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Optimal replacement times for machining tool during turning titanium metal matrix composites under variable machining conditions

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Abstract

Little practical results are known about the cutting tool optimal replacement time, specifically for machining of composite materials. Due to the fact that tool failure represents about 20% of machine down-time, and due to the high cost of machining, in particular when the work piece's material is very expensive, optimization of tool replacement time is thus fundamental. Finding the optimal replacement time has also positive impact on product quality in terms of dimensions and surface finish. In this article, two new contributions to research on tool replacement are introduced. First, tool replacement mathematical models are proposed. These models are used in order to find the optimal time to tool replacement when the tool is used under variable machining conditions, namely, the cutting speed and the feed rate. Proportional hazards models are used to find an optimal replacement function. Second, this model is obtained during turning titanium metal matrix composites. These composites are a new generation of materials which have proven to be viable in various industrial fields such as biomedical and aerospace, and they are very expensive. Experimental data are obtained and used in order to develop and to validate the proportional hazards models, which are then used to find the optimal replacement conditions.

Keywords

Optimal tool replacement, metal matrix composites, cost optimization, availability optimization

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Introduction

Titanium metal matrix composites (TiMMCs) inherit outstanding characteristics such as low weight, high mechanical and physical properties, high stiffness, and strength. For example, the density of conventional TiMMCs is 4040 kg/m^3, and the stiffness is 200 GPa.[1] Although very expensive, metal matrix composites (MMCs) are a new generation of materials which have proven to be viable in various fields such as biomedical and aerospace industrial. Finding the optimal tool replacement time in machining TiMMCs is important in order to decrease the scrapped products and thus the cost of machining, and/or to increase the tool life, and thus to increase the availability of the cutting tool. Replacing the tool only at failure may leave undesired effects on the product's quality characteristics, namely, the dimensions and the surface finish. This may lead to scrapping of the product. The poor tool condition may cause wastage of subsequent production resources and the loss of customer's goodwill.[2] In general, the determination of the optimal replacement time is considered an important economic factor in machining.[3]

The cutting tool cost represents around 25% of the total machining cost.[4,5] The cutting tool failure represents about 20% of machine down-time,[6] and replacing cutting tool earlier or later than necessary will cause either loss of valuable resources or scrapping of products.[7] Moreover, the tool replacement policy is one of the important aspects of tool management.[8] For these reasons, finding the time at which the tool should be

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replaced is fundamental. Much research tried to improve tool life in several ways. For example, Klim et al.[3] proposed a method to improve cutting tool life in machining using the effect of feed variation on tool wear and tool life. By changing feed rate, the reliability function is changed, and thus the tool life is changed. The Weibull distribution was used to fit the data. The experiment was conducted under constant cutting speed. Balazinski and Mpako[9] proposed an improvement of tool life through using two discrete feed rates. The method depends on varying the feed rate throughout the cutting process. By varying the feed, the tool-chip contact area increases, the tool wear rate decreases, and consequently leads to improvement of the cutting tool life. The experiment was conducted under constant cutting speed. Lin and Shyu[10] concluded that using variable feed machining, and constant cutting speed, when drilling stainless steel is a significant method for improving the cutting tool life.

Other researches tried to find the optimal replacement strategy by using proportional hazards models (PHMs) for modeling tool life, then using another technique to find optimal strategy. For example, Mazzuchi and Soyer[11] used a PHM to assess machine tool reliability. Fully Bayesian analysis is used to find optimal machining conditions. Liu and Makis[12] derived a formula to calculate the cutting tool reliability under variable cutting conditions. They used PHMs while considering the machining conditions as covariates. Liu et al.[13] extended the work by developed algorithm based on stochastic dynamic programming for finding the optimal tool replacement times in a flexible manufacturing system. Ding and He[14] used a PHM by considering vibration signals as a time-dependent covariate. The author suggests that vibration signals are good indicators to tool wear. Reliability analysis based on feature extraction from tool vibration signals is introduced. They found remarkable relationship between the tool condition monitoring information and the life distribution of tool wear by using PHMs. Other research used classical Weibull distribution to fit tool life distribution. For example, Vagnorius et al.[15] used the Weibull distribution to fit tool life distribution. The optimal replacement time for metal cutting is determined from a total time on test (TTT) plot.

Some researchers tried to improve the cutting tool life by changing feed rates while the cutting speed is constant;[3,9,10] others consider the PHM as good model for tool life representation.[7,11,16] In most of these models, it was assumed that the machining conditions have significant effect over the entire tool life, but finding tool replacement models is still unavailable. The objective of this article is to find tool replacement optimization models which can be used in order to minimize the cost or to maximize the availability during turning TiMMCs under variable conditions. The PHM is used to model in order to find these models. The Cutting speed (v) and the feed rate (f) are treated as the models' covariates. In section "Model description of a tool operating in varying conditions," a brief description of the PHM of a tool operating in variable conditions is introduced. In section "Optimal replacement policy," the optimal replacement policy for minimizing the cost and maximizing the availability is described. In section "Description of the experiment," the experimental procedure which was carried out in order to collect data that are used for constructing the model is presented. The model developed and the final results are presented in section "Development of the model and results." Practical use and sensitivity analysis are given in section "Practical use and sensitivity analysis." Concluding remarks are given in section "Conclusion."

