Cutting Tools Replacement: Toward a Holistic Framework

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Abstract: The important losses in the machining industry due to improper replacement of cutting inserts induces the necessity of optimizing the maintenance policies in such contexts. However, the variety of industrial practices, end-of-life criteria, and optimization criteria does not allow a clear view on the maintenance policy performance evaluation. The general objective of this paper is to make clear the framework in which the industrial practice may apply the already existing statistical approaches to the specific case of cutting tools, which constitutes the novelty of this paper. In order to do so, a general methodology is presented, that may help identify the maintenance performance criteria to be used for optimizing the tool replacement, as well as statistical procedures for this optimization, of which examples are presented.

Keywords: Machining; Condition monitoring; Manufacturing Modeling; Finite Element Method; Statistical methods; Proportional Hazards Model

1. INTRODUCTION

The replacement of cutting inserts has unique features that require a specific approach to this maintenance operation. First, it is the most frequent maintenance action on machine tools, as the Mean Up Time (MUT) of a cutting edge is typically of 15 min for turning operations and 30 min in milling for carbide tools. Second, the replacement duration is extremely low, and induces only short unavailability for the considered equipment. Yet, the cost of the cutting tools maintenance policy is non-negligible due to unitary costs in the range of 10 to 20 EUR for single point turning inserts in carbon steel machining, for example. The poor replacing policies of cutting tools lead to billions USD losses in the US industry alone (Aramesh et al., 2016), and these losses call for the development of better strategies.

In most machining industries, the replacement decision practices come from three possible approaches (Smith, 2008, chaps. 6 and 9):

(1) the machining worker's experience: the worn tool is detected from experience (often based on a change of tone in the machining noise) or from poor quality of machined surfaces;
(2) consideration to the machining time since the last tool replacement (following preliminary qualification test results);
(3) rarely, tool condition monitoring based on various indicators.

The reliability of the first approach is questionable, as its performances are limited by the workers' intrinsic experience, subjectivity and physiological capabilities. The second approach is a typical scheduled maintenance policy. In the industrial practice, the variability of cutting inserts, workpiece material and machining operations is such that the qualification tests on the machining process leads either to extremely conservative replacement times, or to scrap. Siddhpura and Paurobally (2013) extensively reviewed the possible condition monitoring approaches.

The condition monitoring approaches are usually based on the hypothesis that the tool end-of-life is caused by the tool wear. These methods are either based on off-line observations, which necessitate a machining stoppage for the inspection to be performed (e.g., tool wear microscope pictures), or on on-line measurements of variables that are correlated with the tool wear evolution (e.g., cutting forces, vibratory measurements, etc.) (Siddhpura and Paurobally, 2013). In some cases, such as in survival analysis approaches, the condition monitoring variables are directly linked with the tool life without the intervention of tool wear.

The tool end-of-life criterion may therefore be questioned. Indeed, the ISO 3685:1993 standard, which is dedicated to the tool life testing of tools, uses a flank wear parameter, the flank wear width (denoted VB_B in Fig. 1,) as the tool end-of-life criterion (the end of life is reached when $VB_B = 0.3$ mm). However, in the industrial context, this possibility is only related to the third approach (condition monitoring), and is rarely used. Further, the flank wear value that leads to the replacement of cutting inserts is not homogeneous in the literature and in the industrial practice. For instance, the risk aversion may lead to choose the criterion earlier, at the transition between steady-state wear and accelerated wear. Aramesh et al. (2016) found the value $VB_B = 0.15$ mm for this criterion in machining titanium metal matrix composites. A first parameter to be considered for the maintenance of cutting inserts is therefore the end-of-life criterion of cutting inserts.

