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Rapid Energy Consumption Modelling for CNC Based Milling Process

Wen-Tse Hsu[a], Pang-Hsiang Hung[a], Bing-He Chou[a], Po-Han Chen[a], Shang-Yu Lin[a]

Tay-Jyi Lin[b], Yuh-Chung Hu[c], Pei-Zen Chang[a], and Wei-Chang Li[a]*

[a]*Institute of Applied Mechanics, National Taiwan University, No. 1, Sec 4, Roosevelt Rd., Taipei 106319, Taiwan*
[b]*Computer Science and Information Engineering, National Chung Cheng University, 168 University Rd., Chiayi 621301, Taiwan*
[c]*Department of Mechanical and Electro-Mechanical Engineering, National Ilan University, No. 1, Sec. 1, Shen-Lung Rd., Yilan 260, Taiwan*

* Corresponding author. E-mail address: wcli@iam.ntu.edu.tw

Abstract

This study introduces a methodology for rapidly establishing an energy consumption model based on NC code for CNC milling operations. The approach significantly reduces the time needed to gather training and validation data through two key techniques: (1) magnetic voltage sensors, facilitating direct installation onto electrical joints within the electrical box without the need for modifications to the machine tool electricity, and (2) a greatly reduced amount of cutting experiments required for collecting the training data based on a modified Taguchi method. The power consumption measurements are divided into two parts: (1) experiments conducted at varying spindle speeds and feed rates without cutting, and (2) cutting experiments conducted at varying spindle speeds, feed rates, depth of cut, and width of cut. The combinations of cutting parameters are significantly reduced based on the nature of the dependency of the parameters to the energy consumption, and using the Taguchi method and the cross-validation approach. The overall time required for obtaining the power consumption model is around 30 minutes, including 15 minutes estimated for electrical sensors installation. The methodology is applied to 10 distinct machine tools, demonstrating the versatility and applicability of the modeling process across diverse machining environments. The achieved error rate of up to 3.98% underscores the efficacy of this approach. Furthermore, the energy consumption data gleaned from these 10 machine tools are made readily available for open-source utilization, fostering accessibility and collaborative research in energy-efficient CNC milling processes.

Keywords: CNC milling, CNC machining, energy model, cutting power consumption, power consumption model

1. Introduction

CNC machine tools consume significant energy during the machining process [1], resulting in corresponding carbon emissions [2], and thus impacting the environment. To reduce energy consumption, models for CNC machine tools have been designed to predict the energy used during the machining process [3]. These models help users identify optimal cutting parameters for minimal energy consumption, such as spindle speed and feed rate. In particular, various approaches have been proposed for modeling the energy consumption of machine tool operations. For example, [4] presents a prediction model for estimating the theoretical energy consumption involved in milling prismatic parts. This predictive model is based on 19 spindle experiments and 21 feed experiments, showing that the model operates with a 5% accuracy. [5] creates a model by training an Artificial Neural Network (ANN) to predict the cutting energy for carbon steel machining. The training data are obtained from 27 machining operations with various input parameters (spindle speed, feed rate, depth, and width of cut), resulting in a difference between measured and predicted cutting energy of 1.50%. [6] develops a machine tool power equation and a specific energy consumption model in the cutting stage based on 16 machining operations, predicting the

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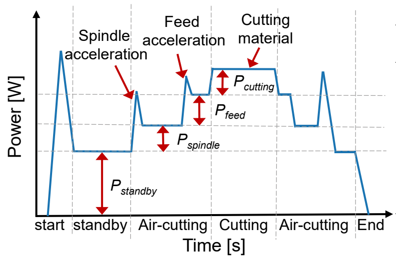

Type	This work	Ref.
$P_{cutting}$	81 → 7	10 [8]
$P_{spindle}$	20 → 12	19 [4]
P_{feed}	64 → 12	28 [4]
$P_{stnadby}$	1	1 [4]