Model description of a tool operating in varying conditions

In 1907, Taylor[17] developed the classical relationship between tool life (T) and cutting speed (v). The Taylor tool life equation is $v\,T^n = K$, where K and n are experimental constants which depend on the machining conditions and the material of cutting tool and the part. The Taylor's equation shows that the tool life is inversely proportional to cutting speed. Taylor's extended equation including machining conditions, namely, the cutting speed v and the feed f, is given in Mazzuchi and Soyer.[11] This equation has the following form

$$T = \frac{C}{(v^x f^y)} \tag{1}$$

where C, x, and y are positive constants. Taylor's extended equation considers only the machining parameters but fails to consider the aging and the progressive wear of the tool's effect.[11] In order to take into consideration the tool's age, the tool life T is considered a random variable. Due to the flexibility of the Weibull distribution, it is extensively used in modeling the tool life. The Weibull failure rate for a tool in constant operating conditions, that is, the speed and feed, is given as follows

$$h(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} \tag{2}$$

where β is the shape parameter and η is scale parameter. In PHM, the failure rate of the cutting tool is not only dependent on the age of the tool but is also affected by covariates which describe the machining conditions.[11] Based on equation (2), the PHM consists of the failure rate as the product of a baseline failure rate $h_0(t)$, which is dependent only on the age of the tool, and an exponential expression which is the linear sum of $\gamma_i Z_i$, where Z represents the covariates of the machining conditions. The failure hazard rate at time t is expressed as in equation (3)

$$h(t, Z; \beta, \eta, \gamma) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} \exp\left\{\sum_{1}^{m} \gamma_i Z_i\right\} \tag{3}$$

Using the Weibull model as a baseline function in modeling the tool failure was considered by Tail et al.[7], Mazzuchi and Soyer,[11] and Makis[16] This model is sometimes called the Weibull parametric regression model. The covariates are the cutting speed (v) and the feed rate (f). The model is given in equation (4), where $m = 2$

$$h(t, Z; \beta, \eta, \gamma_1, \gamma_2) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} e^{\gamma_1 v + \gamma_2 f} \tag{4}$$

In this article, we consider two states: the normal and the failure states. This latter is defined by the tool wear reaching a predefined level $VB_{\mathrm{Bmax}} = 0.2$ mm.The survival function can thus be given as in equation (5)

$$\begin{aligned} R(t; Z) &= P(T > t|Z) = \exp\{-H(t, Z)\} \\ &= \exp\left\{-\int_0^t h(t, Z)dt\right\} = \exp\left\{-\left(\frac{t}{\eta}\right)^{\beta} e^{\gamma_1 v + \gamma_2 f}\right\} \end{aligned} \tag{5}$$

where $H(t, Z)$ is the cumulative hazard function. The survival function $R(t; Z)$ and its derivative $\dot{R}(t; Z) = h(t, Z)R(t; Z)$ are used to estimate the parameters $(\beta, \eta, \gamma_1, \gamma_2)$ by using maximum likelihood (ML) function.[18]

Optimal replacement policy

The classical age replacement strategy recommends replacement of the cutting tool at failure, that is, when the tool wear threshold is reached, or when it reaches a certain age which minimizes the cost per unit time. In the classical strategy, the effects of the covariates are not taken into account. In this article, the effects of the cutting speed (v) and the feed rate (f) are taken into consideration. The failure hazard rate of the cutting tool is a non-decreasing monotonic function, so the control-limit is used to find the minimum expected cost per unit time.[19,20] The control-limit is a control-limit value ($d > 0$). The optimal stopping rule is given in equation (6). The stopping rule is often used in condition-based maintenance (CBM) as an alarm when uncontrollable covariates reach predefined states. In this article, it is used as follows

$$T_d = inf\{t \geqslant 0 : Kh(t, Z) \geqslant d\} \tag{6}$$

where T_d is the preventive replacement time and K is the difference between the failure replacement cost $C + K$ and the preventive replacement cost C. According to the theory of renewal reward processes, the expected cost per unit time can be expressed as

$$\begin{aligned} \phi(T_d) &= \frac{C\,P(T_d < T) + (C + K)\,P(T_d \geqslant T)}{W(d)} \\ &= \frac{C + K\,P(T_d \geqslant T)}{W(d)} \end{aligned} \tag{7}$$

$d^* = \phi(T_d^*)$ is the optimal cost at which the $\phi(T_d)$ is minimum and T_d^* is the optimal time to replace. $P(T_d \geqslant T)$ is the probability of failure replacement, $P(T_d < T)$ is the probability of preventive replacement, and $W(d) = E(\min\{T_d, T\})$ is the expected replacement time. Optimal level d^* can be found by using the fixed-point iteration procedure[18,20] or by using Semi-Markovian Covariate Process.[21]

Similarly, we represent the availability function as in equation (8)

$$\begin{aligned} A(T_d) &= \frac{\text{uptime}}{\text{uptime} + \text{downtime}} \\ &= \frac{W(d)}{W(d) + T_p\,P(T_d < T) + (T_p + K)\,P(T_d \geqslant T)} \end{aligned} \tag{8}$$

When $A(T_d)$ is the availability. The optimal availability is achieved at T_d^* the optimal time to replacement, T_p is the time required to perform the preventive replacement, and $T_f = (T_p + K)$ is the time required to perform failure replacement. We note that in equation (8), K is the difference between T_f and T_p, while in equation (6), it is the difference between the failure replacement cost and the preventive replacement cost.

