Optimizing cutting parameters for energy efficient CNC milling

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Abstract— **Energy efficiency is a very important issue for a sustainable manufacturing. Machining of parts is a very time consuming process and it is directly linked with the energy consumption and its efficiency. The energy consumption depends on some process parameters such as spindle speed and feed rate. In cloud manufacturing environments, the deployed services can use cloud computing resources and parallelization power in order to optimize the cutting coefficients for the different machining operations inside a machining task that better fit the user requests. First trials for the energy consumption reduction for part machining while saving Time and improving Material Removed Rate(MRR) is the aim of this work. For that, Spindle speed and Feed rate input parameters have been analyzed from different simulations and multiobjective optimization approach has been considered. In the presented work, a simple use case has been performed and its results confirmed the correctness of the approach taken into account.**

KeyWords— **Energy efficiency, Optimization, Computer Numeric Control(CNC), Sustainable machining**

I. Introduction

Sustainability in the industrial sector is challenging because the improvement in the energy efficiency on this area has a great impact on the environment. Many different approaches have been considered: on-line systems (working at run time, when the process is going on) or off-line systems.

MC-SUITE european project wants to boost the productivity of manufacturing industry bridging the gap between simulated and real processes.

The main limitation addressed in the previous paragraphs are going to overcome using the latest available ICT technologies in a holistic way, including High Performance Computing (HPC), Advanced Visualization, Cloud Computing, Smart Analytics, Decision Support Systems (DSS) and Big Data with Artificial Intelligence (AI) algorithms.

An optimization process in this context, wants to develop an intelligent machining tool, with elevated level of automation, because it implements functionalities that are hold by human operators.

Human operators are in charge of supervising the cutting process, for example in milling, by acting on spindle speed and feed override controls. Modifications of the values of these controls compensate undesired process conditions that arise due to the tool wear, unexpected work material properties, etc.

It has to be noticed that this analysis of the process parameter values and their impact on the final product can be done in advance, prior to begin the process or, stablishing a controller that implements a supervision and optimization loop (on-line).

To do that, a virtual equivalent of the machining process is needed. A commercial tool as MACHPro was used for this. It includes outputs such as time, energy consumption, MRR and cutting force evaluation. These outputs are used to adjust the solutions to the user needs.

HPC is required to perform this simulations manipulating detailed and heavy models. The output of the multi-objective optimization based on the virtual model is the optimal process program ready to run in the machine.

The remainder of this paper is organized as follows: section 2 presents the literature review, section 3 presents the heuristic models and the parallelization process. In the next section the case study is presented. Section 4 shows the result and finally, section 5 presents concluding remarks.

II. State of the art

This work focuses on the description of the foundations of a system that reduces the energy used for the machining process adapting the parameters to get an energy-aware CNC milling [10][11]. This section will focus on the research of optimisation in machining, energy consumption modelling and cloud based parallelization tasks. All these needs will be put together to provide services through a Cloud manufacturing based environment [12].

Different architectures have been considered. Onboard architectures are one of the them. In this case, the optimal machining conditions are calculated and adapted at runtime, during the machining process. Beckhoffs Twin CAT V3.1 is an example of commercial industrial CNC controller solution with this architecture. Its objective is to stabilize the cutting forces and chatter. So, this is a very specific solution and it does not take into account other parameters to optimize.

Another option is to use combined systems for offline optimization and adaptive adjustments [9]. Our research work focuses on speeding the off-line optimization task and, later on, will work on the adaptive adjustments.

Optimisation of machining processes is a topic that appears often in the literature. Most of them have the details to understand how the process was car-

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ried out. In [2], for example, a multi objective approach was followed. In this case the objective was to mitigate vibration level and to keep surface quality while preserving production times and decreasing tool wear rate. The material used was AA 6082-T6, the diameter of the mill was 63mm and the number of flutes 5. Spindle speed was set to 1500 rpm, depth of cut 2mm and width of cut 63mm. Cutting force constants are Krc, Ktc, Kac, radial, tangential and axial directions. Kre, Kte, Kae are due to the frictions between the edge of the tool and the workpiece. As it is shown, it is very specific problem for a specific material.