Fig. 1. Comparison of recent related research on the number of experiments for different power components.

energy consumption within an error margin of 2.34%. [7] develops an improved cutting power-based energy consumption model for the general end milling process, where milling experiments show that the prediction error of the proposed model is as low as 1.74%. The methodology of [8] is able to estimate the mechanical energy requirements of the spindle and feed axes with respect to 2.5D machining strategies. The training data are obtained from 10 machining operations with various input parameters. The model predicts the energy consumption within an error margin of 13.01%. However, most of the works on this topic have relied on extensive experimentation to establish machine tool energy consumption models including installing measurement equipment and setting up tedious cutting experiments, which all together cause long tool downtime.

To address this, this work combines two techniques: (1) employing voltage sensors with magnetic connectors that can be directly attached onto the electrical connectors inside the electrical box without the need for modifying the power supply of the machine tool, and (2) reducing the number of cutting experiments needed for modeling. Fig. 1 shows the comparison of the number of experiments needed for the modelling between the proposed methodology of this work and the reported works. The required numbers of experiments for the different power components are reduced according to the simply linear trend of the power consumption and the parameters observed in the measurements and based on the Taguchi method.

This process involves calculating the power model coefficients through regression analysis using the experimental data. Following this, a program developed in Python is used to extract the key parameters, such as spindle speed, feed rate, tool path, from NC codes. Finally, a NC code of a validation pattern is used to demonstrate the power consumption prediction. Ten different machine tools are applied with this procedure to validate the effectiveness of the developed method proposed in this study. A case study demonstrates that, compared to the actual measured energy consumption of the machining process, the developed energy consumption model had an average percentage error of 3.98%. Based on the case studies and analysis, it can be concluded that the developed method is a very promising tool for achieving rapid deployment for cutting power modelling in industrial machining processes.

2. Experimental setup

Fig. 2 outlines the workflow of this work. The goal of this work is to be able to rapidly establish the power consumption model of any CNC milling tool and then predict the power

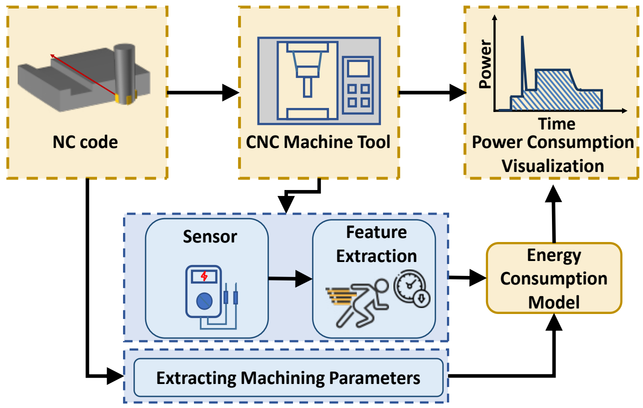

Fig. 2. The workflow of modelling machine tool power consumption.

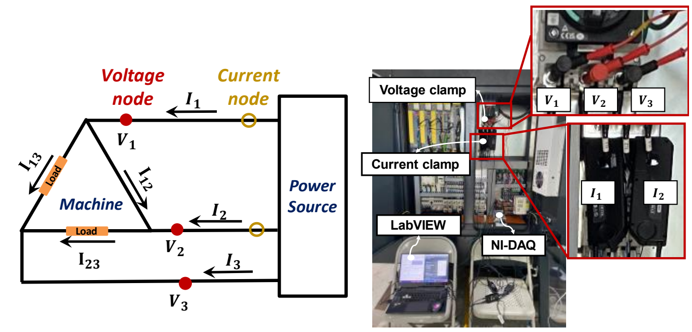

Fig. 3. Experiment setup for collecting machine tool power consumption data.

