Cost and Environmental Assessment of Tool Replacement Strategies Under Imperfect Wear Monitoring in Ti6Al4V Milling

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Abstract

The policy for the replacement of cutting tools has a direct influence on the risk of producing out-of-tolerances workpieces, but can also avoid excessive consumption of new tools and production interruption. Current industrial practice tries to achieve an economical balance that does not directly incorporate the environmental impact of the policy. This often results in systematic preventive replacement of tools after a safely fixed number of produced workpieces, wasting a portion of the tool's useful life (at an environmental cost) and increasing the machine's downtime. In this study, we simulate the production of Ti6Al4V parts under three different tool replacement scenarios: (1) at fixed intervals, (2) using an imperfect cutting tool monitoring system where the tool can only be replaced between the production of two workpieces, and (3) with a cutting tool monitoring system that allows tool replacement every minute during machining. The simulation demonstrates that even with an imperfect monitoring system, condition-based replacement leads to improved economic performance (expressed in EUR) and environmental performance (expressed in kg CO_2-eq). In comparison to systematic replacement, the condition monitoring allows reducing the environmental impact up to $8.7\,\%$ and the cost up to $8.1\,\%$.

1. Introduction

Untimely replacement of cutting tools can produce unacceptable parts (scraps) due to out-of-tolerance roughness, dimensions, geometry, or residual stresses. It can also lead to replacing the cutting tool too early, which wastes a useful portion of the tool's life. Overall, the correct monitoring of cutting tools is expected to reduce machining costs by up to $30\,\%$ (Liu, Li, Hua, Lu, & Mou, 2018). Besides the economic cost, these issues bear an environmental impact compared to an optimal replacement of the cutting tool, either linked to the scraps or increased consumption of cutting tools. Facing the cost of scraps in high added-value parts, the industrial practice tends to favor early replacement of cutting tools in search of an economically optimized strategy.

Advances were scored in tool condition monitoring, allowing to estimate the tool wear from the range of possible monitoring variables (Siddhpura & Paurobally, 2013). The remaining useful life of the tool can be estimated using statistical methods, e.g., through survival analysis, such as the Cox PH model (Ding & He, 2011). Further, successful applications that fall within the Bayesian inference framework were also successfully applied to this problem (Karandikar, Abbas, & Schmitz, 2020; Patange & Jegadeeshwaran, 2021). Finally, recent results show excellent performance of artificial intelligence techniques for estimating the tool wear (Colantonio, Equeter, Dehombreux, & Ducobu, 2021), including models that can estimate the uncertainty of the tool wear prediction (Colantonio, Equeter, Dehombreux, & Ducobu, 2024).

Trying to integrate cutting tools in the circular economy suggests that reducing the use of cutting tools is underrepresented in the literature (Elnourani, Johansen, & Öhrwall Rönnbäck, 2024). The literature offers assessments of the environmental impact of the machining process (Shi, Hu, Ma, & Wang, 2021; Kshitij, Khanna, Yıldırım, Dağlı, & Sarıkaya, 2022) and cutting tool production (Fairoz & Shokrani, 2025; Shokrani, Arrazola, Biermann, Mativenga, & Jawahir, 2024).

Efforts are made to improve the use and life of cutting tools. These efforts revolve around optimizing parameters for improving tool life or sustainability. The tool selection has been shown to influence the environmental impact of machining strongly (Sun, Liu, Pan, Zhang, & Ji, 2020; Tian et al., 2019). Likewise, with a given tool, altering the cutting parameters can also benefit machining sustainability (Sun et al., 2020; Tian et al., 2019; Pimenov et al., 2022; Zhang, Zhang, Bao,

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& Huang, 2018).

This effort can only be fruitful if it considers the link between tool wear and workpiece quality, which is why suggested tool replacement criteria can be linked to surface roughness, for example (Iqbal, Zhao, Cheok, He, & Nauman, 2022). Likewise, knowing that worn tools are used, fine-tuning cutting parameters can also limit the probability of scrap production (De Souza et al., 2022).

The replacement strategy question arises from a practical, industrial point of view. Indeed, the tool end-users can accurately balance the economic and environmental impacts of the cutting tool replacement strategy only with sufficient information on both sides. In this context, the environmental impact of a tool replacement strategy can be evaluated, e.g., in steel turning (Campatelli & Scippa, 2016). Likewise, it is possible to make a joint assessment of environmental, social, and economic impact stemming from tool use and to produce estimates of remaining useful life (Sun et al., 2020).

Such a joint assessment has not yet been attempted on competing tool replacement strategies. Systematizing such an assessment on the scale of competing strategies would allow basing industrial decisions on robust quantification of the impacts. Filling this gap is the objective of the present paper. In this paper, we propose a joint assessment of the economic and environmental impact of Ti6Al4V milling under several scenarios corresponding to different replacement strategies. The compared strategies suggest replacing the tools:

- At a fixed periodicity,
- If an imperfect tool wear estimate from condition monitoring reveals excessive wear (inspection after finishing machining each workpiece),
- Using the same imperfect tool wear estimate from condition monitoring at a faster inspection periodicity

The simulated model consists of three key components:

- Cutting tools, modeled with a lifespan derived from a Weibull distribution, with degradation trajectories simulated using a hyperbolic sine function.
- The machine, represented as a medium-sized unit that consumes a constant amount of energy during machining.
- The Ti6Al4V workpiece, produced from raw material.

Each of these components is characterized by cost and CO_2-eq emission values sourced from the literature. To incorporate variability in the degradation process, the model employs a Monte Carlo simulation. Although this model represents a simplified production system, it effectively highlights the differences between various replacement strategies from both economic and environmental perspectives.

The rest of the paper is organized as follows: first, the methodology used for assessing the environmental and economic impact is explained; second, the results of the simulations for each scenario are presented; then, these results are discussed.