The objective is to find d^*. The replacement function is derived when d^* is obtained and the machining conditions, namely, the cutting speed (v) and the feed rate (f), are known. The replacement function is derived from equation (6) as follows

$$Kh(t, Z) \geqslant d^* \tag{9}$$

$$\frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} e^{\gamma_1 v + \gamma_2 f} \geqslant \frac{d^*}{K} \tag{10}$$

$$e^{\gamma_1 v + \gamma_2 f} \geqslant \frac{d^*\,\eta^{\beta} t^{-(\beta-1)}}{K\beta} \tag{11}$$

$$\gamma_1 v + \gamma_2 f \geqslant \ln\left(\frac{d^*\,\eta^{\beta}}{K\beta}\right) - (\beta - 1)\ln t \tag{12}$$

$$Z^c \geqslant \mathrm{g(t)} \tag{13}$$

$\mathrm{g}(t)$ was defined as a warning function by Banjevic et al.[18] The function $\mathrm{g}(t) = \ln(d^*\,\eta^{\beta}/K\beta) - (\beta - 1)\ln t$ can be considered as "replacement" function. By calculating an "overall" covariate value Z^c, the optimal time to replacement T_d^* is obtained.

Description of the experiment

Equipment: A 6-axis Boehringer NG 200, computer numerical control (CNC) turning center is used in order to conduct experiments, as shown in Figure 1. *Tool material*: TiSiN-TiAlN nano-laminate physical vapor deposition (PVD) coated grades (Seco TH1000 coated carbide grades) is used. *Workpiece material*: A cylindrical bar of Ti-6Al-4V alloy matrix reinforced with 10%–12% volume fraction of TiC ceramic particles is used. *Experimental details*: The experiments were conducted using full factorial designs with two factors,

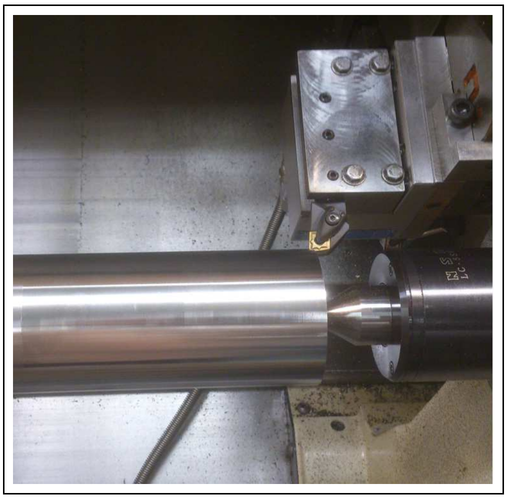

Figure 1. The experimental setup.

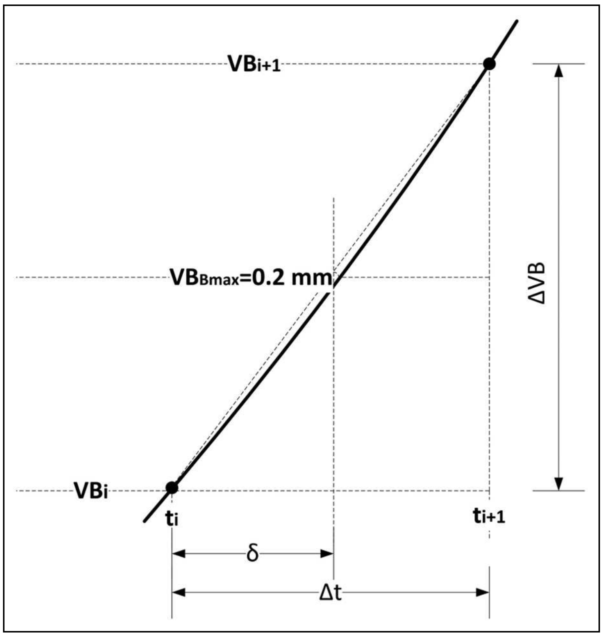

Figure 2. Wear interpolating.

Table 1. The coded design of experiment.

Run	Factor		
	Cutting speed (m/min)	Feed rate (mm/rev)	Depth of cut (mm)
1	−1	−1	1
2	1	−1	1
3	−1	1	1
4	1	1	1
5	0	0	0

Table 2. The design of experiment.

Run	Factor		
	Cutting speed (m/min)	Feed rate (mm/rev)	Depth of cut (mm)
4	80	0.35	0.2
3	40	0.35	0.2
1	40	0.15	0.2
2	80	0.15	0.2
5	60	0.25	0.2

two levels ($v = 40$, 80 m/min and $f = 0.15$, 0.35 mm/rev), and using one center point ($v = 60$ m/min and $f = 0.25$ mm/rev). Full factorial designs are the most conservative of all design types because we try all combinations of the factor settings. Table 1 shows the design of the experiment in a coded form. Table 2 shows all combination of cutting conditions. There are five runs which were done randomly. Each run was replicated at least 5 times.