consumption of a machining job based on the NC code as the input. Fig. 3 shows the three-phase power supply for the machine tools together with the voltage and current sensors. The three-phase voltage source features a phase voltage difference of 220 V and a frequency of 60 Hz, with each phase having a phase angle of 120 degrees. The power calculation for the three-phase circuit can be performed by multiplying the current flowing through each phase of the load inside the machine tool by the voltage difference. The total power is calculated as follows:

$$P_{total} = I_{13} \cdot (V_1 - V_3) + I_{23} \cdot (V_2 - V_3) + I_{12} \cdot (V_1 - V_2) \quad (1)$$

In practical scenarios, directly measuring the line current of machine tools is unattainable due to the intricate nature of their internal circuits, making it impractical to ascertain the load on each phase. Consequently, in instances where the three-phase load of the machine tool remains unidentified and direct measurement of the machine tool's internal line current is impossible, it becomes essential to compute the actual power consumption by analyzing the phase current and phase voltage. To facilitate this, the Kirchhoff's Current Law is applied to validate the method for calculating power in a three-phase circuit, taking the form

$$\begin{cases} I_{13} = I_3 - I_{23} = I_1 - I_{12} \\ I_{23} = I_3 - I_{13} = I_{12} + I_2 \\ I_{12} = I_{23} - I_2 = I_1 - I_{13} \end{cases} \quad (2)$$

Through the derivation of circuit equations, the total power of a three-phase system can be calculated using two channels. Therefore, measurements require the use of two current sensors and two voltage differences, allowing for the calculation of the total power, taking the form

$$P_{total} = I_1 \cdot (V_1 - V_3) + I_2 \cdot (V_2 - V_3) \quad (3)$$

In the calculation of alternating current (ac) power, due to the continuous alternation of voltage and current between positive and negative values, the calculation of ac power involves integrating the instantaneous power over each cycle and then dividing by the cycle time to obtain the average power, taking the form

$$P_{Average} = \frac{1}{T}\int_0^T i(t) \cdot v(t) \tag{4}$$

In Fig. 3, the total electrical power consumption is measured using three voltage magnetic adapters HIOKI 9804-01 and two current transducers CYBER HCP8150 which are connected to the main bus of the electrical cabinet of the machine tools. The magnetic voltage sensors facilitate direct installation onto electrical joints within the electrical box without the need for modifications to the electricity of machine tool. The voltage signal is acquired and sampled by using two NI-9225 and NI-9230 data acquisition cards and a compact NI Cdaq-9189 data acquisition chassis at a sampling frequency of 12800 Hz per channel. The LabVIEW programming interface is developed to store the acquired voltage and current data. The average power is obtained through (4) by accessing the current and voltage.

3. Power modelling of machine tools

The power model devised in our research focuses on the aggregate power consumption of machine tool systems engaged in machining tasks. This model is structured around two primary elements: fixed and variable components. Fixed components encompass the power usage of the auxiliary, control, and other subsystems within the machine tool system when in standby mode. Conversely, the variable components pertain to the power expenditure of the machine tool system during the execution of machining operations.

During the machining process, power consumption is divided into fixed and variable components. The overall power is expressed as P_{total}, where $P_{constant}$ represents the fixed components, and $P_{variable}$ denotes the variable components. The interplay between these components is depicted in the diagram below:

$$P_{total} = P_{constant} + P_{variable} \tag{5}$$

The fixed unit includes power consumption from the lubrication and cooling sub-systems, the auxiliary sub-systems, the controlling sub-systems, etc. The variable unit includes power consumption from the spindle and feeding sub-systems. The fixed unit can be represented below:

$$P_{constant} = P_{control} + P_{aux} + P_{cooler} + P_{other} \tag{6}$$

where $P_{control}$ is from the controlling sub-system, P_{cooler} is from the cooling unit, P_{aux} is from the auxiliary subsystem, and P_{other} is from other sub-systems.

