

A novel approach for integrating the optimization of the lifetime and cost of manufacturing of a new product during the design phase

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Key words: Design; Lifetime; Manufacturing cost; New product; Optimization; Prediction.

Abstract: Maximum lifetime and minimum manufacturing cost for new products are the primary goals of companies for competitiveness. These two objectives are contradictory and the geometric dimensions of the products directly control them. In addition, the earlier design errors of new products are predicted, the easier and more inexpensive their rectification becomes. To achieve these objectives, we propose in this article a novel model that makes it possible to solve the problem of optimizing the lifespan and the manufacturing cost of new products during the phase of their design. The prediction of the life of the products is carried out by an energy damage method implemented on the Finite Element (FE) calculation by using the ABAQUS software. The manufacturing cost prediction is carried out by applying the ABC cost estimation analytical method. In addition, the optimization problem is solved by the method of genetic algorithms.

The proposed model can be successfully applied for the optimization of new mechanical products made by subtractive manufacturing. The products which mostly benefits from this model are those used in machines and in the automotive or aeronautic fields. The proposed approach can be directly used by the designer for an optimal preliminary design of new products whose manufacture is done by the same company or subcontracted entirely or partially by other companies.

1. Introduction

For a manufacturing company to be competitive, it must offer to its customers reliable products and cost effective [1]. Namely, a large part of the product costs is determined during the design phase that makes it difficult to go back and correct the bad decisions made during this phase [2]. To avoid this kind of problem, the company must implement, during the design phase, a prediction study to obtain a product that lasts longer with a reduced cost.

The geometric dimensions of a part are a characteristic that directly impacts the reliability criterion [3] and the manufacturing cost criterion [4]. They are a common characteristic between these two criteria and they influence them in a contradictory way [5]. Therefore, to reach a maximization of the lifetime and a minimization of the manufacturing costs, a search for adequate geometric dimensions that gives a

joint optimization of the service life and the cost of the product must be implemented. Various researches were focused towards this direction, see details in Table 1. Yet, during the design phase, in the paper [6], the authors optimized the reliability and weight of steel structures. They used neural networks as an optimization method, geometric dimensions as optimization variables, and displacement of structures as a predictive indicator of reliability. The study carried out in [7] treated the problem of Multiobjective optimization of reliability and weight by considering the geometric dimensions and the type of material of the variables of the problem. The constraint was obtained as a predictive indicator of reliability, and they used genetic algorithms as an optimization approach. In [8] were developed a Multiobjective optimization model which was performed by the same algorithm to optimize the reliability and the weight of structures. Reliability is predicted using the Reliability Index, and the variables of the problem are geometric dimensions, number of components, and weight of the structure. Regarding the optimization of the manufacturing cost, [9] and [5] have developed an approach which allows to obtain the best dimensions and geometric tolerances which optimize the total cost of a pump. In [10] was proposed a study that focuses on the optimization of the manufacturing cost by genetic algorithms. The manufacturing cost is estimated using an analytical method and the variables of the problem are the geometric dimensions.

Table 1: Literature review

Authors	Objective function	Constraints	Performance indicator	Optimization method
[6]	Minimize weight	Maximum stresses and displacements	Weight of the structure	Neural networks
[7]	Maximize reliability and minimize weight	Maximum displacement	- Stress - Weight	Genetic algorithms
[8]	Maximize reliability and minimize weight	Minimum reliability index	- Reliability index - Weight	Genetic algorithms
[9] [5]	Manufacturing cost	Geometric dimensions	Total manufacturing cost	Not assigned
[10]	Manufacturing cost	Not assigned	Total manufacturing cost	Genetic algorithms

The objective of this article is to establish an approach that allows to jointly optimize the reliability and the cost of manufacturing of new products. The variables considered in the model are the geometric dimensions of the products. The model can be used by the designer during the design phase. This saves businesses time and expense to correct design errors and improve product performance before they are made. The affected products are mechanical components available in machinery, automotive products, aeronautical products, and manufactured by subtractive manufacturing processes. The model can be applied to products whose manufacture is carried out by the same company or which is fully or partially subcontracted by other subcontractors.

The performance indicators used at the level of objective functions are indicators that are more meaningful. The number of failure cycles is the indicator chosen to express the service life and therefore the reliability of the products, and the sum of the costs influenced by the variation in the geometric dimensions of the products is chosen to express the manufacturing cost. The prediction of the first indicator is carried out by the finite element method using the numerical simulation software ABAQUS. To obtain good prediction for this indicator, we have used the continuum damage mechanics method implemented on the same software. The prediction for the second indicator is determined by the ABC (Activity Based Costing) method that is an analytical cost estimation method.

