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Modeling of cutting tool life with power consumption using Taylor's equation

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Abstract Tool wear is a major cause of machinability degradation, so numerous studies have been conducted to predict tool wear and life. However, conventional methods show a trade-off relationship between the accuracy of the model and practicality in implementation in general, thus it is required to find a plausible solution. This study attempted to predict the tool life by using power consumption, which is a real-time monitoring parameter of the machining process with cost competitiveness and easy measurement. Here, to formulate the easily applicable model, Taylor's equation form with a relatively simple configuration compared to conventional polynomial models was considered. Titanium alloy milling was performed, and the flank wear and the cutting power consumption purely required in material removal were calculated. Then, the tool life and the cutting power consumption were fitted with Taylor's equation form. By arranging both equations, a direct tool life model representing the relationship between cutting power consumption and tool life was established. A verification test was performed to evaluate the predictive accuracy and usability of the direct tool life model. Experimental results showed that the cutting power consumption is influenced by the process parameters in a similar way to the tool life, following Taylor's equation form well. It is believed that power consumption can be a significant parameter for not only efficient processing but also process monitoring with ease of implementation.

1. Introduction

Cutting tool wear inhibits machinability by increasing cutting loads [1, 2] and worsening the surface roughness of the workpiece [3, 4]. Tool wear is caused by various factors, such as abrasion [5], chemical reaction (oxidation) [6], or diffusion and adhesion caused by high temperatures on the tool-chip interface [7]. However, it is difficult to accurately predict tool wear in practical cases because material behavior during machining varies in many complex ways. Besides, these wear factors show great interactions with each other [8-10].

Numerous studies have been conducted to predict tool wear and life by analyzing various signals from the process, such as spindle vibration, cutting force, and surface roughness. Chuangwen et al. [11] and Aslan [12] correlated cutting forces and spindle vibrations with tool wear under various cutting conditions. Broderick et al. [13] performed titanium alloy machining with different types of coolants and confirmed the relationship between tool wear and cutting force. Li et al. [14] established a tool wear prediction model based on surface roughness and cutting force.

In general, there is a trade-off relationship between prediction accuracy and ease of measurement/analysis. Here, the ease of measurement includes additional effort required throughout from an experimental configuration to data acquisition. Cutting force shows high accuracy for predicting tool wear, as it directly measures the cutting load when removing materials [13, 15]. However, dynamometers, which are commonly used to measure the cutting forces, are typically very expensive and require considerable setup effort not to interfere with the machining process. Spindle vibration and surface roughness require less effort to measure and are more economical; however, compared to the cutting forces, they show less accuracy for the tool wear predictions, as they are indirectly related to the tool wear [14, 16]. Thus, it is necessary to find a plausible solution both with ease of measurement and high precision.

In addition, a consensus on the tool life model form has not been reached. Empirical tool life models are commonly constructed in polynomial forms, in terms of the cutting conditions [17, 18]. However, the models require higher-order interaction terms to ensure accuracy. The inclusion of many variables and coefficients generally lowers practical applicability as it requires more experiments to complete the model. Zheng et al. [16] analyzed empirical tool life models with polynomial and exponential forms (with respect to cutting force and surface roughness). Nevertheless, there is a need for further practical and reasonable models that can be applied to the actual field based on the certain dominant variables and the smaller number of model coefficients.

Power consumption can be attributed to complex interactions among tool wear factors during machining, thus various causes of tool wear can all be simultaneously considered [19]. Power consumption measurements have the following advantages. It can be measured using relatively inexpensive equipment (e.g., a power meter) compared to dynamometers. Also, the power consumption is measured through the power meter, which is connected to the switchboard of the machine tool, so less effort is required in experimental configuration and the machining process is not disturbed by the data acquisition process at all. However, the power consumption acquired during machining includes power consumption not only required to remove material, but also required to drive the machine components, such as spindle, table, and coolant pump, thus cannot be used as it is. Studies have been thus conducted to extract pure cutting power consumption, which is the power consumed in purely material removal without any influence of the machine tool components. Yoon et al. [20] analyzed the power consumption of driving units of machine tools and derived a model. Lee et al. [21] calculated cutting power consumption by subtracting the power required to drive a machine tool.

