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An Energy Consumption Estimation Method for the Tool Setting Process in CNC Milling Based on the Modular Arrangement of Predetermined Time Standards

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Abstract: Modeling and estimating the energy consumption of computer numerical control (CNC) milling systems have been recognized as essential ways to realize lean energy consumption management and improve energy efficiency performance. As the preparatory phase, considerable time and energy are consumed in the tool setting process. However, research on the tool setting process mainly focuses on accuracy and operational efficiency, and the energy consumption is usually ignored or simplified. Accurately estimating the energy consumption of the tool setting process is thus indispensable for reducing the energy consumption of CNC milling systems and improving their energy efficiency. To bridge this gap, an energy consumption estimation method for the tool setting process in CNC milling based on the modular arrangement of predetermined time standards (MODAPTS) is presented. It includes three steps: (i) operations decomposition and determination of the MODAPTS codes for the tool setting process, (ii) power modeling of the basic action elements of the machine tool, and (iii) energy consumption modeling of the tool setting process. Finally, a case study was conducted to illustrate the practicability of the proposed method via energy consumption modeling of the tool setting process using an XH714D CNC machine center with a square workpiece, in which the estimation values of the operating time and the energy consumption for the tool setting process were 210.786 s and 140,681.68 J, respectively. The proposed method can increase the transparency of energy consumption and help establish labor-hour quotas and energy consumption allowances in the tool setting process.

Keywords: tool setting process; energy consumption estimation; MODAPTS; CNC milling

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1. Introduction

The energy and environmental issues caused by the manufacturing industry are of global concern [1]. According to data released by the International Energy Agency, nearly a third of the world's energy consumption and 36% of CO_2 emissions are from the manufacturing industry [2]. In recent years, the government of China has emphasized the need to bring carbon emissions to a peak before 2030 and achieve carbon neutrality before 2060 (i.e., dual carbon goals) [3]. Machining systems are predominantly responsible for the energy consumed in the manufacturing industry owing to the wide use of machine tools [4,5]. In China alone, about 10 million machine tools are in service in machining plants [6]. Machining systems often run at low energy efficiency: a large number of studies have shown that the energy efficiency of machine tools is less than 30% [7–9]. Large quantities and a wide range of machining systems are available, and they have the characteristics of high energy consumption, low energy efficiency, and huge energy-saving potential [10]. CNC milling, the most common machining process, has complex energy consumption characteristics. Modeling and estimating the energy consumption of CNC milling systems has been recognized as an essential way to realize lean energy consumption management as well as to improve energy efficiency performance.

Extensive studies have been conducted on the energy consumption and energy efficiency modeling of machining systems. Jia et al. [11,12] proposed some models related to drilling power, including the feeding power model, the theoretical drilling power model, and the additional loss power model. Mori et al. [13] established an energy consumption model that considers several different machining stages, including standby, spindle positioning, spindle acceleration, material removal, spindle returning, and spindle deceleration, and Li et al. [14] proposed an empirical model of energy consumption for the CNC milling process. Khan et al. [15] developed a Response Surface Methodology model for active cutting energy in Cu-nanofluid small quantity cooling lubrication-assisted face milling. Yan et al. [16] established a multisource and dynamic energy model of machine tools based on Business Process Model and Notation. The results obtained from the BPMN model showed good agreement with the experimental data, and the maximum error was 3.91%. Hernández et al. [17] presented a simple way to estimate the energy requirements, cost, and environmental footprint to produce a workpiece using standard engineering software. Some scholars have adopted data-driven modeling methods to predict the energy consumption of machining systems. Zhou et al. [18] proposed an energy consumption BP neural network model for a grinding machine processing system, and the results showed that the relative errors between the predicted and actual values of eight groups in relation to grinding energy consumption were less than 9%. Kahraman et al. [19] developed a deep neural network (DNN) model to predict the energy consumption of a semi-autonomous grinding mill. Kim et al. [20] proposed a transfer learning approach for the predictive modeling of machining power. Qin et al. [21] built an energy consumption prediction model for an additive manufacturing system, where a hybrid approach that incorporated clustering techniques and deep learning was used to integrate the multisource data. Brillinger et al. [22] investigated the ability of different machine learning algorithms to predict the energy demands of CNC machining, including decision tree, random forest, and boosted random forest. Some specific energy consumption (SEC) models have been employed to investigate the energy efficiency of different machining processes [23–26]. In addition, some models have been developed to describe the inherent energy performance of machine tools [27–30]. The aforementioned studies provide a good basis for the energy consumption estimation of machining systems. However, the existing research on energy consumption does not focus on the tool setting process.

As a critical link in the use of CNC machine tools, the precision of tool setting determines the machining accuracy of workpieces [31]. Studies on the tool setting process mainly concentrate on accuracy and operational efficiency [31–33]. Zhao et al. [32] proposed an automatic tool setting technology based on machine vision in micro milling, and the results showed that the total time of automatic tool setting was 130 s, and the accuracy was better than 1.359 µm. Zhou et al. [34] proposed a high-precision B-axis tool setting method that combined the charge-coupled device camera tool setting and trial cutting. For this method, the form error was less than 354 nm, and the surface roughness was less than 3.74 nm. Jana et al. [35,36] mathematically demonstrated the effects of the cutting angle on tool setting accuracy. Lee et al. [37] studied an auto tool setting method to improve machining accuracy using a laser tool setter. In fact, as a preparatory phase, the tool setting process takes a long time. In addition, due to the different proficiency levels of operators, the operation time of the tool setting process fluctuates, which leads to variable energy consumption. It is therefore very important to provide a standard for the operation time in the tool setting process. As an effective tool, the MODAPTS has been widely used to estimate operation times [38–41]. Chan et al. [42] used the MODAPTS to analyze the time of the U-bolt assembly task. Cho et al. [43] adopted the MODAPTS to estimate the time required to attach self-adhesive insulators, and the results varied from the actual value by no more than 9.5%. Alkan et al. [44] proposed a complexity assessment model for the manual assembly operations model using the MODAPTS. In this study, the operation time of the tool setting process was therefore estimated using the MODAPTS, which can be considered a reference standard.

The tool setting process constitutes an important part of the total machining energy consumption, so establishing an accurate estimated model is indispensable for lean energy management and energy optimization in CNC milling. To date, research focused solely on energy consumption modeling in the tool setting process is nonexistent. To bridge this gap, an energy consumption estimation method for the tool setting process in CNC milling based on the MODAPTS is presented in this paper. The balance of the paper is organized as follows: The MODAPTS is introduced briefly in Section 2, and the operations decomposition, power modeling, and energy consumption modeling for the tool setting process are delineated in Section 3. A case study conducted using an XH714D experimental platform is described in Section 4. The discussion is presented in Section 5, with the conclusion and proposed future work in Section 6.