In the meantime, the fixed unit can be calculated by the standby power $P_{standby}$. The relationship can be represented below:

$$P_{constant} = P_{standby} \tag{7}$$

When executing a specific NC (Numerical Control) program, the machine tool system performs various command functions, including spindle rotation, rapid movement, and feed along the X, Y, and Z axes, among others. The energy consumption of these different functions can be summed up to obtain $P_{varible}$. The relationship is depicted in the diagram below:

$$P_{varible} = P_{spindle} + P_{feed} + P_{cutting} \tag{8}$$

Several researchers [9] have theoretically modeled the power of spindle rotation. For commonly used variable-frequency controlled spindle motors, it is observed that the spindle exhibits different characteristics when running in non-cutting mode. To account for this, a piecewise linear function is employed to describe the power of spindle rotation, leading to the establishment of a universal model as follows:

$$P_{spindle} = c_0 + c_1 n + c_2 n^2 + c_3 n^3 + c_4 n^4 \tag{9}$$

, where $P_{spindle}$ is the spindle rotation power [W], c_1,c_2, c_3, c_4 is the coefficient of spindle speed, n is the spindle speed [rpm] and c_0 is a constant. The segmentation of power across different regions is based on the relationship graph between the output power of the machine tool spindle and its rotational speed. Experiments are conducted at four different speeds within each segment, which aids in the creation of a universal model, thereby reducing the number of experiments required.

Feed drives are used for positioning the machine tool and the workpiece. The feed power is a function of the feed rate. The feed power at a certain feed rate is measured. Through theoretical analysis of the feed drive structure of the machine tool, the feed power is modeled as a linear function of the feed rate [10]. The model is expressed as:

$$P_{feed} = b_0 + b_1 v_f \tag{10}$$

, where P_{feed} is the axis feeding power [W], b_1 is the coefficient of feed rate, v_f is the feed rate [mm/min] and b_0 is a constant. For the feed axis, the relationship between the motor and the feed rate under different feed speeds is linear. Therefore, only three experiments are needed for each axis direction. This approach also leads to the establishment of a universal model, further reducing the number of experiments needed.

Material removal power refers to the actual power used for removing material. While there are some theoretical calculations for cutting energy, executing these calculations is challenging due to the difficulty in computing all the parameters involved in the theoretical formulas. Consequently, empirical methods are still widely employed for reliable predictions of cutting forces and energy. Empirical models are characterized by their simplicity and high prediction accuracy. Therefore, a universal exponential model is chosen to describe the relationship between material removal power and process parameters [11]. The material removal power model is derived by multiplying the cutting force by the cutting speed:

$$P_{cutting} = k_0 n^{k_1} v_f^{k_2} a_p^{k_3} a_e^{k_4} \tag{11}$$

, where $P_{cutting}$ is the cutting power [W], n is the spindle speed [rpm], v_f is the feed rate [mm/min], a_p is the depth of cut [mm], a_e is a the width of cut [mm] and k_0, k_1, k_2, k_3 and k_4 are the coefficients of the milling power, depth of cut, feed rate per tooth, cutting speed and width of cut, respectively.

For cutting tests, the experimental design is based on the Taguchi L_9 orthogonal array table shown in Table 1. Under the three levels recommended by the tool manufacturers, nine different cutting parameters (depth of cut, width of cut, speed, and feed rate) are established.

Table 1. L9 Taguchi orthogonal tables for Milling Experiment Cutting Parameters

Cutting Parameter	Level 1	Level 2	Level 3
Depth of cut [mm]	0.5	1	1.5
Width of cut [mm]	6	13	20
Cutting speed [m/min]	100	130	160
Feed per tooth [mm/tooth]	0.08	0.12	0.16

3.1. Power modelling base on experimental data

Experiments are conducted to obtain the power data of machine tool motions at different operating parameters. The obtained data are further used for statistical analysis to acquire the power models of machine tool motions. Ten machine tools are used to validate the procedure. The technical specifications of the ten selected machines are listed in Table 2.