Consequently, this study attempted to construct an economical, practical, and accurate tool life model using cutting power consumption. It was aimed to formulate an easily applicable model with a simple form by utilizing the power consumption of the machine tool. Here, Taylor's equation, which has a simple exponential form representing the nonlinear inverse relationship between cutting speed and tool life was considered. Taylor's equation is commonly and widely used to predict tool life due to its reasonable precision and ease of application [22, 23]. Since the cutting speed, a parameter directly related to the energy, is the major term in Taylor's equation, it was hypothesized that cutting power consumption would have a similar form to Taylor's equation. A set of experiments was performed to confirm the hypothesis, and a model was constructed to predict the tool life in terms of power consumption.

Titanium alloy milling was performed under various cutting conditions, and the tool wear and the cutting power consumption of the machine tool were measured. Then, Taylor's equation (tool life) and the cutting power consumption model having a form of Taylor's equation were fitted to the experimental results. By arranging both equations of Taylor's form, a direct tool life model representing the relationship between cutting power consumption and tool life was constructed. Through the verification test for arbitrary cutting conditions, it was proved that it is possible to accurately estimate the tool life using the cutting power consumption, which is a real-time monitoring parameter of the machining, and to establish a direct tool life model more simply than the conventional polynomial tool life models.

The suggested model is practical and competitive to Taylor's equation. Furthermore, the model has advantages even compared to Taylor's equation. Various application ranges of the model were presented, such as predicting the remaining cutting tool life and predicting the tool life with changes of cutting conditions during machining. The direct tool life model is expected to be widely utilized throughout the machinery industries based on its excellent practicality and competitive accuracy of tool life prediction.

2. Experimental details

2.1 Experimental setup

Milling of titanium alloy plates (Grade 5, Ti-6Al-4V; Sejin Titanium, Korea) was conducted in a three-axis machining center (Robodrill, α-K10C; Fanuc Corp., Japan). The power consumption of the machine tool was measured using a power meter (PAC4200; Siemens Industry, Germany) every 0.1 seconds through the customized LabVIEW software. To evaluate the tool wear, a customized optical digital microscope was used. Cutting tools (four-flute plain endmill with a diameter of 12 mm; TSE-4120M-TT5515; Taegutec Ltd., Korea) were used to observe the development of tool wear. All experiments were performed using the same machining system, cutting tools, and materials (Fig. 1).

It is known that the radial depth of cut a_e and axial depth of cut a_p have less influence on tool wear development compared to the spindle rotation speed and feed per tooth [24-27].

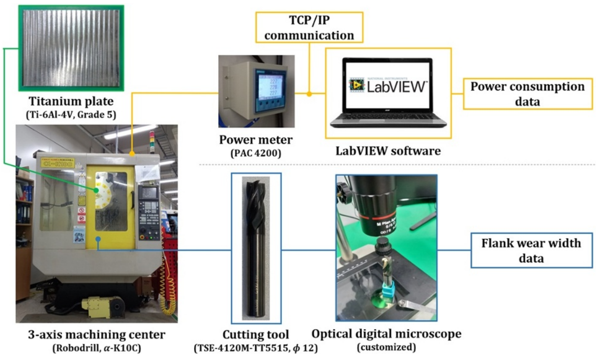

Fig. 1. Schematic of the data acquisition.

Table 1. Cutting conditions for the experiments.

No.	Spindle rotation speed (rev min^{-1})	Feed per tooth (mm per tooth)	Feed (mm min^{-1})
1	800	0.03	96
2	800	0.035	112
3	800	0.04	128
4	1025	0.03	123
5	1025	0.035	144
6	1025	0.04	164
7	1250	0.03	150
8	1250	0.035	175
9	1250	0.04	200

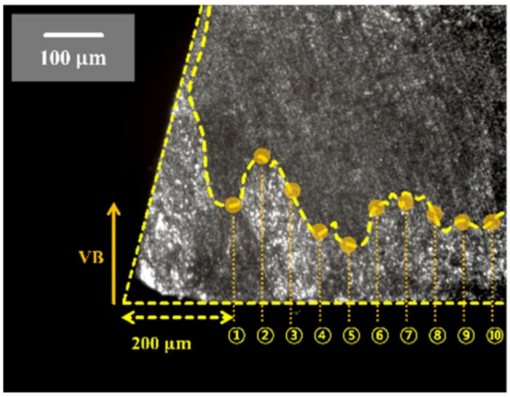

Fig. 2. Measurement of flank wear width.

