



A CAD-based method for multi-objectives optimization of mechanical products

Vincenzo Castorani , Alessio Vita , Marco Mandolini  and Michele Germani 

Università Politecnica delle Marche

ABSTRACT

This paper presents an approach for the product multi-objective optimization by associating the Response Surface Methodology (RSM) and the Design of Experiments (DoE) technique with the CAD/CAE/DfC integration. The goal of this study is to empirically identify the relationships existing between the design features and the product response (stress, strain, cost, etc.). This approach integrates three different levels of analysis: optimization problem definition, virtual prototyping and design optimization. The optimization problem definition concerns in choosing the design variables, setting constraints that have to be observed and goals that have to be achieved. The virtual analysis allows defining the principal parameterization of a geometric model and simulating the performance of each configuration, at a specific working condition, while evaluating the manufacturing cost and time. The proposed approach investigates the effect of the defined parameters and noise factor on the experimental results. In particular, the applied method is based on virtual experiments according to the necessity to reduce time and costs in the early design phase. The loop of design-analysis-redesign during the optimization process is done automatically, without any interaction with the designer, by using a dedicated software tool. A test case is presented to show the characteristics of the methodology and to demonstrate its feasibility. Results demonstrate that the proposed approach significantly expedites the optimization process and reduces the computing cost compared to traditional approaches.

KEYWORDS

Design for cost; CAD parameterization; multi-objective optimization

1. Introduction

Complex dynamics of global markets force companies to adopt new ways in order to increase competitiveness. The multidisciplinary approach has proven to be crucial in developing more competitive and successful products. The designer simultaneously is obliged to consider multiple perspectives in order to determine the optimal solution when tackling extremely complex issues. Engineers are required to achieve the right compromise in terms of product features to optimize the product performance, manufacturing cost and manufacturing lead-time.

This optimization process is often manual [15] and does not allow a comprehensive understanding of what the main problem is, leading to the choice of solutions that are potentially suboptimal. Furthermore, objective functions often cannot be expressed through the use of simple algebraic relations which require the use of specific software for their evaluation. Moreover, a step-by-step approach to identify the right combination of design criteria is a time and cost consuming process. Therefore, the automation of the optimization process, based on the integration of CAD, CAE and Design for Cost (DfC) software, is essential to increase the product quality and

to facilitate and accelerate the identification of the best configuration.

The most used CAD-CAE-DfC tools available on the market are stand-alone systems, which need a relevant user interaction to achieve an actual integrated use [12,13,17]. Additionally, even if integrated software exist (such as SolidWorks), designers tend to use CAD tools for product modeling and other commercial CAE and DfC tools for specific analysis [14].

CAE software tools with optimization modules capable to work with parameterized CAD models, are widespread. Through these modules, it is possible to set constraints that have to be respected and goals that have to be achieved in order to automatically identify the best configuration. However, no economic optimization is taken into account.

Today the need to acquire information about product manufacturing time and cost in a quick and accurate manner has lead to the development of DfC software (Design for Cost). DfC tools, due to internal algorithms, are able to determine machining cycles and machine tools required to produce a part respecting prescribed roughness and tolerance. Also, assembly features, such

as weldings and couplings, can be automatically recognized by analyzing 3D assembly models. However, none of these software programs contain features for a multi-objective optimization process, and designers are forced to manually evaluate the alternative design solutions.

In literature, it is possible to find numerous methodologies for the design and optimization of products. In summary, it is required an efficient multi-objective optimization algorithm to search for optimal solutions instead of using simulation approaches that evaluate the performance of a limited number of configurations. Nonetheless, in general, the focus of these methodologies is the product performance without any consideration about manufacturing time and cost.

The multi-objective optimization is a consuming process from a computational point of view due to the complexity of the FEA codes and the cost assignment process [18]. The general approach used to reduce the computational cost consists in making a limited number of simulations based on the Design Of Experiments (DoE) technique [1,2,7,8]. The simulation results are used to realize an approximated model of system response through the Response Surface Methodology (RSM) [3]. The approximated model is called “surrogate model” or “metamodel” and can be generated using different methods [16]. From the surrogate model it is possible to analyze thousands of configurations that identify, with the support of appropriate optimization algorithms, the optimal one. With optimum configuration we refer to the procedure that reaches the right compromise between objectives, that can also be conflicting, and that does not violate the fixed

constraints. For instance, sometimes, the values assigned to geometric features to optimize the stress, cannot guarantee, at the same time, also the minimum manufacturing cost value.