The cutting tool fails when the tool becomes dull and no longer operates within acceptable quality.[5] The common way of quantifying the tool time to failure (*TTF*) is to put a limit on the maximum acceptable flank wear, VB_{Bmax}. For each tool, sequential inspections were conducted in order to measure the wear. The wear is monitored at discrete points of time through inspections. The wear is measured after each inspection by using an Olympus SZ-X12 microscope. The procedure continues until the tool wear threshold ($VB_{\text{Bmax}} = 0.2$ mm) is reached. The procedure is replicated for 28 tools.

Figure 2 shows the wear interpolation procedure in order to calculate the *TTF*; the wear evolution between two measurements (VB_i, VB_{i+1}) is assumed to be linear. *TTF* is calculated when tool wear threshold ($VB_{\text{Bmax}} = 0.2$ mm) is reached. For example, from Table 3, by interpolating between the 14th inspection at ($t_i = 1530$ s) and the 15th inspection at ($t_{i+1} = 1650$ s), and by using equation (14), the *TTF* is found to be 1623.3 s. This interpolation is repeated for 28 tools. The results for the 28 tools are given in Table 4

$$\frac{\delta}{\Delta t} = \frac{0.2 - VB_i}{\Delta VB}, \quad TTF = \varepsilon + t_i \tag{14}$$

Development of the model and results

The PHM parameters are estimated using EXAKT software.[18] The resulting hazard function is given as follows in equation (15)

$$\begin{aligned} h(t, Z) &= \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} e^{\gamma_1 v + \gamma_2 f} \\ &= \frac{3.71}{23760}\left(\frac{t}{23760}\right)^{2.71} e^{0.195v + 10.86f} \end{aligned} \tag{15}$$

The covariate parameters $\gamma_1 = 0.195$ and $\gamma_2 = 10.86$ are the multipliers for cutting speed (v) and the feed rate (f), respectively, in the hazard function. A small value for γ_1 parameter does not mean that cutting speed (v) has a small effect on the hazard function because the covariate parameter is multiplied by the covariate value which can be large.[22] In order to distinguish between statistically significant and non-significant covariates, a formal statistical test is needed. In Table 5, statistical Wald test shows in column 5 that the cutting speed is more significant than feed rate.

In order to know how the cutting speed and the feed rate affect the hazard rate, a simple normalization procedure is done. Since the cutting speed and the feed are in the range (40, 80) and (0.15, 0.35), respectively, the normalization of the "overall" covariate will be as follows

$$Z^c = \beta_o + \beta_1 x_1 + \beta_2 x_2 = 14.415 + 3.9\,x_1 + x_2 \qquad (16)$$

where $x_1 = ((v - 60)/20)$, $x_2 = ((f - 0.25)/0.1)$, and $x_1, x_2 \in [-1, 1]$.

β_o, β_1, and β_2 are called regression coefficients.[23] In our model, it is obvious that the effect of cutting speed on cutting tool life is approximately four times more than the effect of feed rate.

In order to validate the model, Kolmogorov–Smirnov test (K-S test) and logarithmic reliability function analysis are done. K-S test evaluates the model fit. The test checks the null hypothesis that the $H(t, Z)$ in equation (5) is distributed exponentially (equation (13)). The summary of goodness of fit test is automatically produced in EXAKT as in Table 6.The test shows that the PHM offers a good modeling for the data.

Figure 3 shows the analysis of the logarithmic reliability function (log minus log plot).[24] From equation (5), the linear equation for each run will be as follows

$$\ln[-\ln(R(t; Z))] = \beta \ln(t) - \beta \ln(\eta) + \gamma_1 v + \gamma_2 f \qquad (17)$$

The logarithmic reliability function in equation (17) is linear in $\ln(t)$, and for each run, corresponding functions are parallel.[7] It is concluded, now, that the PHM's assumption is satisfied and the reliability functions of

Table 3. The experimental results showing the wear of tool 1–1.

Inspection no.	Time (s)	*VB* (mm)
1	0	0
2	120	0.0525
3	240	0.06
4	360	0.065
5	480	0.0725
6	600	0.0875
7	720	0.1075
8	840	0.1125
9	960	0.12
10	1050	0.125
11	1170	0.135
12	1290	0.165
13	1410	0.175
14	1530	0.1825
15	1650	0.205

Table 4. Time to failure (*TTF*) for the 28 tools.

Tool ID run-replication	Time to failure (s)	Speed (*v*), m/min	Feed (*f*), mm/rev	Tool ID run-replication	Time to failure (s)	Speed (*v*), m/min	Feed (*f*), mm/rev
1–1	1623.3	40	0.15	3–5	1230	40	0.35
1–2	2087	40	0.15	3–6	1006	40	0.35
1–3	1770	40	0.15	4–1	121.4	80	0.35
1–4	1524	40	0.15	4–2	87.5	80	0.35
1–5	1560	40	0.15	4–3	135	80	0.35
2–1	295	80	0.15	4–4	135	80	0.35
2–2	267.5	80	0.15	4–5	121.7	80	0.35
2–3	281.2	80	0.15	4–6	102.5	80	0.35
2–4	225.3	80	0.15	5–1	233.5	60	0.25
2–5	252.7	80	0.15	5–2	192	60	0.25
3–1	1240	40	0.35	5–3	265	60	0.25
3–2	1002	40	0.35	5–4	190	60	0.25
3–3	1320	40	0.35	5–5	160	60	0.25
3–4	1263.3	40	0.35	5–6	185	60	0.25

Table 5. Summary of estimated parameters (based on ML method).