Li et al. in [3] present an analysis of the cutting parameters and their effect on energy efficiency in CNC milling process. They analyse the energy consumption versus time and use statistical fitting methods to formulate the relationship of energy consumption and cutting parameters. The elements considered are auxiliary power, unload power, material removal and additional load loss. The material removal power is represented as the product of the cutting force F_c and the cutting speed V_c where Kc is the cutting coefficient:

$$\text{Premoval=Fc*Vc=Kc*MRR} \tag{1}$$

It has to be noticed that the entire machining process is divided into seven periods in terms of energy consumption:

1. start-up
2. standby
3. spindle acceleration/deceleration
4. spindle idle
5. rapid feed
6. cutting
7. air cutting periods

On the way of increasing automation level of CNC machines, [6] calculates the optimal sequence of controls for a given toolpath, tool geometry and workpiece material. It simulates the process, finds the optimal solution and then it makes state reconstruction taking into account surface roughness.

Orthogonal turn-milling is considered in [7]. In this case, spindle and work rotational speeds, tool-work eccentricity, depth of cut and feed per revolution are selected as process parameters. The effect of each parameter on tool wear, surface roughness, circularity, MRR and cutting forces were investigated. The results were used to select process parameters through multi-objective optimization. The limitation of the work is that it is very focused in a very specific machining process.

In the presented work, a multi-objective genetic algorithm was used to solve multi-objective optimization problem by identifying the Pareto front (Pareto surface) that is the set of evenly distributed or non-dominated optimal solutions. For this first approach, it was implemented in Matlab. In this work, details about the genetic algorithm and the range of values for the input parameters and the objective values are available.

III. Optimization and Parallelization

For the definition of a multi-objective optimization problem, it is necessary to solve the problem of finding a vector of decision variables that satisfies constraints and optimizes a vector function that represent the objective function. Those objective functions form a mathematical description of the desired performance criteria. Usually, these performance criteria are in conflict with each other.

When the term optimize is used, it means that we are going to find a solution for the decision variables that returns values for the objective function that are acceptable to the decision maker.

A multi-objective optimization (MOO) is the optimization of conflicting objectives. A MOO problem with constraints will have many solutions in the feasible region. If we compare two solutions, A & B, we cannot say that either is superior without knowing the relative importance of the objectives functions for each solution. As an output of the optimization process, we are going to find a bunch of solutions, the ones that give good compromises (or trade-off) instead a good solution (the global optimal value).

Genetic algorithm are well suited for multiobjective optimization because their basic feature is that the search is global and multidirectional, maintaining a population of potential solutions from generation to generation (very useful when exploring Pareto solutions). They can handle many types of objective functions and constraints and can work without knowing specific knowledge of the problem, but, at the same time, they provide flexibility to incorporate conventional methods into the main framework.

To define devices that regulate process parameters and to achieve certain performance, we need, at least, the next ingredients (as it was stated in [2]): parameters and definition of performance (productivity expression, constraints and weights).

The considered parameters could be the next ones:

- s the curvilinear abscissa,
- x(s) the state of the machine,
- u(s) the vector with command controls,
- f(s) axes acceleration,
- w(s) angular acceleration of the spindle

Regarding productivity, quality or efficiency, it could be measured according to the next terms:

- $F_{MRR}(u(s), x(s))$: instantaneous Material Removal Rate
- $F_w()$: tool wear
- $F_{en}(u(s), x(s))$: energy spent during the cut
- $F_{ra}((u(s), x(s)))$: roughness
- $F_{forced}(u(s))$: forced vibrations
- $F_{chatter}(u(s))$: chatter
- $F_{time}(u(s))$: time

For this work, only three of them have been used , MRR(liter/minute), Time(seconds) and Energy(KWh).