Yet, condition monitoring variables measurements are not sufficient by themselves to identify optimal maintenance policies, and necessitate statistical modeling in order to
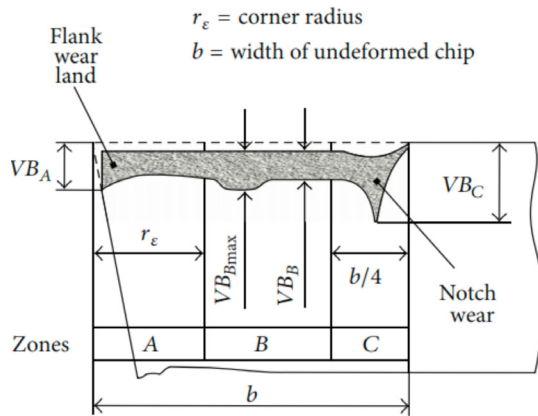
Fig. 1. Flank wear land on a single point turning cutting edge according to the ISO 3685:1993 standard (image adapted from Jozić et al. (2014))

Fig. 2. Industrial implementation of the optimization framework

establish first the Remaining Useful Life (RUL) or current reliability estimates and ultimately lead to a decision (Wang, 2008). The optimization of a maintenance policy first necessitates criteria (e.g., cost-based, scrap aversion, etc.) in order to objectify the performance assessment of a given policy. This maintenance evaluation criterion constitutes a second criterion for the optimization of cutting inserts replacement.

However, it is very well possible that these two parameters are linked: a scrap aversion policy would induce more frequent tool replacements, hence a lower tool wear value at the replacement time. For example, Iqbal et al. (2016) used a multi-criterion optimization to show, in AISI D2 milling, that the maximum width of the flank wear $VB_{B, max} = 0.2\,mm$ is the best end-of-life criterion to minimize the roughness of the produced workpieces.

Once these parameters are identified, literature is abundant concerning the estimation of the tool RUL. Several usual approaches stand out:

(1) stochastic methods (e.g., Zaretalab et al., 2019);
(2) parametric reliability statistical models (e.g., Liu et al., 2020);
(3) survival analysis (e.g., Aramesh et al., 2016);

Further, some authors perform a combination of these approaches: e.g., Equeter et al. (2017) and Zaretalab et al. (2018).

Given the number of parameters and approaches possibilities, the current published literature may be problematic for industrial implementation, as no general framework or global methodology for such maintenance optimization stands out. This observation is reinforced by the current industrial tool replacement methodology, that only rarely uses condition monitoring approaches. In this paper, we suggest a first iteration at such a methodology in order to allow the industrial application of the mentioned methodologies to a particular practical case. The methodology in itself is a recurrent approach in condition-based and predictive maintenance optimization, but its application to the case of cutting tools, given their short lifetimes, constitutes the novelty of this paper. In particular, a consideration is given to the choice of the condition monitoring variables and the quality of their representation of
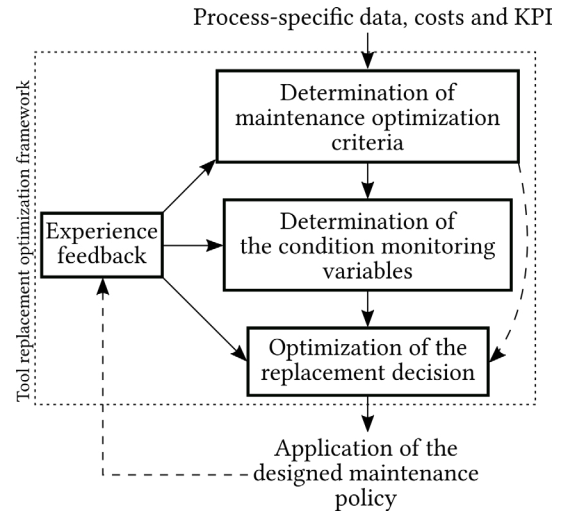
the tool life evolution, and the prospective of workshop implementation, including in the framework of increasing amounts of available data due to 4.0 industry.

In Section 2, a global tool replacement optimization framework is proposed, including the identification of a global maintenance performance assessment indicator and the choice of tool life optimization tools in order to maximize this performance. In section 3, the framework assumptions are discussed. Finally, the paper conclusions are presented with possible objectives for further work.