Parameter	Estimate	Significance	Standard error	Wald
Scale (η)	23,760	–	6174	–
Shape (β)	3.71	Y	0.6077	19.88
v	0.1951	Y	0.03356	33.78
f	10.86	Y	2.735	15.76

Table 6. Summary of goodness of fit test results.

Test	Observed value	*P*-value	PHM fits data
Kolmogorov–Smirnov	0.2266	0.0965714	Not rejected

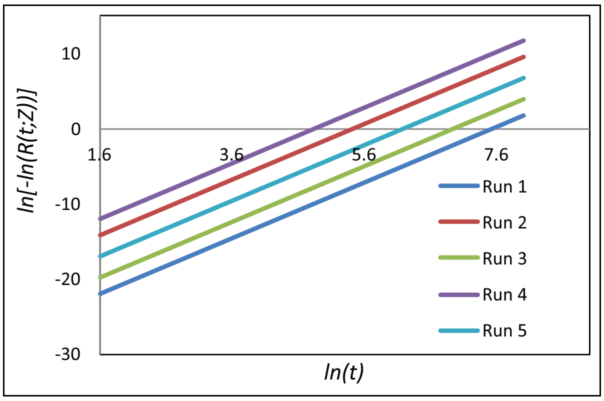

Figure 3. Logarithmic reliability function plot for each run.

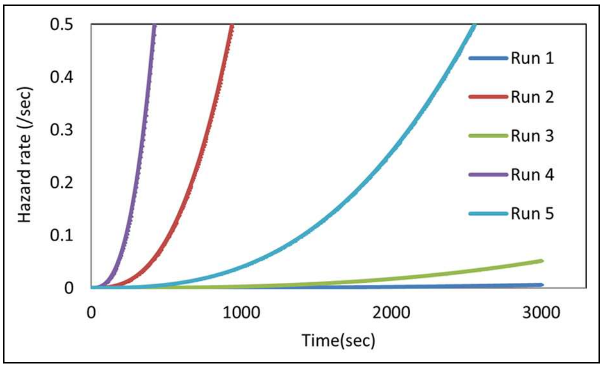

Figure 4. Hazard rate curves for each run.

the cutting tool in the range of the cutting speed and the feed rate are presented.

Based on equation (15), the failure rates are plotted for each run in Figure 4. The effect of machining conditions on the failure risk is clear when we compare between different runs. For example, by comparing between run 1 and run 2 which have the same feeds rates but different speeds, and also by comparing between run 2 and run 4 which have the same speeds but different feed rates, obviously, the effect of cutting speed is much higher than the effect of feed rate.

After determining the PHM, the optimal replacement policy-cost analysis is performed. The optimal replacement function is calculated with a cost ratio r = 2 (preventive replacement cost is estimated to be \$100, and the failure replacement cost is \$200, thus K is equal to \$100); r is the ratio of the failure replacement cost to preventive replacement cost, and it is calculated considering the tool and material cost; r is always more than 1 to make sense to maintain the tool preventively. As shown in Figure 5, the optimal time to replacement

Figure 5. Optimal replacement function-cost analysis.

T_d^* can be calculated. The function $g(t) = \ln(d^* \eta^\beta / K\beta) - (\beta - 1)\ln t = 29.429 - 2.71 \ \ln t$ is the replacement function, applied to an "overall" covariate value $Z^c = 0.195\,v + 10.86f$.

Similarly, we find the optimal replacement function that maximizes the availability. The optimal time to replacement T_d^* is then calculated. The time required to perform preventive replacement $T_p = 160$ s, and the time required to perform failure replacement $T_f = 540$ s. As shown in Figure 6, the function $g(t) = \ln(d^* \eta^\beta / K\beta) - (\beta - 1)\ln t = 31.22 - 2.71 \ln t$ is the replacement function, applied to an "overall" covariate value $Z^c = 0.195\,v + 10.86f$.

In practice, finding optimal replacement policy is generalized. Figure 7 shows the sequence of finding the optimal replacement T_d^* in both cases of cost analysis or availability analysis. For example, in cost analysis, the procedure is as follows

1. Extract the event (tool failure) by sequential inspections for any machining process.
2. Collect the experimental data in order to build the model by estimating the parameters of the PHM.
3. Check the goodness of fit using, for example, Kolmogorov–Smirnov test.
4. Find $d^* = \phi(T_d^*)$ which is the optimal cost where $\phi(T_d)$ is minimum, and then find the replacement function, $g(t) = \ln(d^* \eta^\beta / K\beta) - (\beta - 1)\ln t$ for known costs C and $C + K$.
5. Calculate T_d^* for current machining conditions v and f by defining the composite covariate $Z^c = 0.195\,v + 10.86f$ and using the replacement function.

