A multicriteria optimization method for process planning

LAURENT DELOLME [a], ANNE LISE ANTOMARCHI [a], SEVERINE DURIEUX [a], EMMANUEL DUC [a]

a. Université Clermont Auvergne, CNRS, SIGMA Clermont, Institut Pascal, F-63000 Clermont–Ferrand, France. + email prenom.nom@sigma-clermont.fr

Résumé :

L'objectif de ces travaux est de développer une méthodologie de génération automatique de gammes d'usinage optimisées et innovantes qui permettent aux sous-traitants aéronautiques de faire face aux problématiques de productivité et de compétitivité actuelles. Une méthodologie en quatre étapes est proposée, permettant à l'utilisateur d'obtenir des gammes d'usinage optimisées respectant son savoir-faire et son expérience et introduisant de l'innovation. Cette méthodologie s'appuie sur une représentation du comportement décisionnel des méthodistes dans une situation donnée ainsi que face au risque à l'industrialisation et élargit la formalisation de la performance d'une gamme en prenant en compte d'autres critères de performance autres que le temps d'usinage ou le coût global. Un algorithme génétique est utilisé pour générer des gammes optimisées. La méthodologie présente les meilleures gammes générées et l'utilisation de la théorie du choix social lui permet de cibler les gammes les plus performantes à implanter, en intégrant un critère de risque à l'industrialisation.

Abstract :

The goal of this work is to develop a methodology for the automatic generation of optimized and innovative machining process planning that allow aeronautical subcontractors to deal with current productivity and competitiveness issues. A four-step methodology is proposed, allowing the user to obtain optimized machining process planning respecting his know-how and experience and introducing innovation. This methodology is based on a representation of the decision-making behavior of the user in a given situation as well as on the risk to industrialization and complete the formalization of the process planning performance by taking into account performance criteria other than the machining time or the overall cost. A genetic algorithm is used to generate a large set of various operable processes. An AHP method is used to model the decision process planning and choose the optimal process planning. The methodology presents the best process planning generated and the use of social choice theory allows it to target the most efficient process planning to implement, by integrating a risk criterion to industrialization.

Mots clefs : Mots clefs
Process planning, multicriteria optimization, Ga algorithm, AHP, CAPP

1   Introduction

This paper addresses the problem of decision making and optimization of machining process planning for die-cast aerospace parts made of titanium. The design of the machining process planning of an aeronautical structural part is particularly long because of the complexity of the shape of the part and the need for a high expected performance. The number of parameters to be defined as well as the complexity of their influence on the performances of the manufacturing process planning make that the process of optimization remains difficult to apprehend in its entirety by the human spirit. The user often proceeds by adapting the existing know-how, by iteration and simulation, in order to minimize the level of risk. Indeed, the user must make a compromise between the safety of machining and the search for performance. On the one hand, the more secure the machining is, the longer the machining time and the cost. On the other hand, the search for performance can lead to the use of tools in critical conditions, which cause failures. Thus, the work is long and expensive, without it being possible to ensure the respect of all the constraints. The user can not renew often the development of the process planning.

To obtain rapid productivity gains, it is relevant to propose a new way of optimizing the machining process planning. Optimization must lead to faster and more economical processes, while respecting quality requirements.

A machining process planning is the ordered sequence of a set of machining operations to be applied to the part to achieve the geometric form according to the specifications.

The development of a process planning consists of:

- define all the machining operations, for each machined feature;
- for each operation, determine the tool and optimize the cutting conditions and the machining strategy;
- Sequencing all operations.

This paper presents a decision support method to determine the machining process planning of a new part and to estimate the various performance indicators by quantifying the associated technical risks. After modeling the problem, a genetic algorithm calculates a large population of candidate manufacturing process planning. A ranking method offers the best solutions to the decision maker. Thus, the method offers innovative machining processes whose overall performance is better from a multi-criteria point of view, while generating a level of acceptable risk by the workshop. The trade-off between innovation and risk is the key to success. The remainder of the paper is organized as problem statement (Sections 2); presentation of the general method of resolution (Section 3); and an application case study (Section 4).

2   Problem statement

Optimizing a process planning involves defining performance criteria. The usual criteria are the overall machining time, the cost of manufacture as well as the quality obtained after machining [1]. The optimal process planning can thus be considered as the best compromise obtained between these three criteria. The question is, then, to propose as quickly as possible an optimal process planning.

The automatic generation of manufacturing process planning developed from the 1980s to the 1990s from an idea of Niebel [2]. 55 different systems existed in 1986 [3]. A Computer Aided Process Planning (CAPP) system is broken down according to the following tasks [4], [5], [6] :

- Selection of manufacturing processes and tools;
- Selection of machine tools and technical ressources;
- Sequencing of operations;
- Grouping of operations (phases, sub-phases);
- Selection of clamping systems, bearing faces;
- Selection of control instruments and processes;
- Determination of production tolerances;

- Determination of cutting conditions;
- Calculation of machining and non-machining times, calculation of associated costs;
- Generation of the technical documentation.

Several approaches to the creation of *Computer Aided Process Planning (CAPP)* systems are presented in the literature [7]. The first is based on comparison to existing (process by variant), while the second concerns methods that engineer a process ex-nihilo (generative process).

- Process by variant [7] [8], [9] [10] [11];
- Generative or semi-generative process [7] [8], [9], [12] comprising :
  Process by algorithmic systems [7] [9] [13] [14] [15] [16];
  Process by expert systems [17], [18], [19].