2. METHODOLOGY

This section presents the model developed in this article, detailing the assumptions considered to perform the simulation. Following the presentation of the considered case study, an inventory of the milling operation inputs and outputs and their evaluated economic cost and environmental impact are presented. This section ends with the definition of the three tool replacement scenarios studied in the article.

2.1. Model

The model presented in this article aims to simulate various cutting tool replacement strategies and to evaluate their economic and environmental impacts, while also considering the surface quality produced as a function of the tool's condition. These impacts are measured in euros (EUR) and kilograms of CO_2-equivalent (kg CO_2-eq).

The case study focuses on the machining of Ti6Al4V parts, representative of an industrial scenario involving the production of small, high-value-added titanium components, such as those used in the aerospace industry. It is assumed that the parts are machined using a CNC machine operating in a two-shift system (16 hours per day), 7 days a week, over the course of one month, with the facility located in Belgium.

Figure 1 illustrates the system boundaries, which encompass three main components: the cutting tool, the workpiece, and the electrical consumption of the CNC machine. The system account for the sourcing and processing of raw materials needed to produce coated cutting tools and titanium bars. The electricity used in the process is considered supplied by the Belgian electric grid, whose quantity of CO_2 per consumed kilowatt-hour depends on Belgian energy mix and imported electricity. The outputs of the system include the cutting tool and the machined parts. These parts may either meet quality standards or be classified as scrap if they were produced with a tool that was worn at the time of machining. This study does not consider the use phase of the machined parts, nor the potential end-of-life stages of the tools or workpieces, such as recycling or refurbishing. Additionally, the life cycle of the CNC machine itself is excluded from the evaluation of the system's economic and environmental impacts.

The data for the three components—the tools, the Ti6Al4V workpieces, and the energy mix—are all sourced from the literature and summarized in Table 1. A detailed description of each component is provided below.

Cutting tools

The selected cutting tool is a solid carbide tool used for face milling and coated with TiAlN/TiN using a Physical Vapour

Table 1. Model parameters of the cutting tool, the workpiece and the machine.

Cutting tool		**Workpiece**		**Machine**	
Diameter	5 mm	Raw mass	410 g	Mean electrical consumption for 20 workpieces (1 hour of machining)	15.5 kWh
Number of teeth	4	Useful Mass	320 g		
Coating	TiAlN/TiN (PVD)	Production Time	3 min		
Coated surface	300 mm²				
Mass	15 g				
Cost	40 EUR	Cost	8.20 EUR	Cost	0.15 EUR/kWh
CO_2	234 kg CO_2-eq	CO_2	15 kg CO_2-eq	CO_2	0.2 kg CO_2-eq/kWh

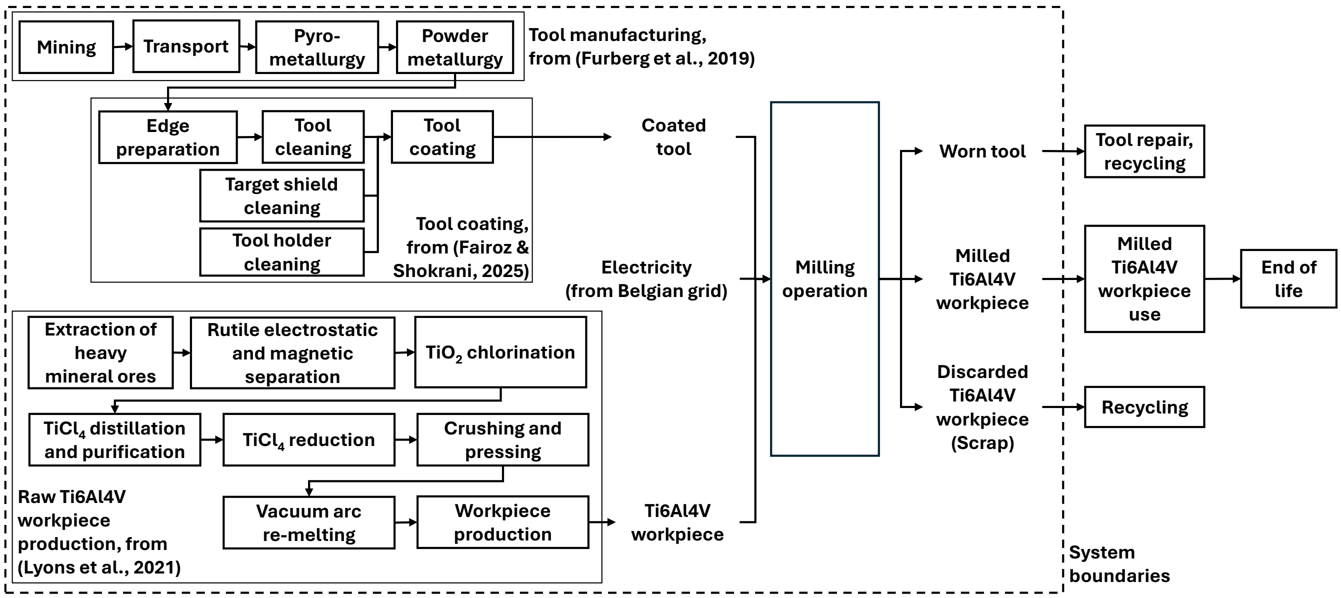

Figure 1. Inventory of the inputs, outputs and processes considered in the environmental impact evaluation of the milling operation. Values for CO_2-eq emissions: tool manufacturing from Furberg et al. (2019); tool coating from Fairoz and Shokrani (2025); raw Ti6Al4V workpiece production from Lyons et al. (2021); electricity from Belgian grid from Electricity Maps (2025).