2. A Brief Introduction to the MODAPTS

Time studies are generally grouped into three categories: stopwatch timing, instantaneous observations, and a predetermined time standard (PTS) [45]. A widely used PTS, the MODAPTS, is an action time analysis method proposed by Heyde [40]. With the MODAPTS, the time for a task can be predicted prior to the task being performed. It has the characteristics of being simple, intuitive, convenient, and fast [41]. In addition, the MODAPTS can be applied to determine the standard time required for human production activities without using a stopwatch [39]. Decomposing human operations into a series of basic actions and assigning predetermined time standards to those actions are two core concepts of the MODAPTS.

The MODARTS is premised on three main assumptions: (i) human operations comprise some basic actions; (ii) under the same conditions, the time required for a skilled person to execute the same action is constant; and (iii) a certain proportional relationship exists between the time spent on the actions performed by different parts of the human body. Based on these assumptions, the time spent on the movement of a finger by 25 mm is defined as 1 MOD in the MODAPTS, which is the unit action time, and the value is 0.129 s. Human operation actions are summarized as 21 types of basic actions in the MODAPTS, the definitions and codes of which are shown in Table 1 [38]. These basic actions consist of three types: movement actions, terminal actions, and auxiliary actions. Each basic action has a corresponding code, and the number in the code presents the time that the action needs to take. For example, one of the movement actions, forearm movement, is coded as M3. This means that, in terms of time, this basic action takes 3 MOD, which equals 0.387 s (3×0.129 s).

Table 1. The 21 types of basic actions in the MODAPTS.

Movement Actions		Terminal Actions		Auxiliary Actions			
Definition	**Code**	**Definition**	**Code**	**Definition**	**Code**	**Definition**	**Code**
Finger movement	M1	Touch	G0	Weight factor	L1	Eye use	E2
Wrist movement	M2	Grasp easily	G1	Walk	W5	Correct	R2
Forearm movement	M3	Grasp with attention	G3	Bend and rise	B17	Judge and react	D3
Whole arm movement	M4	Place easily	P0	Stand and sit	S30	Press	A4
Unbend arm movement	M5	Place with attention	P2	Foot acts on the footboard	F3	Circular movement	C4
		Place with assembly	P5				

3. Energy Consumption Estimation Method in the Tool Setting Process

It is common knowledge in the field that energy consumption estimation in the tool setting process is determined by two factors: accurate power models for the machine tool and the accurate estimation of the duration-on of the tool setting process. However, the power consumption of the machine tool is variable during the tool setting process due to different actions, which makes it difficult to establish accurate power models. Moreover, the duration of the tool setting process depends on the actions of the operator. To solve these problems, the tool setting process is divided into four main stages, and each main stage is further divided into substages. The duration of each substage is determined by the actions of the operator via the MODAPTS. Additionally, the actions of the machine tool during the tool setting process can be divided into basic action elements, which are also defined as basic energy consumption elements. The power models of the basic action elements for the machine tool are thus built on the basis of the features of the basic action elements. The energy consumption estimation model of the tool setting process can then be established.

3.1. Operations Decomposition and the MODAPTS Codes Determination for the Tool Setting Process

The tool setting process of the CNC milling machine tool is indispensable because it directly affects the machining accuracy of workpieces. The purpose of the tool setting process is to find the coordinates of the programming origin in the machine coordinate system. To finely describe the power consumption and estimate the duration of the tool setting process when machining a square workpiece, the tool setting process is divided into four main stages, namely, the preparation stage, the tool setting of the X-axis stage, the tool setting of the Y-axis stage, and the tool setting of the Z-axis stage. Further, each main stage can be divided into a series of substages based on the features of the operations, where the power consumption of the machine tool is invariable in a specific operation. Moreover, the operations of the operator in a substage can be further decomposed into basic actions, as defined in the MODAPTS. Each basic action has a unique code in the MODAPTS; so, the MODAPTS codes of the tool setting process, the main stages, the substages, and the actions of the operator can be determined from bottom to top. As a result, the duration of the tool setting process, the main stages, the substages, and the actions of the operator can be obtained by the corresponding MODAPTS codes without using any time-measuring tools.

For example, the purpose of the tool setting of the X-axis stage is to find the coordinate of the X-axis for the programming origin in the machine coordinate system and to input it into the CNC system. This stage is then divided into five substages: moving quickly to the left side of the workpiece, lowering the Z-axis, slowly closing to the workpiece, adjusting the data on the control panel, and lifting up the Z-axis. In actual operations, almost all the operations are accomplished by the right hand, and the left hand is used to assist the operations of the right hand. In addition, if the left hand applies some actions, they usually appear at the same time as the actions of the right hand. Only the actions of the right hand were therefore taken into consideration in this study. Through the actions of pressing the button and rotating the handwheel to control the X-axis feeding, the mechanical edge finger will move quickly to the left side of the workpiece. The MODAPTS codes for pressing the button and rotating the handwheel are M3A4 and M3C4, respectively. Based on operation experience, the number of turns to rotate the handwheel is around twenty. The MODAPTS code of this substage can therefore be expressed as M3A4(M3C4)*20. Meanwhile, the duration of this substage is 147MOD, which equals 18.963 s (147×0.129 s). The detailed operations decomposition and MODAPTS codes for the tool setting of the X-axis stage are summarized in Table 2. Similarly, the operations of the other three main stages can be decomposed and their duration calculated. The results of the stage division and the corresponding MODAPTS codes for the whole tool setting process are shown in Figure 1.

Table 2. Operations decomposition and MODAPTS codes for the tool setting of the X-axis stage.

Substages	Description of Actions	Action Code	Frequency	Substage Code	MODs
Move quickly to the left side of the workpiece	Press the button	M3A4	1	M3A4(M3C4)*20	147
	Rotate the handwheel	M3C4	20		
Lower the Z-axis	Press the button	M3A4	1	M3A4(M3C4)*20	147
	Shake the wheel	M3C4	20		
Slowly close to the workpiece	Press the button to reduce the feeding rate	M3A4	1	M3A4(M3C4D3)*5	57
	Rotate the handwheel, and judge the position of the edge finger	M3C4D3	5		
Adjust the data on the control panel	Press the button frequently	M3A4	20	(M3A4)*20	140
Lift up the Z-axis	Rotate the handwheel	M3C4	10	(M3C4)*10	70