In this context, this paper aims to develop a methodology that allows, through the effective integration of different design and simulation tools, the product multi-objective optimization considering also manufacturing time and cost. The CAD system is the main actor of this process since it is able to interconnect both the CAE software and the DfC software for the specific analysis. Moreover, thanks to the possibility of parameterizing the geometric model, it is possible to use an optimization tool that enables to vary design criteria in an automated way, allowing the analysis of numerous configurations and the identification of the optimal one, without any interaction with designers.

The integration among the systems used during the design stage, is the key and innovative element that makes applicable the approach within an industrial context. Such integration allows designers spending less time in optimization while the enterprise increasing the cost savings for their products.

2. Methodology

This paper presents a methodology (shown in Fig. 1.) to support the engineers in determining the design parameters, which guarantee the best product performance, while minimizing manufacturing cost and time. This approach, combining opposing objectives and considering constraints defined by the designer, allows coping

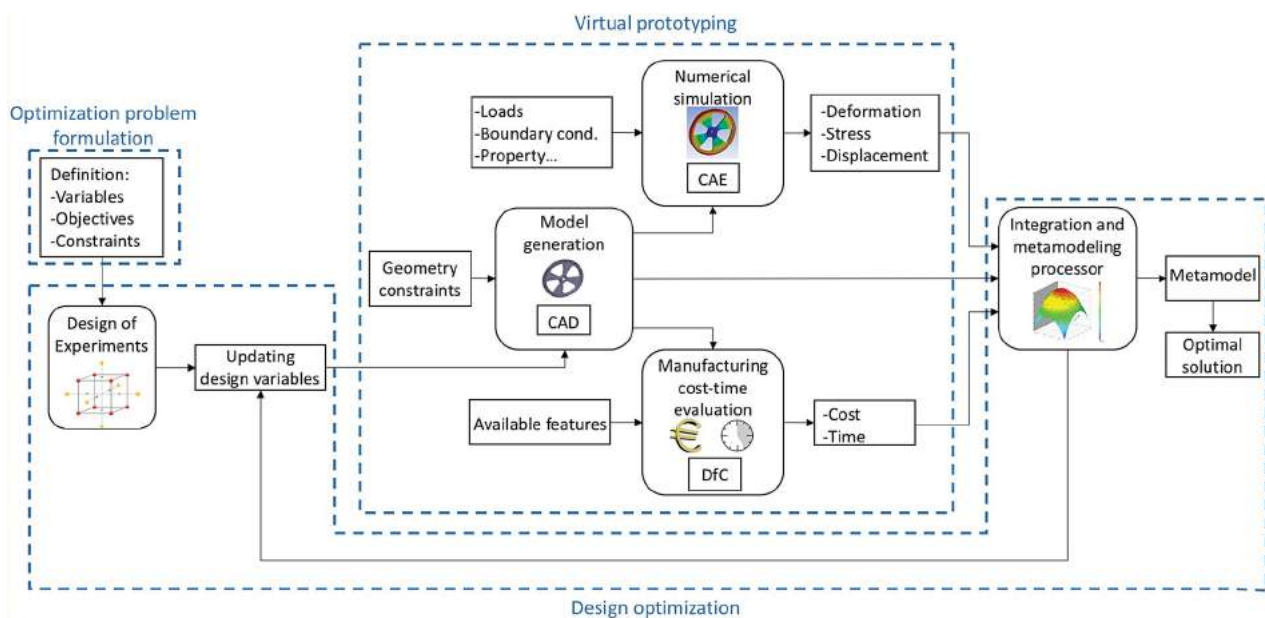


Figure 1. CAD based method for multi-objectives optimization.

with the complexities faced during the process of multi-objective optimization, taking into account multidisciplinary problems.

The proposed methodology integrates three different levels of analysis: optimization problem formulation, virtual prototyping and design optimization.

The first step of this methodology consists in formulating the optimization problem by specifying the objectives, constraints and design variables. The objectives, constraints and design variables can be many and they depend by the cases where the methodology is applied. In addition, it may be necessary to give more relevance to the achievement of certain objectives rather than others ones. It is therefore essential to assign a weight for each objective to achieve, enabling to focus the attention on those ones most important for the designers.

The virtual prototyping level employs modeling and numerical simulation techniques to develop a digital model of the product, containing as many product and process information as possible, in order to allow performance, economic, aesthetic and, if necessary, ergonomic evaluation.

In this level, three classes of software tools must be used and integrated among them:

1. CAD system for three-dimensional geometric modeling;
2. Product simulation system (CAE);
3. System for the manufacturing costs and times evaluation (DfC).