2. TOOL REPLACEMENT OPTIMIZATION FRAMEWORK

The general principle of the tool replacement optimization framework is illustrated in Fig. 2. The first and foremost step is the determination of the maintenance optimization criteria. It is with respect to these criteria that the maintenance policy is optimized. The second step is the identification of the condition monitoring variables. These variables are dependent on the criteria chosen at the first step and their exhaustive listing would go beyond the scope of this paper, but some examples are given nonetheless. As a third step, the replacement decision can be optimized following usual maintenance optimization guidelines. This optimization allows the determination of objective and measurable replacement criteria that may be applied in an industrial context. Finally, the experience feedback allows improving all previous steps.

In order to be as general as possible, the approach describes tool replacement in a predictive maintenance framework, but a step may be bypassed in order to switch to condition-based maintenance or a more traditional reliability-centered maintenance.

2.1 Maintenance Optimization Criteria

The choice of the maintenance optimization criteria will allow assessing the performances of a maintenance strategy. It is with respect to these criteria that any optimization is performed. The most common criterion for single-component systems (in this case, only the tool mainte-

nance is considered) is the cost, or a model of the cost encompassing the different cases that may present (Wang and Pham, 2006, chap. 1). This cost model can be linked with industrial key point indicators (KPI) and may include:

- the new tool cost, including handling and assembly (C_{tool});
- the worn tool handling and recycling costs ($C_{\text{recycling}}$);
- the unavailability cost of the machine ($C_{\text{unavailability}}$);
- scraps (C_{scrap}), etc.

It is worth noting that scraps costs are only induced when the tool is replaced after having failed (i.e. produced scrap), whereas the other items correspond to fixed costs of tool replacement. Depending on the specific application, other cost components may arise. Formally, the total cost C_{tot} for a total tool life cycle can be expressed as:

$$C_{\text{tot}} = C_{\text{tool}} + C_{\text{recycling}} + C_{\text{unavailability}} + C_{\text{scrap}} + \ldots \quad (1)$$

The cost model must be built by taking into account as many factors as possible. In consequence, the performance of the model is expressed as this cost, usually as an asymptotic average cost over time (C_{asy}). This cost model therefore lists the cases of preventive maintenance (when the tool is replaced before reaching its end of life), and corrective maintenance (when the tool has already failed, and induced scraps).

In the present case, the tool failure corresponds to the state where the tool produces scraps. This may be caused either by the tool being worn to a point where it can only produce out-of-tolerances workpieces, or by a broken tool (or similar catastrophic failures such as plastic deformation, etc). The tolerances on the most critical machining operation should be known, in order to determine the possible condition monitoring variables that are most probable to help monitor the evolution of the tool life.

The choice of maintenance optimization criteria should therefore integrate inputs from the entire production environment, and bring production, quality and management to agree on a common evaluation of costs and values. It is to be expected that, while such agreements may prove difficult to reach on bigger assets, the limited number of protagonists and stakes concerned by the tool maintenance may limit the difficulty in this process.

2.2 Condition Monitoring Variables

The choice of the condition monitoring variables stems from the tolerances defined on the machined surface. Without entering the details of the tolerances nature, the condition monitoring variables are usually taken among: the cutting forces, vibratory measurements, direct (off-line) flank wear measurements, etc. Siddhpura and Paurobally (2013) extensively reviewed the potential condition monitoring variable candidates. The complexity of this part is the identification of the monitoring variables that are best correlated to the evolution of the quality variable, e.g., vibratory measurements for cylindricality tolerances.

This research must be performed on a case-by-case basis, and with help of the relevant scientific literature. In some cases, experiments may be necessary in order to determine the appropriate condition monitoring variables. This experimental approach is carried out through correlating the assessed condition monitoring variable with the observed tool life evolution.

Practically, this step is achieved through the identification of the tool failure mode, that corresponds to the cause of rejection as scrap. The nature of this cause may point to specific condition monitoring variable, or to less specific approaches. Identified sensors are then installed on the machine in order to ensure the correlation between the monitored variables and the tool life evolution.