We can formulate the optimisation process as finding the u(s) that minimizes the weighted aggregation next. The i index refers to the current location and Z represents the point at the end of the path. The formula is shown in the equation 2.

$$
\begin{aligned}
&(Min_{u(s)} \int (u(s), x(s)) = \\
&w_i(\frac{f(s) - f_i}{f_{min}})^2 + \int_S^Z W_{MRR}F_{MRR}(u(s), x(s)) + \\
&+ W_{RA}F_{RA}(u(s), x(s)) + W_wF_w(u(s), x(s)) + \\
&+ W_{en}F_{en}(u(s), x(s)) + W_{forced}F_{forced}(u(s), x(s)) + \\
&+ W_{chatter}F_{chatter}(u(s), x(s))
\end{aligned}
\quad (2)
$$

We also need constraints to ensure the feasibility of the solutions. As an example, the angular acceleration of the spindle and/or axes acceleration must be within some upper and lower values.:

$$
\begin{aligned}
(x(s), u(s)) \in \{\} = w_{min} <= w(s) <= w_{max} \\
f_{min} <= f(s) <= f_{max};
\end{aligned}
\quad (3)
$$

The term $\in \{\}$ means that we are finding optimum input parameters based on some output parameters that have some constrains.

Weight associated to each productivity, quality and efficiency item:

- w_i : weight for the geometric error
- w_{MRR} : weight for MRR
- w_{RA} : weight for the roughtness
- w_{en} : weight for the energy spent during the cut
- w_{force} : weight for the forced vibrations
- $w_{chatter}$: weight for the chatter
- w_{time} : weight for the time

There are some elements to consider in this process: encoding methods, recombination operators, fitness assignment, selection and constraint handling.

One of the problems is how to determine fitness value of the individuals according to the multiple objectives. This could be some of the options: vector value optimization, weighted-sum approach, pareto-based approach (without preferences), compromise approach or goal programming approach. It would be possible also to refine the fitness function progressively.

From them, the most extensively used method is probably the method evaluation approach. In this method, having q objectives, the selection step in each generation will become a loop that is repeated q times where only one objective is used in each turn. At each repetition, a portion of the next generation is selected based on one of the objectives.

Pareto ranking is other alternative. In this case, we have to consider two major steps:

- sort the population based on Pareto ranking
- assign selection probabilities to the individuals according to the ranking

The ranking procedure assigns rank 1 to non-dominated individuals and removes them from the contention. Then it finds the individuals among the remaining ones, and gives them ranking 2.

Each element with the same value in the ranking will have the same probability of distribution at the time of being selected. Using the Pareto tournament method, a Pareto solution with the least number of individuals in its neighbour wins the competition. A compromise based fitness assignment method has been suggested where the solutions closest to the ideal solution are determined by some measure distance.

Goal programming is a rank based fitness assignment method used to assess the merit of each individual. Individuals are sorted on the value of objectives and then some positions are selected randomly. Individual fitness values are assigned randomly by interpolating from best to worst according to an exponential function(preemptive) or non-preemptive (all goals of comparable importance).

To handle infeasible solutions, which is important in real situations because it can affect to a large portion of the population, repairing (with Pareto ranking) and penalizing techniques (compromise or weighted-sum) can be used. To maintain the population diversity, fitness sharing can be used. This last technique determines the degradation of an individual's fitness due to crowding by its neighbour.

On the other hand, the general idea of the distance-based method is the concept of potential value. It is a scalar value assigned to each Pareto solution, which is different from the fitness value of a given Pareto solution. After each updating of a Pareto set, an identical value is assigned to all Pareto solutions so that each new solution can be assigned with a reasonable fitness value.

Existing Pareto solutions may have different potential values. For a newly generated solution, the distances to all existing Pareto solutions are calculated and among them, the minimum distance is used to calculate the fitness function for the new solution.

A newly generated solution may fall into any of the following three types:

- A Pareto solution dominates some other Pareto solutions (the fitness value is calculated as the sum of the potential value and the minimum distance and Pareto solutions updated removing dominated solutions and adding the new solution to the set. The potential value of the new solution equals its fitness value)
- A Pareto does not dominate any existing Pareto solution (the fitness value of the new solution is calculated as the sum of the potential value of its nearest Pareto solution and the minimum distance. The solution is added to the existing set of Pareto solutions with the potential value equal to its fitness value).
- A solution dominated by at least on existing Pareto solution (the fitness value of the new solutions calculated by subtracting the minimum