Cutting conditions were thus set by dividing the two cutting parameters of spindle rotation speed (800, 1025, 1250 rev min^{-1}) and feed per tooth (0.03, 0.035, 0.04 mm per tooth) into three levels, respectively (Table 1). The experiments were designed with a full factorial design and were performed in a random order so that other factors would not systematically affect the experimental results. Factors such as radial depth of cut (12 mm) and axial depth of cut (3 mm) were kept constant. All experiments were repeated three times for each condition.

A single 8000 mm slot (a_e = 12 mm, a_p = 3 mm) was machined under each cutting condition, and flank wear was observed through an optical digital microscope at cutting lengths of initial 1000 and 2000 mm, and every 2000 mm thereafter. To accurately measure the flank wear width (VB), ten points spaced at 40 μm intervals were designated at a point 200 μm away from the tool-tip (Fig. 2). The points were averaged over four blades (total of 40 points) per the set cutting lengths for 3 repetitions to improve the repeatability of measurements. According to ISO standard 8688-2, an average flank wear width (VB_{avg}) of 300 μm was considered to indicate the end of tool life.

2.2 Calculation of cutting power consumption

The total power consumption measured by the power meter

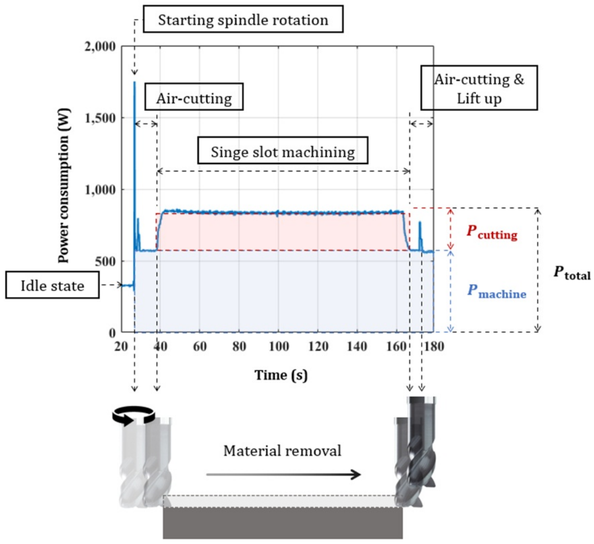

Fig. 3. An example of power profile during slot machining with a spindle rotation speed of 800 rev min^{-1} and feed per tooth of 0.035 mm per tooth.

(P_{total}) is divided into machine power consumption and cutting power consumption. Here, machine power consumption (P_{machine}) is the power consumed to control and drive components of machine tools such as spindles, tables, and coolant pumps. Cutting power consumption (P_{cutting}) is the power consumed purely for material removal. Since the machine power consumption varies depending on the operation conditions of each component, the cutting power consumption was extracted through additional calculation steps.

A basic power consumption model was constructed in the previous study by analyzing the power consumption of the machine tool [21]. As shown in Fig. 3, the idle state of the machine tool, and the air-cutting state (without cutting load) have a constant power consumption value. As slot machining is performed, power consumption increases depending on the cutting conditions. Cutting power consumption can be calculated by subtracting a constant power consumption value for air-cutting from the measured power consumption during slot machining (Eq. (1)).

$$P_{\text{cutting}} = P_{\text{total}} - P_{\text{machine}} . \quad (1)$$

3. Results and discussion

Sec. 3 introduces the process of establishing a direct tool life model to predict tool life using cutting power consumption. First, the tool life at each cutting condition was estimated based on the measured flank wear width and ISO standard, and Taylor's equation was fitted. A cutting power consumption model in form of Taylor's equation was then established based on the extracted cutting power consumption. Finally, a direct tool life model was constructed by organizing Taylor's equation (tool life) and cutting power consumption model, and the usability and accuracy were assessed through the verification test.

