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PREDICTION OF TOOL WEAR BASED ON CUTTING FORCES WHEN END MILLING TITANIUM ALLOY TI-6AL-4V

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ABSTRACT

Research regarding tool wear in the machining of difficult materials is important because it is a significant indicator of process failure in terms of degradation of part quality, and the resulting high cost and increased process time. Prior researchers have investigated the effects of cutting parameters on tool wear and as a result, tool life has seen significant improvement. However, these studies are not concerned with tool flank wear during machining; they instead focus on tool flank wear after a certain amount of cutting distance. This study proposes a new method of predicting tool flank wear during machining that has the capability of suggesting tool failure without directly measuring the tool. For this purpose, a detailed set of experiments on end milling of titanium alloy Ti-6Al-4V was conducted and analyzed. Then, the resultant force output, which can be monitored during machining, was used to establish a predictive algorithm for tool flank wear. Using the increase in the resultant force as well as the total energy spent on the workpiece, it was shown that tool flank wear can be effectively predicted during machining and this can decrease the time spent on tool failure inspection and early tool change, increasing the throughput of the process.

INTRODUCTION

Understanding how Titanium alloys – Ti-6Al-4V in particular – behave in machining processes is a complex endeavor that involves a number of variables yet to be understood. The effect of certain parameters on tool wear is an important issue in manufacturing, because the use of worn tools can cause unforeseen flaws in the surface and dimensional quality of the product. With early identification of a worn tool, manufacturers can maintain a satisfactory product quality and gain valuable time by replacing the tool before a permanent problem arises. The standard measurement of tool wear involves removal of the tool from the machine, which requires the machine operator to stop the machine and delay production, therefore increasing production time and cost.

Several researchers conducted studies on the investigation of the effects of different inputs to the process such as tool material, coolant, tool coating, temperature, and cutting parameters on tool wear [1-12]. By testing these parameters, researchers have made considerable progress in the analysis and minimization of tool wear. The broad outcome of these studies was the understanding that the overall product quality and machining productivity could be greatly increased with advancements in the identification of tool wear during machining. Prior research has indicated that tool life decreases drastically with increase of cutting speeds and feed rate [13-17]. This research helps manufacturers decide on optimal cutting parameters for minimal tool wear, but it does not indicate any quantitative measure of this tool wear during machining. Researchers have suggested a process for selecting the cutting parameters such as feed rate, cutting speed, and depth of cut based on tool life tests [17]. This selection process is used to specify improvements in cutting conditions to minimize tool wear. However, this process cannot predict tool wear or tool failure.

Many researchers have also used cutting forces as an indicator of process characteristics, as it is an easily measurable and understandable output. They have studied the relationship between machining parameters and cutting forces, and how cutting forces change with machining parameters has been well identified [17-18]. However, high cutting forces are not direct indicators of process failure, which means that a machining center operator cannot decide on process failure (or lack thereof) gauging only the cutting forces. For this reason, the operator would not be significantly interested in a model of cutting forces. On the other hand, these operators usually stop the process at certain intervals of tool-in-cut time based on experience to check for excessive tool wear or breakage, which is a direct indicator of process failure. Therefore, a model of tool wear to predict tool failure is more useful for the industry.

There are many models developed in the literature correlating tool wear to machining parameters, however these are either static estimators, or predictors that do not consider stochastic inputs. The static estimators are used to relate machining parameters to tool wear, but the tool wear is only measured after a certain point in cutting length [8,12,19]. Although this is useful information in optimizing machining parameters by estimating tool wear, it is not possible to understand when and how the tool fails during the cutting process. The predictors usually take tool wear measurements at different points of cutting time, and fit a curve to these measurements, indicating that the tool will fail at certain point of cutting length under certain machining conditions. Most research utilizing numerical modeling of machining such as [9,20-24] are in this category; as their outcomes are only indicators of whereabouts of tool wear rather than considering the stochastic effects of the process. These models are also useful in understanding how the tool might behave on average; however, there is no information about variability under the same conditions. In reality, with exactly the same set of machining parameters, every different test might lead to different results, as there are many stochastic inputs to the system. However, these predictors are not able to capture such stochastic behaviors. Doing many replications and including their results in the model would increase the chances of catching outliers and having more command on the process, but there could always be unforeseen disturbances to the process that might be missed with such models.