Practical use and sensitivity analysis

The replacement function is used for a single cutting tool in multitasked machining process under variable machining conditions. For example, the user may use the tool for machining a part with machining conditions $v = 50$ m/min and $f = 0.20$ mm/rev for 200 s, then he or she may want to use the same tool for a second machining process with machining conditions $v = 40$ m/min and $f = 0.15$ mm/rev. The question is "Can he/she use this tool for the second machining process and for how long he/she can use this tool before replacing it with a new one in order to get the cost optimality?" Figure 8 answers this question. The first machining process starts at point 1 while $Z^c = 11.92$ and continues horizontally until point 2 ($T_d = 200$ s). Since Point 2 is below the replacement function curve, the user can use the tool for the second machining process which will start at point 3 while $Z^c = 9.43$ and can go horizontally until it touches the replacement function curve (point 4), which gives the optimal time to replacement $T_d^* = 1610$ s. The optimal remaining time for the second machining process is $T_d^* - T_d = 1410$ s. Obviously, that example shows how the user can follow the status of the cutting tool by knowing its cutting speed v, feed f, and working age.

Sensitivity analysis is performed on the cost ratio (r). Figure 9 shows the cost ratio sensitivity when r = 2 to r = 5. Obviously, the optimal time to replacement is decreasing when the cost ratio (r) is increasing. This is very logical because as the difference between the failure replacement cost and the preventive replacement cost gets higher, the more frequent preventive replacement should be done, thus the new optimal time to

Figure 6. Optimal replacement function-availability analysis.

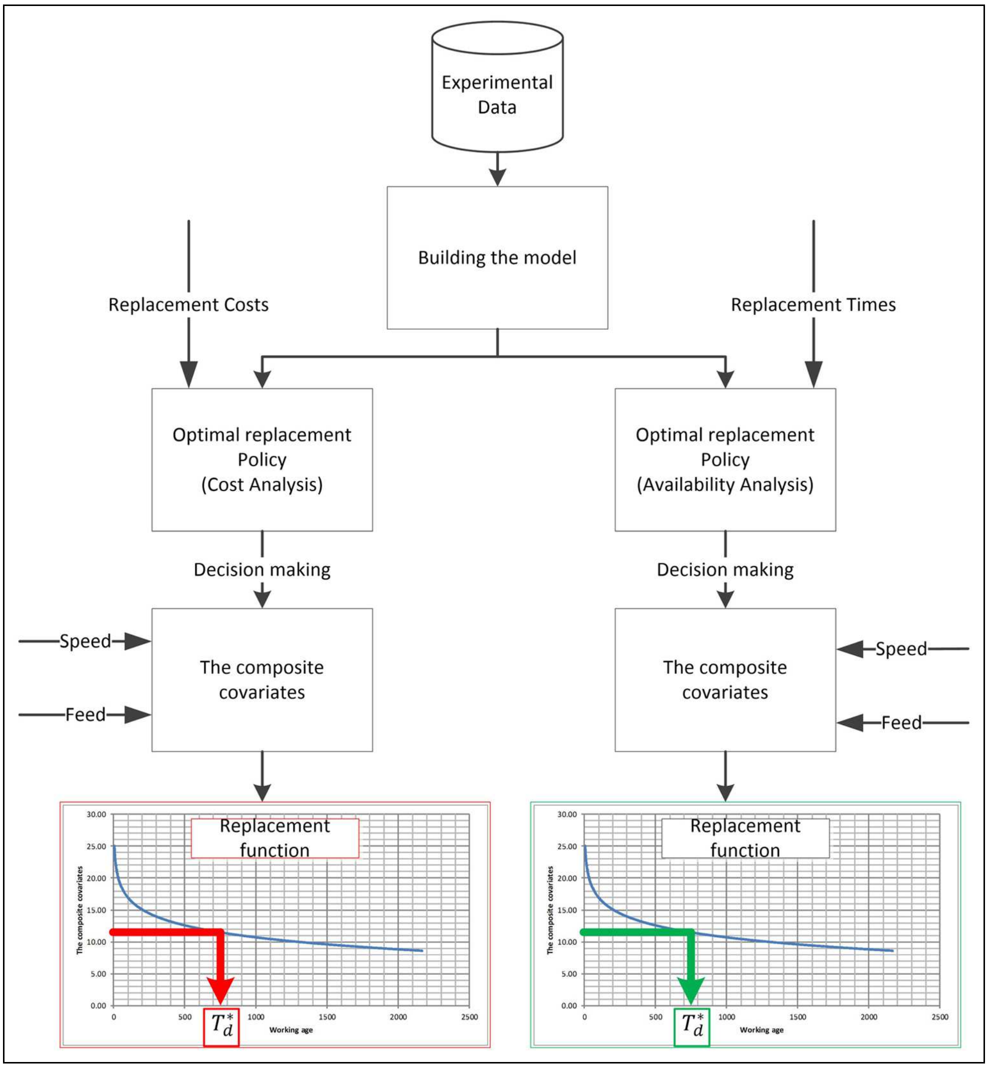

Figure 7. Finding the optimal replacement time in cost and availability analysis.