Since 1984, several publications have studied the various CAPP systems developed by the scientific community [5] [9] [20] [21] [22]. In 2007, Denkena proposes a state of the art based on knowledge management for the generation of production lines [4]. Xu presents a state of the art about the generation of process between 2000 and 2009 [23]. Their conclusions show that Variant systems (by variant) are still used, especially for the mass production industry, where the geometry of parts evolves in a discrete but constant manner. Finally, in 2014, Yusof completes the state of the art by adding functional block technology, used for the generation of process since the late 2000s [24].

Today, ten different technologies are used:

- Technology based on geometric machining entities [25], [26] ;
- Process-based knowledge technology [27], [28] ;
- Technology based on neural networks [29], [30] ;
- Technologies based on genetic algorithms [31], [32] ;
- Theory on fuzzy logic [33], [34] ;
- Petri nets [35] ;
- Multi agent technology [36], [37] ;
- Internet-based technology (evolution of knowledge-based technologies) [38] ;
- Technology based on STEP format (ISO 10303) to facilitate dialogue between design and manufacture [39], [40] ;
- Functional block technology [41], [42].

The evaluation of the performance of a CAPP system is based on the quality of the computed process planning. In particular, two criteria are important. The first concerns the precision of the process planning in the estimation of the performance. The second concerns the reliability of the generated process planning for an actual implementation. The generated process planning must be implemented easily and safely in an industrial workshop, or with a controlled level of risk.

Note that the generation of the manufacturing process planning of small series of high added value parts remains particularly difficult. The process still yet weakly automatized, because it is not easy to take into account automatically the variations and uncertainties on the performance related to humans as well as technology. The size of the series does not permit to reach a high level repeatable process. In particular, the interaction between the operator and the process is an important factor of performance loss if the operator defies the generated process. The confidence between the operator and the process is a very important key issue to reach a high performance. But little researches have studied this point, at least in the field of manufacturing [43]. Thus, an optimization method must propose a machining process whose overall performance is better from a multi-criteria point of view, while generating a risk level acceptable by the workshop.

The main issue of this research is the proposal for a multi-criteria decision support tool for the automatic generation of machining process planning. We propose an original approach based both on the formalization of know-how acquired by the user while introducing innovation (new tool, new machining

strategy, etc.). This method offers several machining process relevant to the {Piece, Material, Machine} triptych and provides performance indicators, incorporating technical risk-taking aspects, and new comparison criteria, in addition to the traditional cost-related indicators by operation and the overall manufacturing time. The choice of the final process is made by the user.

The method is based on the 3 fundamental concepts:
- the use of a genetic algorithm to evolve a population of initial process by crossover and mutation;
- the implementation of the methodological tools of Decision Theory [44], [45] to model user preferences and the decision-making process;
- taking into account the risks associated with the implementation of a process of machining.

The proposed approach takes place in 5 steps:
- # 1 machining process planning modeling;
- # 2 expression of manufacturing constraints, basic performance indicators and a process risk indicator;
- # 3 development of a genetic algorithm to calculate a population of solutions ranges;
- # 4 expression of a process classification macro-criterion using the AHP method;
- # 5 selection of the best range by the user in view of the macro-indicator, the elementary performance indicators and the risk indicator.

3 General method of resolution

3.1 Modelization of the process planning

An individual used by the Genetic Algorithm is formed by a machining process planning: the ordered sequence of machining operations. The decision variables define the parameters to optimize for each operation. Thus, a machining process, denoted G_m, is an ordered list of operations, denoted $Op_{m,n}$. A machining operation is defined by the 12-upplet:

$Op_{m,n}$
$= \{Feature_{op_{m,n}}; Axis_{op_{m,n}}; Top_{m,n}; Tool_{m,n}; Cy_{p,n,m}; Vc_{m,n}; Ap_{m,n}; Ae_{m,n}; Fz_{m,n}; L_{unit\ m,n}; la_{m,n}; H_{m,n}\}$

where :
- $Feature_{op_{m,n}}$ is the geometrical feature to be machined by the operation $Op_{m,n}$;
- $Axis_{op_{m,n}}$ is tool axis orientation for the operation $Op_{m,n}$;
- $Top_{m,n}$ is the type of the operation $Op_{m,n}$;
- $Tool_{m,n}$ is the tool used by the operation $Op_{m,n}$;
- $Cy_{p,n,m}$ is the machining strategy used by the operation $Op_{m,n}$;
- $Vc_{m,n}$; is the cutting speed of the operation $Op_{m,n}$;
- $Ap_{m,n}$ is the axial depth of cut of the operation $Op_{m,n}$;
- $Ae_{m,n}$ is the radial depth of cut of the operation $Op_{m,n}$;
- $Fz_{m,n}$ is the feed per tooth by the operation $Op_{m,n}$;
- $L_{unit\ m,n}$ is the length of the elementary path of the elementary operation n of the process m. It is considered here that a machining operation consists of an elementary trajectory repeated several times, according to the machining strategy and cutting conditions;
- $la_{m,n}$ is the width to be machined for the operation $Op_{m,n}$. $la_{m,n}$ corresponds to the thickness of material removed during this operation in the radial direction of the cutting tool;
- $H_{m,n}$ is the height to be machined for the operation $Op_{m,n}$. $H_{m,n}$ corresponds to the material thickness removed during this operation in the axial direction of the cutting tool.

The part is defined by $Nb_{Feature}$ Feature to be machined.