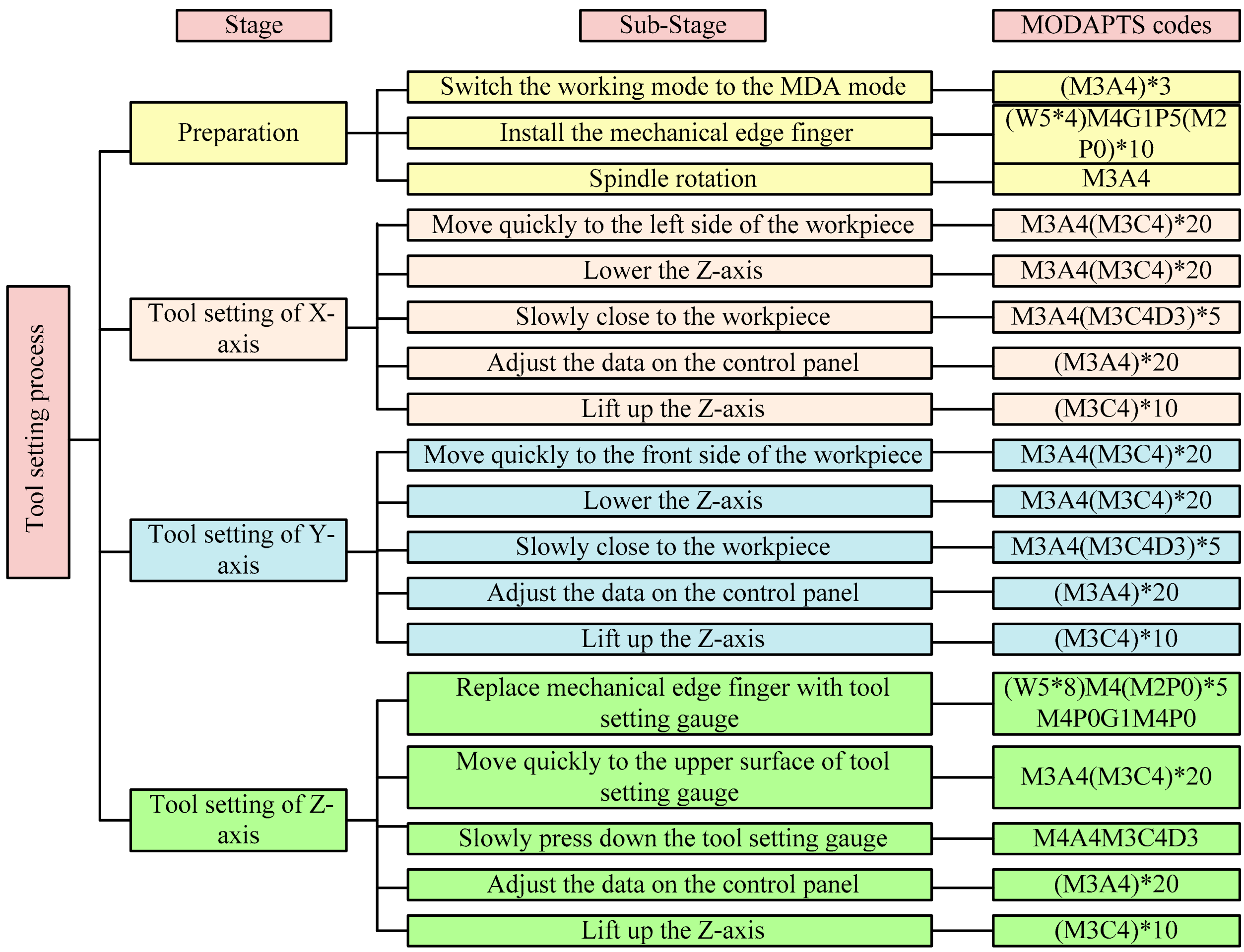

Figure 1. Stage division and the corresponding MODAPTS codes for the tool setting process.

3.2. Power Modeling of the Basic Action Elements of the Machine Tool

In general, the actions of the machine tool during the tool setting process can be divided into five basic action elements: standby operating, spindle rotating, X-axis feeding, Y-axis feeding, and Z-axis feeding. The basic action elements of the machine tool during the tool setting process are summarized in Table 3.

Table 3. The basic action elements of the machine tool.

No.	Basic Action Elements	Code	Description
1	Standby operating	SO	Switch on the main power and keep the electrical control system, the CNC system, lubricating system, etc., running
2	Spindle rotating	SR	Rotate the spindle at a certain speed without cutting a workpiece
3	X-axis feeding	XF	Feed in the X-axis of the feeding system at a certain speed without cutting a workpiece
4	Y-axis feeding	YF	Feed in the Y-axis of the feeding system at a certain speed without cutting a workpiece
5	Z-axis feeding	ZF	Feed in the Z-axis of the feeding system at a certain speed without cutting a workpiece

The basic action elements of the machine tool consume a certain amount of electrical energy, which can also be defined as the basic energy consumption elements. To estimate the energy consumption of the tool setting process, one of the key steps is to establish the power models of the basic action elements.

(1) Standby operating power

Standby operating power is the power consumption of standby operating, which refers to starting the machine tool and keeping it running without operating it. When the machine tool is started, the standby operating power always exists, and the value is mostly stable. The standby operating power is thus a constant and can be obtained by calculating the average value of multiple experimental measurements. It can be expressed as [46]:

$$P_{SO} = \sum_{i=1}^{N} P_{SOi}/N, \quad (1)$$

where P_{SO} [W] is the standby operating power, P_{SOi} [W] is the i-th measured value of the standby operating power, and N is the number of samples collected.

(2) Spindle rotating power

Spindle rotating power is the power consumption of a spindle rotating at a certain speed without cutting a workpiece. Apart from the power loss of the spindle motor, the spindle only needs to overcome friction when it rotates at a certain speed. It can therefore be thought that the spindle rotating power is linear with the rotation speed of the spindle. The power can be expressed as [46]:

$$P_{SR} = \mathrm{a} + \mathrm{b}n, \quad (2)$$

where P_{SR} [W] is the spindle rotating power, n [r/min] is the rotation speed of the spindle, and a and b are the coefficients of the formula.

(3) X-axis feeding power

X-axis feeding power is the power consumption of the feeding system feeding in the X-axis at a certain speed without cutting a workpiece. It needs to overcome the power consumption of friction for the moving feeding parts. Furthermore, considering the power loss of the X-axis feed motor, the X-axis feeding power can be expressed as the linear relation with the feeding velocity [46]:

$$P_{XF} = \mathrm{c}_x + \mathrm{d}_x v_x, \quad (3)$$

where P_{XF} [W] is the X-axis feeding power, v_x [mm/min] is the feeding velocity of the X-axis, and c_x and d_x are the coefficients of the formula.

(4) Y-axis feeding power

Similar to the X-axis feeding power, the Y-axis feeding power can be expressed as [46]:

$$P_{YF} = \mathrm{c}_y + \mathrm{d}_y v_y, \quad (4)$$

where P_{YF} [W] is the Y-axis feeding power, v_y [mm/min] is the feeding velocity of the Y-axis, and c_y and d_y are the coefficients of the formula.

(5) Z-axis feeding power

Considering the direction of gravity, the feeding direction of the Z-axis can be divided into up and down feeding. The Z-axis feeding power can be expressed as [46]:

$$P_{ZF+} = c_{z+} + d_{z+}v_{z+}, \tag{5}$$

$$P_{ZF-} = c_{z-} + d_{z-}v_{z-}, \tag{6}$$

where P_{ZF+} [W] is the Z-axis up feeding power; P_{ZF-} [W] is the Z-axis down feeding power; v_{z+} [mm/min] is the up feeding velocity of the Z-axis; v_{z-} [mm/min] is the down feeding velocity of the Z-axis; c_{z+}, c_{z-}, d_{z+}, and d_{z-} are the coefficients of the formulas.