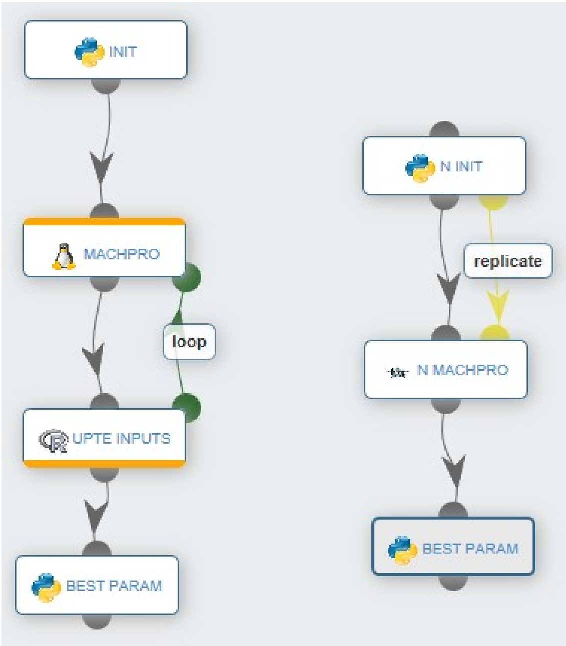

Fig. 1. (left) An iterative approach for the optimization process. (right) A parallel approach for the optimization process.

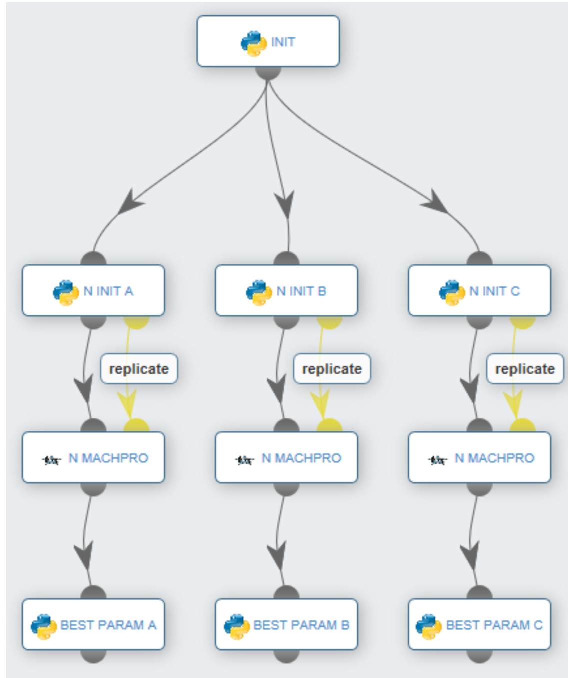

Fig. 2. A parallel approach for the multi-parameter optimization process.

distance from the potential value of its nearest Pareto solution).

Regarding HPC methods, ProActive Workflows and Scheduling is a workflow system that allows writing complex sequence of tasks (R, java, multi nodes MPI task, ...). The scheduler is used to distribute the workloads over computing nodes to boost the execution performance. This latter communicates with ProActive nodes, offering a dynamic workload scheduling among hybrid and distributed infrastructures, whatever the cluster/cloud.

The workflow engine will be enriched with functionalities to cover the full optimization process, and some of them will be reinforced. Workflow parametrization is the basic concept that mostly contributes to the workflows dynamicity. It is now possible to define task variables and to inherit from job variables. Furthermore, the solution takes care of the file transfer between the scheduler and the nodes. This is needed when tasks requires input files, or when generated output files must be gathered into a dedicated tasks shared folder. In a big data point of view, node selection can be dynamically controlled at the task level, for data locality optimization. Figure 1 shows workflow differences between iterative and parallel approaches and figure 2 shows the workflow for multiparameter optimization approaches.

IV. Use cases details

The research group defined a initial scenario to validate that using the techniques and tools presented in the previous section in the manufacturing scenario improves the energy consumption and efficiency. These are the characteristics of the selected scenario:

- A very simple milling task was selected.
- A minimum and maximum range of values was defined for one parameter, setting the other ones constant. An increment on the value of this parameter was set, so we knew the number of values to explore.
- Select some of the terms of the objective function.
- Check all the possible values of the objective function and check that the search was correct.
- Increment the number of values to explore.
- MACHpro simulation tool performed the simulations and gave us information about the performance of the milling process.
- The time used to get the solution from the optimizer was compared.