The first step of this level consists in the CAD model generation with the geometrical and non-geometrical parameterization according to chosen design variables. In this phase engineers define also the product characteristics necessary to the next analysis: materials, roughness, tolerances etc. The subsequent step consists, through CAE and DfC tools, in the product performance and manufacturing cost and time evaluation.

The Design Optimization level guides the analysis of simulations by identifying a certain number of parameters which influence system response. Through the construction of the response surface, it is possible to analyze the behavior and manufacturing cost and time of the product in all operating conditions. The DoE method provides the experiment plan definition related to the parameters chosen in virtual modeling. The engineer can use his know-how to set the parameter range and to evaluate the most suitable configuration. According to DoE approach, a reduced number of experiments is required to elaborate the final best condition. Each test includes a combination of the set of values in order to investigate the influence of every parameter. At the end of this level

the model optimal configuration is found. To support this phase, on the market are available software that allow the product multi-objective optimization.

This approach fully exploits the ability to configure the CAD model in order to allow its integration with other software tools. The optimization software defines the DOE, manages all the connection between CAD-CAE-DfC software and allows to fully automate the process. Furthermore, it allows to analyze the results in order to choose the best solution through different methods.

2.1. Optimization problem formulation

The formulation of the optimization problem is a key level of the presented methodology and it is complementary to the design optimization level. Indeed, an inadequate formulation typically leads to wrong conclusions. It is necessary to define the optimization problem reflecting the situation being studied, with a reasonable resources consumption. In defining the optimization problem, designers must choose the variables to investigate, the objectives to achieve and the constraints to satisfy. The variables to optimize may be many and various: size, geometry, material, tolerance etc. The number of these variables can be very high, and therefore, the designers have the task to reduce this number in order to have a good compromise between accuracy and speed.

Usually, there is not only one possible goal but engineers have to choose from a variety of different goals. An important aspect of problem definition is to select the relevant objectives and, if necessary, to assign them with an importance rate. The more decision alternatives designers have to consider, the more difficult it is to choose a proper alternative. Constraints specify the restrictions and interactions that limit variable values, CAE simulation and manufacturing time and cost.

2.2. Virtual prototyping

2.2.1. Model generation

The first step of the virtual prototyping level is the CAD model generation and parameterization. The modern CAD software allow to easily specify the geometrical features that can be set as parameters. Additionally, for a complete characterization of a product, further non-geometric parameters such as material, tolerance, roughness etc. have to be assigned to the 3D CAD model. Since these parameters are saved only within the CAD proprietary format, in order to avoid loss of data importing CAD models by other software, native formats should be used.

The complexity of the CAD model geometry is proportional to the amount of computational resources needed to perform the numerical simulation; in order to correctly use hardware resources, it is essential to simplify the components to be simulated removing all irrelevant details. However, a simplified model could lead to an inaccurate manufacturing cost and time estimation. Indeed, for example, if alternative values for a fillet radius can be an irrelevant detail for a structural analysis, it is not the same in terms of costs and time. Therefore, the model simplification must be carried out reducing the geometrical complexities that does not impact on the manufacturing processes.

2.2.2. Numerical simulation

Nowadays, numerical simulation and in particular Finite Element Analysis (FEA) is one of the most widely used tools during the design phase. It allows to deal with complex problems and to reduce/avoid the physical prototypes fabrication. Thanks to the creation of a digital model, it is possible to analyze the behavior of a real system and to identify its critical issues. Numerous are CAE software existing on the market that realize these types of analysis. The simulation process is made by three stages, which are independent of the specific commercial software tool:

1. the pre-processing where it is built the finite element model;
2. the processing with the resolution of the finite element problem;
3. the post-processing where the solution is processed and represented.

The pre-processing stage consists in choosing the type of analysis to be performed (static/dynamic/thermal, linear or nonlinear, time-dependent or not, etc.) and the type of finite element, in definition of the parameters that characterize the materials constituent behavior, in mesh generation and in application of the loading and boundary conditions. In this methodology, the pre-processing phase is only necessary the first time because after that, the optimization software automatically upgrade the geometry from the CAD file without the necessity to redefine loads, constraints and boundary conditions at each simulation.

At the end of the processing stage, the results are post-processed in order to verify the simulation reliability and analyze system behavior. Simulation results can be many and various. For example, FEM analysis to determine structural strength, CFD analysis to study heat exchange or electromagnetic analysis to examine mutual inductance.