The workpiece selected for the experiment measures 141.5 ×130 × 60 mm. The material of the workpiece is S50C, with a tensile strength of 610 MPa and a hardness of 179 HB. The milling tungsten carbide cutter chosen has a diameter of 20 mm and 3 flutes.

The power curve of the spindle rotation as a function of spindle speed for VP-6 machine tool is shown in Fig. 4 (a) The rotational power of the CNC milling machine's spindle is a piecewise function divided into three segments. According to (9), different models can be developed through piecewise linear

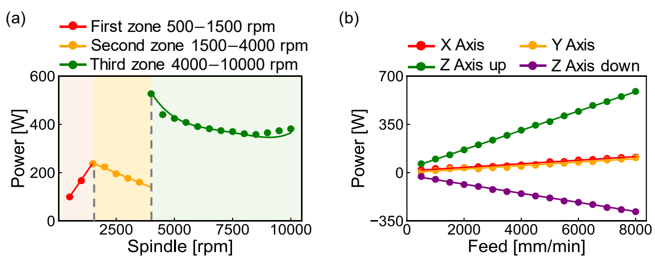

Fig. 4. The modelling results for the VP-6 air-cutting power model with the original data: (a) power of spindle rotation at various speeds (b) power of feeding at various feed rates.

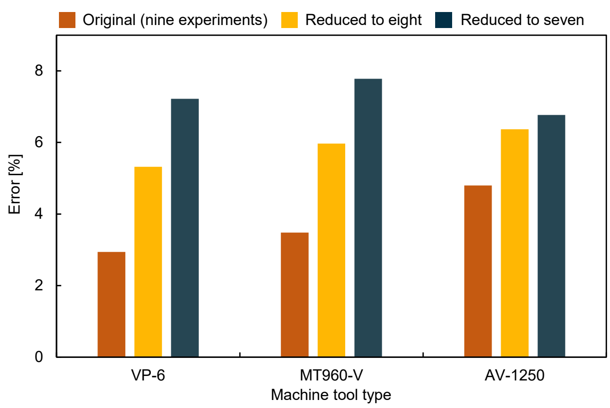

Fig. 5. Comparing cutting power model prediction error across various machines when the number of the experimental data is reduced from nine to seven.

Table 2. Various machine tool datasheets used in this work

Machine tool	Max.travel range [mm]	Spindle speed [rpm]	Rapid traverse [m/min]	Standby power [W]
VP-6	610×410×510	10000	48/48/36	540
MT960V	900×570×570	10000	36/36/36	610
TMV-510A	510×360×300	12000	40/40/48	430
QP1620-L	520×400×380	10000	36/36/24	285
NDV102A	1020×600×600	12000	48/48/32	625
AXILEV7	1200×730×650	12000	40/40/40	878
V-30iT	800×460×387	12000	36/36/24	462
V-40iL	1020×635×610	10000	36/36/24	680
AV-1250	1250×620×620	10000	48/48/36	887
AF-1000	1020×550×635	12000	36/36/24	864

Table 3. The coefficients of the VP-6 spindle power model.

c_0	c_1	c_2	c_3	Spindle [rpm]
30.20	0.14	0	0	500-1500
293.42	-0.04	0	0	1500-4000
1342.63	-0.32	3.44×10^{-5}	-1.18×10^{-9}	4000-10000

Table 4. The coefficients of the VP-6 feed power model.

	b_0	b_1	Feed [mm/min]
P_x	12.26	0.013	500-8000
P_y	-3.98	0.013	500-8000
P_{zu}	29.50	0.069	500-8000
P_{zd}	-12.33	-0.034	500-8000

Table 5. The coefficients of the VP-6 cutting power model.

k_0	k_1	k_2	k_3	k_4
0.037	0.222	0.759	0.9	1.109

Cutting power model: $P_{cutting} = k_0 n^{k_1} v_f^{k_2} a_p^{k_3} a_e^{k_4}$; n is the spindle speed [rpm], v_f is the feed rate [mm/min], a_p is the depth of cut [mm], a_e is a the width of cut [mm].