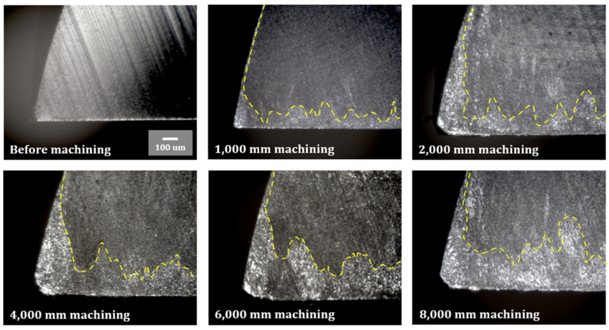

Fig. 4. Increase in flank wear width according to cutting length at a spindle rotation speed of 1250 rev min^{-1} and feed per tooth of 0.035 mm per tooth.

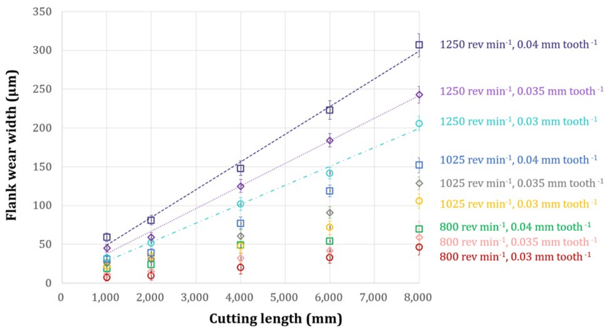

Fig. 5. Development of flank wear according to the cutting conditions and length.

3.1 Flank wear width and the tool life estimation

Figs. 4 and 5 show the development of flank wear with respect to cutting length and conditions. According to Fig. 4, flank wears first developed at the tool tip during the 1000 mm machining, and then gradually increased between the 2000-8000 mm machining. The severe crater wear on the rake face caused by the high temperature affected the development of flank wear by lowering the strength of the tool-tip, and there was prominent early wear. Also, the higher the spindle rotation speed and feed per tooth, the faster the cutting tool wear rate. In particular, as shown in Fig. 5, under the most cutting conditions, the flank wear width increased constantly according to the cutting length. Under the most severe cutting condition, flank wear reached 307 μm at a cutting length of 8000 mm, which was taken to indicate the end of the tool life.

The tool life was estimated according to the measured averaged flank wear width and ISO standards. According to Ref. [28], tool wear was assumed to increase linearly with the machining time and the cutting length. Thus, the tool life here was simply estimated using Eq. (2). T is the tool life, $T_{\text{machining}}$ is the machining time taken up to 8000 mm, and VB_{measured} is the measured flank wear width when the cutting length reached 8000 mm.

$$T = \frac{T_{\text{machining}} * 300}{VB_{\text{measured}}} . \tag{2}$$

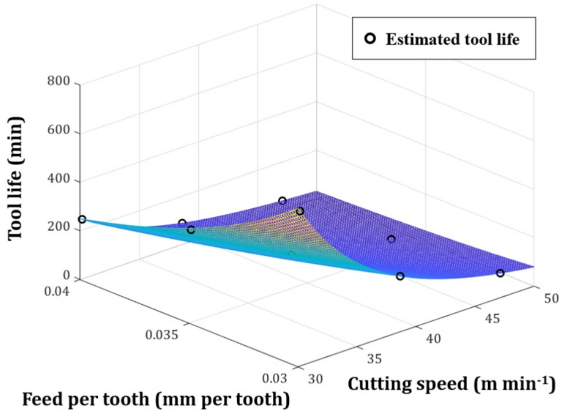

Fig. 6. Tool life estimation.

According to Eq. (2), the tool life of all cutting conditions was estimated. Then, the cutting speed, feed per tooth, and the estimated tool life of each cutting condition were substituted into Taylor's equation. Finally, the coefficients n, m, and C in Eq. (3) were obtained by fitting Taylor's equation to the experimental results. Here, V_c represents cutting speed, f_z represents feed per tooth, and T represents the tool life, where n, m, and C are constants (n = 0.2428, m = 0.0890, C = 8.4864).

$$V_c T^n f_z^m = C . \tag{3}$$

Fig. 6 shows Eq. (3) on a three-dimensional surface plot; the tool life with respect to the cutting speed and feed per tooth is shown. As the cutting speed increases, the tool life tends to decrease. In addition, by the interaction of the cutting speed and feed per tooth, under the high cutting speed condition, the feed per tooth had a negligible effect on the tool life; whereas in the low cutting speed conditions, the tool life was significantly reduced as the feed per tooth increased. The tool life estimated by Taylor's equation (response surface) and the tool life estimated by Eq. (2) under each cutting condition (black 'o' points) were compared to each other. There was a good agreement, with a maximum error of 5.84 %.