The main objective in this study was to understand the relationship between tool wear and the increase in cutting forces during machining the titanium alloy Ti-6Al-4V and use this relationship as a detectable online failure signal. Cutting force can be measured and observed during machining, while the tool is still engaged, which makes it an online output, while tool wear measurement needs the process to stop, which makes it an offline output. Therefore, with relating the online output to the offline output, this study aims to introduce a method to detect tool failure during machining without interrupting the process. This way, (1) premature interruption of the process to check the tool for failure and (2) late detection of tool failure causing end-product related issues would be eliminated, thus allowing the manufacturers to improve the productivity and standardization of their machining processes and eliminate the need for post-processing of the parts out of manufacturing tolerances.

Researchers worked on similar real-time prediction models of tool wear [25] using tool tip temperature; however, thermal load is not the only significant mode on the tool wear. Instead, the mechanical load has a more significant effect on tool flank wear, and it is essential to capture this effect in order to have a better indicator. Al-Sulaiman et al. [26] used electrical power consumption to monitor tool wear in a drilling process, and Shao et al. [27] did a similar analysis for face milling of cast iron, whereas other researchers did cutting force-based analyses with mild slot milling on Inconel 718, face milling on aluminum alloy T6061, and mild end milling on C45 steel [28-31]. Although researchers conducted similar studies, those studies fail to capture the relationship between the cutting force and tool flank wear in the end milling of titanium-alloys.

For this purpose, an adaptive prediction model is introduced, where the measured cutting forces are used to understand first the level of tool wear due to machining conditions, then the increase in it during the process due to the progress in machining. The initial level of the resultant force is used as an indicator of how much the tool wears on average under the specific machining conditions (that can be represented with material removal rate), and the increase in the resultant force is used as an indicator of progressing tool wear. When the process behavior is similar to expected results (no significant stochastic input), the predicted tool wear would be similar to those estimated by the static estimators. However, when a disturbance from the expected state occurs in the process (which will also cause tool wear), there will be an unforeseen increase in the resultant force, and this is used as an indicator of increasing tool wear leading to tool failure. Using this prediction model, it is possible to stop the process at the right moment where the tool wears as much as the predetermined amount.

EXPERIMENTAL SETUP

The experimental portion of this study involves the milling of Ti-6Al-4V blocks using a Sandvik tool. The workpiece is a rectangular prism with dimensions of 80mm x 60mm x 25mm. This allows for a 60mm length of cut, which was previously determined to be a good distance before typical failure for such operations [5]. The Sandvik tool has a diameter of 15.875mm and consisted of two flutes. Fresh Sandvik Coromill 390 inserts (R390-11T308M-PM-1030) were used in this study for each test, which are TiAlN coated via physical vapor deposition (PVD) methodology. Coolant is flooded over the workpiece for the duration of testing. Where most of the prior research for this material used milder machining conditions, this study utilized both mild and aggressive machining conditions with high depth of cut, feed, and cutting speed. TABLE 1 shows (in ascending order of depth of cut, then feed, then cutting speed) the machining conditions used in this study, and the run order is also presented to show the randomization. In addition to the low, medium, and high values of the three parameters (50, 150, 250 m/min cutting speed, 0.1, 0.3, 0.5 mm/rev feed, and 0.5, 1, 1.5 mm depth of cut), additional sets of experiments at interpolated and extrapolated values of parameters were also conducted. Since the output values were closer to each other for milder experimental conditions, additional experiments were focused to investigate the small changes in that part of the domain. These nine extra tests provided a more thorough understanding of the relationship, and strengthened the correlation study. Therefore, a total of 36 tests were finished, and outputs from all of these tests were analyzed.