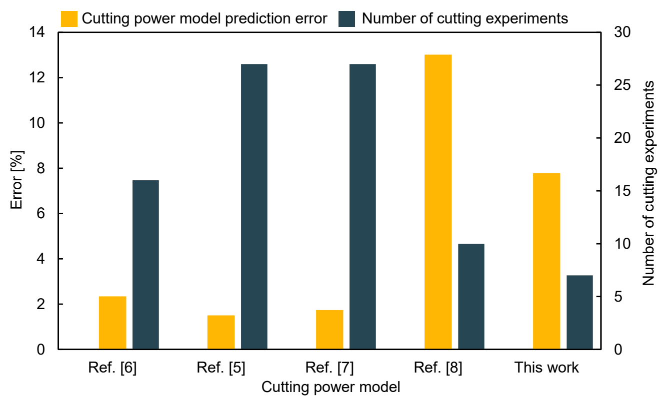

Fig. 6. Comparison the number of cutting experiments and prediction error between the cutting power models of reference and this work.

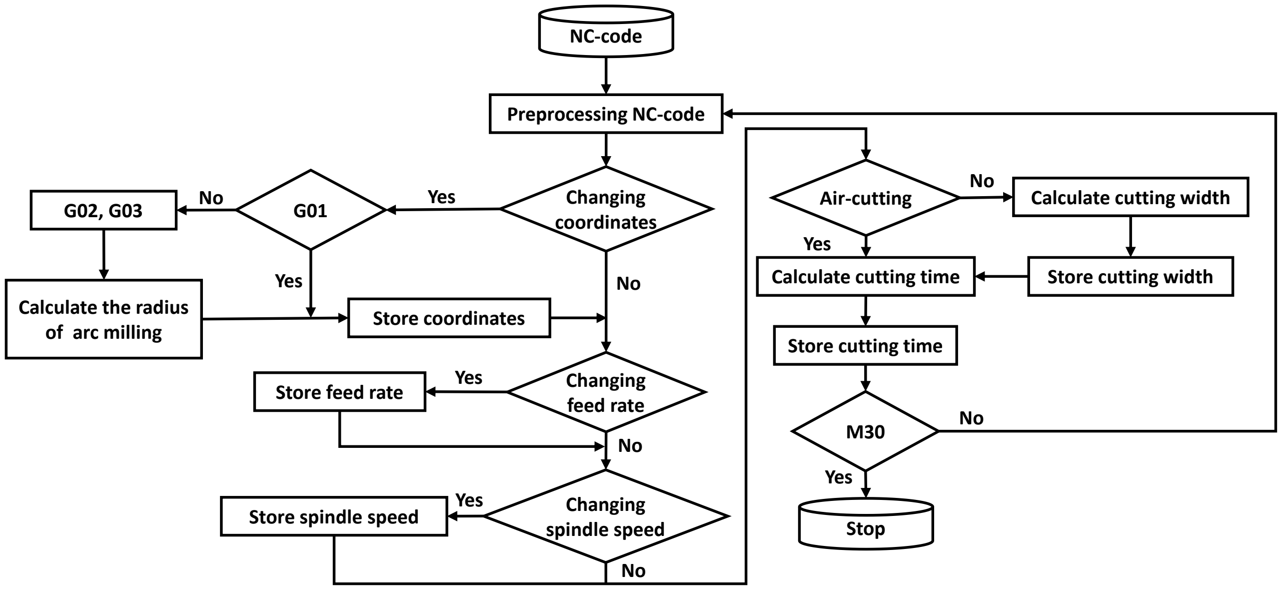

Fig. 7. Flowchart for the automatic extraction cutting parameters.

regression to predict spindle rotation power during air-cutting motions. Table 3 shows the spindle rotation power model coefficients.