As a starting point, we changed only 2 parameter: the value of the Feed Rate (mm/min) +/- 50% of the nominal value (300mm/min) and the Spindle Speed +/- 50% of the nominal value (900 rpm).

In the output, we looked only at three values: the Energy consumed (KWh) , the duration of the process(Time in seconds) and the MRR(lt/min).

The figure 3 shows the schema of the use case:

These are the expected outputs from the described scenario: If the feedrate (mm/min) goes up:

- the machining time goes down
- the torque max of the head (Nm) goes up
- the MRR (liter/minute) goes up

What was expected for preliminary trials was that if feed rate(FR) (mm/min) was higher, the machining time was faster (less time) but the energy consumed in Kwh and the MRR (mm3/s) were bigger. We checked this for a very simple milling task and

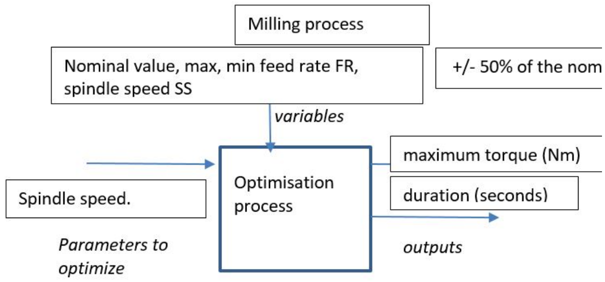

Fig. 3. Description of the Optimisation process of the Use Case

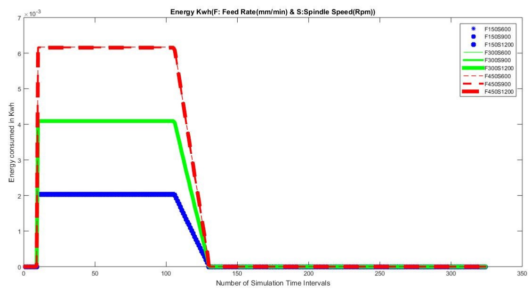

Fig. 4. Energy consumed: Kwh goes up if the Feed rate goes up

in the next section we will see the obtained results.

V. Results

In the figures 4, 5 and 6, we can see how were the parameters of the Energy consumption, Feed Rate and MRR and their relations.

Once we analysed the results, we selected another milling task(conditions in figure 7). The results after simulating 28 different input parameter combinations(SS= Spindle Speed(1040,1200,400,560,720,880) rpm, FR=Feed Rate(1100,1300,500,700,900)mm/min) we can observe the results plotted in a three dimensional space in figure 8.

The figures 9 and 10 show the results for the energy consumption related to MRR and energy consumption related to Time for the checked pair values of spindle speed and feed rate.

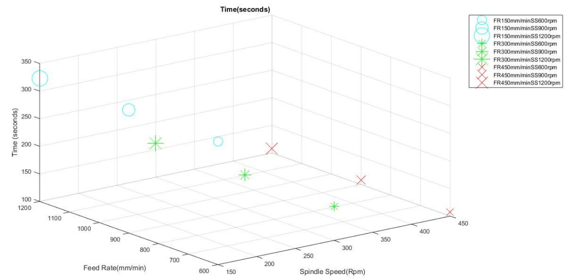

Fig. 6. As the Feed rate goes up, the machining Time goes down.

Machine limits:	Cutting condition limits:
Spindle Speed max: 6000 rpm Axis velocity max: 30 m/min Max spindle power: 50 kW	Max cutting speed: 400 m/min Min cutting speed: 80m/min Min feed per tooth: 0.05 mm/z Max feed per tooth: 0.3 mm/z
Toolpath: Maximum depth cut: 6mm	

Fig. 7. Use case milling conditions.

The worst case between the considered ones in terms of energy consumption is SS400 FR 300 (time in seconds=1171 ;MRR in Lt/min=1904 and energy in KWh =0.2250). The best of the analyzed combinations was(SS 1200, FR=500 (Time=3017, Mrr=732, Energy=0.1860).

VI. Conclusions and Future Lines

The preliminary results that the research group obtained have been analized and the manufacturer experts have confirmed that the results are the expected ones. We needed this first confirmation, based on a simple use case in order to go through the next steps and confirm that the tools and the algorithms we are using are the correct ones.