TABLE 1: CUTTING PARAMETERS USED FOR TESTING

Test #	Run #	Cutting Speed	Feed	Depth of Cut
		[m/min]	[mm/rev]	[mm]
1	28	25	0.1	0.5
2	23	50	0.1	0.5
3	1	150	0.1	0.5
4	33	200	0.1	0.5
5	11	250	0.1	0.5
6	30	250	0.2	0.5
7	8	50	0.3	0.5
8	16	150	0.3	0.5
9	2	250	0.3	0.5
10	31	50	0.4	0.5
11	32	250	0.4	0.5
12	12	50	0.5	0.5
13	29	100	0.5	0.5
14	22	150	0.5	0.5
15	7	250	0.5	0.5
16	18	50	0.1	1
17	4	150	0.1	1
18	9	250	0.1	1
19	21	50	0.3	1
20	34	100	0.3	1
21	27	150	0.3	1
22	35	200	0.3	1
23	15	250	0.3	1
24	26	50	0.5	1
25	36	100	0.5	1
26	6	150	0.5	1
27	17	250	0.5	1
28	24	50	0.1	1.5
29	3	150	0.1	1.5
30	25	250	0.1	1.5
31	13	50	0.3	1.5
32	19	150	0.3	1.5
33	20	250	0.3	1.5
34	5	50	0.5	1.5
35	14	150	0.5	1.5
36	10	250	0.5	1.5

In addition to the cutting conditions given in this table, the width of cut was held constant at 9.5mm, as maximum 60% engagement of the tool diameter in end milling was advised by the insert manufacturer. Since the workpiece width was 80mm, 8 tests on each workpiece were conducted, which was 4 sets of test conditions with 2 replications. Tests were run for 36 different high-range cutting parameter combinations. Each trial was conducted twice to isolate possible outliers, but all replications followed original tests within acceptable ranges. The output values from replications were averaged. During the tests conducted on an OKUMA ACE center MB-46VAE 3-axis CNC vertical milling machine, forces were measured with a Kistler 9257B 3-component dynamometer in three directions, and spindle power was measured using Caron Engineering equipment and software. After the completion of each test, the inserts were removed for tool wear measurements, which were completed using an Olympus SZX12 optical microscope. Average and maximum tool flank wear were measured on each cutting tool to make sure any tool wear failure mode can be captured. Sample tool wear pictures for a mild and an aggressive test can be found in FIGURE 1 and FIGURE 2 respectively, where the distance between each tick mark represents 1 mm.

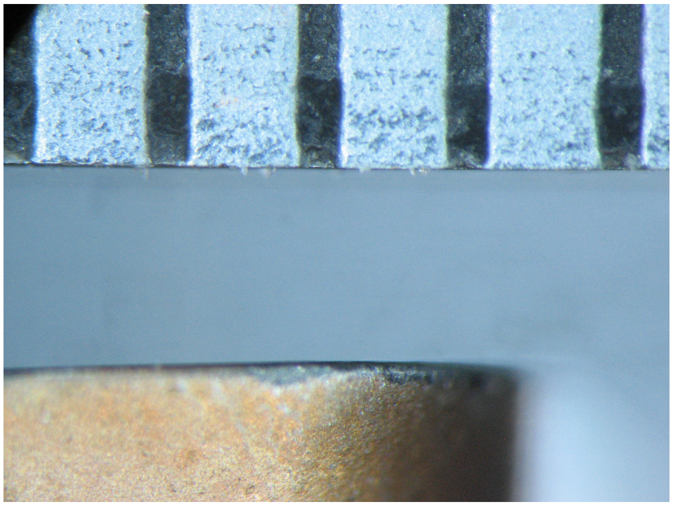

FIGURE 1: TOOL WEAR FOR MILD CUTTING CONDITIONS (TEST 2)

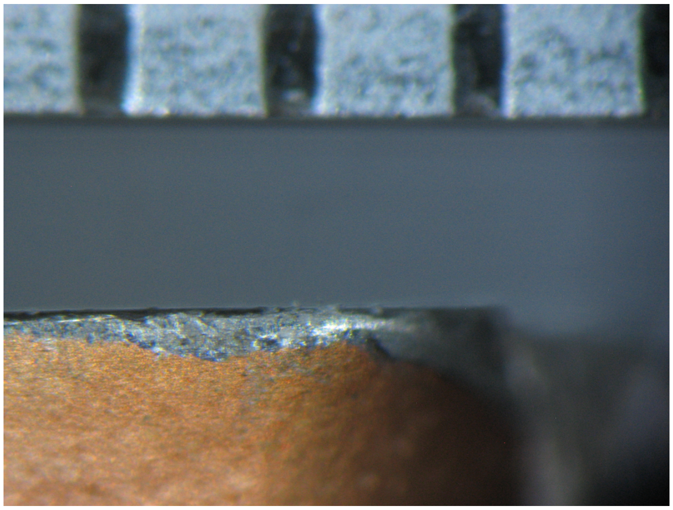

FIGURE 2: TOOL WEAR FOR AGGRESSIVE CUTTING CONDITIONS (TEST 36)