2.2.3. Manufacturing cost and time evaluation

Manufacturing cost and time evaluation is carried out using DfC software tools [10]. The first step of cost analysis consists in importing the CAD model and the related not geometrical information, required to identify the right manufacturing process. The manufacturing process calculation is carried out through a topological analysis of all geometrical entities. The software generates an ordered set of advanced manufacturing features related to geometrical entities, such as dimensions, tolerances, roughness, etc. Then, the set of ordered advanced manufacturing features is converted in a set of operations, establishing the necessary processes to manufacture the component. This kind of tools interact with external customizable databases containing machine tools, materials and cutting parameters. At the end, DfC tool calculates manufacturing time and cost by using proper computation functions related to different processes.

The cost analysis is carried out considering geometrical and non-geometrical features. The first ones, such as the product overall dimensions and the dimensions of each advanced manufacturing feature, influence, for instance, the tool selection, machine size and kind of clamp. The second ones, such as the roughness, tolerance and batch quantity, which do not impact on the simulation, are required, for instance, to select the most convenient manufacturing process considering also the cost for initial set-up and investment costs. For example, a molding process is economically feasible only when the production batch is greater than a threshold.

2.3. Design optimization

In this paper, the Response Surface Methodology (RSM) [3] is used to carry out the design optimization. RSM consists of a group of statistical and mathematical techniques useful in the development, improvement and optimization of systems/processes/services. This method is widely used in industry, especially in situations where there are many input variables that potentially affect the measurements of the system characteristics [6]. The goal is to simultaneously optimize the levels of these variables in order to obtain the best performance. Input variables (or independent variables), the values of which can be controlled and set by the experimenter, are called factors. The response variable (or dependent variable) is the measured quantity, the value of which is affected by the levels factors changes.

The application of RSM takes concrete form by determining the approximate functional relationship between the input variables and the response of the system to be optimized. Typically, second order polynomials expressions are used.

The relationship between the response and the inputs is given by:

$$y = f(x_1, x_2, \dots, x_n) + \varepsilon \quad (2.1)$$

where y is the response, f is the unknown function of response, x_1, x_2, \dots, x_n denote the independent variables, n is the number of the independent variables and ε is the statistical error. Epsilon is generally assumed to have a normal distribution with mean zero and variance.

RSM consists of the following steps:

1. Choice of the factors of major effect on the system and delimitation of the experimental domain;
2. Design a set of experiments in order to have adequate and reliable measures of the interest response;
3. Determine the mathematical model that best interpolates data obtained from designed experiments;
4. Identify the optimum values for the input variables that lead to the maximum (or minimum) value of the response.

The Design of Experiments [2] is a statistical methodology to approach the design and organization of experiments that allows to get as much information as possible with the minimum amount of resources (i.e. with the smaller number of experiments).

Usually, the most immediate experimental procedure consists in performing one or more tests, for each value of the investigated independent variable, leaving unchanged all the other conditions: One Factor At a Time (OFAT) approach. OFAT method does not study contemporary the variations effects of two or more parameters. On the other hand, the DoE methodology is based on tests characterized by the simultaneous variation of more parameters [4].

The first step of the DoE is the choice of the factors, the number of the levels, the range of the variability intervals and the response variable. Then, the proper experimental design is defined and the experiment is realized. Finally,

the obtained data are statistically processed to generate the response surface.

There is a large amount of experimental designs in the literature. The Central Composite Design (CCD) method has been used in this work [11].

The response of a system may be affected by several factors and it is practically impossible to identify and study each minimum contribution. Additionally, more are the effects to consider and less accurate will be the experimental fitting of the obtained data. Therefore, to limit the usage of computational resources and to increase the accuracy of the analyses, it is necessary to choose those factors with the greatest impact on the response. In case of complex design, where it is not easy to know the cause-effect relationship between factors and response, a screening design should be carried out to find out those variables with the most significant effects.

In this paper, the Multi-Objective Genetic Algorithm (MOGA) [5] has been used to solve the multi-objective optimization. It is recognized as one of evolutionary algorithms with higher performance and, therefore, is one of the most used for multi-objective optimization. This algorithm, based on the Darwin's evolutionary theory, starting from a population of individuals that evolves from generation to generation, it performs a heuristic search that favors the areas of the search space where it is most probable to find optimal solutions.

3. Case study

In order to facilitate the understanding of the proposed approach, a case study will be presented and discussed. This method has been used to redesign a modular structure used for the rotation of the armchairs under the floor level (to hide it), with the goal to reduce manufacturing cost and time. An Italian leading company in the production of sofas and armchairs actively participated at the test of the proposed method.