3.2 Cutting power consumption model

Fig. 7 shows the average cutting power consumption according to the cutting length at 200 mm intervals. Cutting power consumption increased with the cutting length, as per flank wear width (Fig. 5), and increased more steeply as the cutting conditions became more severe. As the cutting length increases and the cutting conditions become more severe, the tool wear develops more rapidly (the higher tool wear rate), which increases the cutting load for material removal and so as the cutting power consumption. Also, according to Fig. 7, the spindle rotation speed had a greater effect on the increase in the cutting power consumption compared to the feed per tooth; especially at the highest spindle rotation speed (1250 rev min^{-1}),

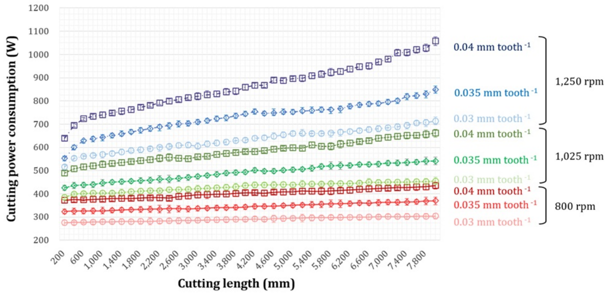

Fig. 7. Cutting power consumption according to cutting conditions and length.

major increases in tool wear and cutting power consumption were confirmed.

In the previous study [29], an empirical cutting power consumption model was constructed in the polynomial form including second order cutting condition terms. To recall the conventional methods, a polynomial empirical cutting power consumption model was shown herein by applying the response surface method (RSM) to the calculated cutting power consumption values for each cutting length and condition (Eq. (4)). The empirical model included spindle rotation speed (N), feed per tooth, and cutting length (L) terms, expressed up to the second-order term (R^2 = 0.9835). Here, $c_0 - c_9$ are model coefficients. From Eq. (4), it can be confirmed that the terms of spindle rotation speed, feed per tooth, and cutting length have an interaction with each other.

$$P_{\text{cutting}} = c_0 + c_1*(N) + c_2*(f_z) + c_3*(L) + c_4*(N^2) + c_5*(f_z^2) + c_6*(L^2) + c_7*(N*f_z) + c_8*(N*L) + c_9*(f_z*L). \quad (4)$$

To apply the polynomial form of cutting power consumption to arbitrary machining, ten coefficients of c_0 to c_9 constituting the empirical model must be known. It is impractical to establish an empirical model and is not suitable for field applications. Therefore, it is intended to establish a practical tool life model utilizing cutting power consumption in the form of Taylor's equation that requires fewer coefficients.

Here, a cutting power consumption model in the form of Taylor's equation was suggested and then fitted to the experimental results (Eq. (5)), including the cutting conditions of cutting speed and feed per tooth. Here, q , r , and K are coefficients. The cutting power consumption model requires only three coefficients, so it has a practical advantage in formulating the model over the polynomial empirical model (Eq. (4)).

$$V_c P_{cutting}{}^{-q} f_z^{\,r} = K . \quad (5)$$

The coefficients q , r , and K are expressed as a function of the cutting length, as well as the cutting power. Eqs. (6a)-(6c) are linear/nonlinear regression models from the experimental results according to the cutting length per each coefficient. Whereas q , and K regressed to the linear model, r was regressed to the nonlinear model because of the degree of influence of the cutting power length.