Aggressive cutting parameters such as the ones investigated in this study (*i.e.* high depth of cut, high feed, and high cutting speed) allow for development of models with broader and more extreme conditions that could expose more productive operating points. Therefore, if a machining process that is completed at more aggressive machining conditions has results similar to those at milder conditions, then the manufacturer can get more worth for its expenditure by running the machine at more aggressive conditions. However, since titanium alloys are difficult-to-machine, prior researchers have focused on running tests with traditional low-range parameters [13,32,33].

MODELING

In order to model the relationship between the cutting forces and tool wear, first a MATLAB program has been written and utilized to analyze the raw cutting force data. The 3-component dynamometer outputs three components of cutting force at 6000 Hz sampling rate, which allows 36 measurements per tooth at every revolution of the cutter even at the highest speed (250 m/min), so that measurements do not miss any interaction between the insert and the workpiece. In order to eliminate the noise within the signal, the force output is filtered. The output is also bounded to the cutting region so that only the relevant portion of the data is analyzed, and it is offset to zero force at the start point to eliminate sensor offset. The resultant force is found by the vector summation of three orthogonal components of the force output. Such filtered and bounded resultant force data can be observed in FIGURE 3 and FIGURE 4 for mild and aggressive sets of machining conditions, respectively. These sets of experiments also correspond to the tool wear pictures in FIGURE 1 and FIGURE 2. One can see from these figures that with milder conditions, cutting force follows a horizontal trend for the duration of the cutting length, indicating a mild tool wear, whereas with more aggressive conditions, cutting force increases (upward slope) with cutting length, indicating constantly-increasing tool wear, and a trend toward tool failure.

The end of the initial exponential incline in FIGURE 3 or FIGURE 4 shown with trim lines indicates that full contact between the tool and the workpiece was achieved, therefore that value is accepted as the amount of force incurred due to machining conditions. The increase in cutting force along the cutting length, on the other hand, is attributed to the tool wear, as there is not a parameter change during the process. Hence, if the resultant force stays constant throughout the cutting length (in between the trim lines shown in FIGURE 3 and FIGURE 4), the tool is considered to have worn insignificantly, which was also confirmed with the tool wear measurements. Tool flank wear equivalent to or less than 30μm is considered as insignificant, because it is found that even with the mildest conditions experimented, the cutting tool wears more than 30μm due to machining dynamics such as intermittent loading. As a result of this analysis, linear regression was used to fit a line to the portion of the data that indicates tool wear, or lack thereof.

It is also possible to conduct a very similar analysis for increasing spindle power consumption, and use it as an indicator for tool wear. In fact, power consumption was measured during experiments, and its relation to tool wear was investigated. Since spindle power is proportional to the corresponding component of the resultant force, the capability of predicting tool wear with power consumption is similar to with the resultant force. This causes a high degree of multicollinearity in the model, so one of the predictors should be eliminated. Because spindle power consumption is related more to the spindle condition compared to the resultant force being a direct mechanical load on the tool flank, resultant force was selected for use as a tool wear indicator. Also, since the normal component of the resultant force is not considered in power consumption measurement, the resultant force is a better predictor for tool wear.