This step may be bypassed if no adequate condition monitoring variable is found, or if the failure time distribution is well modeled by a parametric reliability model, such as a Weibull distribution for example, as it is classically done in preventive maintenance policy optimization. The bypass of this condition monitoring approach reduces the framework to reliability-centered maintenance, which can still be optimized as mentioned below.

2.3 Optimization of the Replacement Decision

The decision of replacing a cutting tool must be taken through a careful optimization of several aspects of the question.

Machining is not a continuous operation that can be stopped at any time for tool replacement. Unless a tool breakage occurs, it is usually necessary to wait for the end of a machining cycle before the process may be interrupted for the maintenance action to take place. Therefore, the question of the replacement decision is often interpreted as the comparison between an estimate of the tool RUL and the duration of a machining cycle. Further, this cycle duration is often known in advance, as it can be easily deduced from the G-code that is implemented in the machine.

Therefore, the replacement question can be reduced to the estimation of the RUL of a cutting insert. This assessment can be done through a series of approaches, depending on the maintenance paradigm that is chosen (predictive maintenance, condition-based maintenance, or reliability-centered maintenance). Regardless this choice, the objective is to produce a RUL estimation that optimizes the optimization criteria that are chosen.

Depending on the retained paradigm, and whether condition monitoring variables were identified, several RUL evaluation approaches can be considered.

Without Condition Monitoring, the choice is limited to traditional statistical analysis of failure times. The strategy is then to identify tool lifetimes, corresponding to the time at which the productions ceased to be within tolerances. This time may prove difficult to evaluate, given the quality sampling of machined workpieces, but should be evaluated nonetheless.

The cutting tools may be considered to only deteriorate during machining, and their lifetime should therefore be expressed as the time during which they are in contact with the materials, or as a number of machining cycles if they undergo repetitive cycles.

The lifetime database that is collected in this manner may lead to traditional lifetime analysis through single-unit system reliability distributions (Werbińska-Wojciechowska, 2019). A statistical distribution may be fitted to describe the behavior of these lifetimes, with the appropriate statistical procedures and tests (see for example Kalbfleisch and Prentice, 2002, chap.2).

A failure occurs (leading to scraps) occurs before a fraction (k_f) of tool replacements, whereas the tool is replaced through a preventive maintenance in the rest of the cases $(k_p = 1 - k_f)$.

Further, the statistical distribution of failure times will provide an expected tool lifetime, and the associated percentiles allow identifying k_f, given the preventive maintenance periodicity (PMP). The choice of percentile at which the preventive replacement is planned constitutes the parameter for optimization with respect to the chosen optimization criterion, hence as a risk-aversion parameter. If the cost is retained as this criterion, and as always in preventive maintenance, the cost of maintenance when the PMP tends to zero is infinite (Nakagawa, 2008, chap.8):

$$\lim_{\text{PMP} \to 0} C_{\text{asy}} = \lim_{n \to 0} C_{\text{asy}} = \infty \qquad (2)$$

However, because of the additional cost of scrap, an optimal value of the preventive maintenance criterion exists, that minimizes the asymptotic cost of maintenance. The expression of C_{asy}, k_p and k_f as expressions of the PMP allow an optimization of this parameter with respect to the chosen criterion.

Nevertheless, an optimization of the proportion of inserts that are allowed failing with respect to the chosen optimization criterion can be done and usually lead to a finite optimal value depending on the statistical distribution describing the tool failure. Several variations can also be considered, based on several different costs models corresponding to different situations that the industrial context may encounter: priority to the quality, priority to the availability, etc. In turn, to each situation, a target tool replacement time may be identified, and at any given time, the reliability, and the probability of failure during the next cycle may be estimated.

Practically, an history of the tools replacement must be gathered, and expressed as a function of machining time. This can be done by comparing the replacement time with the production history in order to obtain the actual contact duration between the tool and the material. Alternatively, a number of machining cycles would be acceptable. The statistical analysis of these data allow fitting a reliability distribution describing the tool life behavior, and lead to the optimization described above.

