DYNAMIC FE MODEL UPDATING USING PARTICLE SWARM OPTIMISATION METHOD: A METHODOLOGY TO DESIGN CRITICAL MECHANICAL COMPOSITE STRUCTURES

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Abstract:

To increase the performance of an industrial cutting machine, this work studied the possibility of replacing its current main steel gantry by a Carbon Fibre Reinforced Polymer (CFRP) composite solution. This component strongly influences the most relevant characteristics of the equipment, namely accuracy and maxima allowed accelerations.

The flexibility of composites in terms of number, thickness and orientation of layers and the challenging trade-offs between weight and stiffness motivated the development of an optimisation process. The Particle Swarm Optimisation method (PSO) was used to develop a solution able to ensure higher accelerations and the required accuracy of the equipment, by optimizing continuously the FE model algorithm input and output assessment and updating it. The process resulted in a near optimal solution allowing a 43% weight reduction and an increase of the maximum allowed acceleration in 25%, while ensuring the same accuracy.

Keywords: Optimisation process; Particle Swarm Optimisation; Composites; Fibre-reinforced polymers, Laser cutting

1. Introduction

The ever-growing trend of global consumption leads to the continuous increase of products produced to meet human needs and desires. The current situation is characterized by a mix of huge product portfolios, reduced lead-time, and increased quality standards and competitive costs, which leads to the need to the immediately development of faster cutting systems able to overcome these roadblocks. Such high demands of consumption led almost whole currently market to choose to use just only plasma, laser and waterjet cutting machinery using computer numerical control (CNC) or programmable logic control (PLC). In between these processes, laser-cutting is the latest among the sheet and plate metal-cutting technologies and one of the most widely used thermal energy based non-contact type advanced machining method [1, 2].

The combination of low density, high stiffness, strength, toughness, design flexibility, corrosion resistance and faster assembly have led to a continuous growth on the application of Polymer Matrix Composites (PMCs) in the past 50 years. Nowadays, CFRPs and other composite materials, which were early just predominantly used in high advanced applications and prototypes, are rising their number of applications among most common industrial markets [3].

  doi:10.5075/epfl-298799_978-2-9701614-0-0

CFRP lightweight structures improve the basic functions of a machine tooling: the manufacture of a workpiece having the required geometric form, acceptable surface finish and imperative accuracy at the highest feasible production-rate and lowest possible cost [4]. Achieving maximum positioning accuracy is only feasible if machine moving parts present high stiffness and low mass. One main reason for reducing productivity is the large mass of the moving parts of machine tools, which cannot afford high accelerations and decelerations during working operations and simultaneously maintaining the same accuracy [5]. Thus, the importance of structural optimisation and lightweight design is evident [6]. Also, it leads to energy efficiency, reduces the environmental impact, cost, and increases the performance of structures [7].

Analysing the mechanical behaviour of fibre-reinforced laminates and composite structures presents huge modelling challenges. As they are not homogeneous and isotropic, anisotropic laminated composite structures present unique phenomena at different geometric scales: the global (or laminate), the ply and the fibre-matrix levels. Hence, the global deformation of composite laminate structures is often characterised by complex couplings between extension, bending, and shearing modes. Due to the study complexity, Finite Elements Analysis (FEA) is a common methodology used in the analysis of composite structures mechanical behaviour.

As many variables can be manipulated in composite structures, they also need to be evaluated to determine the best design configuration [8]. Therefore, an optimisation process becomes of great value and complexity when such a high number of variables are involved. For problems with hard and complex numerical procedures for objective function evaluation, the optimisation by derivative calculation might be deemed as undesirable because computer simulations usually do not return derivative information [9].

Metaheuristic algorithms offer an alternative by using combination of heuristics, making the method a more general framework and not problem-specific [10, 11]. This type of techniques includes both simple (such as local search procedures) and complex processes (ranging up to sophisticated learning processes) [11]. Amongst them, Swarm algorithms demonstrated to present better results in problems presenting larger design vectors or a larger number of local optima, reaching global optima with less evaluations and requiring less computational resources [12, 13].

The machine studied in the present work is a 2-dimensional $C0_2$ Industrial laser cutting machine, having 2-axis flying optics powered by linear motors, produced by the manufacturer Adira. The Finite Element Analysis (FEA) was used to simulate the effect of the machine operation on its structure. A formal optimisation process is implemented, resorting to a population-based optimisation algorithm having the objective function (focused on the acceleration and part stiffness) evaluated through FEA. The result of the optimisation process is to obtain a composite gantry able to ensure the same level of accuracy at an acceleration 25% higher and having less 43% weight than the current conventional metallic one.