3.3. Energy Consumption Estimation Modeling Based on the MODAPTS for the Tool Setting Process

After achieving the operations decomposition, determining the MODAPTS codes for all the substages, and establishing the power models for the basic action elements of the machine tool, the energy consumption of the tool setting process can be estimated. The framework of the energy consumption estimation modeling for the tool setting process is shown in Figure 2.

Stage	Sub-Stage	Power	MODAPTS codes	Duration	Energy
Preparation	Switch the working mode to the MDA mode	P_{SO}	(M3A4)*3	t_{11}	$P_{SO}\times t_{11}$
	Install the mechanical edge finger	P_{SO}	(W5*4)M4G1P5(M2P0)*10	t_{12}	$P_{SO}\times t_{12}$
	Spindle rotation	$P_{SO}+P_{SR}$	M3A4	t_{13}	$(P_{SO}+P_{SR})\times t_{13}$
Tool setting of X-axis	Move quickly to the left side of the workpiece	$P_{SO}+P_{SR}+P_{XF1}$	M3A4(M3C4)*20	t_{21}	$(P_{SO}+P_{SR}+P_{XF1})\times t_{21}$
	Lower the Z-axis	$P_{SO}+P_{SR}+P_{ZF\text{-}1}$	M3A4(M3C4)*20	t_{22}	$(P_{SO}+P_{SR}+P_{ZF\text{-}1})\times t_{22}$
	Slowly close to the workpiece	$P_{SO}+P_{SR}+P_{XF2}$	M3A4(M3C4D3)*5	t_{23}	$(P_{SO}+P_{SR}+P_{XF2})\times t_{23}$
	Adjust the data on the control panel	$P_{SO}+P_{SR}$	(M3A4)*20	t_{24}	$(P_{SO}+P_{SR})\times t_{24}$
	Lift up the Z-axis	$P_{SO}+P_{SR}+P_{ZF+}$	(M3C4)*10	t_{25}	$(P_{SO}+P_{SR}+P_{ZF+})\times t_{25}$
Tool setting of Y-axis	Move quickly to the front side of the workpiece	$P_{SO}+P_{SR}+P_{YF1}$	M3A4(M3C4)*20	t_{31}	$(P_{SO}+P_{SR}+P_{YF1})\times t_{31}$
	Lower the Z-axis	$P_{SO}+P_{SR}+P_{ZF\text{-}1}$	M3A4(M3C4)*20	t_{32}	$(P_{SO}+P_{SR}+P_{ZF\text{-}1})\times t_{32}$
	Slowly close to the workpiece	$P_{SO}+P_{SR}+P_{YF2}$	M3A4(M3C4D3)*5	t_{33}	$(P_{SO}+P_{SR}+P_{YF2})\times t_{33}$
	Adjust the data on the control panel	$P_{SO}+P_{SR}$	(M3A4)*20	t_{34}	$(P_{SO}+P_{SR})\times t_{34}$
	Lift up the Z-axis	$P_{SO}+P_{SR}+P_{ZF+}$	(M3C4)*10	t_{35}	$(P_{SO}+P_{SR}+P_{ZF+})\times t_{35}$
Tool setting of Z-axis	Replace mechanical edge finger with tool setting gauge	P_{SO}	(W5*8)M4(M2P0)*5 M4P0G1M4P0	t_{41}	$P_{SO}\times t_{41}$
	Move quickly to the upper surface of tool setting gauge	$P_{SO}+P_{ZF\text{-}1}$	M3A4(M3C4)*20	t_{42}	$(P_{SO}+P_{ZF\text{-}1})\times t_{42}$
	Slowly press down the tool setting gauge	$P_{SO}+P_{ZF\text{-}2}$	M4A4M3C4D3	t_{43}	$(P_{SO}+P_{ZF\text{-}2})\times t_{43}$
	Adjust the data on the control panel	P_{SO}	(M3A4)*20	t_{44}	$P_{SO}\times t_{44}$
	Lift up the Z-axis	$P_{SO}+P_{ZF+}$	(M3C4)*10	t_{45}	$(P_{SO}+P_{ZF+})\times t_{45}$

Figure 2. The framework of the energy consumption estimation modeling.

As shown in Figure 2, based on the four main stages, the total energy consumption of the tool setting process can be expressed as:

$$TSEC = \sum_{i=1}^{4} TSEC_i, \tag{7}$$

where $TSEC$ [J] is the total energy consumption of the tool setting process, $TSEC_i$ [J] is the energy consumption of the main stage i during the tool setting process, and i (i = 1, 2, 3, 4) is the number of the main stage.

For the main stages, we assume that the main stage i can be divided into m_i substages. The energy consumption of the main stage i can therefore be expressed as:

$$TSEC_i = \sum_{j=1}^{m_i} TSEC_{ij}, \tag{8}$$

where $TSEC_{ij}$ [J] is the energy consumption of substage j in the main stage I, and m_i is the number of substages in the main stage i.

Because the basic action elements of the machine tool do not change during a substage, the power of the machine tool for the substage is invariable for a specific operation. Hence, the energy consumption of substage j in the main stage i can be calculated as:

$$TSEC_{ij} = P_{ij}\ t_{ij}, \tag{9}$$

where P_{ij} [W] is the power of substage j in the main stage I, and t_{ij} [s] is the estimated duration of the substage j in the tool setting stage i, which is determined by the MODAPTS codes shown in Figure 1.

For the machine tool, one or more of the basic action elements exist in a substage. The power of substage j in the main stage i can thus be calculated as:

$$P_{ij} = \sum_{k=1}^{5} P_k e_k, \tag{10}$$

$$e_k = \begin{cases} 1 & \text{ifthebasicactionelement}k\text{isexecuted} \\ 0 & \text{else} \end{cases}, \tag{11}$$

where P_k (k =1, 2, 3, 4, 5) [W] represents the power of the basic action element k, as shown in Table 2 (in other words, P_1 represents P_{SO}, P_2 represents P_{SR}, P_3 represents P_{XF}, P_4 represents P_{YF}, and P_5 represents P_{ZF+} or P_{ZF-}), and e_k denotes the execution state of the basic action element k.

Based on Equations (7)–(10), the total energy consumption of the tool setting process can be expressed as:

$$TSEC = \sum_{i=1}^{4}\sum_{j=1}^{m_i} TSEC_{ij} = \sum_{i=1}^{4}\sum_{j=1}^{m_i} P_{ij}t_{ij} = \sum_{i=1}^{4}\sum_{j=1}^{m_i} (\sum_{k=1}^{5} P_k e_k) t_{ij}. \tag{12}$$

As shown above, the energy consumption estimation model can be established by decomposing the operations into basic action elements for the operator and machine tool. The basic action elements of the operator based on the MODAPTS are used to determine the operating time, and the basic action elements of the machine tool are used to establish the power models. With the proposed method, the energy consumption of the whole tool setting process, the main stages, the substages, and even a basic action element can be estimated accurately. Furthermore, the proportion of energy consumed in each stage can be analyzed.