The product is made up of commercial and machined parts, for a total of about 300 components (Fig. 2(a)). The

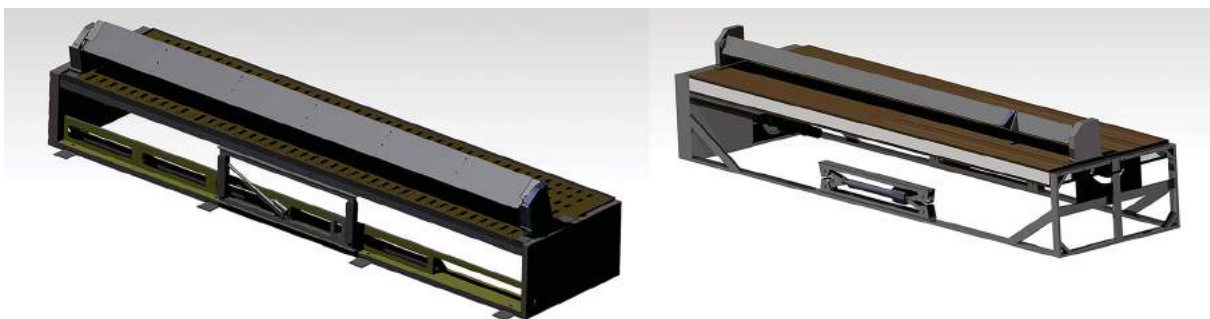


Figure 2. (a) Original product, (b) Redesigned product.

existing product has been analyzed by the design team in order to identify both the economic and functional system weak points.

During the redesign phase (in Fig. 2(b), the redesigned product is shown), designers proposed different possibilities for the resolution of the design criticalities, which have been subjected to a technical and economic assessment to be validated. In order to find the optimal solution, the method previously described has been used, by setting the most relevant parameters concerning the CAD model. Among these parameters there are, for example, the diameter of the shafts, the thickness of the sheetmetals, the modules of the toothed wheels, fillet radius etc. The CAD model has been analyzed with a FEM software (ANSYS® Workbench®) to examine the structural behavior and with a DfC tool (LeanCOST® by Hyperlean®) to evaluate the manufacturing cost and time. The automatic integration of these software tools and the changing of the CAD model parameters has been handled by the optimization software modeFRONTIER® (by ESTECO®). It firstly creates a DOE with the geometric and non-geometric variables of the model and then generates a metamodel using response surface methodology with the structural results as well as manufacturing time and cost. Lastly, through specific optimization algorithms, it is possible to proceed with the determination of the optimal solutions.

3.1. Cogwheel optimization

The proposed method has been used to optimize a cogwheel, an idler gear (Fig. 3(b)) to increase the wheelbase between two shafts in the handling system (Fig. 3(a)) without affecting the reduction ratio.

According to the proposed methodology, the first step concerns the design variables choice and the constraints and objectives determination.

Tab. 1 contains the considered design variables, constraints and objectives. The thickness of teeth, the module

Table 1. List of constraints, design variables and objectives.

Factors	Type	Value/Note	u.o.m.
Module	Constraint	3	[mm]
Pitch diameter	Constraint	384	[mm]
Thickness of teeth	Constraint	35	[mm]
Safety factor (yield point)	Constraint	> 2.5	
Deformation	Constraint	< 0.3	[mm]
Fillet radius	Variable	1÷4	[mm]
Excavation angle	Variable	40÷60	[°]
Internal thickness	Variable	5÷15	[mm]
Material	Variable	Steel S355JR Steel C75 Nodular Cast Iron	
Manufacturing Time	Objective	To Minimize	[min]
Manufacturing Cost	Objective	To Minimize	[€]
Mass	Objective	To Minimize	[Kg]

and the pitch diameter are constraints because reduction ratio and transmission torque are imposed by the coupling with the other cogwheels that make up the handling system. Obviously, another constraint is the structural strength, represented by the safety factor and the deformation. In some cases, the choice of the raw material can have a significant impact on the manufacturing cost and time and product performance. Therefore, in this analysis, three different materials have been tested: carbon steel (C75), structural steel (S355JR), nodular cast iron (EN GJS 400). Another important goal was the mass reduction. Indeed, the large size of the cogwheel could lead to transportation and assembly problems. Thus, the designers decided to set as variables the internal thickness (spoke thickness) of the wheel and the cutout area. Considering the low rotation speed (about 2 rpm) and the number of drives per day (about 10), fatigue strength it is not important. Therefore, it was possible to decrease the fillet radius without the risk of fatigue fractures. Lastly, the manufacturing time was set as a secondary objective to be achieved (according to the company indication) with a weight of 0.5 in the optimization process, in a range from 0 to 1. The production batch quantity was set at 52.

