Decision-making for multi-criteria optimization of process planning

Laurent Delolme, Anne-Lise Antomarchi, Séverine Durieux, and Emmanuel Duc*

Université Clermont Auvergne, CNRS, SIGMA Clermont, Institut Pascal, 63000 Clermont–Ferrand, France

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Abstract. The objective of this work is to develop a methodology for the automatic generation of optimised and innovative machining process planning that enable aeronautical subcontractors to face current productivity and competitiveness issues. A four-step methodology is proposed, allowing the user to obtain optimised machining ranges that respect his know-how and experience and introduce innovation. This methodology is based on a representation of the decisional behaviour of the user in a given situation as well as in the face of the risk of industrialisation and broadens the formalisation of the performance of a process by taking into account other performance criteria other than machining time or overall cost. A genetic algorithm is used to generate optimized process planning. An AHP method is used to represent the decision-making process. The methodology presents the best processes generated and the use of social choice theory enables it to target the most efficient ranges to be implemented, by integrating a risk criterion to the industrialization.

Keywords: 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-forged 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 (Sect. 2); presentation of the general method of resolution (Sect. 3); and an application case study (Sect. 4).

* e-mail: Emmanuel.Duc@sigma-clermont.fr

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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 [4–6]:

- Selection of manufacturing processes and tools;
- Selection of machine tools and technical resources;
- 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 [7–11];
- Generative or semi-generative process [7–9,12] comprising:
  - Process by algorithmic systems [7,9,13–16];
  - Process by expert systems [17–19].

Since 1984, several publications have studied the various CAPP systems developed by the scientific community [5,9,20–22]. In 2007, Denkera 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) while the second concerns methods that engineer a process ex-nihilo (generative process).

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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 literature review shows that much work has been done on this issue. We consider that the technical obstacles related to the recognition of entities and their application to pre-defined processes have been overcome. Nevertheless, we note that little software is used in companies, especially in SMEs with small production runs. Indeed, this software does not correspond to their needs and requires significant support resources. For a SME, 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 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. The development of a complete process in a CAD/CAM software can take several months. Also, the user tends to secure the work by repeating reliable processes, which does not bring any performance gains.

On the other hand, he is usually able to optimize the process according to a single criterion. Then, the user does not have the time to develop several processes in a CAD/CAM software because it becomes too expensive. In addition, special attention must be paid to the interaction between the operator and the process. Indeed, it is an important factor of performance loss, if the operator is suspicious of the generated process. Confidence between the operator and the process is a very important key element to achieve high performance. 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. We consider that the problem is now in the choice and the search for the performance of a process.

The main issue of this research is the proposal for a multi-criteria decision support tool for the automatic generation of machining process planning. The purpose is to quickly propose alternative processes to the user. It must be quick and easy to implement, that is why a simple geometric model of the features is used. This choice can make the calculations less accurate. 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 user makes the choice of the final process. Then, this method allows him to evaluate a large number of alternative solutions before an actual development, according to a set of criteria. The method therefore generates counter-intuitive processes, the credibility of which is verified. Even if the solution is not retained, his skills are enriched. Indeed, the proposed solutions allow the user to identify unusual processes or processes that he would not have thought of. But these alternatives must be compatible with the company’s industrial constraints. It is a question of finding the right balance between innovation and safety, or between performance and credibility. In the aeronautics industry, investments are very important and it is difficult to question an industrial establishment to optimize a process. The methodology does not allow to assist in the design of parts because the geometrical models of the features are too simple. However, this method has subsequently been adapted to also take into account design-related performance indicators.

The method is simple to implement. Interfacing with a CAD software to identify the features seems feasible, according to the literature, but we have not done any research on this point. Using the Vba language available in Microsoft Excel®, it can be easily interfaced with CAD/CAM software that allow application development. But the performance of the method is based on the use of a reliable, accurate and up-to-date database of tools. It is a key point.

Thus, 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.

