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Optimization of Machining Process for Improved Sustainability

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Abstract. Optimization procedures can be considered useful for machining applications. Most commonly, the optimization method is applied to search a trade-off between costs and profits, and it allows searching for the optimum cutting parameters to maximize the useful tool-life, minimize the time of production, etc. The selection of the optimal machining conditions which could maximize the process sustainability performance and the fatigue life of the machined product is the objective of the work presented. The numerical model developed is useful to have integrated results as input for the optimization algorithm in order to drastically reduce the number of experimental tests needed. In the present work, the optimization of the performance measures is carried out using a self-written Genetic Algorithm code implemented using the MATLAB software.

Introduction

The need for achieving the overall sustainability in industrial activities is dictated by different drivers such as the stricter regulations related to occupational safety and health, national and international standards for environmental protection, diminishing of non-renewable resources and consumer preferences for more environmentally-friendly products, processes and services, etc [1].
The manufacturing sector must follow this sustainability trend in order to be competitive and to preserve the high standards of living of the modern society.
Machining is the major manufacturing process in the industry and it has the largest volume of production and economic returns [2]. Thus, the evaluation of its sustainability performance is significant and essential. For this reason, numerous improvements have been made in order to deeply analyse the effects of the process parameters on the resulting machining performance and component surface integrity. The surface integrity concept has been introduced to satisfy the necessity of linking component features with working conditions. It includes both surface and sub-surface features such as morphology, surface finish, microstructure, hardness and residual stresses, which directly affect component reliability. [3]
The coolant/lubricant application in machining process is considered an area of potential improvement since surface and sub-surface integrity of the machined products are strongly influenced by their use. Furthermore, metalworking fluids MWFs are considered as one of the top five health hazards in the workplace [4] as well as contaminant and pollutant for the environment, so that the government has issued strict regulations limiting the dumping of cutting fluid wastes. A reduction or the elimination of the MWFs in machining could also translate into a cost reduction for their purchasing, disposal and treatment. The approaches generally employed in machining processes are:

- Dry machining;
- Flood lubrication;
- Minimum quantity of lubrication (MQL) or near-dry;
- Cryogenic cooling.

Dry machining, also called green machining is the method which potentially avoids the negative environmental impact as it does not pollute the atmosphere. Also, in absence of lubrication, health hazards related to the working environment are reduced. However, on the other hand, tool wear, processing temperatures and surface integrity are generally negatively affected. Flood lubrication involves a continuous and high flow of lubricant which completely covers the tool-workpiece contact area while MQL involves spraying a small quantity of lubricant onto the area of interest in order to perform local lubrication and temperature lowering [2] Cryogenic machining involves using cryogenic gases such as nitrogen in order to enhance machinability and lower tool wear without increasing pollution.

To identify ways to simultaneously enhance the machining technology, address environmental and health risks and improve product performance, a better knowledge of the relationships among the process parameters, cooling/lubricant conditions and product surface integrity is necessary. In fact, enhancing process performance and simultaneously improving the product performance by manipulating the process-induced surface integrity proves to be a significant sustainability contribution. Thus, when evaluating the sustainability of a machining process, its effects on the product sustainability cannot be neglected. A more sustainable process cannot generate a less competitive product, or a less sustainable product. A long lasting product, with high quality standards can be considered also more sustainable, since it has to be replaced less often, its reliability is high so the safety issues related with its usage are less severe.

Models capable of predicting the surface characteristics and product performance for machined components, are needed to obtain feedback information on how to improve the process, thereby meeting the desired surface and sub-surface property specifications and improving the product quality, including the fatigue life of the final product[5, 6].

For this purpose, genetic algorithms (GA) are a growing topic of artificial intelligence discipline, of which procedure is based on the Darwinian principle of survival of the fittest. This takes place because the constant mutation and recombination of the chromosomes in the population yield a better gene structure. An initial population is set containing a predefined number of solutions (individuals). Each individual contains the variable information represented by a genetic string. Each individual has an objective value or fitness measure. The next population is generated by the reproduction of the best individuals in a population. At each generation selected, individuals are chosen for reproduction (or crossover) with an appropriate mutation factor to randomly modify the genes and to develop the new population. The next set of individuals will form a population with a better individual fitness. Therefore, the algorithm discards individuals with lower fitness by optimizing the fitness values. Figure 1 explains the GA working logic in a flowchart.