The power curves for each feed axis as a function of feed rate are shown in Fig. 4 (b) The feed power in CNC milling machines is a linear function. As listed in (10), the feed power model can be obtained simply through first-order polynomial regression. The feed power model is summarized in the Table 4.

For air-cutting motions, the power is also dependent on the process parameters such as spindle rotational speed, feed rate, etc. The obtained spindle rotation and feeding power models can be used to calculate the energy consumption of CNC machine tools using given process parameters.

The energy consumption data collected from nine different cutting parameters then undergo a cross validation to progressively determine the minimum number of experiments required. Fig. 5 shows that a minimum of seven experiments is necessary to achieve an error within 8%. To streamline the cutting experiments, the number of trials can be reduced from nine to seven. To set up the initial nine experiments, an L_9 Taguchi orthogonal array is employed. When the experiments are reduced from nine to eight, nine training sessions are required to determine which eight experiments yield better results. Similarly, reducing the experiments from eight to seven necessitated eight training sessions to decide which seven experiments achieve acceptable outcomes. Consequently, when reducing the experiments from nine to seven, a total of 36 training sessions are needed after a combinatorial analysis. Subsequently, regression analysis is performed on the cutting power data. The resulting milling power model is summarized in Table 5. Finally, Fig. 6 compares the experiments needed for training the cutting power model and the resultant error for the proposed methodology and reported work. The error is calculated based on

$$\text{Error} = \frac{|P_{meas} - P_{predict}|}{P_{meas}} \times 100\% \tag{12}$$

, where P_{meas} is the value obtained by averaging the power values recorded during the number of experiments and $P_{predict}$ is the predicted power from cutting power model.

4. Automatic extraction of cutting parameters

The structure of NC (Numerical Control) programs is based on NC coding standards and semantics, consisting of multiple functional words. An NC program is composed of address characters and instruction values, including G functions, spindle speed, feed rate, and tool coordinates. Analyzing the composition of NC programs reveals the inherent relationship between the execution instructions and the actions of the machine tools [12]. By obtaining segmented energy consumption of the actions according to the NC codes and integrating it into the previously established energy consumption model, the total energy consumption can be calculated by summing up the segmented energy consumption.

Fig. 7 summarizes this procedure for extracting the energy consumption based on the NC program. Based on the number of lines in the NC program, each character in the lines of the NC program is iterated through the calculation program, followed by the extraction of subsequent machining parameter information, as follows: If the character is “G”, it indicates readiness for a function address symbol, and the instruction value is then determined. If the character is “00”, it is judged as "rapid positioning", and the machining parameters for rapid positioning are stored. If the character is “01”, it is judged as "straight line cutting", If the character is “02,03”, it is judged as "arc milling", and the machining parameters for feed cutting are stored. If the character is “X, Y, Z”, the coordinates of the tool movement endpoint are obtained. If the character is “F”, the feed rate f (mm/min) is extracted. If the character is “S”, the spindle speed n (rpm) is captured. The machining parameter information obtained through the steps above, including the tool coordinate values, feed rate, spindle speed, width of cut information, is stored in the machining parameters array.

5. Energy consumption prediction

Fig. 8 shows a pattern designed for verifying the power consumption estimation. The 3D design is exported into NC-code using the Mastercam® software. The NC-code is then used as the input into the previously established program for