Each feature is defined by :

- $X_{Feature_i}$: The X length of the bounding box;
- $Y_{Feature_i}$: The Y length of the bounding box;
- $Z_{Feature_i}$: The Z length of the bounding box.
- $Axis_{Feature_i,1}$: The first admissible orientation of the tool axis;
- $Axis_{Feature_i,2}$: The second admissible orientation of the tool axis;
- $\overline{H}_{Feature_i,1}$: The average height of the feature $Feature_i$ according the tool axis $Axis_{Feature_i,1}$;
- $\overline{H}_{Feature_i,2}$ The average height of the feature $Feature_i$ according the tool axis $Axis_{Feature_i,2}$;
- $\overline{la}_{Feature_i,1}$: The average width of the feature $Feature_i$ according the tool axis $Axis_{Feature_i,1}$;
- $\overline{la}_{Feature_i,2}$: The average width of the feature $Feature_i$ according the tool axis $Axis_{Feature_i,2}$;
- $\overline{long}_{Feature_i,1}$: The average length of the feature $Feature_i$ according the tool axis $Axis_{Feature_i,1}$;
- $\overline{long}_{Feature_i,2}$: The average length of the feature $Feature_i$ according the tool axis $Axis_{Feature_i,2}$;
- $Rconv_{min}(Feature_i.)$: The minimal concav radius of the Feature, that contrains the maximal radius of the finishing tool;
- $Rtool_{max}(Feature_i)$: The maximal admissible radius of the tool;
- $Ltool_{min}(Feature_i)$: The minimal length of the tool for the machining of the Feature, without collision ;
- $Step(Feature_i)$: The maximal admissible step between successive lateral paths, according to the specifications of the part.
- $Defect(Feature_i)$: The maximal admissible form defect, according to the specifications of the part.
- $ReTech_{Feature_i}$: The set of other features, that can be machined similarly to the $Feature_i$,
- $Ant_{Feature_i}$: The set of other features, that must necessary be machined before the $Feature_i$.

Each tool $Tool_k$, $k \in \{1, ..., Nb_{Tool}\}$, is defined by :

- An associated machining strategy, noted Cy_{out_k}. Cy_{out_k} can take the following values:
Reaming, Chamfering, Contouring, Copying, Threading-Tapping, Drilling, Grooving, Surfacing, Face-dressing, Tapping, Placing, Cutting
- The diameter D_{tool_k},
- The lenght L_{tool_k},
- The corner radius Rc_{tool_k},
- The number of teeth Z_{tool_k},
- The number of inserts $Nb_{tool_k}^{ins}$.
- The set Top_{tool_k} of different types of machining for which the tool can be used. The possible types of machining are as follows : *Roughing, Re-roughing, Semi-finishing, finishing, Superfinishing*, organized according to the following hierarchy :
  $$Roughing > Re - roughing > Semi - finishing > finishing > Superfinishing$$
- The cost Cct_{tool_k} by cutting edge,
- The maximum chip section As_{tool_k} admissible by the tool. This section is defined by the experience of the user, relatively to the cutting conditions acceptable by the tool, but also by discussion with the supplier of the tool that can help refine this value, especially in the case of new cutting tools.

$Cy_{p,n,m}$ et $Vc_{m,n}$ are deduced from the tool database knowing that $Ap_{m,n}$, $Ae_{m,n}$ et $Fz_{m,n}$ are calculated according to the usual methods.

3.2   Genetic Algorithm

Genetic algorithms are part of evolutionary algorithms inspired by the theory of evolution [46], [47], [48].

The genetic algorithm is composed of five steps:
- creation of the initial population;
- evaluation of the performance of individuals;
- election of individuals to form a new population;
- creation of new individuals through crossover or mutation operators;
- The results of the genetic algorithm are obtained once the stopping criterion is achieved.

The choice of the initial population of individuals determines the convergence velocity of the algorithm [49].

Each individual is defined as an process planning according to the precedent modelization.

To create a diversified population, the user declares several possible and operable sequences of operations per feature to be machined. Thus, the user ensures that the process is achievable and the algorithm can use this diversity to perform crossovers and mutations.

The percentage of individuals thus generated P_{init}^{seq} and the size of the initial population Nb_{init}^{pop} are parameters of the algorithm.

For each computed individual, a fitness function or macro-indicator is calculated for the output variables [50]. The macro-indicator, MCP_m is calculated from a weighted sum of standardized Ind_i performance indicators.

$$\text{MCP}_m = \sum p_i * \text{Ind}_i \qquad (1)$$

A new N + 1 population is created from the Nb_{bests} individuals, from a percentage $P_{tournament}$ of individuals retained after tournament selection and from a portion obtained by crossover and then mutation from an intermediate population. Tournament selection increases the chances of low quality individuals participating in the improvement of the population and avoiding to stay in local optimum. The tournament compares the relative quality of individuals, 2 by 2, drawn at random.

New individuals are created from their respective parents by crossover and mutation. The crossover is computed from two parents and corresponds to a combination by the reproduction of the features of the selected individuals. For each pair of randomly selected individuals, a crossover probability is calculated according to a Bernouilli law. Mutations are obtained from a single parent, with a probability Pm. Pm relates to the probability P_{ms}, to change the sequencing, the probability P_{mGE} to change a basic process also called feature mutation and the probability P_{mo} to change the cutting tool.

$$\text{P}_m = \text{P}_{ms} + \text{P}_{mGE} + \text{P}_{mo} \qquad (2)$$

3.3   Manufacturing constraints

Two types of constraints are taken into account during optimization. The first concerns the tool which must respect the maximum diameter, the minimum length and the minimum concave radius allowed in the feature to be machined.