$$q = 0.6564 - (1.60*10^{-5})*L, \ (R^2 = 0.8501) \quad (6a)$$

$$r = 0.6485 - (1.30*10^{-5})*L + (2.37*10^{-9})*L^2, \ (R^2 = 0.8688) \quad (6b)$$

$$K = 0.0869 + (5.99*10^{-6})*L, \ (R^2 = 0.8415) . \quad (6c)$$

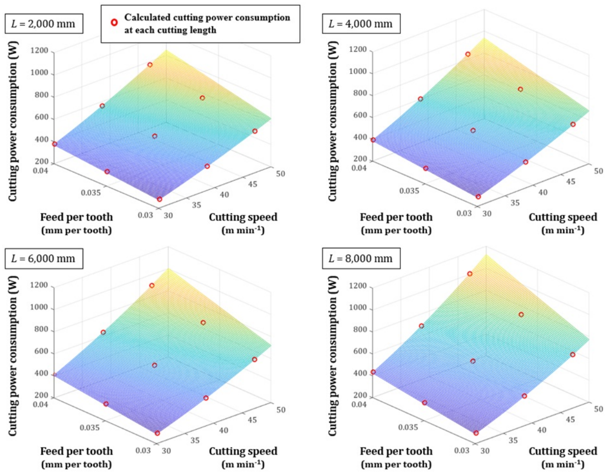

Fig. 8. Cutting power consumption model.

Fig. 8 is a three-dimensional surface plot of the cutting power consumption model in terms of cutting speed and feed per tooth at different cutting lengths. The cutting power consumption increased as the levels of cutting speed and feed per tooth increased. At the beginning of machining, the effect of feed per tooth on the cutting power consumption was less severe than that of cutting speed. However, due to the development of tool wear according to the cutting length, the increasement of cutting power consumption by feed per tooth became more influential. When comparing the calculated cutting power consumption (red 'o' points) at each cutting length with the surface plot of the cutting power consumption model, there was a good agreement with 6.12 % maximum error, inferring that the cutting power consumption can be fit well with Taylor's equation form.

3.3 Direct tool life model

In Sec. 3.1, Taylor's equation (Eq. (3)), which is a common tool life model, was fitted, and in Sec. 3.2, the cutting power consumption model in Taylor's equation form (Eq. (5)), was formulated. Since both equations contain terms of cutting speed and feed per tooth, the two equations can be arranged for cutting speed, respectively, as shown in Eq. (7).

$$V_c = \frac{C}{T^n f_z^{\,m}} = \frac{K}{P_{\text{cutting}}{}^{-q} f_z^{\,r}} . \quad (7)$$

By rearranging the two sides for the cutting speed of Eq. (7), a direct tool life model was constructed to express the relation between the cutting power consumption and the tool life as in Eq. (8). The direct tool life model includes cutting power consumption, feed per tooth, and tool life terms in an exponential relationship. Through the direct tool life model, tool life can be calculated using the cutting power consumption as an input parameter while controlling the cutting condition (feed per tooth). Here, x, y, and Z are coefficients.

$$P_{\text{cutting}} T^{x} f_{z}^{\,y} = Z \,. \tag{8}$$

Coefficients x, y, and Z constituting the direct tool life model were calculated by fitting the experimental results. The coefficients q, r, and K are expressed as functions of the cutting length, hence the calculated coefficients of x, y, and Z can also be expressed as linear/nonlinear functions of the cutting length. Eqs. (9a)-(9c) are linear/nonlinear regression models for the cutting length of the coefficients x, y, and Z.

$$x = 0.3662 + \left(1.13{*}10^{-5}\right){*}L, \left(R^2 = 0.9747\right) \tag{9a}$$

$$y = 0.3147 - \left(1.08{*}10^{-5}\right){*}L + \left(6.55{*}10^{-10}\right){*}L^2, \left(R^2 = 0.9644\right) \tag{9b}$$

$$Z = 835.8163 + \left(1.94 * 10^{-1}\right) * L, \; (R^2 = 0.8467) \,. \tag{9c}$$

Fig. 9 is a three-dimensional surface plot of the direct tool life model. Feed per tooth had little effect on tool life, which monotonically decreased as cutting power consumption increased. As the cutting length increased under the same cutting conditions, the tool life remains constant, but the cutting power consumption and the coefficients of the direct tool life model (which are functions of cutting length) changed. Accordingly, the inclination of the direct tool life model was changed as the cutting length increased. The surface plot of the direct tool life model was compared to the previously calculated tool life and cutting power consumption (blue 'o' points) at each cutting length. And the direct tool life model showed a maximum error of 6.51 %,