A set of indices is used to identify the elements of the planning process.
- \( m \) is the index of a process \( G \) in the process population computed by \( GA \);
- \( n \) is the index for an operation \( Op \) in a process;
- \( i \) is the index of a Feature identified on the part;
- \( k \) is the index of a tool in the database of usable tools.

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 (see Fig. 1):

\[
Op_{m,n} = \{ \text{Feature}_{op_{m,n}}; \text{Axis}_{op_{m,n}}; \text{Top}_{m,n}; \text{Tool}_{m,n}; \text{Cy}_{Op_{n,m}}; \text{Vc}_{m,n}; \text{Ap}_{m,n}; \text{Ae}_{m,n}; \text{Fz}_{m,n}; \text{Lunit}_{m,n}; \text{la}_{m,n}; \text{H}_{m,n} \},
\]

where:
- \( \text{Feature}_{op_{m,n}} \) is the geometrical feature to be machined by the operation \( Op_{m,n} \);
- \( \text{Axis}_{op_{m,n}} \) is tool axis orientation for the operation \( Op_{m,n} \);
- \( \text{Top}_{m,n} \) is the type of the operation \( Op_{m,n} \);
- \( \text{Tool}_{m,n} \) is the tool used by the operation \( Op_{m,n} \);
- \( \text{Cy}_{Op_{n,m}} \) is the machining strategy used by the operation \( Op_{m,n} \);
- \( \text{Vc}_{m,n} \) is the cutting speed of the operation \( Op_{m,n} \);

Fig. 1. Settings of the toolpath for the operation \( n \) of the planning \( m \).
Face-dressing, Tapping, Placing, Cutting.

Threading—Tapping, Drilling, Grooving, Surfacing, machined.

Axis – X

Axis – Y

Axis – Z

An associated machining strategy, noted ReTech, noted

Feature – the machining of the Feature, without collision;

Feature – the tool;

Feature – the tool axis;

Feature – the set of other features, that can be machined similarly to the Feature;

Feature – the set of other features, that must necessarily be machined before the Feature.

Each tool Toolk, k ∈ {1, ..., NbTool}, is defined by:

- An associated machining strategy, noted Cym,n, Czm,n.

- The diameter Dtoolk,
- The length Ltoolk,
- The corner radius Rctoolk,
- The number of teeth Ztoolk,
- The number of inserts Nbtoolk.

The set Topk of different types of machining for which the tool can be used. The possible types of machining are as follows: Roughing, Re-roughing, Semi-finish, finishing, Superfinishing, organized according to the following hierarchy:

Roughing > Re-roughing > Semi-finish > finishing > Superfinishing

- The cost Cctoolk by cutting edge,
- The maximum chip section As toolk, 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.

Cym,n and Vcm,n are deduced from the tool database knowing that Ap,m,n, Am,n et Fm,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 [46–48].

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 $P_{\text{seq}}$ and the size of the initial population $N_{\text{init}}$ 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, MCPm is calculated from a weighted sum of standardized Indi performance indicators, described in Section 3.4.

\[
MCP_m = \sum p_i \times \text{Ind}_i. \tag{1}
\]

A new $N + 1$ population is created from the $N_{\text{bests}}$ individuals, from a percentage $P_{\text{tourn}}$ 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 $P_m$. $P_m$ relates to the probability $P_{ms}$, to change the sequencing, the probability $P_{mGE}$ to the probability of replacing, for a feature, a machining operation by another operation from another process also called feature mutation and the probability $P_{mo}$ to change the cutting tool.

$$P_m = P_{ms} + P_{mGE} + P_{mo}$$ (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 [51–56]. 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 [59–62];
- by artificial intelligence.

The bibliographic study has shown that an accurate estimation of the machining time requires a 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].