Deposition (PVD) process. The cutter has a diameter of 5 mm, 4 teeth, and is suitable for machining titanium alloy. The cost of the tools is estimated at 40 EUR per tool. This estimate is based on prices from various tool manufacturers, such as Holex (Hoffmann Group, n.d.). In practice, the actual cost may vary depending on the negotiations between the company and the tool supplier. To account for potential price fluctuations, a sensitivity analysis is provided in the supplementary material of this article. The impact on Climate Change of the tool is calculated in two parts:

1. The CO_2-equivalent emissions induced by the production of the tungsten carbide tool, going from the extraction of raw materials to the sintering of the tool (Furberg et al., 2019).
2. The CO_2-equivalent emissions induced by the deposition of the TiAlN/TiN coating on the tool, considering tool edge preparation, tool cleaning, tool holder cleaning, target shield cleaning and tool coating process itself (Fairoz & Shokrani, 2025)

It is estimated that producing $1\,\mathrm{kg}$ of sintered tungsten carbide emits 17 kg CO_2-eq (Furberg et al., 2019). This type of cutter generally weighs around $15\,\mathrm{g}$, thus the carbon footprint associated to the uncoated tool is $0.255\,\mathrm{kg}$ CO_2-eq. On the other hand, CO_2-eq emissions related to the coating deposition process is $0.78\,\mathrm{kg}$ CO_2-eq per square millimeter (Fairoz & Shokrani, 2025). Based on the general geometry of the cutter, the coated surface area is approximately $300\,\mathrm{mm}^2$. The total CO_2-eq emissions induced by the production of a tool is $234\,\mathrm{kg}$ CO_2-eq (as mentioned in Table 1).

A tool end of life is assumed to be reached when the flank wear width of the tool's teeth reaches $300\,\mu\mathrm{m}$ (shown in blue in Figure 2) as recommended by ISO 8688-2:1989 (International Organization for Standardization, 1989). Assuming constant cutting parameters, the Mean Time To Failure (MTTF) of cutting tools is estimated to be $20\,\mathrm{min}$. To create random variations around this MTTF, individual tool lifespans are generated randomly from a Weibull distribution with a fixed shape parameter (β) of 7 as suggested by Aramesh et al. (2016)

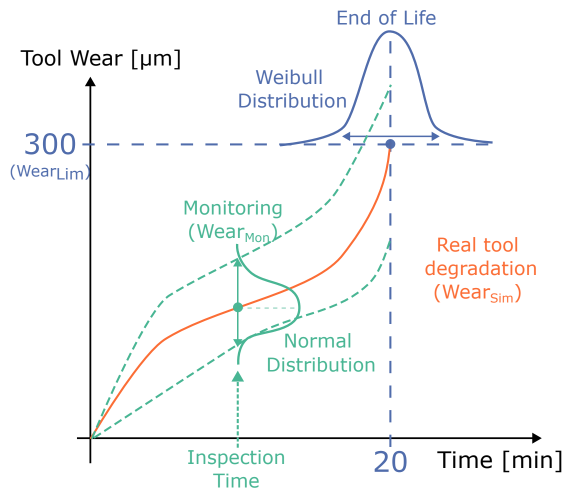

Figure 2. Cutting tool degradation simulated in the model. The end-of-life is modeled using a Weibull distribution (blue). The orange curve is simulated using a hyperbolic sine (sinh) function. Imperfect monitoring is represented in green and modeled using a normal distribution, illustrating either an overestimation or underestimation of the actual cutting tool wear.

(Figure 2). The Weibull's scale parameter (η) is calculated from the MTTF through Eq. (1).

$$\eta = \frac{MTTF}{\Gamma\left(1+\frac{1}{\beta}\right)} = 21.38\,\mathrm{min} \quad (1)$$

The degradation trajectory ($\mathrm{Wear_{Sim}}$) of the tool from its initial point to its end of life is approximated by the following equation (in orange in Figure 2) (Nystad, Gola, & Hulsund, 2012):

$$\mathrm{Wear_{Sim}} = c \times (\sinh(a \times b) + \sinh(a \times (t - b))) \quad (2)$$

In equation 2, the parameter a defines the intensity of the derivative at the inflection point, b the position of the inflection point, and c is a proportional parameter. To generate a degradation trajectory, the tool's lifetime is first randomly sampled using a Weibull distribution (an example with a duration of $20\,\mathrm{min}$ is shown in Figure 2). This sampled lifetime corresponds to the point at which the tool reaches its maximum allowable wear, denoted as $\mathrm{Wear_{Lim}}$. To model the degradation from the initial moment (when the tool has no wear) to the end of its life, Equation (2) is used. The parameters a and b are randomly drawn from uniform distributions ($a \in [0.2, 0.5]$, $b \in [5, 10]$) to reflect the natural variability of the wear process. The parameter c is then fitted based on the values of a, b, and the final point of the trajectory ($\mathrm{Wear_{Lim}}$) in order to complete the degradation curve.

Workpiece

The workpiece is composed of Ti6Al4V. It is assumed that the produced part is of high added value and that its mass before machining is $410\,\mathrm{g}$. It is considered that the machining operation will remove around $20\,\%$ of the workpiece mass, resulting in a finished product weighing $320\,\mathrm{g}$ after $3\,\mathrm{min}$ of machining. These conditions leads to a chip removal rate of $7.5\,\mathrm{cm^3/min}$ and is in accordance with the tool provider's online calculator (Seco Tools, 2025).

Based on the current price of titanium alloy, the cost of the raw material is estimated at $20\,\mathrm{EUR/kg}$ (Pakshal Steel, 2025). The production of $1\,\mathrm{kg}$ of this alloy emits approximately $33\,\mathrm{kg}$ CO_2-eq (Lyons et al., 2021). In the model, the workpiece weighs $410\,\mathrm{g}$; therefore, the production of the workpiece emits $15\,\mathrm{kg}$ kg CO_2-eq, with a cost of $8.10\,\mathrm{EUR}$. The manufactured workpiece can either be good or scrap depending on the condition of the cutting that was used to produce it. For a workpiece to be considered scrap, it must be machined by a tool whose actual wear ($\mathrm{Wear_{Sim}}$) exceeds the limit of $300\,\mathrm{\mu m}$ at any time during machining (i.e., if $\mathrm{Wear_{Sim}} > 300\,\mathrm{\mu m}$ at the end of machining).