The second concerns the respect of priority between machining operations of different features and priority between operations in the same feature.

3.4   Basic performance indicators

The basic performance indicators permits to qualify the performance of a machining process according to different criteria. An analysis of the literature shows that the criteria conventionally used to define the performance of a machining process are based on the triptych Productivity / Delay - Cost – Quality [51], [52], [53], [54], [55], [56]. Productivity is related to the machining time. The machining cost is obtained from a cost model that takes into account all the expenses involved during machining. The geometric quality of the product is a minimum compliance criterion to be satisfied. We consider that it is not an indicator of performance but a constraint to be respected.

Several indicators are used to estimate productivity: *value-added time*, *non value-added time*, *cutting tool usage time*. That permits to estimate the costs of use of machine tools and the costs related to tool wear.

Value Added Time (VA) is the time during which the machine is considered to be generating added value to the part in production, i.e. remove matter.

According to Liu, there are currently four types of methods for estimating machining times [25]:
-   based on chip flow, easy and fast but approximate [26], [57];
-   geometric based on the generated machining program [58];
-   kinematic based on the machining program taking into account the dynamic characteristics of the machine [59], [60], [61], [62];
-   by artificial intelligence.

The bibliographic study has shown that an accurate estimation of the machining time requires an complete and accurate model of the machine tool and long computations, that cannot be done before the complete definition of a process planning, in most cases [63].
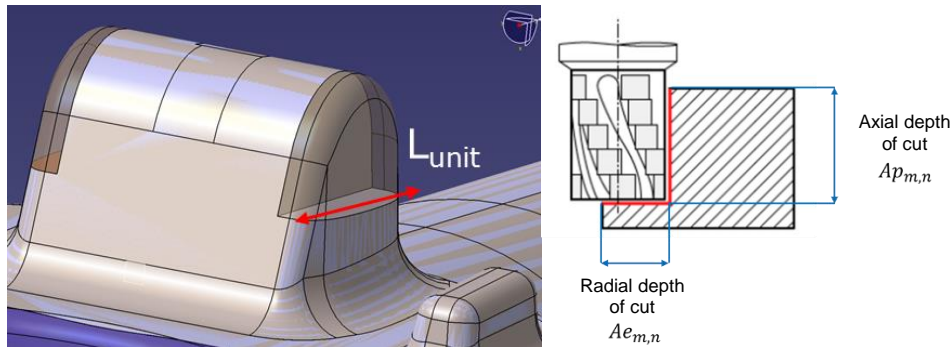

Figure 1 : Settings of the toolpath for the Operation n of the planning m.

In these works, the machining time of the elementary operation n of the process *m*, denoted $Tc'_{m,n}$, is calculated from $L_{unit\ m,n}$ the estimated length of the elementary path of the elementary operation *n*, $Vf_{m,n}$ the feedrate of the tool, $Npax_{m,n}$ the number of axial toolpath and $Nprad_{m,n}$ the number of radial toolpath. The machining time of the process Tc_m is the sum of the machining time of operations.

$$Tc_m = \sum_{n=1}^{N} Tc'_{m,n} = \sum_{n=1}^{N} \frac{L_{unit\ m,n} \times Npax_{m,n} \times Nprad_{m,n}}{Vf_{m,n}} \qquad (3)$$

Non-Value Added times (NVA) are times the tool does not remove matter. These are times of handling, reorientation or change of cutting tools, or change of accessories. The cutting tool orientation change time depends on a unit change time $Toch_{unit\ \propto}$ and the configuration $Vect_{\alpha,n}$ of the tool orientation before and after the change of the tool. Indeed the orientation time is depending of the initial and final orientation.

$$Toch_{tot\,m} = \sum_{n=2}^{N} Vect_{\alpha_n} \times {}^{T}Ttch_{unit\,\propto} \tag{4}$$

The computation is the same for accessories. The time $Tach_{tot\,m}$ of change of accessories of the process m, can therefore be determined as a function of $Tach_{unit}$: unitary change time of accessories and the indicator $Xacc_{n,\alpha}$ accessory changes for operation n. The indicator $Xacc_{n,\alpha}$ is equal to 1 if the change is necessary, and equal to 0 if not.

$$Tach_{tot\,m} = \sum_{n=2}^{N} Xacc_{n,\alpha} \,.\, Tach_{unit} \tag{5)}$$

The tool change time $Ttch_{tot\,m}$ of the process m is calculated, as a function of $Ttch_{unit}$, the unit change time of the tool and the indicator $Xacc_{n,m}$ requesting a tool change between the elementary operation n and the elementary operation *n-1* of the process m.

$$Ttch_{tot\,m} = \sum_{n=1}^{N} Xacc_{n,m} \times Ttch_{unit} \tag{6}$$

The insert change time $Tich_m$ for the process m is calculated from the insert change times $Tich_{m,n}$ of each operation. $Tich_{m,n}$ concerns the time necessary for the changing of a complete tool cutter. It is computed from the unmasked time $Tich_{unit}$ change of the tool inserts set, from the number $Nbit_{n,m}$ of inserts, from the tool life $TLt_{n,m,p}$ of the $Tool_{n,m}$, and from the effective cutting time $Tc_{m,n}$ of the tool.

$$Tich_m = \sum_{n=1}^{N} Tich_{m,n} = \sum_{n=1}^{N} \left\lfloor \frac{Tc_{m,n}}{TLt_{n,m,p}} \right\rfloor \times Nbit_{n,m} \times Tich_{unit} \tag{7}$$