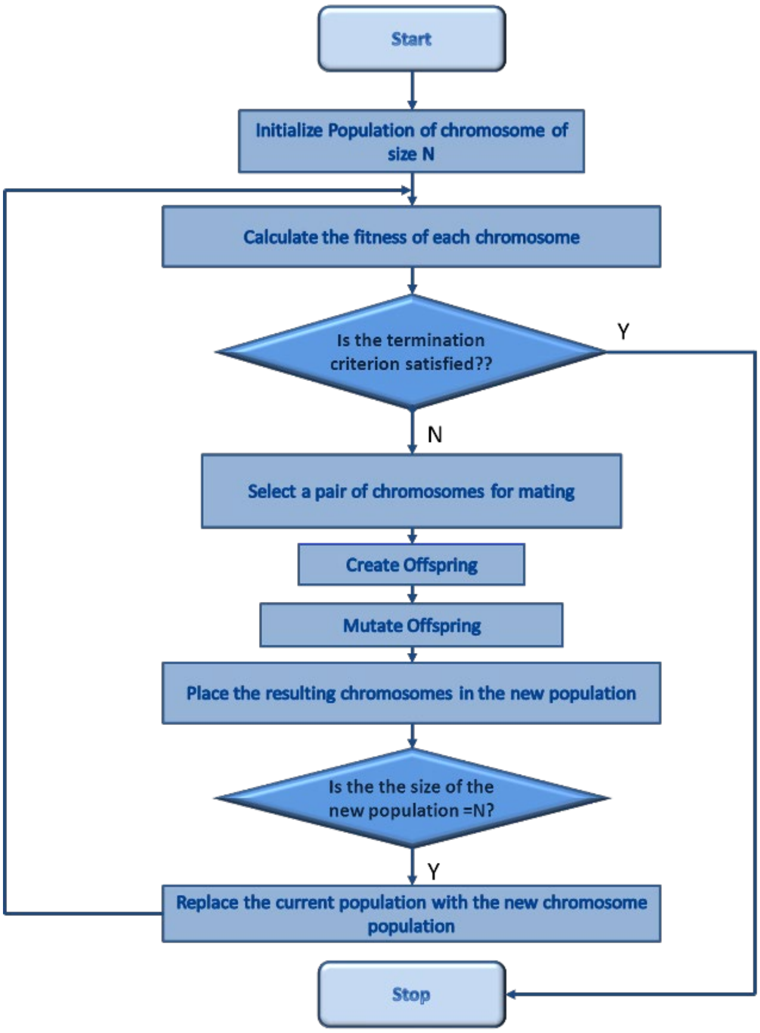

Fig. 1. GA operational process.

The GA technique, as a global optimum solution search algorithm, has advantages over traditional non-linear solution techniques that cannot always achieve a global optimal solution.

Non-linear programming solvers, for example, use some form of gradient search technique to search for the optimum solution, but they may be unable to find a feasible solution or it can be subject to problems of convergence to local optima. In this context, the starting search point plays a key role. A starting point outside the feasible region may result in no feasible solution, even though it may exist. A reasonable starting point may lead to an optimal solution, but it is not possible to determine if it is a local or global optimum point. The GA method works in such a way that the population encompasses a range of possible outcomes. Since the possible solutions are identified purely on a fitness level, local optima are not distinguished from other equally fit individuals, but the higher fitness values they will have, the closer to the global optimum they will be. At the next step, new generations will improve the fitness of individuals in the population until the optimization convergence criterion will be satisfied. Thus, GA can provide a global optimum.

Thus, it is observed that traditional manufacturing processes have to be modified in order to achieve the sustainability goals and to meet, at the same time, the needs to manufacture more efficient and sustainable products.

The alloy analyzed in this work is the alloy *AA7075*. Aluminum alloys are widely employed as structural materials owing to a number of advantages including good ductility and formability, high strength to density ratio, and elevated corrosion resistance, together with good vibration-damping characteristics and stiffness, which make them suitable for a number of weight-critical structural applications. [7]

It is used in a number of important engineering applications that span from low to room temperature such as: transport applications, including marine, automotive and aviation applications, due to their high strength-to-density ratio. Its strength and light-weight are also desirable for structural parts in helicopters and in other fields. [7]
A systematic study is greatly needed since various simultaneous factors, as well as changes during processing, are involved in manufacturing processes such as machining. The scope of this research is to evaluate the process/product sustainability performance for aerospace materials and the major objectives are:

- Improve the process sustainability performance by improving the environmental impact in terms of hazard, energy consumption and tool-wear;
- Optimize the process in order to evaluate the overall product/process sustainability.