2. Methods

2.1 Part Geometry

The simulated gantry geometry is displayed in Figure 1. The domain of the simulation comprises two parts: the CFRP beam (in grey) and the metallic mask along which the laser cutting head moves (in green).

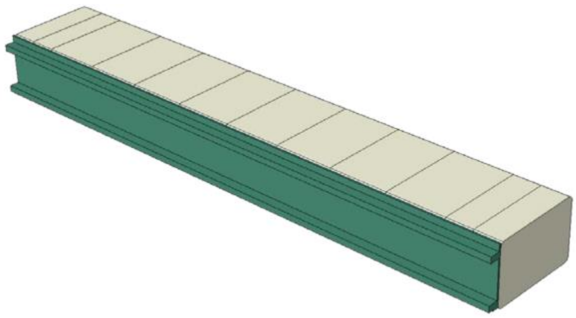

Figure 1 . Part geometry used for thickness optimisation

As the external shell and ribs were represented in a single part and the connection between them considered rigid. These simplifications, adopted to keep the model simple and lighter, means that details such as tabs from ribs and external shell connections (by adhesion and/or other process) and other production process features coming were not considered. The metallic and composite parts were also considered linked by a rigid connection. This simplification means that load will be transmitted throughout all contact surface and that is not possible splitting the two components.

The composite gantry is 2385 mm long and has a cross section of 382.5 mm x 246 mm. The outer ribs (3 on each end) were spaced by 110 mm and the middle ones by 243 mm. These ribs are responsible for ensuring that the loads are effectively distributed to the entire beam section. The metallic mask has overall thickness of 7 mm and the rails considered to have the same configuration and positioning as in the original metallic part.

2.2 Finite Elements Model

When the gantry suffers acceleration (as it is moved towards the cutting spot), it becomes subjected to forces and suffers deformations, which have implications in the precision of the optical path components attached to the gantry. As these components suffer displacements in the 6 degrees of freedom, the precision of the machine and the point of incidence differs from the desired one. The deviations from the target must be minimum, as to ensure a precise cut. In the study, the analysis considered as mostly critical case in term of accuracy loss, the laser head localised at the centre of the gantry when the maximum acceleration was applied to it.

The numerical model emulates the working conditions while not considering geometrically represented the surrounding components. Instead, they were replaced by all their weight located in a point localised in each centre of gravity. All loads applied to those components were also considered localised in the previously mentioned centres of gravity. The connection between the centres of gravity of components and gantry were replaced by kinematic coupling.

Table 1 summarises the properties considered for laminates, which were used in the thickness optimisation process.

Table 1. Properties of the laminate layers

Fabric Type	Property					
	E1 (MPa)	E2 (MPa)	v1	G12 (MPa)	G13 (MPa)	G23 (MPa)
Unidirectional 0º	134	7	0.1	4.2	4.2	3.85
Plainweave ±45º	15	15	0.1	34.5	34.5	3.85

  doi:10.5075/epfl-298799_978-2-9701614-0-0

The properties described above were the basis of the definition of the sections to all composite components. Because the gantry was represented by shell elements (which have no graphic representation of thickness), different properties can be given to different regions, resorting to the thickness and section definitions. Such method has a huge advantage for the optimisation process as a geometry does not have to be defined each time a different configuration needs to be considered. The geometric part is kept the same when its section is changed before each utility function evaluation. The layup definition requires the definition of mechanical properties of each layer (resorting in those listed in Table 1), the number and order of plies, their thickness and orientation and how the layup is placed relative to the surface defined by the shell elements.

2.3 Optimisation

The optimisation has aimed therefore to determine the optimal layup of CFRP at each section of the gantry, which was considered produced by vacuum infusion. Therefore, the number of layers with a given fibre orientation can vary from section to section. The layers were considered to have fibres orientated just at 0º (along the beam's axis) and ±45º. Layers with fibres at 90º were also considered, mainly due to local loadings. A total of six sections was considered, as displayed in *Figure 2*.