Once the designers have chosen the variables, the constraints and the objectives, they have been transformed

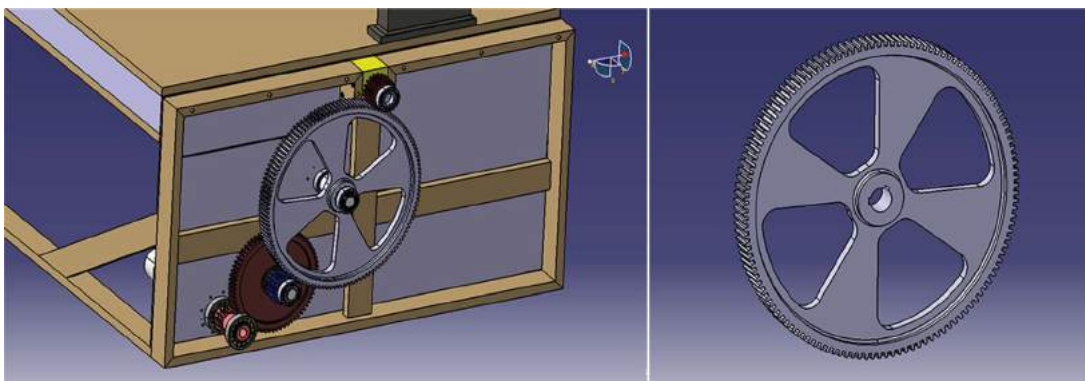


Figure 3. (a) Handling system, (b) Idler gear.

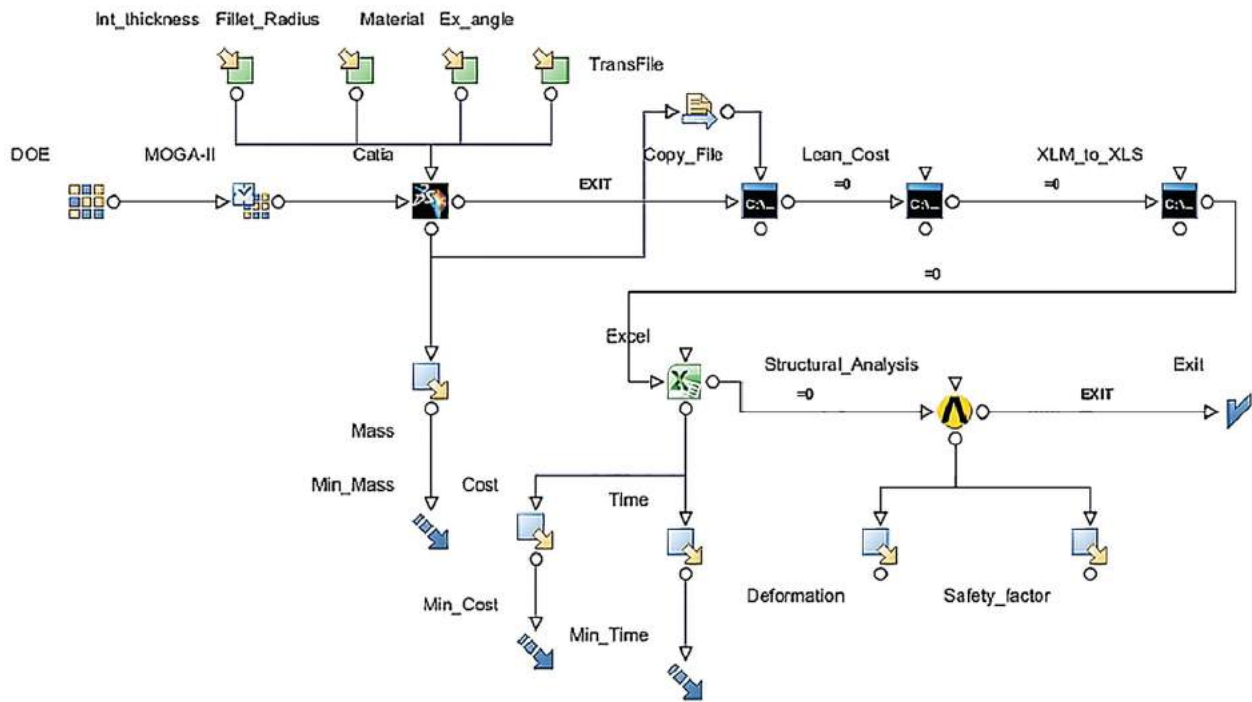


Figure 4. Workflow of the optimization process.