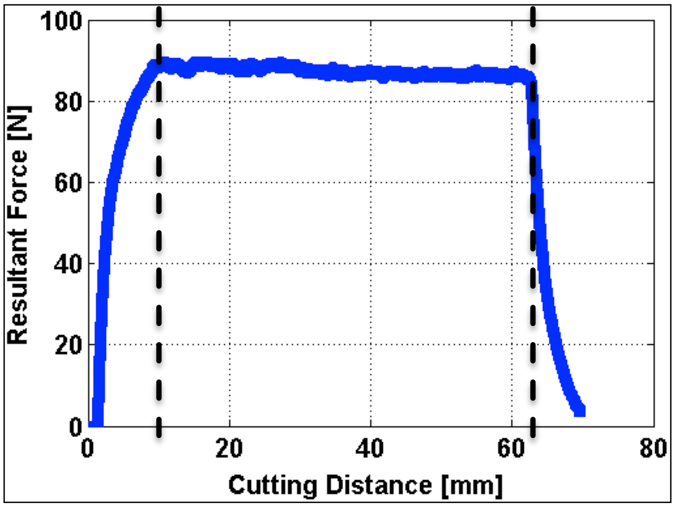

FIGURE 3: CHANGE IN RESULTANT FORCE WITH CUTTING DISTANCE FOR MILD CUTTING CONDITIONS (TEST 2)

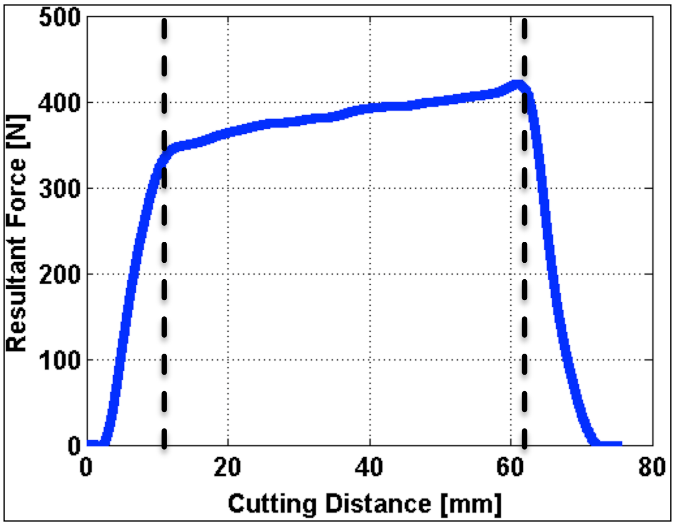

FIGURE 4: CHANGE IN RESULTANT FORCE WITH CUTTING DISTANCE FOR AGGRESSIVE CUTTING CONDITIONS (TEST 36)

It is also predicted that the amount of energy used to remove the material during machining is related to tool wear. Therefore, this energy is also calculated and correlated to tool wear. For this purpose, the resultant force vs. cutting distance graph is integrated to find the total work done on the workpiece. Although this work is due to different mechanisms such as friction, shearing, and ploughing, it is assumed that the portion of energy that causes tool wear is proportional to the total work done on the workpiece, and this proportion does not change significantly with machining parameters.

RESULTS

It is known that with increasing machining parameters, tool wear also increases [3,14,15,34,35]. Many researchers have studied the effects of different machining parameters such as cutting speed, feed, and depth of cut. However in this study, it is observed that such relationships only occur as weak correlations, with R^2 values smaller than 0.2. Despite this finding, all of the correlations are found to be positive, meaning with increasing machining parameters studied within this work, tool wear increased as well. On the other hand, material removal rate (*MRR*) is a parameter that combines these machining parameters, and it is found using Eq. (1) where v_c is the cutting speed, D is the diameter of the cutting tool, f is the feed, a_p is the depth of cut, and w is the width of cut. It is observed that using this combined parameter, a good correlation with tool wear is possible (R^2 value of 0.79). FIGURE 5 shows this relationship, where the equation for the linear regression is found to be as shown in Eq. (2) where *VB* is the tool flank wear in μm, and *MRR* is in mm^3/sec. This equation shows that regardless of how small of an MRR is selected, there will be approximately 53μm of tool wear after machining 60mm cutting distance. This equation also reveals that with every 5mm^3/sec increase in *MRR*, tool will wear approximately 1μm more at the end of the cut.