In these works, the machining time of the elementary operation $n$ of the process $m$, denoted $T^c_{m,n}$, 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 $T_{cm}$ is the sum of the machining time of operations.

$$T_{cm} = \sum_{n=1}^{N} T^c_{m,n} = \sum_{n=1}^{N} L_{unit,m,n} \times Npax_{m,n} \times Nprad_{m,n} / Vf_{m,n}$$ (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 $Toch_{unit}$ 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.

$$Toch_{totm} = \sum_{n=2}^{N} Vect_{\alpha,n} \times T^{c'}_{ch_{unit}}.$$ (4)

The computation is the same for accessories. The time $Tach_{totm}$ 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 $Xacc_{\alpha,n}$ accessory changes for operation $n$. The indicator $Xacc_{\alpha,n}$ is equal to 1 if the change is necessary, and equal to 0 if not.

$$Tach_{totm} = \sum_{n=2}^{N} Xacc_{\alpha,n} \times Tach_{unit}.$$ (5)

The tool change time $Ttch_{totm}$ 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 $m$.

$$Ttch_{totm} = \sum_{n=1}^{N} Xacc_{n,m} \times Ttch_{unit}$$ (6)

The insert change time $Tich_{m,n}$ 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 $T_{\text{ich}}$ change of the tool inserts set, from the number $N_{\text{bit}}$ of inserts, from the tool life $T_{\text{Lt}}$ of the tool, and from the effective cutting time $T_{\text{c}}$ of the tool.

$$T_{\text{ich}} = \sum_{n=1}^{N} T_{\text{ich},n} = \sum_{n=1}^{N} \left| \frac{T_{\text{c},n}}{T_{\text{Lt},n,m,p}} \right| \times N_{\text{bit},n,m} \times T_{\text{ich}}. \tag{7}$$

The cost $C_{\text{ct}}$ of tools is calculated according to the unit cost $C_{\text{to}}$ of an insert of the tool, and the number of insert $N_{\text{ct},m}$ changed during an elementary operation, calculated, according to the tool life.

$$C_{\text{ct}} = \sum_{n=1}^{N} N_{\text{ct},m} \times C_{\text{to}}$$

$$= \sum_{n=1}^{N} \left| \frac{T_{\text{c},n}}{T_{\text{Lt},n,m,p}} \right| \times N_{\text{bit},n,m} \times C_{\text{to}}. \tag{8}$$

### 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 $R_{\text{op}}$ compared to a maximum step $R_{\text{threshold}}$ 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 $R_{\text{op}}$ according to the geometrical characteristics of the machining operation and the associated risk index $IR_{\text{op}}$. An operation is considered as safe if $IR_{\text{op}} < 1$

$$IR_{\text{op}} = \frac{R_{\text{op}}}{R_{\text{threshold}}}$$

$$= \frac{F_{z,n} \times Z_{\text{outil},n} \times A_{p,n} \times A_{e,n,m} \times L_{\text{outil},n,m}^{3}}{R_{\text{threshold},n,m}}. \tag{9}$$

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):
  $$\min_{m} (IR_{\text{g},m}^{\text{pessimist}}) = \min_{m} \left( \max_{n} \left( IR_{\text{op},m,n} \right) \right),$$

- compromise attitude:
  $$\min_{m} (IR_{\text{g},m}^{\text{compromise}}) = \min_{m} \left( \sum_{n=1}^{N} IR_{\text{op},m,n} / N \right),$$

- preference for risk (optimistic attitude):
  $$\min_{m} (IR_{\text{g},m}^{\text{optimist}}) = \min_{m} \left( \min_{n} IR_{\text{op},m,n} \right).$$

### 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 Analytic Hierarchy Process (AHP Method) is a method proposed by Saati in 1980, to calculate weights reliably. The 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?
  - 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.