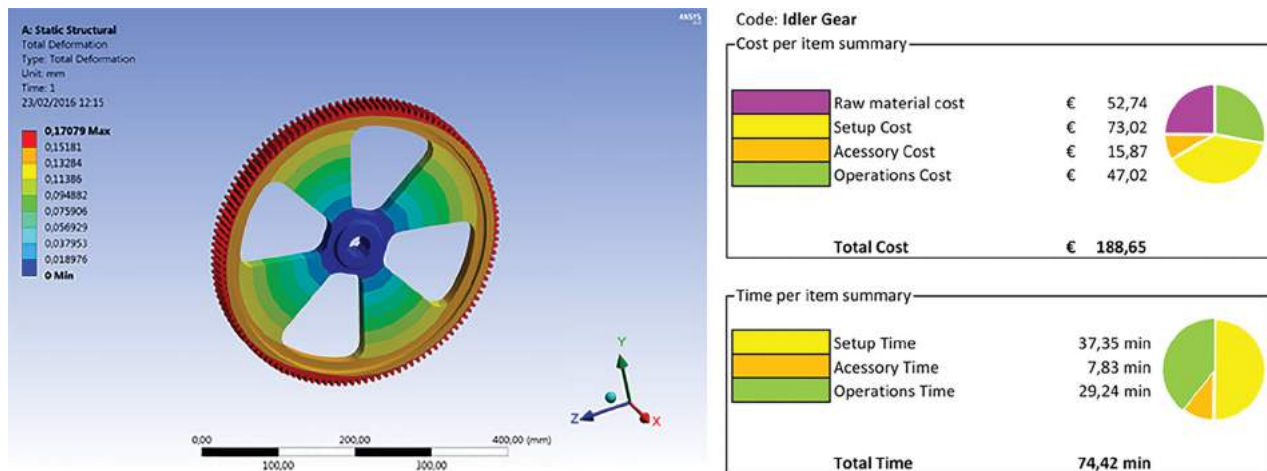


Figure 5. (a) Deformation of the idler gear, (b) Cost and Time results.

into parameters of the CAD model. In this case study, Catia[®] V.5 (by Dassault System[®]) has been used as CAD system. The integration between Catia[®] and modeFRONTIER[®] was possible thanks to a specific tool of the latter, used to set parameters of the CAD model as inputs for the optimization problem, as shown in Fig. 4.

While the optimization process is running and the CAD model is update with the new parameters set by the DOE, the new CATpart file is copied into a folder to be read by LeanCOST[®]. This software is opened in background thanks to a batch tool of modeFRONTIER[®] and, after the analysis, it generates a file from which the cost

and the time of manufacturing are extrapolated with the objective of minimize them (Fig. 5(b)).

After that, the structural analysis starts. Ansys[®] Workbench[®] reads the updated CAD file from Catia[®] and sets loads and constraints as the predefine analysis to give as outputs deformation (shown in

Fig. 5(a)) and safety factor. This analysis simulates the operating conditions of the idler gear and it has been set as load the transmission torque.

All of these steps are made automatically and consequently by modeFRONTIER[®]. In Fig. 4. the workflow of the optimization process by modeFRONTIER[®]