The cost Cct_m of tools is calculated according to the unit cost $Ccto_{n,m}$ of an insert of the $Tool_{n,m}$, and the number of insert $Nci_{m,n}$ changed during an elementary operation, calculated, according to the tool life.

$$Cct_m = \sum_{n=1}^{N} Nci_{m,n} \,.\, Cct_o = \sum_{n=1}^{N} \left\lfloor \frac{Tc'_{m,n}}{TLt_{n,m,p}} \right\rfloor \times Nbit_{n,m} \,.\, Cct_o \tag{8}$$

3.5 Technical milling risks

Increasing the performance of a machining operation can also raise the risk level of the operation and thus cancel the productivity gains. Loss of confidence plays a critical role in optimizing a process and gains in performance because it can wipe out the expected gains. Indeed the operator can reduce the cutting speed or the feedrate to obtain a more safe process.

Machining hazard analysis shows that tool wear and tool bending predominate in the formalization of risk criteria, as they directly impact the risk of non-compliance of the part, related to poor surface conditions or related to marks or steps too important.

The risk is estimated from the computation of the bending of the tool $Rop_{n,m}$ compared to a maximum step $Rthreshold_{n,m}$ permissible specified by the requirements. The tool is considered as a full bending beam under the action of cutting forces. The application of the usual bending models makes it possible to calculate the indicator $Rop_{n,m}$ according to the geometrical characteristics of the machining operation and the associated risk index $IRop_{n,m}$. An operation is considered as safe if $IRop_{n,m} < 1$

$$IRop_{n,m} = \frac{Rop_{n,m}}{Rthreshold_{n,m}} = \frac{Fz_{n,m} \times Z_{outil_{n,m}} \times Ap_{n,m} \times Ae_{n,m} \times \dfrac{L_{outil_{n,m}}{}^3}{D_{outil_{n,m}}{}^5}}{Rthreshold_{n,m}} \qquad (9)$$

To minimize the risk index of the process, it is necessary to aggregate the different risk indices of the different operations into a single indicator. The risk attitude (pessimistic, compromised or optimistic) permits to calculate the aggregation factors of the different risk indicators [64], [65]. The risk index of the process can thus be expressed according to three different behaviors:

- risk aversion (pessimistic attitude),

$$\min_m\left(IRg_m^{pessimist}\right) = \min_m\left(\max_n(IRop_{m,n})\right)$$

- compromise attitude :

$$\min_m\left(IRg_m^{compromise}\right) = \min_m\left(\sum_{n=1}^{N} IRop_{m,n}\bigg/ N\right)$$

- preference for risk (optimistic attitude) :

$$\min_m\left(IRg_m^{optimist}\right) = \min_m\left(\min_n(IRop_{m,n})\right)$$

3.6   Optimal process selection using AHP method

The last step of the method corresponds to the choice of the optimal solution based on elementary performance indicators and elementary risk indices. It is necessary to solve a multicriteria decision-making problem. Multicriteria decision support helps to formalize the decision-making process and to model the decision-maker's reasoning [66]. Edwards and Raiffa propose to formalize the preferences of the decision-makers through a numerical function, called "utility function", which allows to assign scores to the different choices that are presented to decision-makers [67], [68]. In this way, a ranking of actions can be set from the least preferred to the most preferred [69]. But, the literature offers little application study in the field of manufacturing. The majority of optimization methods used in manufacturing generally seek the maximization or minimization of a single criterion, such as the total cost of manufacture [56], [70], [71]. Mardani does not identify systems using a multicriteria decision support method for optimizing part machining [72].

When the problem is approached from a multi-objective point of view, a weighted sum of the criteria is then introduced. The determination of weights is critical. Ong proposes to use AHP method that allows designers to calculate and to weight indices of the manufacturability of different features in a part in the context of Design For Manufacturing (DFM) methodology [73]. Similarly, Yurdakul uses the AHP method, to help in the choice of machining machines [74].

The AHP method is composed of five principles [75]:

- decomposition of the complex decision problem into a multi-level hierarchical structure [76];
- binary comparisons;
- calculating relative priority values;
- verification of the consistency of judgments;
- synthesis of the score of each solution to the problem.

The ability to structure a complex, multi-criteria hierarchical and systematic problem as well as the unlimited number of potential criteria to be taken into account, constitute the major advantages of the AHP method.

At first, the satisfaction of each criterion is computed for a population of individuals. Then, the AHP method is used to estimate the relative importance or the relative weight of each criterion, in order to compute a global satisfaction criterion, used to classify the individuals of the population

In this paper, an AHP method is used to aggregate these indicators and facilitate decision making. The performance of the process is calculated from 3 level 1 indicators: *process time, cost of used tool* and *efficiency*. The *process time* criterion is calculated from 5 level 2 indicators: *machining time, orientation change time, accessory change time, tool change time* and *insert change time*. *Efficiency* is calculated as the ratio of *value added time* to *total manufacturing time*.

The user compares these criteria two by two to calculate the weights, by answering a set of questions such as:

- Question: Equal time value, to which do you give the most importance?
  Response: Between 3 minutes of machining time and 3 minutes of tool change time, it is best to optimize the machining time. It therefore has more importance.
- Question: Which criterion do you give the most importance to?
  Response: Between an effective process with a longer machining time than another process with less efficiency, it is preferable to choose the process with the shortest machining time. Machining time is therefore more important than efficiency.