4. Case Study

A three-axis machining center, a square workpiece, a power analyzer, and a skilled operator formed the energy consumption experimental platform employed to demonstrate the feasibility of the proposed energy consumption estimation method. The case study consisted of two steps. First, a series of experiments were carried out to obtain the coefficients of the established power models of the basic action elements. Second, a tool setting process was performed to demonstrate the effectiveness of the proposed method.

4.1. Experiment Details

The experiment was conducted using an XH714D three-axis machining center made by the Hanchuan CNC Machine Tool Co., Ltd., in China. The main parameters of the machine tool are listed in Table 4. The power and energy consumption of the machine tool during the tool setting process were measured with a Yokogawa WT1800 power analyzer. The power sensor was installed in the electric cabinet, and it measured the main power input, as shown in Figure 3. A mechanical edge finger was installed in the spindle of the machine tool for the tool setting of the X- and Y-axes. A tool setting gauge superposed on the upper surface of the workpiece was used in the tool setting of the Z-axis. The workpiece material was aluminum, and the dimensions were 100 × 80 × 50 mm. A skilled operator was employed to execute the tool setting process. The experimental platform was established as shown in Figure 3.

Table 4. The main parameters of the machine tool.

Items	Spindle Speed Range [r/min]	Spindle Power [KW]	Distance of Travel XYZ [mm]	Maximum Feeding Velocities [mm/min]
Values	60–8000	7.5	650 × 400 × 500	20,000

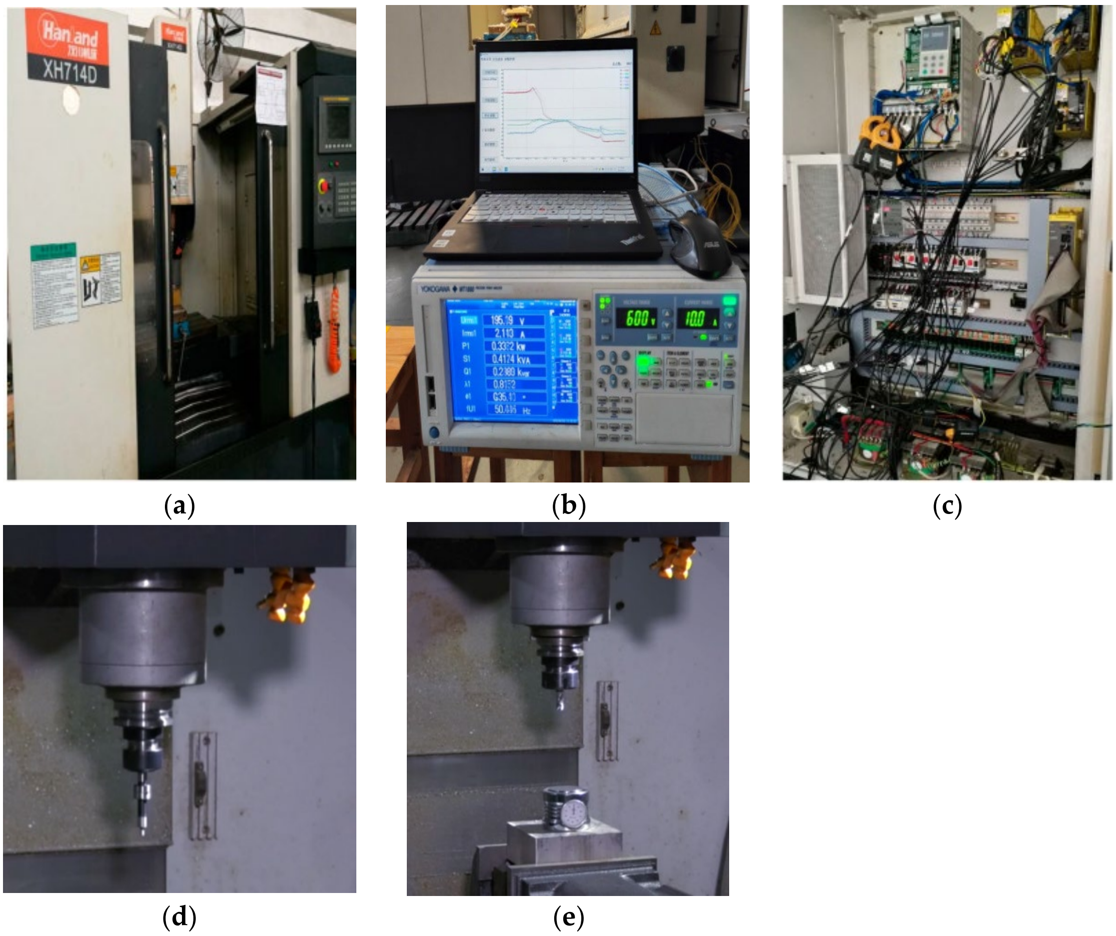

Figure 3. XH714D experimental platform. (**a**) Machine tool. (**b**) Data acquisition instrument. (**c**) Wiring diagram. (**d**) Mechanical edge finger. (**e**) Tool setting gauge and workpiece.

In line with Figure 2, the values of the corresponding parameters during each substage, such as the rotation speed and feeding velocity, are listed in Table 5.

Table 5. Parameter values of the tool setting process.

Items	n **[r/min]**	v_x **[mm/min]**		v_y **[mm/min]**		v_{z+} **[mm/min]**	v_{z-} **[mm/min]**	
		v_{x1}	v_{x2}	v_{y1}	v_{y2}		v_{z-1}	v_{z-2}
Values	700	1500	500	1500	500	1500	1500	500

4.2. Results

The coefficients of the power models for the basic action elements are provided below.

(1) Standby operating power

Based on the experimental tests and data, which were collected 50 times, the average standby power was 530 W.

(2) Spindle rotating power

For the CNC machining center (XH714D), the total power values of the rotating spindle were collected at different rotation speeds. The power of the rotating spindle could be calculated by subtracting the standby operating power from the total power of the rotating spindle. The measured values of the spindle rotating power at various rotation speeds are shown in Table 6.

Table 6. The measured power values of the rotating spindle.

Items	**Values**										
Spindle rotation speed [r/min]	250	300	350	400	450	500	550	600	650	700	750
Measured power [W]	107	115	122	125	131	141	138	154	166	183	200

Based on the measured values, the fitting result of the spindle rotation power function is presented in Figure 4. The spindle rotating power can therefore be expressed as shown in Table 7.