Materials and Methods

The experimental tests were performed under dry, MQL and cryogenic conditions. The workpiece material is *AA 075-T651* aluminum alloy. The *T651* treatment consists of artificially aging of the material and then stress-releasing it. A 3D model was also previously implemented through the SFTC FE software Deform 3D and utilized to simulate the microstructural changes happening during turning of *AA7075-T651* alloy, to support process optimization. [8, 9]

The determination of the optimum cutting conditions in the machining process can be defined as a constrained optimization problem. The objective is to search for the optimum values of the operating parameters which can minimize/maximize the selected criterion, while satisfying the imposed constraints. More specifically, the objective function has to take into consideration the process performance elements of the power consumption, tool-wear and the product quality requirements defined by hardness, surface roughness and the microstructure of the finish surface described by the grain size, which are directly related to the final fatigue life of the component [10].

A previous work developed by [11] has been used as a basis for developing the optimization procedure. The GA problem is based on the experimental single pass turning operation and orthogonal cutting and it has been set with a total population size of 200 individuals, the chromosome length has been set to 70, the maximum number of generations is 2000, the crossover probability has been assigned to be 0.8 and the mutation probability is 0.01. The objective function is defined in Equation 1 as:

$$U(v,n,f) = C_R\left(\frac{R_a - R'_a}{R_a}\right) + C_P\left(\frac{P-P'}{P}\right) + C_M\left(\frac{M'_R - M_R}{M'_R}\right) + C_H\left(\frac{H'_V - H_V}{H'_V}\right) + C_D\left(\frac{D-D'}{D}\right) + C_T\left(\frac{T-T'}{T}\right) \quad (1)$$

where R_a is the surface roughness, P is the cutting power, M_R is the material removal rate, H_V is the surface hardness, D is the surface grain size, T is the cutting edge radius variation.

R_a*'* is the maximum surface roughness value set to be equal to 0.5. P*'* is the maximum power consumption chosen according to the maximum power of the turning machine, M_R*'* is the minimum material removal rate set to be equivalent to that calculated when the minimum cutting speed is used. H_V*'* is the minimum hardness value set to be equal to the bulk material, D*'* is the maximum grain size fixed at the value of the virgin material, finally, T*'* is the tool wear corresponding to a completely worn tool.

The generic C_i is the weighting factor considered as the contribution coefficient of the *i-th* machining performance variable to the value of the operation, and it has to satisfy the following conditions:

$$C_R + C_P + C_M + C_H + C_D + C_T = 1 \quad (2)$$

$$0 \le C_i \le 1 \quad (3)$$

In this analysis, the weighting factors are equally assigned since three indicators for the process performance and product performance are reported respectively.

The optimization problem can be written as:

Minimize $U(v_i, n_i, (i = 1 \dots N))$ (4)

With respect to $v_i, n_i (i = 1 \dots N)$ (5)

Subject to $Ra_i \leq Ra'_i,\ P_i \leq P'_i,\ M_{R\,i} \geq M'_{R\,i},$ (6)

$H_{V\,i} \geq H'_{V\,i}, D \leq D', T \leq T'$ (7)

$v_{\min i} \leq v_i \leq v_{\max i}, n_{\min i} \leq n_i \leq n_{\max i}$ (8)

It is worth pointing out that the mathematical expression of each variable behavior has been derived from the experimental data so the equations are empirically determined.

Results

The optimization method was applied to all three cooling conditions. Figure 2 shows the objective function under dry condition at varying of feed rates. In particular, the objective function values tend to decrease at higher feed rate and the cutting speed and by selecting a smaller nose radius.

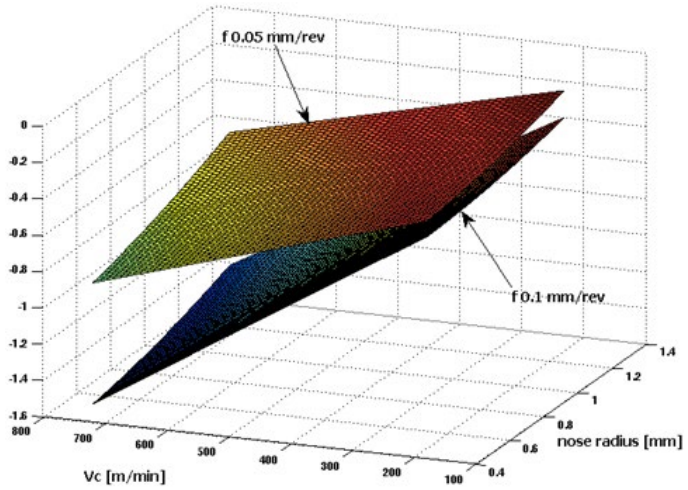

Fig. 2. Objective function for *AA7075-T651* under dry condition at varying feed rates.