### Table 1. GA settings.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Tested values</th>
<th>Chosen value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of iterations $Nb_{it}$</td>
<td>50, 150, 300</td>
<td>300</td>
</tr>
<tr>
<td>Size of the population $Nb_{pop}^{init}$</td>
<td>20, 50, 100</td>
<td>100</td>
</tr>
<tr>
<td>Percentage of sequencing change $P_{seq}$</td>
<td>25%, 50%</td>
<td>25%</td>
</tr>
<tr>
<td>Percentage of best preserved individuals $P_{bests}$</td>
<td>10%, 30%</td>
<td>10%</td>
</tr>
<tr>
<td>Percentage of individuals kept $P_{tournament}$</td>
<td>10%, 25%</td>
<td>10%</td>
</tr>
<tr>
<td>Probability of crossover $P_c$</td>
<td>0.2, 0.4, 0.6</td>
<td>0.6</td>
</tr>
<tr>
<td>Probability of sequencing mutation $P_{ms}$</td>
<td>0.1, 0.2, 0.3</td>
<td>0.1</td>
</tr>
<tr>
<td>Probability of feature mutation $P_{mGE}$</td>
<td>0.1, 0.2, 0.3</td>
<td>0.1</td>
</tr>
<tr>
<td>Probability of mutation of cutting tools $P_{mio}$</td>
<td>0.2, 0.4, 0.6</td>
<td>0.6</td>
</tr>
</tbody>
</table>

Table 1 shows the different parameters of the algorithm, the values tested and the final choice.

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

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 $P_c$. It is observed that only the value $P_c = 0.6$ produces the best value of the MCP independently of the other parameters.

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 represent 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.

Tables 2 and 3 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.

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.

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.

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
Table 2. Preference matrix and decision-making vector for level 2 criteria.

<table>
<thead>
<tr>
<th>User 1</th>
<th>Process Time</th>
<th>Orientation change time</th>
<th>Accessory change time</th>
<th>Cutting tool change time</th>
<th>Insertchange time</th>
<th>Machining time</th>
<th>Priority vector</th>
<th>Inconsistency</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Orientation change time</td>
<td>1,00</td>
<td>0,33</td>
<td>0,17</td>
<td>0,17</td>
<td>0,17</td>
<td>4.24%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Accessory change time</td>
<td>3,00</td>
<td>1,00</td>
<td>0,33</td>
<td>0,20</td>
<td>0,25</td>
<td>8.37%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Cutting tool change time</td>
<td>6,00</td>
<td>3,00</td>
<td>1,00</td>
<td>0,33</td>
<td>0,20</td>
<td>15.75%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Insert change time</td>
<td>6,00</td>
<td>5,00</td>
<td>3,00</td>
<td>1,00</td>
<td>0,50</td>
<td>29.40%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Machining time</td>
<td>6,00</td>
<td>4,00</td>
<td>5,00</td>
<td>2,00</td>
<td>1,00</td>
<td>42.24%</td>
</tr>
</tbody>
</table>

Table 3. Preference matrix and decision-making vector for level 1 criteria.

<table>
<thead>
<tr>
<th>User 1</th>
<th>Process time</th>
<th>Tools cost</th>
<th>Efficiency</th>
<th>Priority vector</th>
<th>Inconsistency</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Process Time</td>
<td>1,00</td>
<td>2,00</td>
<td>1,00</td>
<td>41.11%</td>
</tr>
<tr>
<td></td>
<td>Tools Cost</td>
<td>0,50</td>
<td>1,00</td>
<td>1,00</td>
<td>26.11%</td>
</tr>
<tr>
<td></td>
<td>Efficiency</td>
<td>1,00</td>
<td>1,00</td>
<td>1,00</td>
<td>32.78%</td>
</tr>
</tbody>
</table>

Table 4. Performance values of 5 best computed process planning.