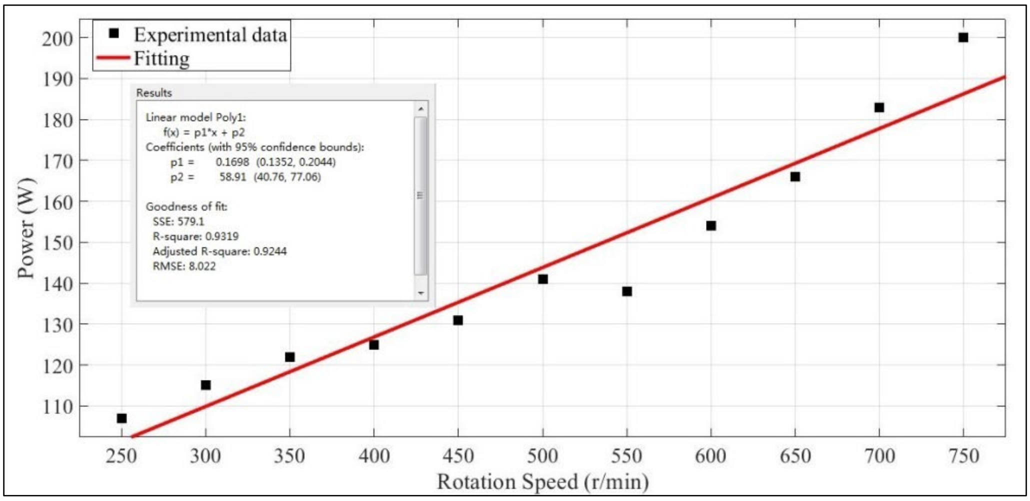

Figure 4. The spindle rotating power function fitting.

The R-squared value of 0.9319 indicates that the obtained spindle rotating power model could describe the relationship between the spindle rotating power and the rotation speed well.

Table 7. Summary of the power models for the basic action elements.

Power Models	R-Square
P_{SO} = 530 W	-
$P_{SR} = 58.909 + 0.1698n$	0.9319
$P_{XF} = 19.867 + 0.0109v_x$	0.9972
$P_{YF} = 0.2667 + 0.0107v_y$	0.9771
$P_{ZF+} = 21.933 + 0.0212v_{z+}$	0.9962
$P_{ZF\text{-}} = 2.6667 + 0.0048v_{z-}$	0.9648

(3) Feeding power of the X-, Y-, and Z-axes

For the X-axis feeding power, the total power values of the machine tool were collected at different feeding velocities, where the basic action elements of the machine tool were standby operating and Z-axis feeding. The X-axis feeding power could then be acquired by subtracting the standby power from the total power of the machine tool. The measured values of the X-axis feeding power at various velocities are shown in Table 8. Similarly, the measured values of the Y-axis and Z-axis feeding power at different feeding velocities could be obtained as shown in Table 8.

Table 8. The measured values of the feeding power of the X-, Y-, and Z-axes.

Items		Values									
Feeding velocity [mm/min]		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
Measured X-axis feeding power [W]		26	32	36	41	46	52	58	63	69	76
Measured Y-axis feeding power [W]		8	12	13	17	30	33	38	44	50	52
Measured Z-axis feeding power [W]	Z+	35	45	53	61	73	86	94	108	119	129
	Z−	6	8	10	13	13	14	20	21	25	28

Based on the measured values, the fitting results of the feeding power functions of the X-, Y-, and Z-axes are presented in Figures 5–8. The respective feeding powers can be expressed as shown in Table 7.

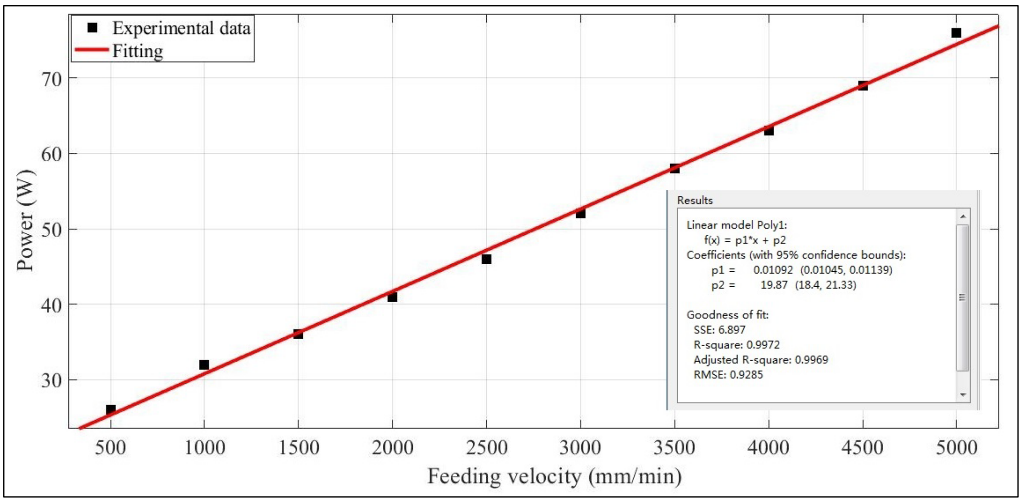

Figure 5. X-axis feeding power function fitting.

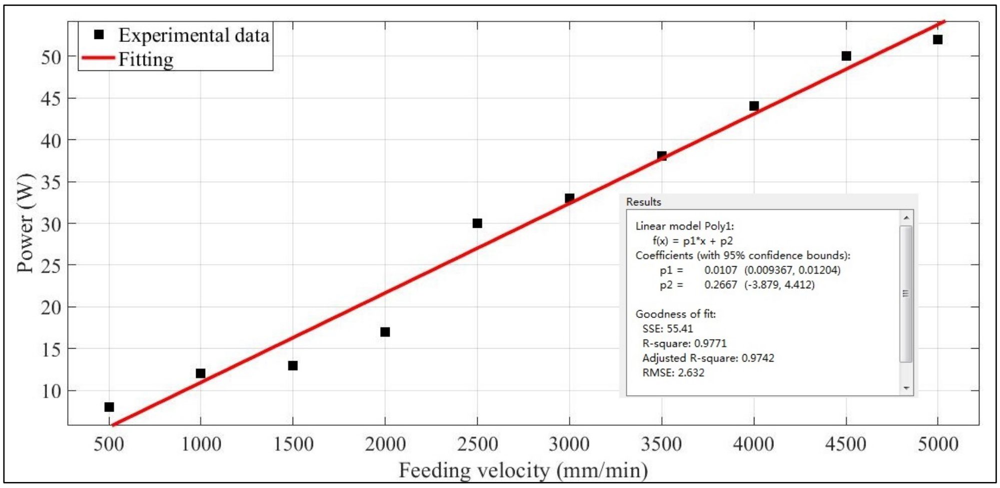

Figure 6. Y-axis feeding power function fitting.