Figure 3 shows the differences between dry, cryogenic and MQL objective functions. The dry conditions always perform worse than cryogenic and MQL cooling conditions, which are very close each other.

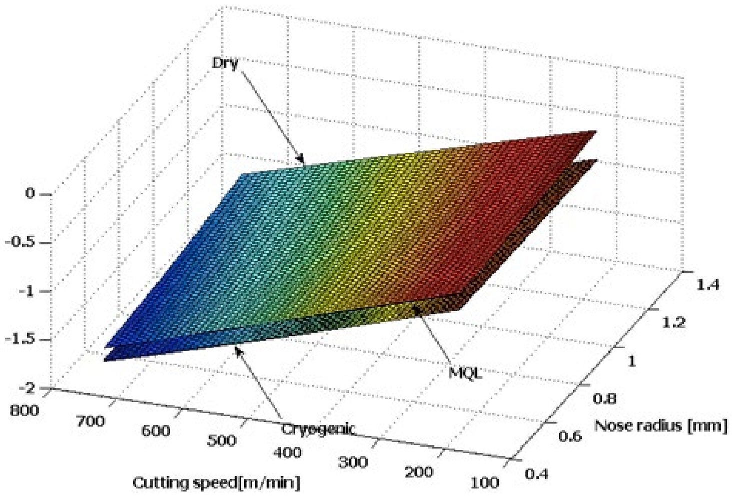

Fig. 3. Comparison between dry, cryogenic and MQL conditions for *AA-7075* objective function.

Figure 4 reports the feasible regions for the optimal condition. The cryogenic condition is the one which results in a better fitness function and assures the feasibility of the highest cutting speed and feed rate. Furthermore, cryogenic coolant offers better results than dry conditions, but very close to that obtained by using MQL conditions.

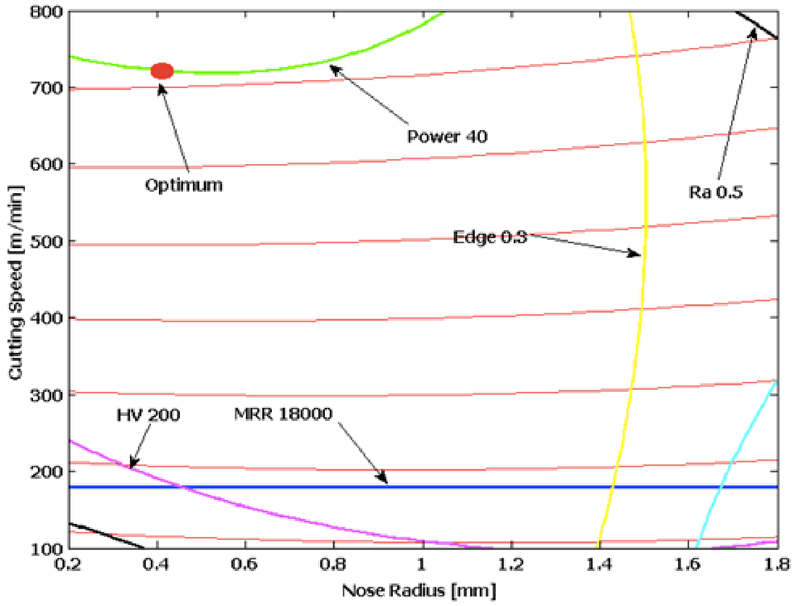

Fig. 4. Feasible region for cryogenic condition of *AA 7075-T651*.

Table 1 reports the overall results of the optimum values for each cooling condition showing as the maximum cutting speeds and feed rates always correspond to the optimum value for every cooling condition. However, the cryogenic cooling conditions always show a better fitness value when compared with dry and MQL conditions, ensuring better product and process performance.

Table 1. Optimum results for different cooling conditions.

GA Optimum Results			
	Dry	Cryogenic	MQL
V_c	720	720	720
f	0.1	0.1	0.1
r	0.4	0.4	0.4
Fitness	-0.3	-0.43	-0.41

Conclusions

In the current research, experimental studies on the influence of various machining conditions (dry, MQL and cryogenic cooling, cutting edge radius, cutting speed, feed rate, etc.) on surface integrity changes of *AA7075 –T651* alloy have been carried out in order to evaluate the sustainability of the machining process and machined product.

The influence of the process on the product quality and reliability have been considered as key parameters to evaluate the sustainability of both process and product.

An optimization procedure has been developed to find the optimal cutting parameters for each cooling condition.

The overall optimization results highlight a superior performance of cryogenic cooling application in improving the process, product and sustainability performance.

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