Machine

The machine considered is a standard CNC well suited for machining Ti6Al4V. The model considers only the machine in its active machining state. The energy consumption of such a machine includes not only the machining process itself but also all auxiliary systems required for lubrication, cooling, and other functions. Although energy consumption can vary depending on the specific machining operations, for the purpose of simulation and simplicity, the machine's power consumption is assumed to be constant and approximated at $15.5\,\mathrm{kW}$. This value represents a compromise between the machining-phase consumption of both small ($7\,\mathrm{kW}$) and large machines ($24\,\mathrm{kW}$), as described by Triebe, Mendis, Zhao, and Sutherland (2018). It is considered that the carbon footprint of the Belgian electricity production mix is equal to $0.2\,\mathrm{kg}$ CO_2-eq/kWh (Electricity Maps, 2025). In this context, it is also assume that the machine is capable of automated tool replacement; therefore, the tool replacement duration is assumed to be negligible over the simulated period.

In all scenarios, the machine is assumed to be a modern CNC system equipped with various sensors suitable for tool condition monitoring. These may include, for example, built-in power sensors that monitor the machine's energy consumption during operation to estimate tool wear (Colantonio et al., 2021). The machine and the monitoring system economic and environmental costs are considered to be out of the scope of the model. This assumption is justified by the fact that, compared to the cost of cutting tools and raw materials, such machine and monitoring systems represent an upfront investment that can be amortized over time (Dahmus & Gutowski, 2004; Fratila, 2013). Therefore, their impact on the overall economic and environmental assessment of one workpiece is not considered.

2.2. Simulated Scenarios

The model is evaluated under three scenarios, each varying the tool replacement criterion (Figure 3):

- Scenario 1: In this scenario, the tool can be replaced between the production of two parts. The replacement criterion is based on the tool's lifetime (T_{Mach}) and is compared to a predefined replacement time (T_R). If the T_{Mach} is greater than T_R then the tool is replaced (Figure 3). This is the industry standard for tool replacement.
- Scenario 2: This scenario involves monitoring tool degradation. Literature on the subject shows that, on average, tool wear monitoring techniques can achieve a Mean Absolute Percentage Error (MAPE) of approximately 15 % (Colantonio et al., 2024). To simulate the monitoring, a Normal distribution with a standard deviation equivalent to a MAPE error of 15 % is used to create an estimate of the wear ($Wear_{Mon}$) (Figure 2). It is also observed that monitoring methods either overestimate or underestimate the wear error. For each tool, the monitoring randomly selects between overestimating and underestimating the state. The replacement criterion is thus based on the monitored value of wear ($Wear_{Mon}$). As in scenario 1, the tool can only be replaced between the production of two parts. If $Wear_{Mon}$ is greater than the determined wear limits ($Wear_{Lim}$) the tool is changed (Figure 3).
- Scenario 3: This scenario builds on the assumptions of Scenario 2, but with a key difference: the tool can be replaced at any given time. A monitoring system is simulated and inspects tool degradation once per minute (Figure 3). This means that the manufacturing process can be briefly interrupted for an automated tool replacement and then resumed to continue the machining operation.

For each scenario, the economic and environmental impacts of the tools, materials, and electricity are compared. These impacts are then normalized to the production of a good part through Eq. (3):

$$\text{Impact} = \frac{\text{Impact}_{\text{Good}} + \text{Impact}_{\text{Scrap}}}{\text{Number of Good parts}} \tag{3}$$

Where Impact is the average equivalent economic (EUR) or environmental impact (in kg CO_2-eq) of a good part produced in the simulation run, taking into account the scrap produced in order to achieve the production of good parts. $\text{Impact}_{\text{Good}}$ is the total economical (EUR) or environmental (in kg CO_2-eq) impact of all good parts produced in a simulation run, and $\text{Impact}_{\text{Scrap}}$ is the total economical (EUR) or environmental (in kg CO_2-eq) impact of all bad parts produced in a simulation run.

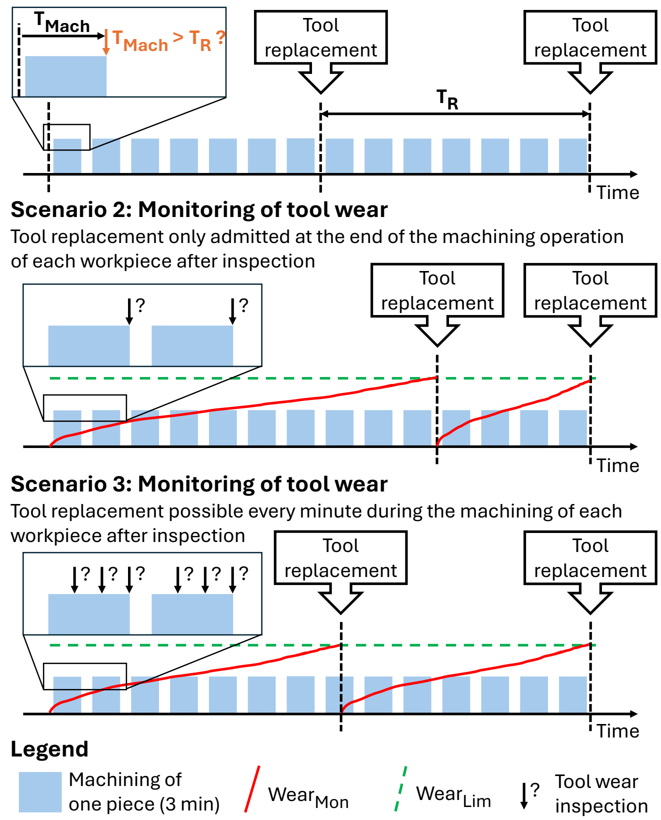

Figure 3. Timeline of all scenarios. T_{Mach}: tool lifetime at a given inspection time. T_R: predefined tool replacement time. $Wear_{Mon}$: monitored tool wear at a given inspection time. $Wear_{Lim}$: predefined tool wear limit.