<table>
<thead>
<tr>
<th>Process N°</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Macro Indicator Value (MCP)</td>
<td>0.12155</td>
<td>0.12191</td>
<td>0.12312</td>
<td>0.12383</td>
<td>0.12476</td>
</tr>
<tr>
<td>VA time</td>
<td>1805.8</td>
<td>1792.7</td>
<td>1887.7</td>
<td>1874.5</td>
<td>1892.9</td>
</tr>
<tr>
<td>NVA time</td>
<td>208.2</td>
<td>214.2</td>
<td>217.2</td>
<td>223.2</td>
<td>231.2</td>
</tr>
<tr>
<td>Efficiency</td>
<td>0.8966</td>
<td>0.8933</td>
<td>0.8968</td>
<td>0.8936</td>
<td>0.8912</td>
</tr>
<tr>
<td>Accessory change time</td>
<td>50</td>
<td>50</td>
<td>50</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td>Tool change time</td>
<td>80</td>
<td>72</td>
<td>80</td>
<td>72</td>
<td>64</td>
</tr>
<tr>
<td>Orientation change time</td>
<td>1.2</td>
<td>1.2</td>
<td>1.2</td>
<td>1.2</td>
<td>1.2</td>
</tr>
<tr>
<td>Inserts change time</td>
<td>77</td>
<td>91</td>
<td>86</td>
<td>100</td>
<td>116</td>
</tr>
<tr>
<td>Tool cost</td>
<td>2568</td>
<td>2228</td>
<td>2792</td>
<td>2452</td>
<td>2942</td>
</tr>
<tr>
<td>Optimistic rik</td>
<td>0.0964</td>
<td>0.0964</td>
<td>0.0964</td>
<td>0.0964</td>
<td>0.0964</td>
</tr>
<tr>
<td>Compromise risk</td>
<td>2.0284</td>
<td>1.9198</td>
<td>3.165</td>
<td>3.0564</td>
<td>2.9483</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Process planning N°</th>
<th>Initial process planning</th>
<th>Usual optimized process planning</th>
<th>New optimized process planning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Macro Indicator Value (MCP)</td>
<td>0.27514</td>
<td>0.25767</td>
<td>0.12155</td>
</tr>
<tr>
<td>VA time</td>
<td>2650.1</td>
<td>1600.9</td>
<td>1805.8</td>
</tr>
<tr>
<td>NVA time</td>
<td>833.8</td>
<td>726.4</td>
<td>208.2</td>
</tr>
<tr>
<td>Efficiency</td>
<td>0.7607</td>
<td>0.6879</td>
<td>0.8966</td>
</tr>
<tr>
<td>Accessory change time</td>
<td>50</td>
<td>30</td>
<td>50</td>
</tr>
<tr>
<td>Tool change time</td>
<td>176</td>
<td>104</td>
<td>80</td>
</tr>
<tr>
<td>Orientation change time</td>
<td>2.8</td>
<td>2.4</td>
<td>1.2</td>
</tr>
<tr>
<td>Inserts change time</td>
<td>605</td>
<td>590</td>
<td>77</td>
</tr>
<tr>
<td>Tool cost</td>
<td>7460.8</td>
<td>3169.8</td>
<td>2568</td>
</tr>
<tr>
<td>Optimistic rik</td>
<td>0.3952</td>
<td>0.0964</td>
<td>0.0964</td>
</tr>
<tr>
<td>Compromise risk</td>
<td>2.6661</td>
<td>2.4478</td>
<td>2.0284</td>
</tr>
<tr>
<td>Pessimistic risk</td>
<td>13.4034</td>
<td>7.9461</td>
<td>6.6217</td>
</tr>
</tbody>
</table>

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 (see Tab. 5). 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 respect to the know-how of the company while promoting innovation.
Table 6. Preference matrix and Decision-Making vector for level 1 criteria applied to 3 different users.

