is the optimal solution of the overall particle. The corresponding coefficients are $w = 0.6$, $c_1 = 0.6$ and $c_2 = 0.5$. To enhance the convergence, adaptive linear adjustment of learning factors for PSO algorithm can be used [37]–[39].

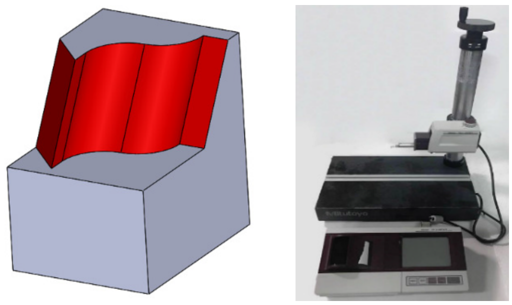
The establishment steps for the IMS are as follows.

1) **Data-Collection:** The CNC machining parameters are selected, and a rhombus path is designed to test the machine tool and collect the axial position data (obtained by linear scales). In this study, we collect 414 data in total, 95% data for training ANFIS and the remained 5% for testing.
2) **Data Analysis:** MATLAB software is used to analyze the collected data, and calculate the machining time, contouring error, and tracking error.
3) **Train ANFIS:** The ANFIS and data-driven approaches are used to establish the corresponding relationship model between the machining parameters and the three performance indices.
4) **Optimization:** The PSO algorithm is combined with the ANFIS model to establish the IMS.
5) **Validation:** Machining and measurement.

The operation screen of an intelligent mode is shown in Fig. 9(b). As shown in Fig. 9(b), users select the requirement position in part (A). Part (B) shows the optimum CNC machining parameters after selecting the machining requirements. Part (C) displays the prediction results (milling accuracy and smooth surface) and current priority index; part (D) provides the graphical information of each predicted index. These levels are classified as low, medium, and high.

B. EXPERIMENTAL RESULTS

To verify the effectiveness of the proposed IMS, practical machining tests are performed by using Microcut-MCU-5X. A machining path that contains the lines, corners, and circular arcs is designed; the corresponding CAD drawing of the workpiece is shown in Figure 10(a). Herein, we utilize the IMS to generate the four cases of the CNC machining parameters based on the requirements of the speed priority, accuracy priority, smooth surface priority, and standard condition. Table 3 lists the four groups of optimized CNC machining parameters. In this experiment, we consider the finish machining, the cutting depth is 0.2 mm; only the



(a) (b)

FIGURE 10. Experimental results of the IMS, (a) CAD drawing for the machining workpiece; (b) Surface roughness tester (SJ-400).

TABLE 3. Optimized CNC machining parameters.

Parameters	Speed Priority	Accuracy Priority	Smooth Surface Priority	Standard
J_{max} [m/ s^3]	19	7	14	17
A_{max} [m/ s^2]	1.11	0.4	0.74	0.69
F_{max} [mm/min]	4220	2243	1054	2683
$J_{c,max}$ [m/ s^3]	38	14	56	26
$A_{r,max}$ [m/ s^2]	0.82	0.088	0.524	0.399

TABLE 4. Optimized CNC machining parameters.

Parameters	Speed Priority	Accuracy Priority	Smooth Surface	Standard
Machining time [s]	107	143	179	122
Contouring error [mm]	0.296268	0.02368	0.054419	0.047404
Surface roughness [μm]	0.55	0.48	0.39	0.46

CNC parameters are modified, and the other conditions are fixed and standardized. The cutting tool is a two-flute ball end mill whose tool length and diameter are 90 mm and 6 mm, respectively; the spindle speed is 11000 rpm; the work piece material is aluminum. Further, the accuracy and surface smoothness are measured using SJ-400 (as shown in Fig. 10(b)) and linear scale data analysis. The final machining results and finished products are listed in Table 4 and shown in Fig. 11, respectively. The finished product is divided into four parts from top to bottom. Each one of these parts relate to the speed priority ($\gamma_1 = 1; \gamma_2 = \gamma_3 = 0$), accuracy priority ($\gamma_2 = 1; \gamma_1 = \gamma_3 = 0$), smooth surface priority ($\gamma_3 = 1; \gamma_1 = \gamma_3 = 0$), and standard condition($\gamma_1 = \gamma_2 = \gamma_3 = 1/3$). The machining time of each index is clocked during the practical machining process.

From these results and the finished product, the following points is summarized:

1) Speed Priority ($\gamma_1 = 1; \gamma_2 = \gamma_3 = 0$): The machining speed is fast in all the tests; however, the accuracy and surface smoothness are relatively poor.

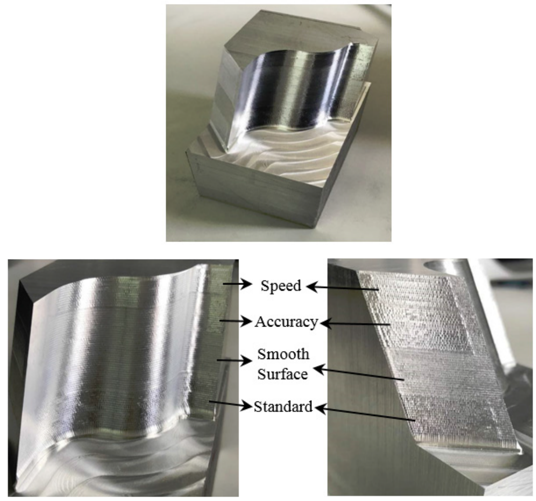


FIGURE 11. Machining-finished product.

2) Accuracy Priority ($\gamma_2 = 1; \gamma_1 = \gamma_3 = 0$): In comparison with other tests, the contouring error is minimal. This implies that this group of parameters have the best accuracy; however, it requires additional machining time.
3) Smooth Surface Priority ($\gamma_3 = 1; \gamma_1 = \gamma_3 = 0$): In all the tests, this index takes the longest time; however, it can be seen that it has a relatively good surface quality.

The practical machining results show that the proposed IMS achieves the desired product specifications. The IMS system can effectively help technicians to identify the most appropriate CNC machining parameters based on their product requirements. In this experiment, we consider the finish machining, the cutting depth is 0.2 mm; only four cases of CNC parameters are used to for the machining test, and the other conditions are fixed and standardized. However, users can still allocate different proportions of the performance indices according to their machining requirements. Finally, the IMS will return the best CNC machining parameters to the users.

IV. CONCLUSION

Since the variations in the CNC machining parameters significantly affect the product quality during the operation of a machine tool, these parameters can be selected to vary the machining capabilities of the machining procedures. This paper introduced an intelligent machining system (IMS) using the ANFIS predictor and PSO algorithm with a hybrid objective function for users. The presented IMS provided suitable machining parameters for users to satisfy different machining requirement, e.g., accuracy, surface smoothness, and speed. Finally, four cases of CNC machining parameters were used to test the efficacy of the proposed IMS by actual machining. The experiments verified the effectiveness and performance of the proposed IMS; it could assist manufacturers to enhance productivity and product quality. Even though the experimental conditions considered only four groups of parameters to test, users can still assign the proportion of each performance index according to their requirements. The IMS will identify the optimum CNC machining parameters based on these requirements.

As above, the IMS can provide a comparative result of machining performance. However, the machining performance is related to the factors such as tool material, tool geometry, product material, spindle speed, cutting depth, cutting width and etc. This approach can be extended to consider these factors by data driven approach and suitable experiment design in the future. In addition, the IMS only provides a selection of optimization, the actual estimation in cycle time should be considered.

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