3. RESULTS

This section compares the model with the scenarios presented previously. First, to ensure a proper comparison, the process of selecting the optimal scenario is described. Once each scenario has been optimized, the optima results are then analyzed from an economic and environmental point of view.

3.1. Optimization of Scenarios

Each scenario is optimized to identify the best-performing parameter values and to enable comparison across strategies. In Scenario 1, the optimization parameter is the tool replacement time. For instance, if this time is set to 6 minutes, the tool is replaced whenever a workpiece change occurs after 6 minutes of tool usage. In Scenarios 2 and 3, the optimization parameter is the monitored wear threshold that triggers tool replacement. In Scenario 2, this wear value is checked at each workpiece change. In Scenario 3, tool wear is estimated once per minute and as soon as the estimated wear exceeds the defined threshold, production is stopped and the tool is replaced. To evaluate each parameter setting, the simulation models one month of production under the corresponding conditions, generating outputs such as the number of parts produced, the number of tools used, and other relevant metrics. To account for variability, each simulation is repeated ten times. The results are then averaged, and the standard deviation is calculated for each output value.

Figure 4 illustrates the optimization results. It combines the optimization of Scenario 1 in terms of replacement time and Scenarios 2 and 3 in terms of monitored wear values. The solid line represents the cost, while the dashed line indicates the CO_2 emissions associated with producing one good part. The shaded area around these lines shows the $95\,\%$ confidence interval (CI). This figure highlights the economic and environmental impacts of each scenario.

From an economic perspective, Scenario 1 performs worse than Scenario 2, which in turn is outperformed by Scenario 3. A similar trend is observed for environmental impact: Scenario 3 is the most favorable, followed by Scenario 2, then Scenario 1. The figure also highlights a key insight: the economically optimal point does not align with the environmentally optimal one. This discrepancy arises because the economic impact of a tool relative to the material is less significant than its environmental impact. Consequently, scrapping a functional tool may be economically advantageous compared to the potential production of scrap parts. However, from an environmental perspective, given the tool's greater environmental footprint, the optimal approach prioritizes maximizing its use, even if it leads to some scrap, as the material's environmental impact remains lower. This leads to an environmental optimum that differs from the economic optimum. Interestingly, the economic optimum appears relatively flat across all three scenarios optima, indicating that within a certain range, economic performance is not significantly affected by changes in the replacement strategy. This opens the possibility of identifying a compromise solution that optimizes both the economic and the environmental impact.

3.2. Optimal Results Comparison

To enable a meaningful comparison, the scenarios that optimize both economic and environmental aspects were selected. For Scenario 1, this corresponds to a replacement time of $19\,\mathrm{min}$. For Scenario 2, the optimal condition is a monitored wear value of $210\,\mu\mathrm{m}$, and for Scenario 3, it is $250\,\mu\mathrm{m}$.

Table 2 presents a comparison of production outcomes across the different optimized scenarios over a one-month production period. It includes the number of good-quality workpieces produced, the amount of scrap generated, the number of tools used, as well as the total and per-piece economic and environmental costs for each scenario. The percentage is used to compare the average economic and environmental costs relative to Scenario 1, which serves as the baseline ($100\,\%$). Scenario 1 results in the lowest number of good-quality parts produced and the highest tool consumption. This is reflected in its economic and environmental cost per part, which is the highest among the three scenarios. In contrast, Scenarios 2 and 3 achieve higher production volumes compared to Scenario 1, although they require more tools. While this leads to higher overall economic and environmental costs, the efficiency gains translate into lower costs per good-quality part. Specifically, Scenario 2 reduces the cost per part by $3.5\,\%$ and CO_2-eq emissions by $1.5\,\%$, while Scenario 3 achieves even greater improvements, with a $8.7\,\%$ reduction in cost and an $8.2\,\%$ decrease in emissions per part.

Figure 5 illustrates the average production cost per good-quality part across the different scenarios. The total cost includes contributions from tools, materials, and electricity. While tool and material costs vary between scenarios, electricity costs remain low and constant throughout. Compared to Scenario 1, Scenario 2 involves higher tool costs due to increased tool usage. However, it benefits from lower material costs, as it generates less scrap. Scenario 3 further reduces both tool and material costs by using fewer tools and producing even less scrap, resulting in the most cost-efficient outcome among the three scenarios.

Figure 6 shows the average environmental impact of producing a good part across different scenarios. As before, this impact is calculated based on the cutting tool, the material, and the electrical energy consumed. Similar conclusions to those observed in Figure 5 can be drawn. The introduction of cutting tool monitoring has a beneficial effect on the environmental impact. In this case study with coated tools, the environmental impact of the tool is very significant. Therefore, optimizing the number of tools is crucial to reducing the environmental impact of production, as the tool is responsible for around $70\,\%$ of the emissions in producing a part.