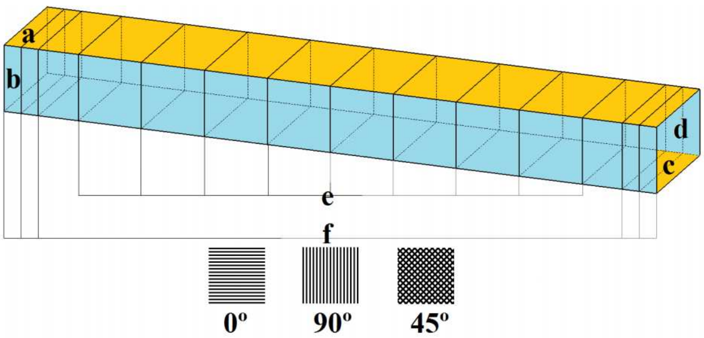

Figure 2. Different sections to be optimised, resulting in different variables

The sections considered are: the top horizontal face (a), the frontal vertical face on which the rails are applied (b), the bottom face (c), the back opposite vertical face (d)), one for the central ribs positioned throughout the gantry (e) and one for the ribs in the extremity (f). As result, a total of 18 variables were created, each denominated by a letter corresponding to the region and by the fibre orientation, for example e45 relates to the thickness of the ±45º fibres in the internal ribs of the gantry. These account for most of the considered variables, having being added one more variable to account the maximum acceleration. This variable was introduced to evaluate the objective function as the loads applied to the centres of gravity of the surrounding objects were calculated based on the value assumed by the acceleration in each run.

The optimisation loop consists of a PSO algorithm that resorts to FEM to evaluate the objective function. The selected algorithm was PSwarm, a Pattern Search and Particle Swarm hybrid algorithm. PSwarm is a derivative free, optimisation algorithm and, therefore, suitable for working with FEA as a method to evaluate the objective function. It aims at the minimization of a function with variables restricted to upper and lower bounds. Being PSwarm a hybrid algorithm, it has the ability of initiating a poll step resorting to pattern search, to determine the direction that the population should follow based on the best element from the previous search (particle swarm) step [14, 15].

2.4 Constraints

To ensure that the machine's behaviour is analogous to the performance with the metallic gantry, this component was firstly analysed by using a FEA similar to the one used for the composite gantry. The displacement suffered by a critical component carrying the optical system (cutting head) resulting of this analysis will serve as a maximum limit for dimensioning the composite part, thus ensuring the current accuracy is respected.

Also, if the acceleration imprinted to a given configuration exceeds the maximum force the linear motors are capable of exerting, the solution parametrized by those 19 variables is deemed not viable. In this case, and since PSwarm is a minimisation algorithm, a high value of the objective function is returned, as a penalty is imposed to the solutions that violate the rigidity or acceleration constraints. Regarding the thickness variables, each is constrained to a maximum thickness of 12 mm and a minimum of 0 mm, allowing the inexistence of a given type of orientation in each section. However, any section must have, at least 0.01mm.

2.5 Objective function

Given that the goal is to maximise the acceleration and PSwarm is a minimisation algorithm, the value to be evaluated is the symmetric of the acceleration (-a). With this in mind, and to input the penalties for breaching the maximum mass possible for a desired acceleration or the rigidity constrains, the objective function is represented by the following equation:

$$f = \begin{cases} -a & if\ dof_i \leq dof_{i_{max}}, i \in [1,6]\ and\ m \leq m_{max}(a) \\ 1E+20 & if\ dof_i > dof_{i_{max}}, i \in [1,6]\ or\ m > m_{max}(a) \end{cases} \tag{1}$$

where, f is the objective function, *a* is the acceleration, dof_i is translation or rotation in any of the six degrees of freedom of the centre of mass of the cutting head for the composite part, $dof_{i_{max}}$ is translation or rotation in any of the six degrees of freedom of the center of mass of the cutting head for the metallic part, *m* is the mass of the composite gantry and m_{max} is the maximum mass the linear motor can apply the defined acceleration to.

Based on the knowledge from previous optimisation processes, the population size was set to 40 elements. Each evaluation corresponds to changing the 19 variables, inputting those changes in the FEA, performing the simulation for each of the population elements, and extracting the relevant outputs. Each run requires a maximum of 2000 evaluations to ensure convergence to a near optimal value.