With Condition Monitoring, the range of possibilities is wider. The next steps depend on the identified condition monitoring variables.

For a wide variety of cases, the tool wear may be considered as one of the major variables describing the evolution of the tool life. The direct measurement of tool flank wear necessitates optical imagery, hence off-line measures, with sometimes manual image post-processing that would be
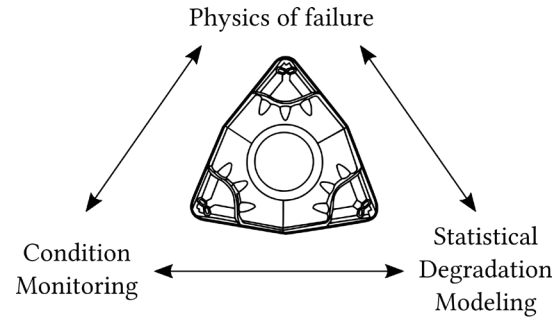

Fig. 3. Triple approach to the tool life determination when condition monitoring is available

time-consuming, would induce delays in the wear evolution estimate that are incompatible with the tool life duration, or would increase the unavailability of the machine hence the cost of this approach.

Fortunately, a large range of tool wear estimation methods were developed (see for example Li, 2012). Fig. 3 represents the possible approaches to the estimation of the tool life:

- The physics of failure can be modeled with methods such as the Finite Element Method (FEM), using usually hard to obtain variables such as the temperature at the flank face of the tool. Such methods can be used in order to evaluate the relationship between the wear evolution and other potential condition monitoring variables (e.g., cutting forces) (see for example Ducobu et al., 2015). This approach can also be useful in studying the reverse problem: the evolution of tool wear on the basis of cutting parameters (see for example Attanasio et al., 2010).
- Experimental work can link the evolution of tool wear with several condition monitoring variables, either linked with the process (e.g., vibratory measurements: Rmili et al. (2016)) or linked with the quality (e.g., workpiece roughness: Equeter et al. (2020a)).
- In addition to the statistical models that were presented without condition monitoring, stochastic models can also be produced in order to represent the statistically distributed nature of the tool wear increments (e.g., Letot et al., 2016).

The retained condition monitoring variables can be correlated to the tool failures as previously. In that case, instead of only evaluating the time during which the tool was in contact with the material during its life, the value of the condition monitoring variable is also estimated at the tool end-of-life, and the tool replacement can then be triggered by the tool condition monitoring variable value. This approach corresponds to the condition-based maintenance. Further, more complex models may be used, such as survival analysis, taking for example the history of cutting parameters or condition monitoring values as an input, in order to produce a reliability curve, that can yield an estimate of the RUL (Aramesh et al., 2016).

Finally, predictive maintenance may be achieved through the use of models taking into account the influence of the planned following machining cycles in their RUL prediction. The relative complexity of such approaches may suggest reserving this approach to variable machining

cycles, whereas repetitive machining cycles would already benefit from the condition-based maintenance approach. Stochastic models or the extended Proportional Hazards model may be considered for this final approach.

The variety of condition monitoring options make this step more complex, but can also dramatically increase the accuracy of the replacement decision, depending on the quality of the correlation between the condition monitoring variable and the remaining useful life. Specific improvements of the statistical methodologies can be suggested to further improve the statistical results (see for example Equeter et al., 2020b).

Practically, the selected condition monitoring variable and failure data must be collected in order to fit a statistical model that links them together. Survival analysis, stochastic modeling and other statistical methodologies provide an estimate of the remaining time until the tool failure, and in some cases a probabilistic distribution of this remaining life. In turn, this estimate and its statistical properties may be used in a methodology analogous to the case without condition monitoring in order to minimize the asymptotic cost.