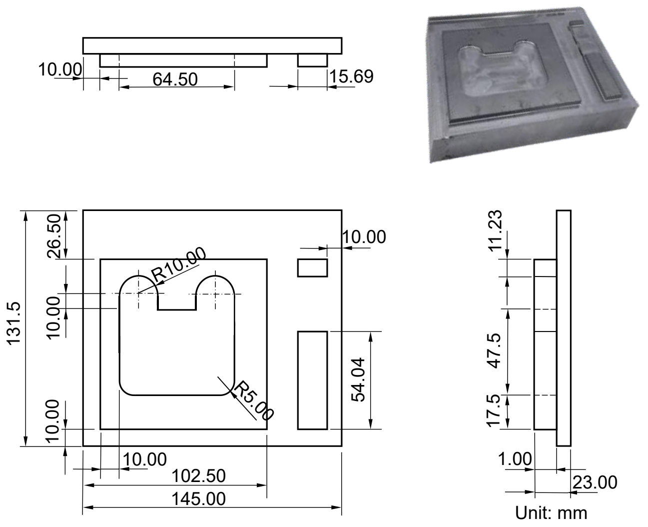

Fig. 8. The pattern for verifying the power model accuracy.

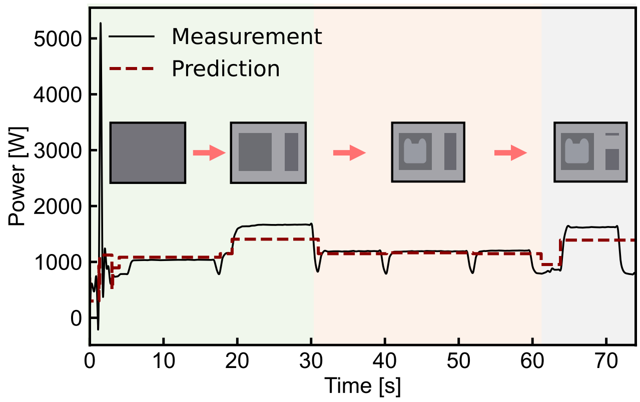

Fig. 9. Predictions and measurements of energy consumption curves in the VP-6 machining process.

Table 6. Predicted energy consumption results for different machine tools

Machine tool	Measurement	Prediction		
	Energy [kJ]	Energy [kJ]	Error [%]	MAPE
VP-6	90.66	88.32	2.58	
MT960V	95.17	95.38	0.22	
QP1620-L	66.26	62.83	5.18	
NDV102A	101.54	95.86	5.59	
V-30iT	143.78	140.57	2.23	3.98%
V-40iL	97.84	94.63	3.28	
AV-1250	107.55	102.50	4.70	
AF-1000	108.10	102.06	5.59	
AXILEV7	114.06	111.53	2.22	
TMV-510A	68.24	73.85	8.22	

the automatic extraction of cutting parameters. The extracted cutting parameters are applied to the energy consumption model, resulting in a power curve graph. Fig. 9 displays the measured and predicted power curves for the VP-6 out of the ten machine tools. The Mean Average Percentage Error (MAPE) of the energy prediction for the overall ten machine tools is calculated for the material cutting state using

$$\mathrm{MAPE} = \frac{1}{N}\sum_{i=1}^{N} \frac{|E_{measurement} - E_{prediction}|}{E_{measurement}} \times 100\% \qquad (13)$$

, where N is the total number of data points i, $E_{measurement}$ is the real power measured during the experiment and $E_{prediction}$ is the predicted power, as shown in Table 6.

6. Conclusion

This work presents a modelling method for swiftly deriving an energy consumption model based on NC code for CNC milling operations. The approach significantly reduces the time needed to gather training and validation data by proper selection of both sensor hardware and experiment parameter combinations. Validation experiments are conducted across ten distinct machine tools, demonstrating the versatility and applicability of the modeling process across diverse machining environments. The achieved error rate of up to 3.98% underscores the efficacy of this approach. The overall time for establishing the power model for a given CNC machine is less than one hour, which would greatly improve the user acceptance. Furthermore, the energy consumption data gleaned from these ten machine tools together with the developed Python codes for NC code extraction are made readily available for open-source utilization, fostering accessibility and collaborative research in energy-efficient CNC milling processes.

Data availability

The data are available on https://github.com/Atse123/NTU_PZ_PowerData.git.

Acknowledgements

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