4. DISCUSSION

The scenarios modeled in this study demonstrate that cutting tool management has a significant impact on both the production cost and the environmental footprint. The results indicate that replacing cutting tools based on their machining time does not optimize the economic cost and environmental impact of manufacturing parts as effectively as monitoring the tool's degradation state. Although the quality of the wear monitoring in the simulations is intentionally made imperfect to match current monitoring accuracies, the impact on production is still positive. While directly monitoring tool wear remains a technical challenge, the results presented in this study highlight the substantial benefits such monitoring could offer. In such a highly competitive sector, implementing tool condition monitoring could lead to production cost savings of up to $8.7\,\%$

The simulation results also show the benefit of using cutting tool degradation monitoring from an environmental perspec-

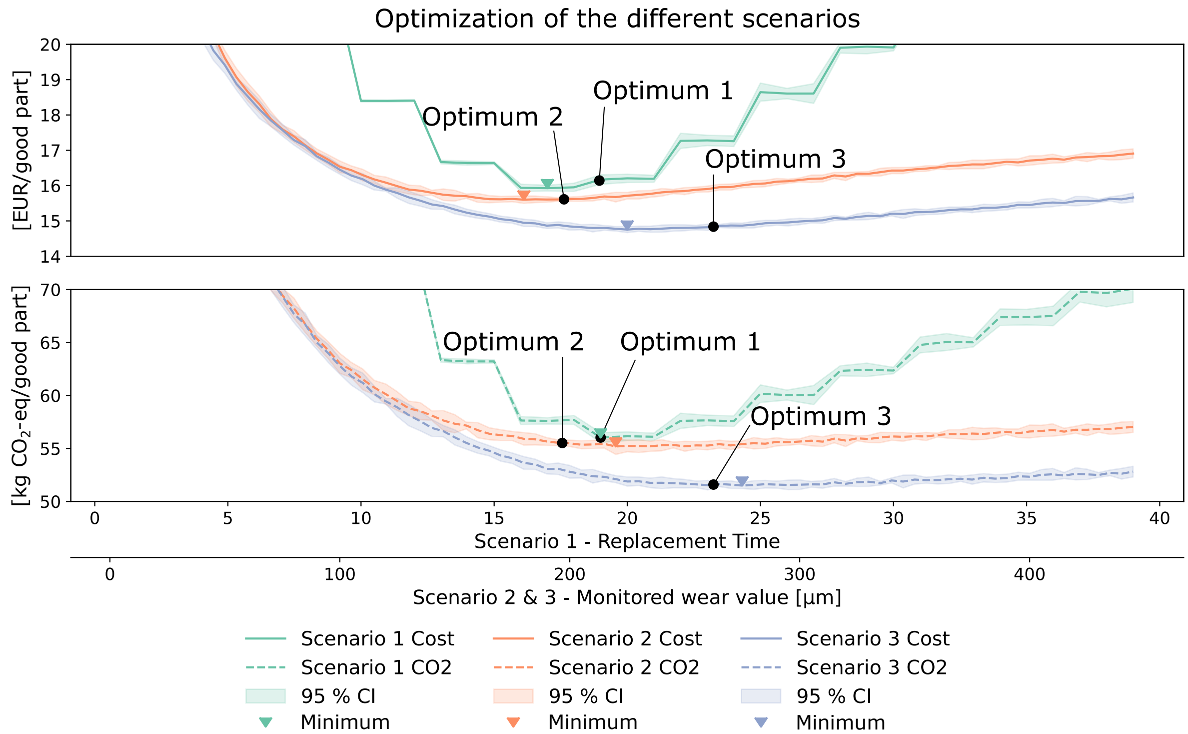

Figure 4. Results for the different scenarios presented showing the cost and CO_2-eq of the different scenarios. The confidence interval estimation is computed from 10 simulations and the optimal points are highlighted with dots. The optimal scenarios are pointed by a dot.

tive with a reduction in CO_2 emissions by nearly $8.1\,\%$. In the current environmental and political context, this further justifies adopting tool condition monitoring methods in industrial practice. This environmental impact is mainly due to the manufacturing of cutting tools, especially due to the application of their coating, which accounts for more than $90\,\%$ of a tool's environmental impact (Fairoz & Shokrani, 2025).

5. CONCLUSION

This article compares the performances of three maintenance strategies for replacing cutting tools in the production of Ti6Al4V parts.

The economic impact of maintenance strategies is strongly linked to how cutting tools are managed. The method predominantly used in the industry today, which involves replacing the tool at a predetermined machining time (Scenario 1), is not as effective as replacing the tool based on imperfectly monitoring its degradation. In a scenario where the tool can be replaced between the production of two parts (Scenario 2), monitoring the tool's condition results in a $3.5\,\%$ reduction in economic impact (EUR) and a $1.5\,\%$ reduction in environmental impact (kg CO_2-eq). These values increase to $8.7\,\%$ and $8.1\,\%$ if the tool can be replaced during the machining of a part (Scenario 3). These values highlight the benefits of monitoring cutting tools. Since the model is a simplified version of an actual production machine, several factors must also be considered, such as the integration and cost of a tool monitoring system, the risk of false alarms, the associated downtime, and other challenges specific to tool monitoring that were not simulated in the presented model.

Based on the model's assumptions, tool cost constitutes a significant portion of the average production cost per part, underscoring the importance of optimizing this parameter. Moreover, since the tool is coated, its environmental impact is substantial—accounting for nearly $70\,\%$ of the total environmental footprint associated with part production (kg CO_2-eq). The model demonstrates that improved tool management is a key lever for achieving more sustainable manufacturing, while also enhancing economic performance.

Future research can focus on integrating the machine and monitoring system into the economic and environmental assessment. Additionally, it should consider aspects such as tool recycling, re-sharpening and recoating as well as the possibility of using uncoated tools with different cutting conditions and shorter lifespans to find the optimal economic and environmental balance. Likewise, the influence of other parameters could be explored in coordination with tool wear estimates, such as the selection of the used cutting tool (Sun et al., 2020), lubrication (Pimenov et al., 2022), cutting parameters (De Souza et al., 2022), etc.

Table 2. Optimal results for each scenario over a one-month production simulation. Standard deviations are calculated based on 10 repeated simulations under identical conditions. Percentages are calculated in relation to the average value obtained in scenario 1.