<table>
<thead>
<tr>
<th>User</th>
<th>Process Time</th>
<th>Tools Cost</th>
<th>Efficiency</th>
<th>Priority vector</th>
<th>Inconsistency</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>User 2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Process Time</td>
<td>1.00</td>
<td>3.00</td>
<td>5.00</td>
<td>60.70%</td>
<td>11.88%</td>
</tr>
<tr>
<td>Tools Cost</td>
<td>0.33</td>
<td>1.00</td>
<td>5.00</td>
<td>30.33%</td>
<td></td>
</tr>
<tr>
<td>Efficiency</td>
<td>0.20</td>
<td>0.20</td>
<td>1.00</td>
<td>8.97%</td>
<td></td>
</tr>
<tr>
<td>User 3</td>
<td>Process planning Time</td>
<td>Tools Cost</td>
<td>Efficiency</td>
<td>Priority vector</td>
<td>Inconsistency</td>
</tr>
<tr>
<td>Process Time</td>
<td>1.00</td>
<td>5.00</td>
<td>2.00</td>
<td>58.13%</td>
<td>0.32%</td>
</tr>
<tr>
<td>Tools Cost</td>
<td>0.20</td>
<td>1.00</td>
<td>0.33</td>
<td>10.96%</td>
<td></td>
</tr>
<tr>
<td>Efficiency</td>
<td>0.50</td>
<td>3.00</td>
<td>1.00</td>
<td>30.92%</td>
<td></td>
</tr>
<tr>
<td>User 4</td>
<td>Process Time</td>
<td>Tools Cost</td>
<td>Efficiency</td>
<td>Priority vector</td>
<td>Inconsistency</td>
</tr>
<tr>
<td>Process Time</td>
<td>1.00</td>
<td>3.00</td>
<td>4.00</td>
<td>61.96%</td>
<td>9.42%</td>
</tr>
<tr>
<td>Tools Cost</td>
<td>0.33</td>
<td>1.00</td>
<td>0.50</td>
<td>15.60%</td>
<td></td>
</tr>
<tr>
<td>Efficiency</td>
<td>0.25</td>
<td>2.00</td>
<td>1.00</td>
<td>22.43%</td>
<td></td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>User</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Macro Indicator Value (MCP)</td>
<td>0.122</td>
<td>0.1</td>
<td>0.142</td>
<td>0.122</td>
</tr>
<tr>
<td>VA time</td>
<td>1805.84</td>
<td>1458.612</td>
<td>1811.048</td>
<td>1792.706</td>
</tr>
<tr>
<td>NVA time</td>
<td>208.2</td>
<td>212.4</td>
<td>222.2</td>
<td>214.2</td>
</tr>
<tr>
<td>Efficiency</td>
<td>0.897</td>
<td>0.873</td>
<td>0.891</td>
<td>0.893</td>
</tr>
<tr>
<td>Accessory change time</td>
<td>50</td>
<td>60</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td>Tool change time</td>
<td>80</td>
<td>96</td>
<td>64</td>
<td>72</td>
</tr>
<tr>
<td>Orientation change time</td>
<td>1.2</td>
<td>4.4</td>
<td>1.2</td>
<td>1.2</td>
</tr>
<tr>
<td>Inserts change time</td>
<td>77</td>
<td>52</td>
<td>107</td>
<td>91</td>
</tr>
<tr>
<td>Tool cost</td>
<td>2568</td>
<td>1939.8</td>
<td>2718</td>
<td>2228</td>
</tr>
<tr>
<td>Optimistic rik</td>
<td>0.192</td>
<td>0.192</td>
<td>0.192</td>
<td>0.192</td>
</tr>
<tr>
<td>Compromise risk</td>
<td>4.056</td>
<td>3.066</td>
<td>3.624</td>
<td>3.84</td>
</tr>
<tr>
<td>Pessimistic risk</td>
<td>13.244</td>
<td>15.684</td>
<td>9.644</td>
<td>13.244</td>
</tr>
</tbody>
</table>

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 (Tab. 6).

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.

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 multicriteria 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.

The particularity of this work lies in the modelling of the necessary data, which must be fast and sufficiently precise, in order to quickly calculate alternative processes. Another particularity lies in the expression of the manufacturing constraints, which allow to guarantee the feasibility of the proposed processes. Indeed, the counterintuitive process proposal must not lead to unfeasible processes.

Finally, a last key point concerns the modelling of the risk linked to the development of a new alternative range. Even if a process is particularly efficient, the risk involved may make it unusable. A technological risk indicator is proposed, by modelling the bending of tools, which can induce vibrations and defects on the part. To make his decision, the user has access to the value of the macroindicator, the value of the various elementary indicators and the value of the risk.

Thus, 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.

In perspective, future work is based on this method to develop a Design For Manufacturing methodology, which allows to optimize the geometry of an aeronautical part by respecting performance indicators from design, die-forging and machining.

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