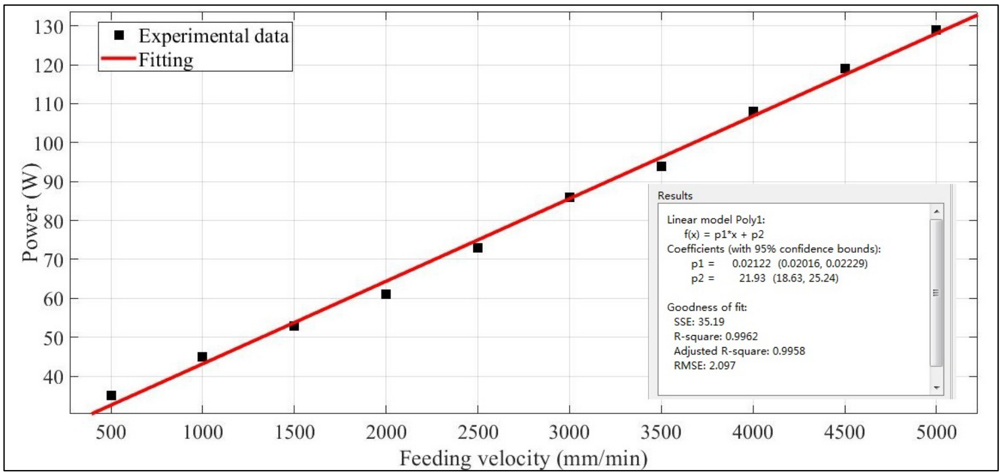

Figure 7. Z-axis feeding power function fitting (Z+).

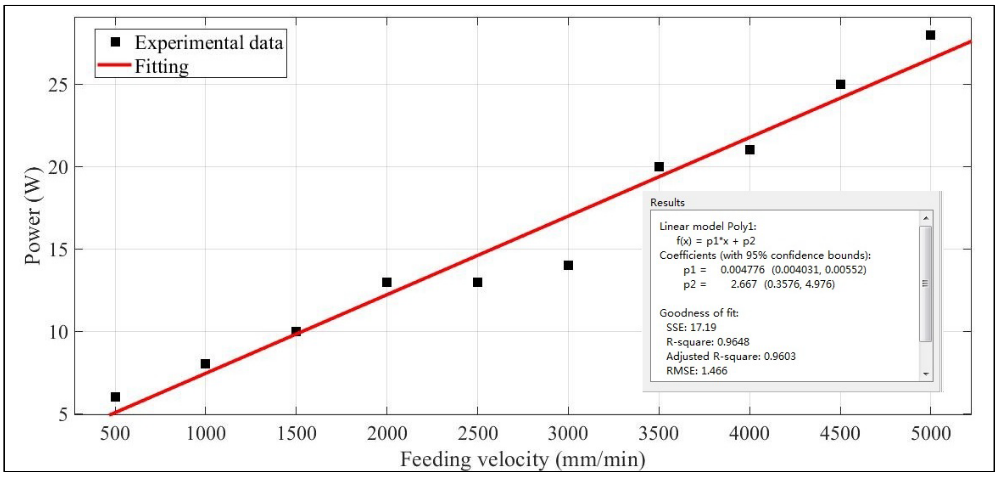

Figure 8. Z-axis feeding power function fitting (Z−).

The R-squared values of the X-axis, Y-axis, and Z-axis feeding power function fitting were all close to 1, which indicated that these feeding power models could describe the relationships between the feeding powers and feeding velocities well.

Energy Consumption Estimation

Based on Tables 5 and 7, the power values of the basic action elements for the machine tool during each substage could be calculated, and the results are shown in Table 9.

Table 9. Basic element power values of the tool setting process.

Power [W]	P_{SO}	P_{SR}	P_{XF}		P_{YF}		P_{ZF+}	P_{ZF-}	
			P_{XF1}	P_{XF2}	P_{YF1}	P_{YF2}		P_{ZF-1}	P_{ZF-2}
Values	530	177.85	36.22	25.32	16.32	5.62	53.73	9.87	5.07

Based on Figure 2 and Table 9, the energy consumption for each substage was calculated. Taking substage 1 in the tool setting of the X-axis stage as an example, the energy consumption estimation can be expressed as $TSEC_{21} = P_{21} \times t_{21} = (P_{SO} + P_{SR} + P_{XF1}) \times$ (M3A4(M3C4)*20) = (530 +177.85 + 36.22) W $\times$ (147 $\times$ 0.129) s = 14109.8 J.

The energy consumption of the other substages can be calculated in the same way. The energy consumption details calculated based on the models are shown in Table 10.

Table 10. The energy consumption details calculated based on the models.

Stages	Substages	t_{ij} [s]	P_{ij} [W]	$TSEC_{ij}$ [J]	$TSEC_i$ [J]
Stage 1 (preparation)	Substage 1	(M3A4)*3 = 2.709	530	1435.77	5493.46
	Substage 2	(W5*4)M4G1P5(M2P0)*10 = 6.45	530	3418.50	
	Substage 3	M3A4 = 0.903	707.85	639.19	
Stage 2 (tool setting of the X-axis)	Substage 1	M3A4(M3C4)*20 = 18.963	744.07	14,109.80	52,771.76
	Substage 2	M3A4(M3C4)*20 = 18.963	717.72	13,610.12	
	Substage 3	M3A4(M3C4D3)*5 = 7.353	733.17	5391.00	
	Substage 4	(M3A4)*20 = 18.06	707.85	12,783.77	
	Substage 5	(M3C4)*10 = 9.03	761.58	6877.07	
Stage 3 (tool setting of the Y-axis)	Substage 1	M3A4(M3C4)*20 = 18.963	724.17	13,732.44	52,062.38
	Substage 2	M3A4(M3C4)*20 = 18.963	707.85	13,422.96	
	Substage 3	M3A4(M3C4D3)*5 = 7.353	713.47	5246.14	
	Substage 4	(M3A4)*20 = 18.06	707.85	12,783.77	
	Substage 5	(M3C4)*10 = 9.03	761.58	6877.07	
Stage 4 (tool setting of the Z-axis)	Substage 1	(W5*8)M4(M2P0)*5M4P0G1M4P0 = 8.127	530	4307.31	30,354.08
	Substage 2	M3A4(M3C4)*20 = 18.963	539.87	10,237.55	
	Substage 3	M4A4M3C4D3 = 1.806	535.07	966.34	
	Substage 4	(M3A4)*20 = 18.06	530	9571.80	
	Substage 5	(M3C4)*10 = 9.03	583.73	5271.08	
Total		210.786	/	140,681.68	140,681.68

The analysis results show that the estimation values of the operating time and the energy consumption for the tool setting process were 210.786 s and 140,681.68 J, respectively. The estimated operating times for the main stages 1, 2, 3, and 4 were 10.062 s, 72.369 s, 72.369 s, and 55.986 s, respectively. At the same time, the energy consumption estimation values for the main stages 1, 2, 3, and 4 were 5493.46 J, 52,771.76 J, 52,062.38 J, and 30,354.08 J, respectively.

Meanwhile, the actual values of the operating time and energy consumption for the tool setting process measured by the Yokogawa WT1800 power analyzer were $t' = 227$ s and $TSEC'$ = 153,352.8 J, respectively. Accordingly, the errors of the operating time and energy consumption estimations were 7.14% and 8.26%, respectively.