3.7   Conclusion

The proposed method propose to generate a large number of different process by introducing a lot of variability and innovation and by guaranteeing their viability. The genetic algorithm leads to the identification of some process that are particularly effective, according to their macro-indicator value. The macro-indicator is computed as a weighted sum of elementary indicators. AHP method is used to estimate weights by comparison 2 by 2. Finally, the user can then choose the optimal process according to his experience, by analyzing the macro-indicator, the elementary indicators and a risk indicator.

4   Application to an industrial case

4.1   Setting the genetic algorithm

In order to determine the optimal settings of the genetic algorithm, a complete plan of experiments is realized. The following table shows the different parameters of the algorithm, the values tested and the final choice.

Parameters	Tested values	Chosen value
Number of iterations Nb_{it}	50, 150, 300	300
Size of the population Nb_{init}^{pop}	20, 50, 100	100
Percentage of sequencing change P_{init}^{seq}	25%, 50%	25 %
Percentage of best preserved individuals P_{bests}	10%, 30 %	10 %
Percentage of individuals kept $P_{tournament}$	10%, 25%	10 %
Probability of crossover Pc	0.2, 0.4, 0.6	0.6
Probability of sequencing mutation P_{ms}	0.1, 0.2, 0.3	0.1
Probability of area mutation P_{mGE}	0.1, 0.2, 0.3	0.1
Probability of mutation of cutting tools P_{mo}	0.2, 0.4, 0.6	0.6

Table 1 : GA Settings

Figure 5 shows the evolution of the *MCP* value during the iterations for the 300 iteration tests, that obtained the best *MCP* values.
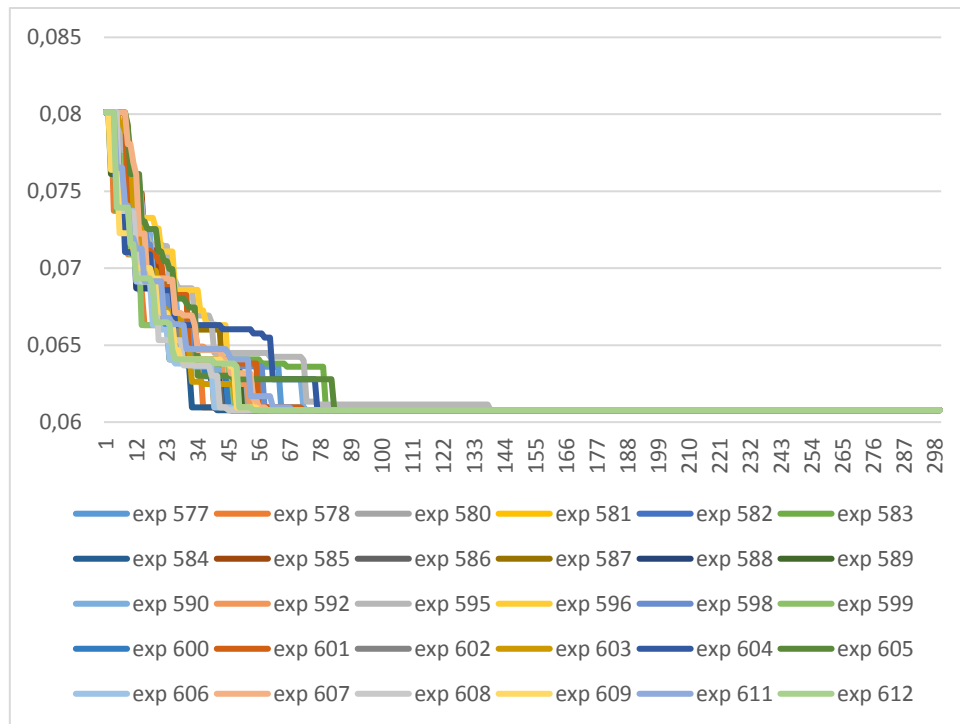
Figure 2 : MCP Convergence after 300 iteration tests

Percentage values of individuals kept $P_{tournament}$ have no significant impact on the velocity of convergence of the tests. The same conclusion is reached by analyzing the results obtained for the percentages P_{bests} of the best preserved individuals. In order to encourage innovation and exploration of the field of possible solutions by the algorithm, these values are set to 10%.

To define the settings to be applied to the crossover and mutation probability values, an additional analysis is implemented. Figure 3 shows the minimum values obtained as a function of the value of the probability Pc. It is observed that only the value $Pc = 0.6$ produces the best value of the *MCP* independently of the other parameters.
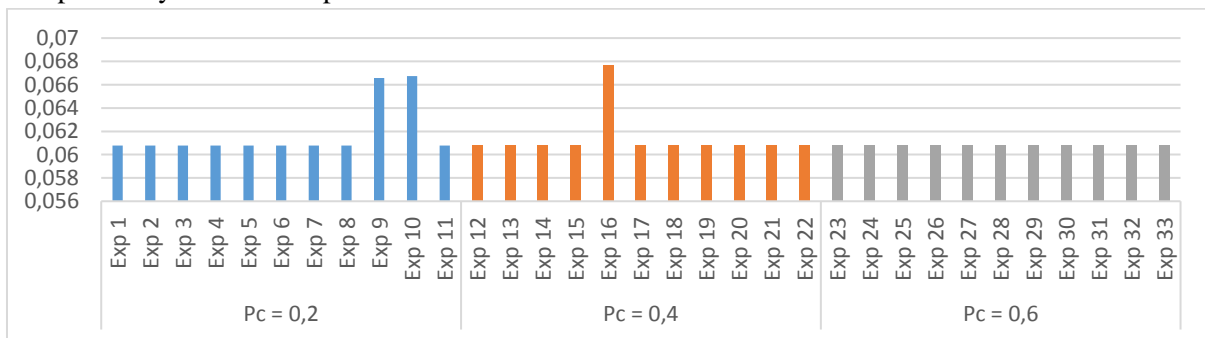