	Scenario 1	Scenario 2	Scenario 3
Global Results for the Whole Simulated Period			
Number of good workpieces	8310.6 ± 30.7	8880.7 ± 17.3	9194.7 ± 17.5
Number of scrap	1289.4 ± 30.7	719.8 ± 17.19	405.3 ± 17.5
Number of tools	1372 ± 0.0	1479.2 ± 5.5	1408.3 ± 6.52
Total Cost [1000 EUR]	134.6 ± 0.0	138.9 ± 0.2	136.1 ± 0.26
Total CO_2 [1000 kg CO_2-eq]	466.6 ± 0.0	491.7 ± 1.3	475 ± 1.529
Results for the Production of One Good Part			
Cost/good part [EUR]	16.20 ± 0.06 (100 %)	15.64 ± 0.04 (96.54 %)	14.80 ± 0.04 (91.35 %)
kg CO_2-eq/good part [kg CO_2-eq]	56.15 ± 0.21 (100 %)	55.3 ± 0.20 (98.48 %)	51.6 ± 0.20 (91.89 %)

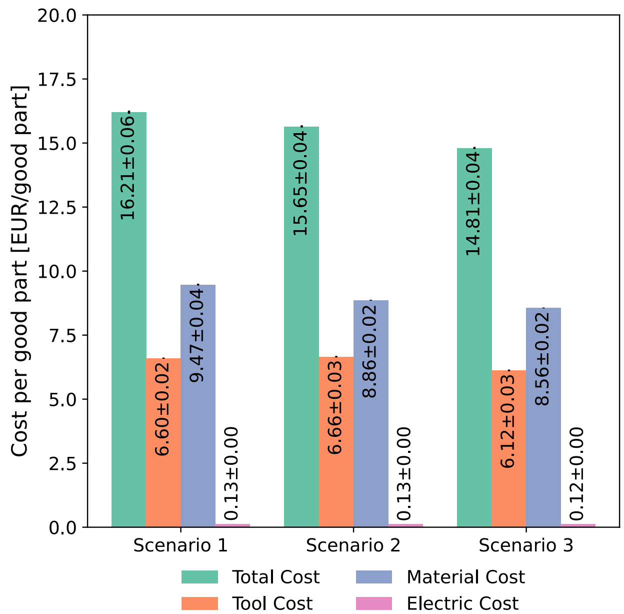

Figure 5. Cost repartition to produce a good part in the different tool replacement scenarios. Deviation computed on 10 simulations.

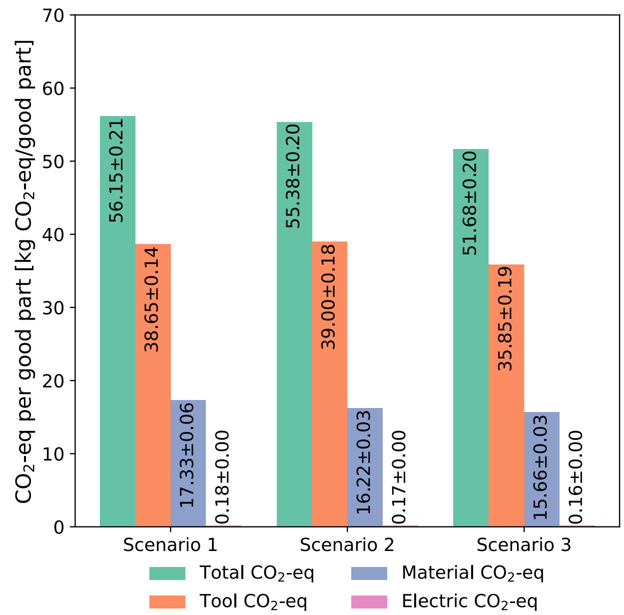

Figure 6. CO_2 repartition to produce a good part in the different tool replacement scenarios. Deviation computed on 10 simulations.

REFERENCES

Aramesh, M., Shaban, Y., Yacout, S., Attia, M. H., Kishawy, H. A., & Balazinski, M. (2016, January). Survival life analysis applied to tool life estimation with variable cutting conditions when machining titanium metal matrix composites (Ti-MMCs). *Machining Science and Technology*, *20*(1), 132–147. doi: 10.1080/10910344.2015.1133916

Campatelli, G., & Scippa, A. (2016). Environmental Impact Reduction for a Turning Process: Comparative Analysis of Lubrication and Cutting Inserts Substitution Strategies. *Procedia CIRP*, *55*, 200–205. doi: 10.1016/j.procir.2016.08.020

Colantonio, L., Equeter, L., Dehombreux, P., & Ducobu, F. (2021). A Systematic Literature Review of Cutting Tool Wear Monitoring in Turning by Using Artificial Intelligence Techniques. *Machines*, *9*(12), 351. doi: 10.3390/machines9120351

Colantonio, L., Equeter, L., Dehombreux, P., & Ducobu, F. (2024, May). Confidence Interval Estimation for Cutting Tool Wear Prediction in Turning Using Bootstrap-Based Artificial Neural Networks. *Sensors*, *24*(11), 3432. doi: 10.3390/s24113432

Dahmus, J. B., & Gutowski, T. G. (2004, November). An environmental analysis of machining. *Proceedings of IMECE2004.*.

De Souza, L. G. P., Gomes, J. E. M., Arruda, É. M., Silva, G., De Paiva, A. P., & Ferreira, J. R. (2022, December). Evaluation of trade-off between cutting time and surface roughness robustness regarding tool wear in hard turning finishing. *The International Journal of Advanced Manufacturing Technology*, *123*(9-10), 3047–3078. doi: 10.1007/s00170-022-10354-5

Ding, F., & He, Z. (2011). Cutting tool wear monitoring for reliability analysis using proportional hazards model. *The International Journal of Advanced Manufacturing Technology*, *57*(5-8), 565–574. doi: 10.1007/s00170-011-3316-4

Electricity Maps. (2025). *Electricity Maps - Belgium, January 2025.* https://app.electricitymaps.com/zone/BE/12mo/monthly.