5. Discussion

The tool setting process is a key link before formal cutting, and its positional accuracy determines the machining accuracy of workpieces. Furthermore, the proportion of time spent on the tool setting process while machining a workpiece is considerable, which means that large amounts of electrical energy are consumed in the tool setting process. In one of our previous studies [47], we found that in a machining experiment, the proportions of time and electrical energy consumed in the tool setting process were 33.84% and 21.60%, respectively. Nevertheless, on the one hand, most of the previous studies on the tool setting process have focused on the principles and new methods [31,35], accuracy control and enhancement [34], and operation efficiency [32], among other topics. On the other hand, in terms of energy consumption modeling, no related studies have focused on energy consumption in the tool setting process. This study is thus the first to concentrate on the tool setting process from the perspective of energy consumption.

In terms of time estimation, a PCA-based method for motion analysis and segmentation in the form of a software package has been proposed in the literature [41]. The accuracy rate of the time estimation using this approach was 80.08%. In another study [40], a maintenance time estimation method for a Boeing 737 APU starter motor's maintenance process based on the MODAPTS and virtual simulation was presented, and the accuracy of the time estimation was 97%. In this study, the error of the operating time estimation using the MODAPTS for the tool setting process was 7.14%, which verifies that the MODAPTS method estimated the operating time effectively, accurately, and stably.

With respect to energy consumption estimation in machining systems, the mainstream methods are traditional methods and data-driven methods. In the traditional methods, the power and energy consumption models are usually established based on clear energy consumption characteristics. Jia et al. [48] proposed an energy demand modeling method of key state transitions of turning processes, and the predictive accuracy was generally above 90%. According to the established SEC model, the average accuracy is 97% [14]. Data-driven methods are used if the energy consumption characteristics are not clear, but big data related to machining and energy consumption have been acquired. Cao et al. [49] proposed a novel milling energy consumption prediction method based on program parsing and parallel neural networks, and the prediction error of energy consumption per line of instruction was within 5%. The method proposed in this paper can therefore be classified as a traditional method. The error of the energy consumption estimation was 8.26%, which indicates that the proposed energy consumption estimation method is effective.

The proportions of the operating times and energy consumption in the main stages were obtained from the calculated results and are shown in Figure 9, which indicates the direction of energy conservation. In stages 2 and 3, the proportions of energy consumption were 37.51% and 37.01%, respectively. The energy consumption in these two stages was thus dominant. This is because the basic action element spindle rotating appears, and the operating time is longer in stages 2 and 3. The energy consumption in stages 2 and 3 can therefore be reduced by lowering the rotation speed of the spindle. As shown in Figure 10, when the rotation speed of the spindle was reduced from 700 r/min to 500 r/min, the energy consumption of the tool setting process was reduced by 3.52%. With the proviso that the requirements of tool setting are met, the total energy consumption of the tool setting process can be reduced by lowering the rotation speed of the spindle properly.

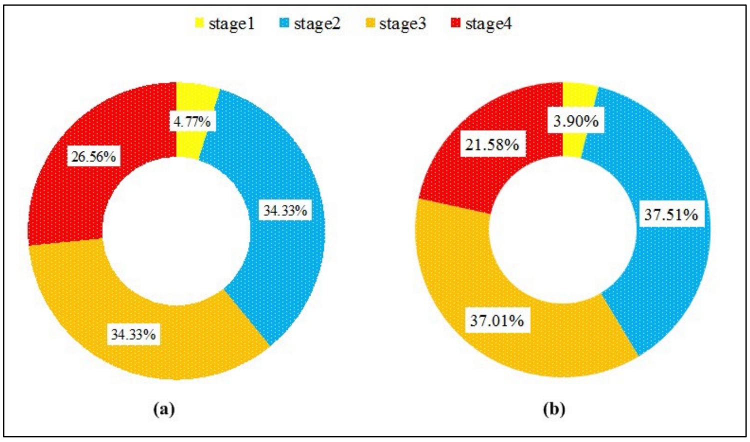

Figure 9. The proportion distributions of the operating times and energy consumption in the four main stages. (**a**) The operating time proportions. (**b**) The energy consumption proportions.

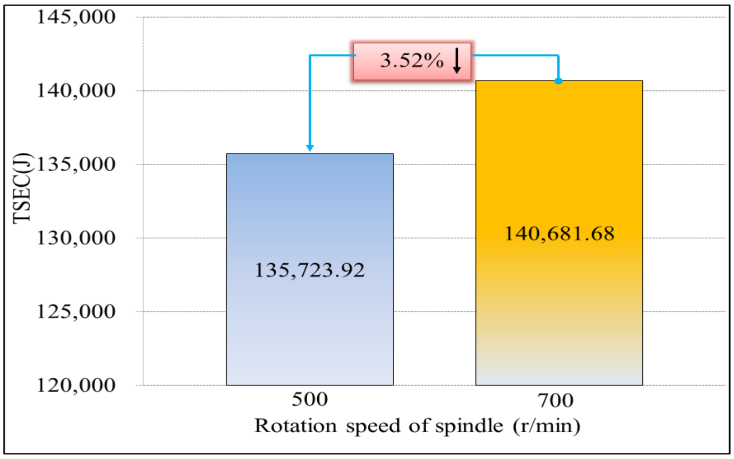

Figure 10. Effect of the reduced rotation speed of the spindle on energy consumption.

To strengthen the monitoring and management of energy consumption in the mechanical manufacturing industry, some scholars are trying to establish the energy consumption allowance for a machining system or a workpiece [50,51]. The method proposed in this paper can help establish the labor-hour quotas and energy consumption allowances in the tool setting process for CNC milling. After evaluating and optimizing the actions of human operations and adding a certain coefficient of relaxation, the man-hour quotas of the tool setting process will be determined. The energy consumption allowance of the tool setting process will then be established using the proposed method.

6. Conclusions

The issues of energy consumption and energy efficiency in mechanical machining systems have been studied extensively. However, no attention has been paid to energy consumption in the tool setting process. In this paper, an energy consumption estimation method based on the MODAPTS is proposed to investigate the energy consumption of the tool setting process for CNC milling. The main contributions are as follows:

1. The energy consumption of the tool setting process is considered for the first time.
2. Human operations in the tool setting process are decomposed into basic actions as defined in the MODAPTS. Based on these, the operating times are determined without any measurements.
3. Detailed power models for the machine tool are established from the perspective of the basic action elements.

4. The energy consumption estimation model is established based on action decomposing both for the operator and the machine tool.

The case study showed that the proposed method was effective in estimating the energy consumption of the tool setting process using modeling. The results obtained from the consumption estimation model showed good agreement with the experimental data, and the errors of the operating time and energy consumption estimations were 7.14% and 8.26%, respectively. The method can be used to establish labor-hour quotas and energy consumption allowances in the tool setting process for CNC milling. In this paper, only square workpieces were taken into consideration in the tool setting process. The tool setting process of round workpieces will be studied in the next step. In addition, the energy consumption of the operator, the fatigue of the operator, and the wasted energy consumption caused by operator fatigue will be studied thoroughly in the future.

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