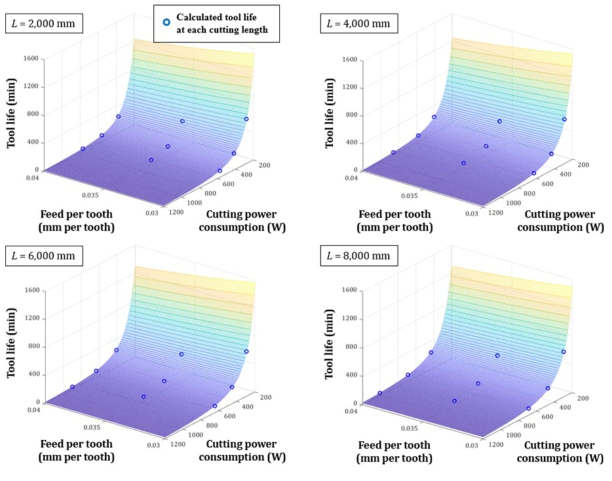

Fig. 9. Direct tool life model.

and it can be confirmed that the suggested direct tool life model is accurate enough when compared to Taylor's equation.

The direct tool life model is practical to construct a model with arbitrary machining environments. The direct tool life model can be constructed by obtaining the three unknown coefficients of x, y, and Z. This is equivalent to the original Taylor's equation for the three coefficients of n, m, and C. Therefore, to construct a simultaneous equation of three equations to obtain three unknown coefficients, machining at three different conditions up to a certain cutting length is required. In addition, since the change of the coefficients x, y, and Z according to the cutting length can be known in the three times of machining, it is possible to grasp the spatial function of the direct tool life model, as in Eqs. (9a)-(9c). Namely, the direct tool life model and its spatial function can be configured with only machining at three different conditions minimum, and the tool life can be then predicted through the cutting power consumption for any cutting conditions.

3.4 Verification test

To evaluate the accuracy and usability of the direct tool life model, a verification test was performed. The machining environment, such as cutting tools, materials, and machine tools, was conducted in the same way as in the experiments. The radial and axial depth of cut (a_p = 3 mm, a_e = 12 mm) and cutting length (8000 mm) were the same as in the experiment, but the spindle rotation speed and feed per tooth were set to 1100 rev min^{-1} and 0.035 mm per tooth, respectively.

To prove the accuracy of the suggested model, first, the tool life for the corresponding cutting conditions was calculated through Taylor's equation. Then it was compared to the tool life predicted by the suggested direct tool life model calculated with the cutting power consumption measured at the cutting length of 8000 mm. And finally, the flank wear width of the 8000 mm machined cutting tool was measured, and the tool life was estimated according to the linear relational expression of Eq. (2).

Table 2 shows the estimated tool life through three different methods. According to Taylor's equation, the tool life was calculated to be about 103.13 minutes under the given cutting conditions. As a result of the machining, the measured cutting power consumption at 8000 mm was 642.66 W, and tool life

Table 2. Estimated tool life with Taylor's equation and direct tool life model.

Taylor's equation	$T = \left(\dfrac{C}{V_c f_z^{\,m}}\right)^{\frac{1}{n}}$	103.13 minutes
Direct tool life model	$T = \left(\dfrac{Z}{P_{\text{cutting}} f_z^{\,y}}\right)^{\frac{1}{x}}$	109.98 minutes
Flank wear width	$T = \dfrac{T_{\text{machining}} {*}300}{VB_{\text{measured}}}$	105.87 minutes

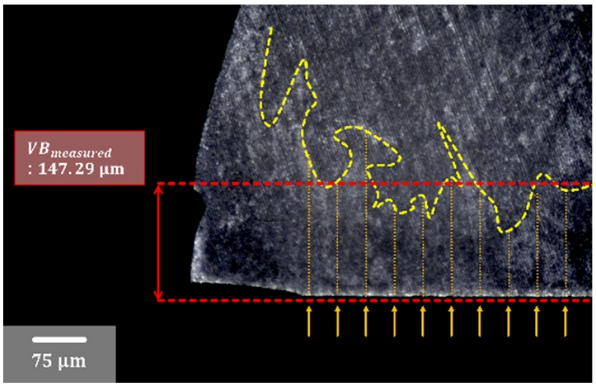

Fig. 10. An optical image of the tool after the verification test.