3. Results and discussion

The output of the optimisation process is presented in the form of the plot shown in Figure 3. As can be seen, the initial configuration presents an acceleration of 2.3 G, as the one provided as best guess. As the optimisation process evolved, the system tended to present best solutions with higher maximum accelerations, meaning the algorithm is able to extract values from the simulations run and generate new configurations based on the population elements that present better results. One can see that the search step, performed resorting to the swarm population, results in discontinuous improvements in the results. However, it then has difficulties in converging to higher accelerations, as happens, for example, after iteration ten. When this is verified, the algorithm creates a poll step that, starting from the best value obtained, tries to find the direction that will be more prone to lead to better results. With the first objective function, the maximum acceleration achieved is just below 2.45 G, which is already an improvement regarding the current machine's performance.

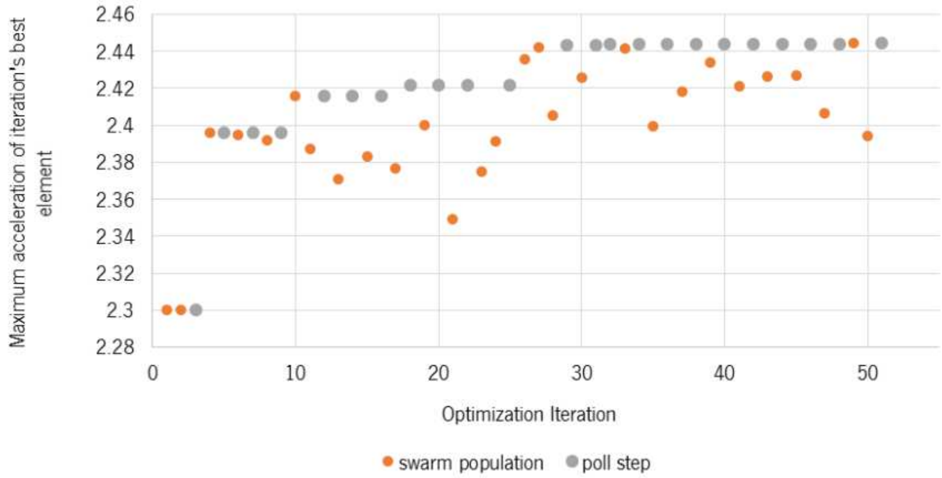

Figure 3. Results of initial optimisation process

Nevertheless, it was deemed as interesting to test new objective functions as to understand if other performance indicators are also introduced in the objective function. Another reason as why this could be interesting was the fact that the best element for each optimisation process was not suffering a steady decrease, as initially expected. The mass of the best element of each iteration is plotted in *Figure 4*.

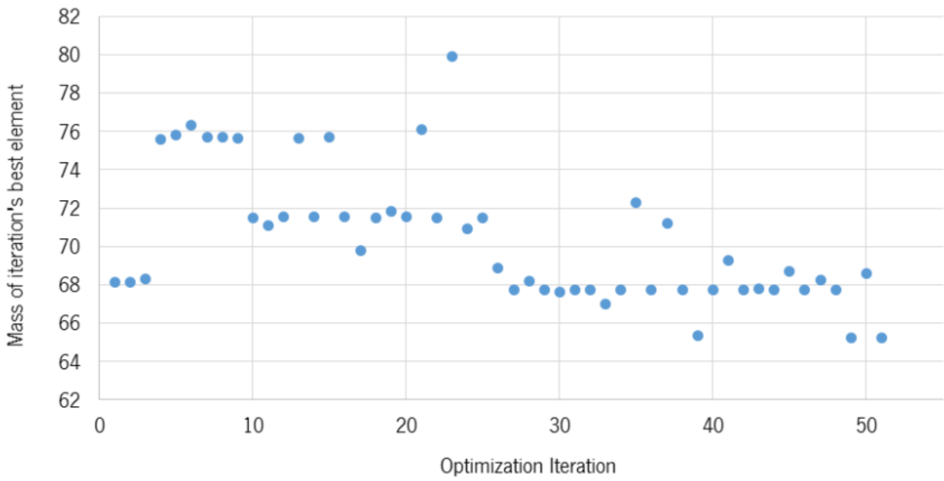

Figure 4. Mass of the best elements of each iteration as optimisation process evolves