$$MRR = \frac{v_c}{\pi D} f w a_p \tag{1}$$

$$VB = 53 + 0.2MRR \tag{2}$$

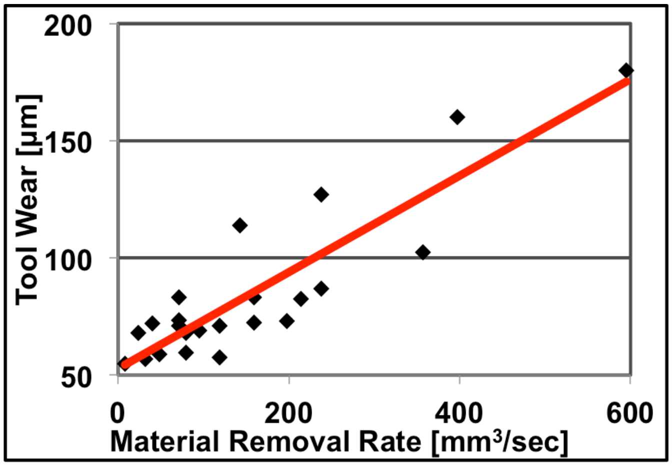

FIGURE 5: TREND OF INCREASING FINAL TOOL WEAR WITH INCREASING MATERIAL REMOVAL RATE

After ensuring that the experiments adhere to the common trends in the literature regarding the relationship between machining parameters and tool wear, the increase in the force graphs (such as the increasing trend observed during machining in FIGURE 4) are investigated. FIGURE 6 shows the relationship between the force increase (slope of the increasing trend in filtered resultant force vs. cutting distance plot) and tool flank wear, where the red solid line shows the best linear fit, and green dotted line shows the 95% confidence intervals of the linear regression. The linear regression for this relationship resulted in an R^2 value of 0.82, which indicates a strong correlation. This means that when an increasing force trend is observed, the tool can be expected to wear more in accordance with this model, increasing with higher slope of force increase. The equation for the linear regression line in this relationship is given in Eq. (3) where *VB* is in μm and F' is the force increase in N/mm, which shows the increase in force with every millimeter of cutting distance traveled by the cutting tool.

$$VB = 65 + 32F' \tag{3}$$

This equation shows that if there is no force increase in the force vs. cutting distance graph, approximately 65μm of tool flank wear is expected at the end of the 60mm cutting distance. It is also possible to combine Eq. (2) with Eq. (3) to make a more advanced interpretation of these two findings: Since Eq. (2) suggests that 65μm of tool wear occurs approximately at 60mm^3/sec *MRR*, no increase in the resultant force graph would be expected up to that value.

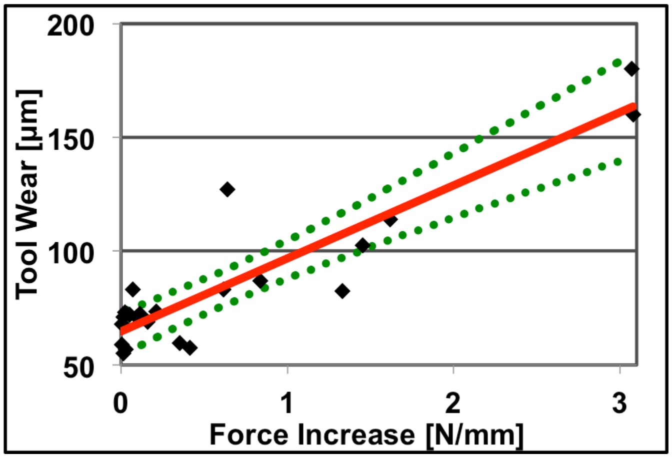

FIGURE 6: TREND OF INCREASING FINAL TOOL WEAR WITH INCREASING SLOPE IN THE CUTTING FORCE DURING MACHINING

The relationship between tool wear and the increase in the resultant force during cutting also contributes to significant findings. Since there is a strong linear relationship between the two, the offline measure of process failure that is tool wear can be easily predicted with certain confidence only by observing the increase in the resultant force, which is an online output. For example, when extrapolated, the linear regression line indicates that at the time the operator observes (or a controller signals) approximately 4N/mm increase in the resultant force, the tool flank would have worn 200µm. Therefore, if 200µm is the defined tool failure value for that process, the operator can stop the machine and change the cutting tool without having to check it prior to that point, only by observing the cutting force output and paying attention to the curve getting steeper. This process can also be automated to simply alert the operator when the cutting force increase becomes big enough to consider the tool worn. This will decrease the total machining time, increasing the throughput of the process.