Figure 3 : Minimum MCP value computed for each test based on Pc value

In our study, the part is defined by simple geometrical features. These features offer few different machining solutions. Thus, feature and sequencing mutations do not represent significant source of gain or innovation. Conversely, a large number of different cutting tool references, known or unknown, can be exploited. They represents an important level for improving the performance of the machining. Thus, the tool mutation probability P_m is set to 0.6 and consequently $P_{mGE} = 0.1$ and $P_{ms} = 0.1$.

4.2   Application

The method is applied to a large aeronautical structural part, machined from a titanium alloy. The raw is obtained by stamping. 12 independent machining features are extracted, by the user. This part is

machined on a 3 axes NC machine-tool with the possibility of adding a angle head. A list of 36 tools is defined as the database.

For each entity, the user declares at most 5 possible machining solutions for a given feature. A machining solution can be formed by a sequence of 5 elementary machining operations. The user declares the machining operation (*Chamfering, Contouring, Copying, Thread-Tapping, Drilling, Grooving, Surfacing, Surfacing-Dressing, Tapping, Trimming, Cutting*), the type of machining operation (*Roughing, Re-roughing, Semi-finishing, finishing, Superfinishing*), the tool selected in a database and the maximum permissible cutting conditions. The variety of the declared solutions is a factor of richness for the genetic algorithm. The user verify that each elementary operation is suitable.

The following tables present the weights of the various performance indicators, calculated by the AHP method, from a questionnaire. The calculation of a consistency index permits to validate the choice of the decision maker. In this example, the decision maker has a consistent behavior that favors productivity at costs.

User 1

Process Time	Orientation change time	Accessory change time	Cutting tool change time	Insert change time	Machining time	priority vector	Inconsistency
Orientation change time	1,00	0,33	0,17	0,17	0,17	4,24%	8,20%
Accessory change time	3,00	1,00	0,33	0,20	0,25	8,37%	
Cutting tool change time	6,00	3,00	1,00	0,33	0,20	15,75%	
Insert change time	6,00	5,00	3,00	1,00	0,50	29,40%	
Machining time	6,00	4,00	5,00	2,00	1,00	42,24%	

Table 2 : Preference Matrix and Decision-Making vector for Level 2 Criteria

User 1	Process Time	Tools Cost	Efficiency	priority vector	Inconsistency
Process Time	1,00	2,00	1,00	41,11%	4,63%
Tools Cost	0,50	1,00	1,00	26,11%	
Efficiency	1,00	1,00	1,00	32,78%	

Table 3 : Preference matrix and Decision-Making vector for level 1 criteria

During the computation, the GA algorithm calculates 50 different usable machining process planning, while the usual method produce only one process planning.

Table 4 groups the values of each performance indicator for the 5 best process planning.

Process N°	1	2	3	4	5
Macro Indicator Value	0,12155	0,12191	0,12312	0,12338	0,12476
VA time	1805,8	1792,7	1887,7	1874,5	1892,9
NVA time	208,2	214,2	217,2	223,2	231,2
Efficiency	0,8966	0,8933	0,8968	0,8936	0,8912
Accessory change time	50	50	50	50	50
Tool change time	80	72	80	72	64
Orientation change time	1,2	1,2	1,2	1,2	1,2
Inserts change time	77	91	86	100	116
Tool cost	2568	2228	2792	2452	2942
Optimistic rik	0,0964	0,0964	0,0964	0,0964	0,0964
Compromise risk	2,0284	1,9198	3,165	3,0564	2,9483

Pessimistic risk	6,6217	6,6217	23,1148	23,1148	23,1148

Tableau 4 : Performance values of 5 best computed process planning

The MCP values are close, but the values of the elementary indicators can show deviations of more than 50%, which shows that the process strategies are clearly different. The main difference lies in the choice of particular tools.

The process planning optimized by this method is compared to the initial process planning and to a process planning optimized by a usual engineering method.

Process planning N°	Initial rocess planning	Usual optimized process planning	New optimized process planning
Macro Indicator Value	0,27514	0,25767	0,12155
VA time	2650,1	1600,9	1805,8
NVA time	833,8	726,4	208,2
Efficiency	0,7607	0,6879	0,8966
Accessory change time	50	30	50
Tool change time	176	104	80
Orientation change time	2,8	2,4	1,2
Inserts change time	605	590	77
Tool cost	7460,8	3169,8	2568
Optimistic rik	0,3952	0,0964	0,0964
Compromise risk	2,6661	2,4478	2,0284
Pessimist risk	13,4034	7,9461	6,6217

Table 5 : Comparison of performance levels between initial process planning, usual optimized and new optimized provide by the method

It should be noted that the new optimized process planning has a lower MCP of more than 50% compared to other process planning. This difference is explained by the strong difference between the times composing the NVA time, which creates an increase in the efficiency of the process planning optimized by this method compared to the other process planning. The initial process planning and the usual optimized process planning seem close, with a similar sequencing of machining operations. The new optimized process planning offers a very different sequencing, while also respecting the imposed conditions of priority. It makes it possible to confront the user with original solutions.