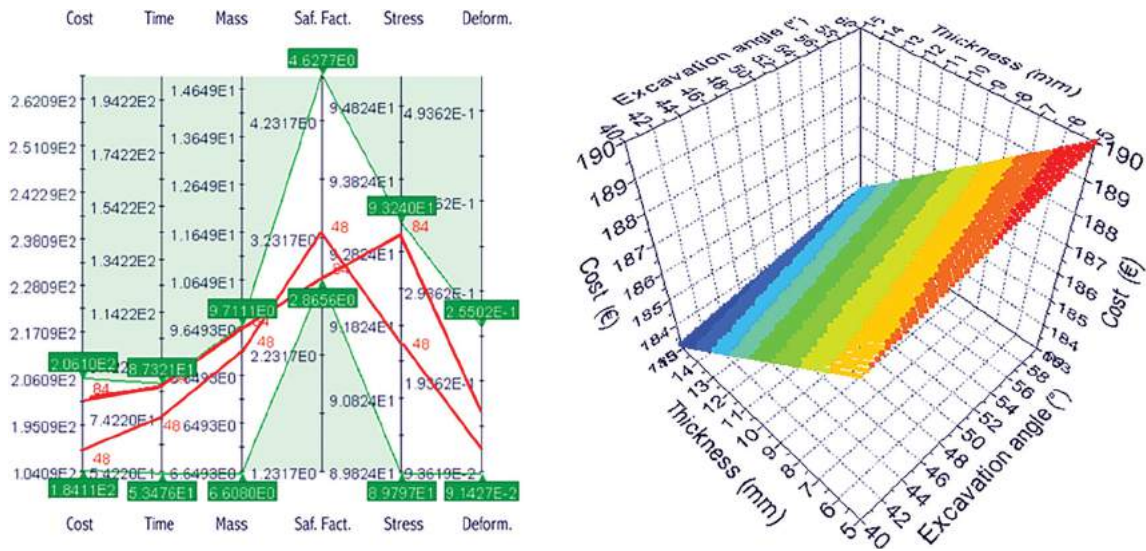


Figure 6. (a) Objectives achieved by two experiments, (b) Cost response surface as function of thickness and excavation angle.

Table 2. The two best solutions.

	Fillet Radius	Excavation Angle	Internal Thickness	Material	Manufacturing Cost	Mass	Manufacturing Time
Value	3.5 mm	47°	12 mm	Cast Iron	188€	8 Kg	74 min
	3.7 mm	49°	14 mm	Carbon Steel (C75)	197€	9.5 Kg	82 min

is shown. At the end of the simulation of all the experiments, the graphs which allow to find the optimal solution and to understand the influence of the variables on the achievement of the objectives are shown. The simulation results are visible in

Fig. 6(a). and the response surface of the cost as function of thickness and excavation angle is visible in Fig. 6(b).

A couple of solutions respecting the constraints are listed in Tab. 2. where the first row represents the optimal solution. This optimal solution, automatically indicated by the software tool, has been validated by a specific simulation to verify that the achieved results were not influenced by the errors regarding the regression of response surface.

The presented methodology has been used in a case study and it has been compared with the traditional (manual) optimization process. Two design teams carried out the same optimization analysis of the modular structure, the first (two engineers) using the presented methodology, and the second (three engineers) following the traditional method. The aim was to test the functionality of the automated process and to compare the results achieved. The team that used the mentioned approach was able to identify the optimal solution, saving 13% of manufacturing cost and 17% of manufacturing time, compared to the solution achieved by the other group.

Thanks to the automation of this methodology, it is possible to save the engineers employment time required

for the optimization processes. Indeed, in the traditional approach, the design-evaluation-redesign phase requires a high degree of interaction with the designers while, in the proposed one, it is automatically handled by the optimization tool. Therefore, designers are able to employ the saved time in other business activities.

The redesign of the whole modular structure lead to a strong reduction of the components number, from 300 to less than 200 (-30%), manufacturing costs by 40% and the total time of production by 35%.

4. Conclusion

The paper presented an optimization method for supporting the definition of the design solution optimizing an objective function while respecting the constraints imposed. This method is based on a parametric CAD system and FEM and DfC software tools respectively for multiphysics and manufacturing cost analysis. By linking these systems with an optimization software, it is possible to seek automatically the parameters of the CAD model that allow to reach specific goal/s.

The presented methodology has been designed to be used both for the study of a single component and for complex assemblies. The latter enables designers to focus on the global analysis of the system and not only on the individual parts. Thus, the use of this method leads to a significant time saving and it allows to evaluate a number of configurations that otherwise would not be possible

to consider. However, it is not possible to choose a number of variables that is too vast because of the metamodel limits [9]. In addition, the analysis of complex systems, especially for FEM simulation, requires a significant computational effort and therefore limiting the considered design variables turns out to be a winning strategy to save time and costs. It is up to the designer, through a proper correlation analysis, to limit the number of design variables only to those that have a greater impact on set goals. Furthermore, an accurate initial set-up of the methodology is important due to the limited real-time control of the running analysis and, to assess the results accuracy, regular checks during the simulation should be introduced.

Future works will be focused on the study of methodologies to support designers in detecting the low impacting variables that can be neglected by the optimization analysis, in order to save the computational resources. This improvement will allow designers to reduce the time for the configuration of the analysis.

ORCID

Vincenzo Castorani  <http://orcid.org/0000-0001-8514-5548>

Alessio Vita  <http://orcid.org/0000-0003-2151-744X>

Marco Mandolini  <http://orcid.org/0000-0003-0962-5982>

Michele Germani  <http://orcid.org/0000-0003-1988-8620>

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