Moreover, it is also possible to gauge the necessity of tool change depending on the criticality of the process. When dealing with a critical process, the 95% upper confidence level can be used to make sure that tool failure is not missed and its consequences not faced. Whereas if the process is noncritical such as a roughing operation, the 95% lower confidence level can be used to ensure maximum utilization of the tool at the expense of machining with a worn tool for some while. Regardless of which strategy is chosen, the benefit of having such a relationship is that the operator will have a more accurate idea of when to change the cutting tool without losing time for unnecessary checks and risking significant use of the tool after it is worn.

Finally, the cutting energy was also calculated by integrating the resultant force vs. cutting distance plot, and its relationship to tool flank wear was investigated. FIGURE 7 shows this relationship together with the linear regression line fitted to the trend that has an R^2 value of 0.63. As eq. (4) shows, the linear relationship between the cutting energy (E_F) and tool flank wear (VB) indicates that with every joule of total energy increase, the tool wear increases 4.5µm. Assuming a somewhat constant or a linearly increasing cutting force profile, 1 Joule of energy increase corresponds to an overall increase of approximately 15N in the resultant force. Therefore, regardless of the increase in the force during machining, if the resultant force level in the beginning of the cut is too high, the operator may want to change the parameters of the process to avoid early tool failure, or decide to change the tool earlier than planned.

$$VB = 44 + 4.5E_F \tag{4}$$

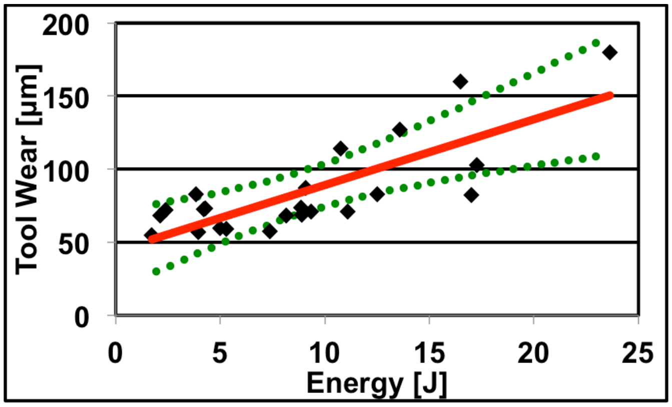

FIGURE 7: TREND OF INCREASING TOOL WEAR WITH INCREASING TOTAL ENERGY DURING MACHINING

CONCLUSIONS

Researchers have established that tool flank wear during machining titanium alloy Ti-6Al-4V can be correlated to machining parameters. It is very common to use certain sets of parameters to predict and optimize tool flank wear after a certain cutting distance using such relationships. However, these algorithms do not provide any method for predicting real-time tool failure during machining. In this study,

1. A detailed set of experiments is conducted on end milling titanium alloy Ti-6Al-4V. Using the results of these tests, first the traditional relationship between material removal rate (representing a combination of machining parameters investigated) and tool flank wear during end milling Ti-64 is reiterated. With an R^2 value of 0.79, it is confirmed that with increasing material removal rate, the tool wear at the end of a 60mm cutting distance increases. This finding represents the possibility of predicting an expected value of tool wear when using a certain set of machining parameters, which is useful in understanding how these parameters affect the overall process performance.
2. The resultant force graphs from these tests are investigated. The increase in resultant force during machining is correlated to tool wear, and it is shown that with an R^2 value of 0.82, force increase can be used as an online predictor of the tool failure indicating process failure. In order to do this, the machine operator would need to check the resultant force during machining and stop the process

(because of predicted tool wear) only when a certain amount of increase per cutting length (or time) is observed, rather than checking the tool for flank wear at estimated intervals. By accurately predicting the process failure due to tool flank wear, machining time can be reduced by eliminating unnecessary checks for tool failure, and end product quality can be increased by avoiding machining with a worn tool due to a missed tool failure that occurred between tool wear checks.

3. The total cutting energy during a 60mm cut is calculated by integrating the resultant force vs. cutting distance plot. With an R^2 value of 0.63, it is suggested that the total cutting energy can be used as an indicator of tool life. The findings can be used to alter machining parameters after the process starts, which can be helpful in real time optimization of the cutting process.

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