was estimated to be about 109.98 minutes by the suggested direct tool life model. In addition, the average flank wear width at 8000 mm machining was 147.29 μm (Fig. 10), and the tool life was estimated to be 105.87 minutes (Eq. (2)). Based on the estimated tool life through the actual measurement of flank wear width, the tool life estimated through Taylor's equation and the direct tool life model showed errors of 2.66 % (2.74 minutes) and 3.74 % (4.11 minutes), respectively. As a result, it was confirmed that the direct tool life model is competitive enough when compared to Taylor's equation in terms of accuracy.

Besides, the direct tool life model has advantages in terms of usability, such as predicting the remaining tool life even with changes in cutting conditions during machining. If the spatial function for the cutting length of the direct tool life model is known, the remaining tool life can be known through the cutting power consumption even if the cumulated machining time is not known. While Taylor's equation provides only the total tool life for the cutting condition, the direct tool life model predicts the remaining tool life of used cutting tools. The direct tool life model can also be applied to changes in cutting conditions such as cutting speed (or spindle rotation speed), and feed per tooth.

Furthermore, it is strongly believed that it can also be applied to changes in radial and axial depth of cut during machining. The presented research focused on the flat endmill for rough cutting, and constant radial and axial depth of cuts were used. On the other hand, in fine finish cutting, cutting volume usually varies largely during the process. Varying cutting volumes contribute to the varying cutting loads or the tool wear developments. However, it is known that the material removal rate (MRR), which can be expressed by the product of radial and axial depth of cut and feed, has a linear relationship with the cutting power consumption [21, 30]. The material removal rate can be estimated in real-time from the cutting power consumption. From this aspect, the suggested model is expected to be valid by considering a volumetric factor to the cutting power consumption of the full slot cutting. However, more research is still required to cope with a wide variety of machining conditions.

4. Conclusion

The direct tool life model with high prediction accuracy and practicality was constructed using cutting power consumption. The cutting power consumption model with a form of Taylor's equation was established in titanium alloy milling. The tool life and cutting power consumption models were arranged in terms of cutting speed, and the direct tool life model was formulated. The experimental results imply that the cutting power consumption is influenced by the cutting speed and feed per tooth in a similar way to the flank wear, or the tool life, following Taylor's equation form. Through the experiments and verification test, it was confirmed that the direct tool life model is competitive in tool life prediction accuracy when compared to the original Taylor's equation. Further, the cutting power consumption is a significant parameter that can estimate and predict the current and remaining tool life.

Also, the direct tool life has the following advantages in terms of practicality. First, since the direct tool life model has three unknown coefficients, the model and spatial function can be constructed through only machining at three different conditions minimum, making it easy to apply to a new machining environment. Next, if the spatial function for the cutting length of the direct tool life model is known, the remaining tool life of the previously used cutting tool can be estimated from the cutting power consumption. Finally, the tool life can be estimated even if the cutting condition changes during machining. When the cutting condition changes during machining, the corresponding cutting power consumption changes, so it is possible to predict the tool life.

It is strongly believed that power consumption is an important parameter for not only sustainable manufacturing but also accurate diagnosis and prognosis with practicality. With proper empirical models or process knowledge, power consumption can be utilized for real-time process monitoring with ease of measurement. Considering that a certain amount of energy contributes to the dissipation of tool and work materials, the cutting energy, or cumulative cutting power, will be further analyzed with respect to the tool life with arbitrarily changing cutting conditions.

Acknowledgments

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Nomenclature

a_e : Radial depth of cut
a_p : Axial depth of cut

f : Feed
f_z : Feed per tooth
L : Cutting length
MRR : Material removal rate
N : Rotational speed of the spindle
$P_{cutting}$: Power consumed in material removal
$P_{machine}$: Power consumed by a machine when the material is not removed
P_{total} : The total power consumed during cutting
T : Tool life
$T_{machining}$: Time consumed for material removal
V_c : Cutting speed
VB : Flank wear width

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