2.4 Industrial Implementation of the Framework

The implementation of such maintenance policies is not a simple endeavor in industrial contexts. Brutal implementations, based on incomplete databases, may lead to poor results. It is therefore advisable to begin such implementation with a data collection. Replacement history, and the causes of the replacements constitute a first step in the evolution toward the maintenance policies described in this framework. The data collection should be as careful as possible and at least allow evaluating whether the replacement was preventive or corrective (i.e., scrap was produced or not). The maintenance model (predictive, condition-based, etc.) should be defined on the basis of the needs and specificity of the machining process, but simpler models (e.g., without condition monitoring) can be considered first in order to evaluate the benefits of the maintenance analysis. In successive phases, it is possible to evolve from a maintenance model to another, given sufficient data.

Likewise, feedback on the proportion of maintenance actions due to scrap after the implementation of the maintenance policy may allow questioning the decided policy and help update the entire chain leading to the replacement decision. In some cases, it may also appear that some factors were not taken into consideration for the determination of the optimization criteria. In general, the definition of such maintenance policies should not lead to fixed situations and policies, but rather to iterative models and discussions.

In the foreseeable future, multiple sensors may be progressively added to machine tools as a consequence of industry 4.0 evolution. In this context, the choice of condition monitoring variables must be made in accordance with the identified best indicators of production quality degradation in order for the integrated condition monitoring to be usable for tool replacement decision. In a context of large data availability, it may be envisioned that the entirety of the presented framework would be included as a module of computerized maintenance management systems.

3. FRAMEWORK DISCUSSION AND EXPERIMENTAL ASSESSMENT

The holistic point of view that is chosen for the definition of this work leads to a series of general assumptions that can be discussed.

The variability of cutting tools and materials is a good example of these assumptions. Regardless the constancy of the material and cutting tools supply chain, inherent variability on the quality of these elements is to be expected, that contribute to the variability of the lifetime of cutting inserts. As a consequence, a slight variation in the tool or material grade may significantly alter the results of the chosen maintenance policy, which should therefore be challenged regularly.

The definition of tolerances (dimensional, geometrical, related to roughness, residual stresses, etc.) should also be unequivocal, in order for the different participants to the manufacturing chain to have a common definition of acceptable workpieces. Some machines include compensation capabilities for some of these quality drifts (especially dimensional). The use of these technologies should be included in the analysis if possible, in order to delay the tool replacement as late as possible while the production quality is kept in the target values.

On the other hand, the implementation iterations of this framework can be progressive and regularly compared to other methods, and may be integrated to a general quality approach as a corollary to other toolboxes (e.g., total productive maintenance, etc.)

4. CONCLUSIONS AND OUTLOOK

In response to high losses in the machining industries, due to poor tool replacement decisions, and to uncertainty on the relevance of usual end-of-life criteria, a framework was developed. The proposed framework encompasses pre-existing approaches in maintenance optimization methods including reliability-centered maintenance, condition-based maintenance and predictive maintenance. The general principle of this framework is to rely upon indicators dictated by the industrial context, rather than generalist wear criteria.

The objective is to optimize the tool replacement decision on the basis of indicators regrouping key interests to the studied case. As an example, it was suggested to use a cost model as the basis for optimization, considering losses due to scraps, unavailability and tool-related costs.

It was also highlighted that the replacement decision should occur close, but prior to the moment when the tool is no longer capable of producing within the specified tolerances that define the product quality. Therefore, a selection of possible condition monitoring variables, and reviews of such variables, were presented in order to help monitor the evolution of the tool production capability, and as an indicator of the tool RUL. Several possibilities for optimizing the tool life with respect to the chosen indicators were shown, based on three maintenance paradigms.

It is expected that this framework may allow a clearer view of the tool replacement optimization methods that are available to the industrial world with well known and proven statistical methods. Such methodologies are also already common practice for most industrial equipment (Pintelon and Van Puyvelde, 2006).

In turn, the progressive evolution to 4.0 industry may induce the appearance of sensors and data feedback from machine tools, including potential condition monitoring variables. This evolution, along with data mining capabilities and physics of failure models, may significantly improve the capabilities of the cutting tools maintenance through the identification or measurement of additional condition monitoring variables pertaining to the replacement of cutting inserts.

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