In addition, the system also offers solutions known by the user, but not implemented for technological reasons. Thus the method is coherent and reassuring with respect to the know-how of the company while promoting innovation.

This remark also concerns the choice of tools and cutting conditions. The tools used by the new optimized process planning are close to those chosen by the usual optimized process planning in engineering, also validating the respect of the method vis-à-vis the know-how and knowledge of the company. The usual optimized process planning offers a lower VA time and a lower macro performance than the new optimized process planning proposed by the method, because the usual optimized method minimizes only VA time. The performance is therefore lower on the other indicators. So the new method would not necessarily been retain this solution. This underlines again that the expression of the priority vector plays an important role in the behavior of the optimization. It is therefore necessary that the user defines precisely its priorities. However, in a manual method such as classical engineering, it is difficult to comprehensively understand all the criteria and to optimize the compromise.

4.3   Impact of AHP on results

In order to illustrate the impact of the decision-making behavior on the algorithm, three other users were invited to respond to the questionnaire of the AHP (Table 6).

User 2	Process Time	Tools Cost	Efficiency	priority vector	Inconsistency
Process Time	1,00	3,00	5,00	60,70%	11,88%
Tools Cost	0,33	1,00	5,00	30,33%	
Efficiency	0,20	0,20	1,00	8,97%	
User 3	Process planning Time	Tools Cost	Efficiency	priority vector	Inconsistency
Process Time	1,00	5,00	2,00	58,13%	0,32%
Tools Cost	0,20	1,00	0,33	10,96%	
Efficiency	0,50	3,00	1,00	30,92%	
User 4	Process Time	Tools Cost	Efficiency	priority vector	Inconsistency
Process Time	1,00	3,00	4,00	61,96%	9,42%
Tools Cost	0,33	1,00	0,50	15,60%	
Efficiency	0,25	2,00	1,00	22,43%	

Table 6 : Preference matrix and Decision-Making vector for level 1 criteria applied to 3 different users

The consistency indicator is an indicator of quality of judgment. Users 2 and 4 have very similar values. Nevertheless, the user 4 has a consistency of judgment more satisfactory than the user 2 and would therefore be better able to obtain process of machining that meet required expectations. Finally, the user 3 has a very strong consistency of judgment. He did not nuance the judgment significantly between the criteria. His preferences have been reflected in a coherent way, lowering the level of inconsistency but not bringing out a real position on the relative importance of the criteria.

The understanding of the questionnaire regarding the experience of each user, as well as the level of insights of the concepts of the AHP can induce a significant fluctuation of the coherence of the judgment, which underlines the importance of the formulation of the questions. These fluctuations of coherence as well as these differences of judgment also have a certain impact on the behavior of the optimization. The algorithm was used on the case study by replacing the behavior of user 1 with the other three behaviors. Table 7 groups the values of the performance and risk indicators for the best process generated by the algorithm for each decision maker.

User	1	2	3	4
Macro Indicator Value	0,122	0,1	0,142	0,122
VA time	1805,84	1458,612	1811,048	1792,706
NVA time	208,2	212,4	222,2	214,2
Efficiency	0,897	0,873	0,891	0,893
Accessory change time	50	60	50	50
Tool change time	80	96	64	72
Orientation change time	1,2	4,4	1,2	1,2
Inserts change time	77	52	107	91
Tool cost	2568	1939,8	2718	2228
Optimistic rik	0,192	0,192	0,192	0,192
Compromise risk	4,056	3,066	3,624	3,84
Pessimist risk	13,244	15,684	9,644	13,244

Table 7 : Values of performance indicators of the best process planning generated for each decision maker

For user 1, 3 and 4 the sequencing of the process planning is the same, only one or two cutting tools change, which is consistent with their performance, also close on each indicator.

The process planning of user 2 is fundamentally different for the process planning sequencing as well as in some cutting tool choices. This process planning is less effective. The process planning incorporates cutting tools that are more productive during machining operations but penalize during non-value-added phases. In addition, the process planning allows more change of accessories and orientation to use more productive cutting tools. Thus, despite similar behaviors, the computed process planning for user 2 and 4 are very different in term of performance.

The sensitivity of optimization to user decision-making behavior is therefore important. The decision-making behavior guides the algorithm in the optimization, and the generated solutions are only an image of this behavior. It is important to note the method compute the most optimum process planning, but compute the optimum process planning, according to specific requirements of each decision maker.

5   Conclusion

This work proposes an innovative approach in the design and optimization of machining process planning. The key problem is to propose innovative and operable process planning and whose associated risks are mastered. The objective is to test a number of varied process planning in a limited time, and to classify them in terms of their perceived multicriterian performance, in order to obtain the most efficient process planning. To overcome these two difficulties, the approach relies on a genetic algorithm for the testing and generation of a large number of different process planning, which are classified using the Analytic Hierarchy Process method to weight the different elementary performances indicators. Finally, we wanted to formalize in this work, the concept of risk related to the implementation of a process of machining. The estimation of the risk is fundamental, to consider the implementation of a new process of machining, in security. The gain is always estimated against the risk that can be taken. At first, the risk is estimated by the bending of the cutting tools during machining.

This method enables company know-how to be taken into account, while introducing innovation to develop new tool and machining strategies. An application to an industrial case shows that the new solutions are consistent with the industrial innovation potential, and that the best process will be superior to the optimized industrial process.

Subsequently, a similar approach is applied to a DFM methodology, from Design to the manufacturing of the part by stamping and machining.

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