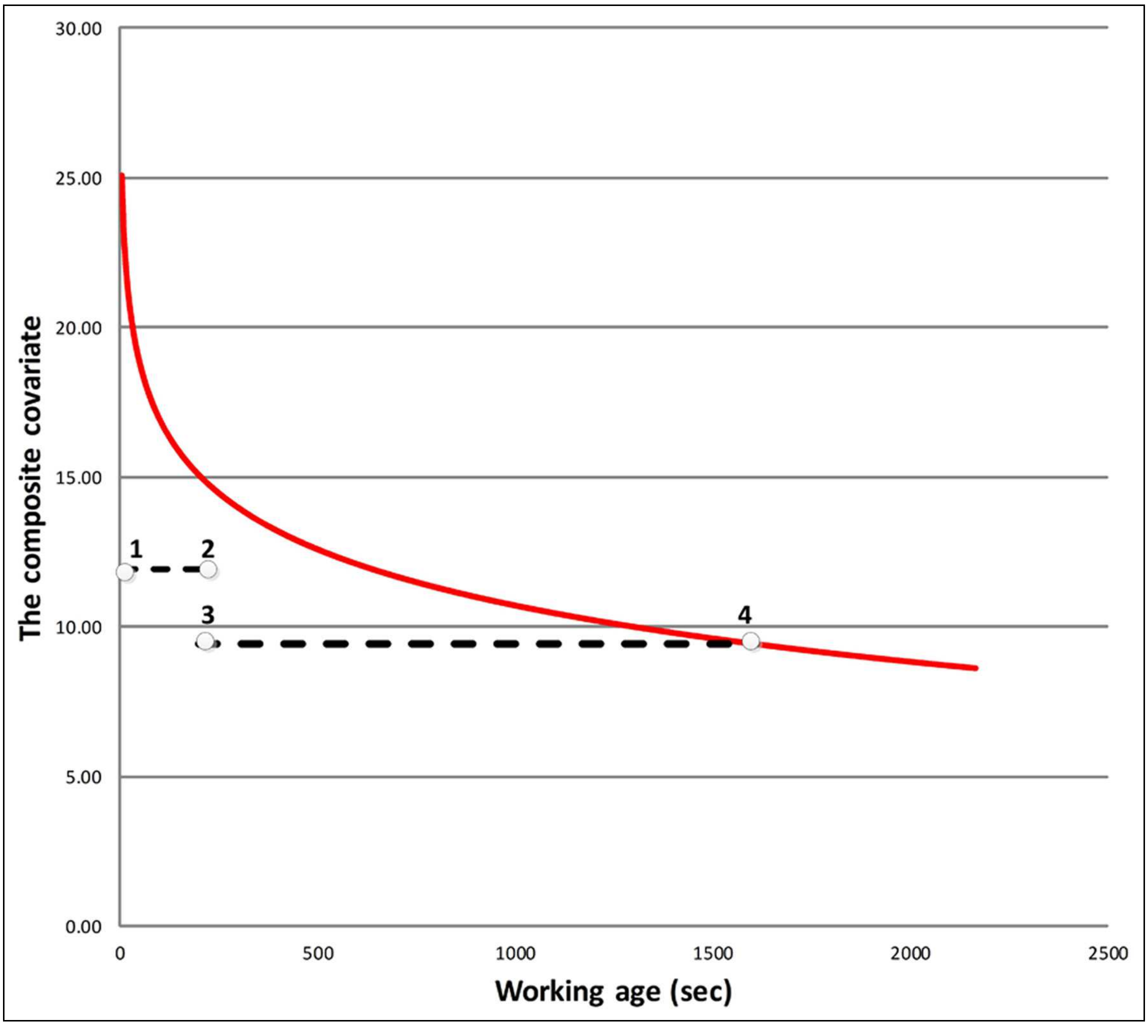

Figure 8. Optimal replacement example-cost analysis.

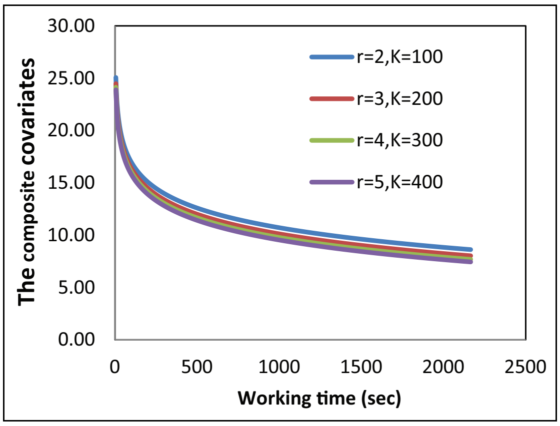

Figure 9. The cost ratio sensitivity.

replacement will be less than the original one, in order to minimize the cost per unit time.