At this stage, the hypothesis that the inclusion of the system's mass in the objective function would lead to better optimisation results was formulated. This comes from the fact that including mass in the objective function will increase the tendency of lower mass solutions being selected. On the other hand, lower mass solutions can be subjected to higher acceleration without compromising the limitations imposed by the force required from the linear motors. To test this, the objective function was formulated to force the algorithm to consider not only the acceleration, but also the mass of each configuration tested. Because PSwarm is a single objective optimisation algorithm, both objectives must be combined in a single one. To do this, each of the objectives (acceleration and mass) were multiplied by a factor that will represent the relative importance of each factor. The new objective function is expressed in the following equation:

$$f = \begin{cases} -a \times \alpha + m \times \beta \; if \; dof_i \leq dof_{i_{max}}, i \in [1,6] \; and \; m \leq m_{max}(a) \\ 1E+20 \qquad if \; dof_i > dof_{i_{max}}, i \in [1,6] \; or \; m > m_{max}(a) \end{cases} \quad (2)$$

where α is the factor attributed to the acceleration and β is the factor attributed to *m*, the mass of the gantry. The ratio between α and β dictate the relative importance of each of the two system properties considered.

The best results were obtained for α=1 and β=0.1. The results obtained are shown in *Figure 5*.

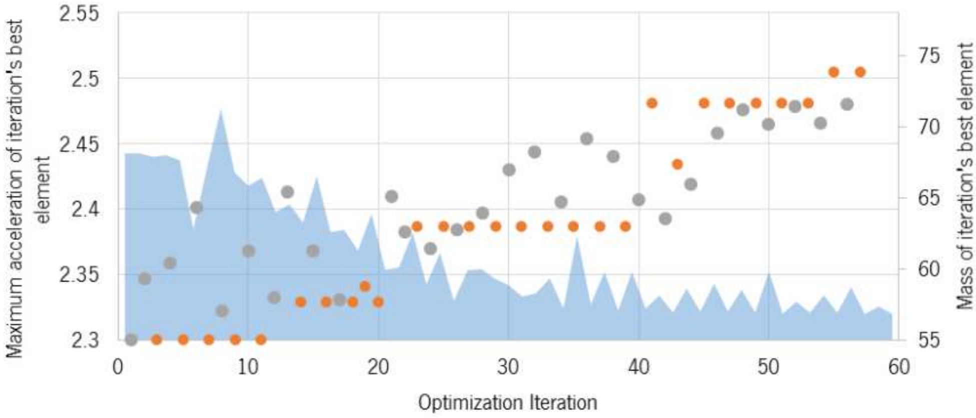

Figure 5. Acceleration and mass evolution for an α = 1 and a β = 0.1

As may be seen, not only the mass decreased faster, the maximum acceleration reached is also above 2.5 G. Overall, the optimisation seemed to converge in a smoother manner and reach better acceleration results. Thus, it was possible to achieve CFRP gantry dimensioned using optimisation resulting in a part that presents 43% lower mass than the current metallic part and allowing for a maximum acceleration increase of 25% without accuracy loss or the need to reconfigure the linear motors that are responsible for moving the gantry.

4. Conclusions

The optimisation process implemented allows to develop a laser cutting machine capable of withstand a higher acceleration with minimal impact on the structure and present the same cutting accuracy level. The optimisation loop implemented consisted in (I) a population-based derivative-free metaheuristic optimisation algorithm, and (II) an objective function evaluation based in FEA. The objective function addressed the deformation of the system and the variation in the 6 degrees of freedom of the laser cutting head, which were critical to assess the accuracy of the machine. The variables considered were related to the thickness of different fibre orientations in different areas of the part and to the maximum acceleration. From the first trials of the new method implemented it was possible to get to a viable near-optimal solution that presents capability for being subjected to higher accelerations while reducing the mass. There was a clear tendency in the algorithm output to increase the acceleration within allowed values. However, the mass variation did not present such a clear trend. The strategy to overcome this was introducing the mass as part of the objective function. Because the optimisation algorithm is single objective, the relative relevance between accuracy and mass had to be defined. Among the several ratios tested, the one with better results lead to the selection of a configuration capable of sustaining an allowed maximum acceleration 25% higher than the current one without loss of accuracy. Regarding mass, the gantry dimensioned by the optimisation process presented 43% lower weight than the current metallic part.

5. Acknowledgements

This work has been supported by FCT – Fundação para a Ciência e Tecnologia within the R&D Units Project Scope: UIDB/00319/2020 and the scholarship SFRH / BD / 51106 / 2010.

6. References

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