Elnourani, M., Johansen, K., & Öhrwall Rönnbäck, A. (2024, April). Enabling Factors for Circularity in the Metal Cutting Industry – With Focus on High-Value Circular Tools. In J. Andersson, S. Joshi, L. Malmsköld, & F. Hanning (Eds.), *Advances in Transdisciplinary Engineering.* IOS Press. doi: 10.3233/ATDE240193

Fairoz, I., & Shokrani, A. (2025). Life cycle assessment of cutting tool coatings (in press). *Procedia CIRP*.

Fratila, D. (2013). Sustainable manufacturing through environmentally-friendly machining. In: Davim, J. P. (ed.), *Green Manufacturing Processes and Systems* (pp. 1-21). Springer. doi: 10.1007/978-3-642-33792-5_1.

Furberg, A., Arvidsson, R., & Molander, S. (2019, February). Environmental life cycle assessment of cemented carbide (WC-Co) production. *Journal of Cleaner Production*, *209*, 1126–1138. doi: 10.1016/j.jclepro.2018.10.272

Hoffmann Group. (n.d.). *Hoffmann Group.* https://www.hoffmann-group.com/.

International Organization for Standardization. (1989). *ISO 8688-2:1989 Tool life testing in milling - End milling.*

Iqbal, A., Zhao, G., Cheok, Q., He, N., & Nauman, M. M. (2022, May). Sustainable Machining: Tool Life Criterion Based on Work Surface Quality. *Processes*, *10*(6), 1087. doi: 10.3390/pr10061087

Karandikar, J. M., Abbas, A., & Schmitz, T. L. (2020, November). Remaining useful tool life predictions in turning using Bayesian inference. *International Journal of Prognostics and Health Management*, *4*(2). doi: 10.36001/ijphm.2013.v4i2.2122

Kshitij, G., Khanna, N., Yıldırım, Ç. V., Dağlı, S., & Sarıkaya, M. (2022, December). Resource conservation and sustainable development in the metal cutting industry within the framework of the green economy concept: An overview and case study. *Sustainable Materials and Technologies*, *34*, e00507. doi: 10.1016/j.susmat.2022.e00507

Liu, C., Li, Y., Hua, J., Lu, N., & Mou, W. (2018, July). Real-time cutting tool state recognition approach based on machining features in NC machining process of complex structural parts. *The International Journal of Advanced Manufacturing Technology*, *97*(1-4), 229–241. doi: 10.1007/s00170-018-1916-y

Lyons, R., Newell, A., Ghadimi, P., & Papakostas, N. (2021, January). Environmental impacts of conventional and additive manufacturing for the production of Ti-6Al-4V knee implant: A life cycle approach. *The International Journal of Advanced Manufacturing Technology*, *112*(3-4), 787–801. doi: 10.1007/s00170-020-06367-7

Nystad, B. H., Gola, G., & Hulsund, J. E. (2012, July). Lifetime models for remaining useful life estimation with randomly distributed failure thresholds. *PHM Society European Conference*, *1*(1). doi: 10.36001/phme.2012.v1i1.1442

Pakshal Steel. (2025). *Titanium price per kg.* https://www.pakshalsteel.com/titanium-metal-price.html.

Patange, A. D., & Jegadeeshwaran, R. (2021, March). Application of Bayesian Family Classifiers for Cutting Tool Inserts Health Monitoring on CNC Milling. *International Journal of Prognostics and Health Management*, *11*(2). doi: 10.36001/ijphm.2020.v11i2.2929

Pimenov, D. Y., Mia, M., Gupta, M. K., Machado, Á. R., Pintaude, G., Unune, D. R., … Kuntoğlu, M. (2022, September). Resource saving by optimization and machining environments for sustainable manufacturing: A review and future prospects. *Renewable and Sustainable Energy Reviews*, *166*, 112660. doi: 10.1016/j.rser.2022.112660

Seco Tools. (2025). *Seco Tools cutting data calculator.* https://www.secotools.com/.

Shi, J., Hu, J., Ma, M., & Wang, H. (2021, August). An environmental impact analysis method of machine-tool cutting units based on LCA. *Journal of Engineering, Design and Technology*, *19*(5), 1192–1206. doi: 10.1108/JEDT-06-2020-0247

Shokrani, A., Arrazola, P., Biermann, D., Mativenga, P., & Jawahir, I. (2024). Sustainable machining: Recent technological advances. *CIRP Annals*, *73*(2), 483–508. doi: 10.1016/j.cirp.2024.06.001

Siddhpura, A., & Paurobally, R. (2013). A review of flank wear prediction methods for tool condition monitoring in a turning process. *The International Journal of Advanced Manufacturing Technology*, *65*(1-4), 371–393. doi: 10.1007/s00170-012-4177-1

Sun, H., Liu, Y., Pan, J., Zhang, J., & Ji, W. (2020, January). Enhancing cutting tool sustainability based on remaining useful life prediction. *Journal of Cleaner Production*, *244*, 118794. doi: 10.1016/j.jclepro.2019.118794

Tian, C., Zhou, G., Lu, Q., Zhang, J., Xiao, Z., & Wang, R. (2019, July). An integrated decision-making approach on cutting tools and cutting parameters for machining features considering carbon emissions. *International Journal of Computer Integrated Manufacturing*, *32*(7), 629–641. doi: 10.1080/0951192X.2019.1610575

Triebe, M., Mendis, G., Zhao, F., & Sutherland, J. (2018). Understanding Energy Consumption in a Machine Tool through Energy Mapping. *Procedia CIRP*, *69*, 259–264. doi: 10.1016/j.procir.2017.11.041

Zhang, L., Zhang, B., Bao, H., & Huang, H. (2018, April). Optimization of Cutting Parameters for Minimizing Environmental Impact: Considering Energy Efficiency, Noise Emission and Economic Dimension. *International Journal of Precision Engineering and Manufacturing*, *19*(4), 613–624. doi: 10.1007/s12541-018-0074-3