Conclusion

In this article, we have introduced two new contributions to the research on tool replacement, which are two optimality models for cost minimization and availability maximization, and we applied it to a new generation of composites, namely, the TiMMCs. Experimentally, data were collected during turning TiMMCs under variable machining conditions. The collected data were used to construct the PHM. The PHM offered a statistically good model for the problem. An optimal replacement function was obtained and built into a simple chart. While changing the machining conditions, we showed how the user can find the optimal time to replacement that optimizes either the machining cost or the availability per unit time. In these cases, the machining cost per unit time and availability were found to be equal to 0.13 $/s and 80.77%, respectively. If these models are not used, the run to failure cost and availability are found to be 0.20 $/s and 64.57%, respectively. This represents a saving of 35.7% in case of cost analysis and an increasing of 16.20% in the case of availability analysis.

Declaration of conflicting interests

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References

1. Singerman S, Jackson J and Lynn M. (eds). Titanium metal matrix composites for aerospace applications. In: *Superalloys 1996, proceedings of eighth international symposium on superalloys*, Champion, PA, September 1996. Warrendale, PA: TMS.
2. Hui Y and Leung L. Optimal economic tool regrinding with Taguchi's quality loss function. *Eng Economist* 1994; 39(4): 313–331.
3. Klim Z, Ennajimi E, Balazinski M, et al. Cutting tool reliability analysis for variable feed milling of 17–4PH stainless steel. *Wear* 1996; 195(1): 206–213.
4. Sakharov G, Ilinykh V and Konyukhov VY. Improvement of fastening elements in an assembled cutting tool. *Sov Eng Res* 1990; 10: 102–103.
5. Gray AE, Seidmann A and Stecke KE. A synthesis of decision models for tool management in automated manufacturing. *Manage Sci* 1993; 39(5): 549–567.
6. Liang SY, Hecker RL and Landers RG. Machining process monitoring and control: the state-of-the-art. *J Manuf Sci Eng* 2004; 126(2): 297–310.
7. Tail M, Yacout S and Balazinski M. Replacement time of a cutting tool subject to variable speed. *Proc IMechE, Part B: J Engineering Manufacture* 2010; 224(3): 373–383.
8. Jeang A. Reliable tool replacement policy for quality and cost. *Eur J Oper Res* 1998; 108(2): 334–344.
9. Balazinski M and Mpako C. Improvement of tool life through the use of two discrete feed rates during machining of 4140 steel. *Mach Sci Technol* 2000; 4(1): 1–13.
10. Lin T and Shyu RF. Improvement of tool life and exit burr using variable feeds when drilling stainless steel with coated drills. *Int J Adv Manuf Tech* 2000; 16(5): 308–313.
11. Mazzuchi TA and Soyer R. Assessment of machine tool reliability using a proportional hazards model. *Nav Res Logist* 1989; 36(6): 765–777.
12. Liu H and Makis V. Cutting-tool reliability assessment in variable machining conditions. *IEEE T Reliab* 1996; 45(4): 573–581.
13. Liu PH, Makis V and Jardine AK. Scheduling of the optimal tool replacement times in a flexible manufacturing system. *IIE Trans* 2001; 33(6): 487–495.
14. Ding F and He Z. Cutting tool wear monitoring for reliability analysis using proportional hazards model. *Int J Adv Manuf Tech* 2011; 57(5–8): 565–574.
15. Vagnorius Z, Rausand M and Sørby K. Determining optimal replacement time for metal cutting tools. *Eur J Oper Res* 2010; 206(2): 407–416.
16. Makis V. Optimal replacement of a tool subject to random failure. *Int J Prod Econ* 1995; 41(1): 249–256.
17. Taylor FW. *On the Art of Cutting Metals*. New York: American Society of Mechanical Engineers, 1907.
18. Banjevic D, Jardine A, Makis V, et al. A control-limit policy and software for condition-based maintenance optimization. *Infor* 2001; 39(1): 32–50.
19. Aven T and Bergman B. Optimal replacement times: a general set-up. *J Appl Probab* 1986; 432–442.
20. Makis V and Jardine AK. Optimal replacement in the proportional hazards model. *Infor* 1992; 30(1): 172–183.
21. Bergman B. Optimal replacement under a general failure model. *Adv Appl Probab* 1978; 431–451.
22. *EXAKT Help Version 4.20.1*. Toronto, ON, Canada: Optimal Maintenance Decisions (OMDEC) Inc., 2007.
23. Montgomery DC. *Introduction to statistical quality control*. Hoboken, NJ: John Wiley & Sons, 2007.
24. Kalbfleisch JD and Prentice RL. *The statistical analysis of failure time data*. Hoboken, NJ: John Wiley & Sons, 2011.

Appendix 1

Notation

A	availability
C	preventive replacement cost
$C + K$	failure replacement cost
d	control-limit value
d^*	optimal cost
f	feed rate
g	warning function
$h(t)$	failure hazard rate at time (t)
$h_0(t)$	baseline failure rate
H	cumulative hazard function
P	probability
r	cost ratio
R	survival function
t	cutting time
T	cutting tool life
T_d	preventive replacement time
T_d^*	optimal time to replacement
v	cutting speed
VB	tool wear
VB_{Bmax}	tool wear threshold
W	expected replacement time
Z	covariates of the machining conditions
Z^c	overall covariate
β	shape parameter
β_o, β_1, β_2	regression coefficients
η	scale parameter
ϕ	expected cost per unit time