In the next steps, new and more complicated scenarios will be selected and also an User Interface and Proactive tool will be linked.

MC-SUITE project has other related modules (MC-VIRTUAL, MC-BRIDGE, MC- ANALYTICS and more) and this MC-OPTIM module will be linked with the others in order to offer a solution for the European manufacturing industry.

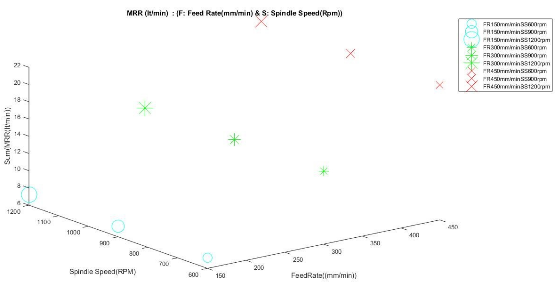

Fig. 5. Variability of MRR on the two variables: Feed rate and Spindle speed. When Feed rate increases, MRR increases significantly. When Spindle Speed increases, MRR has not significant changes.

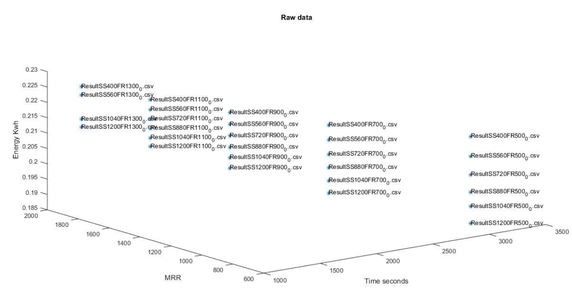

Fig. 8. Results of the use case milling tasks displayed in a three dimensional space according to values of Time, MRR and Energy consumption. When Feed rate increases then energy consumption increases but the process goes faster (time decreased).

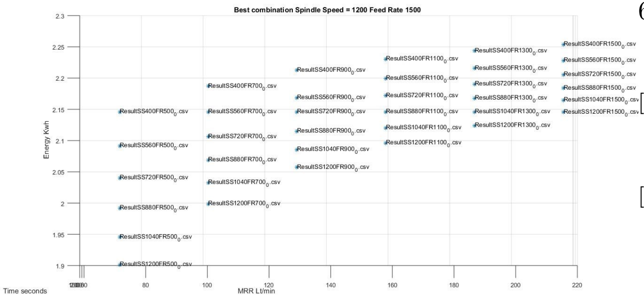

Fig. 9. Energy consumption related to MRR, every point labeled with the pair of values for the input parameters(SS=spindle speed; FR=feed rate)used to run the simulations. When MRR increases, energy consumption also increases.

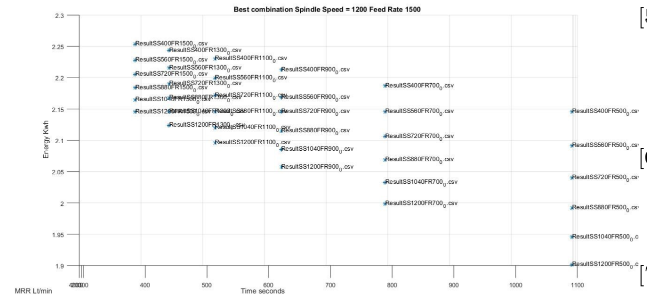

Fig. 10. Energy consumption related to Time, every point labeled with the pair of values for the input parameters(SS=spindle speed; FR=feed rate)used to run the simulations.

A. Future Lines

Once the first step of the development is finished and based on the simulation results and using the generated historical data, these are the planned next steps:

- to develop real machining processes experiments in same conditions as the simulated ones
- to verify and validate the Optimizer, using for that some results coming from the real machining processes.

For the real processes, same geometries and some of the input conditions previously used for the optimization process will be used. To check if the real process outputs and the optimization process outputs are correlated, some combinations of the input parameters giving good, bad and medium estimations for all or some of the objectives functions will be selected.

Laboratory measurements will be necessary in order to obtain some of the objective functions real values.

Acknowledgements

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