The model is programmed on MATLAB computer programming and mathematical analysis software. Lifetime modeling is performed by coupling ABAQUS and MATLAB using the Abaqus2matlab toolbox and manufacturing cost modeling is performed on MATLAB. The optimization process is performed by genetic algorithms implemented on the Optimization toolbox on MATLAB. Finally, the Taguchi method is used to calibrate the parameters of the NSGA-II.

The second section of the article defines the reliability parameter and the methods of its prediction available in the literature. The third section describes the process for developing the production range as well as the different methods of estimating manufacturing costs. The fourth section is devoted to the presentation of the Multiobjective optimization problem. The fifth section consists of the presentation of the method used to predict the lifetime as well as the Abaqus2matlab coupling toolbox, the formulation of the estimate of the manufacturing cost using the ABC method, the formulation of the problem of Multiobjective optimization and the Optimization toolbox used, and to the formulation of the proposed model as well as the algorithms used to program it. The last section presents a numerical example that illustrates the utility of the proposed model.

2. Reliability prediction

The reliability parameter is the probability that a product will perform the function for which it was designed, under given conditions and during a given time interval. A cessation of the performance of a system's function is called failure or damage. The reliability of each product is measured by its lifetime T , which represents the time between the instant of start-up $t = 0$, and the instant when operation fails and breaks down the product.

There are different models for predicting lifetime, such as the S-N (Stress vs Number of Cycles) method and the linear elastic fracture mechanics method for predicting fatigue life. The first method defines the relationship between the applied stress and the number of cycles at failure based on empirical data. Both methods have been widely applied, except that their use is difficult under multiaxial loading conditions, and their forecasting indicators are not practical for technical implementation [11].

Other alternative methods appeared during the last decade, like the method of the density of strain energy [12], and the method of the mechanics of damage of the continuum [13]. These methods have proven the ability to deal with complex load cases, easily implemented in numerical techniques, such as finite element methods [14] where they have demonstrated their power of simulation of the initiation and propagation of the crack.

3. Manufacturing cost prediction

There are generally three categories of manufacturing technology: subtractive, additive and hybrid manufacturing. Subtractive manufacturing is the classic technology, characterized by making the products in two main phases: a forming phase (process for obtaining the raw parts) and a material removal phase, also called the machining processes. Additive manufacturing consists of building the parts by adding the material layer by layer under computer control. And hybrid manufacturing which combines the first two methods mentioned above. In our article, we are interested in modelling subtractive manufacturing technology.

Whichever method is used to estimate the manufacturing cost, an elaboration of the product's process planning must be established to extract the data that contributes to the modelling. The design of the process-planning constitutes five main stages [15]:

- Selection of technologies, manufacturing tools as well as the various manufacturing operations;
- Choice of machine tools;

- Determining the sequence of operations;
- Choice of reference surfaces and the positioning of the parts on the assemblies;
- Calculation of the manufactured machined dimensions, then, based on this, the process planning designer establishes the raw manufactured dimensions;
- Determining the manufacturing conditions (cutting speed, feed, depth of cut, etc.);
- Estimating time and then the cost of manufacturing operations;
- Writing the manufacturing file.

The choice of manufacturing processes and machine tools also depends on the equipment available and the technological capacity of the company [16]. The unavailability of equipment and the technological inability of the company pushes it to subcontract entirely or partially the manufacture of its products. Cost estimation is a key step in product lifecycle decision-making, and represents all the costs of resource consumption by the activities required to achieve it.

Three types of manufacturing cost prediction approaches are available in the literature: analogical, parametric, and analytic approaches. Cost estimation using analogue methods is based on the costs of products already produced [15,16]. The principle of parametric methods [19] is the grouping of all methods for cost estimation based on mathematical relationships that relate the quantifiable parameters of the product. Finally, the analytical methods, that are based on the operations and activities that contribute to the manufacture of the product.

Each of these methods has advantages and disadvantages. Parametric methods are accurate and quick to apply, but limited by their area of validity. The collection of the knowledge base and the discriminant parameters make the preparatory phase of the parametric methods too long. Like the parametric methods, the preparatory phase of the analytical methods is as long, except that they remain appealing by their flexibility and accuracy, and these last two characteristics are the most interesting for any prediction study.

4. Multi-objective optimization

We talk about a multi-objective problem if there is a compromise between several contradictory objectives to search. Its solution yields a set of non-dominated solutions known as the set of optimal Pareto solutions.

A multi-objective optimization problem is mathematically written as follows:

$$\left\{ \begin{array}{l} \text{minimize } \vec{f}(\vec{x}) \left(\begin{array}{l} \text{function to be optimized grouping} \\ l \text{ objective functions} \end{array} \right) \\ \vec{g}(\vec{x}) \leq 0 \text{ (} m \text{ inequality constraints)} \\ \vec{h}(\vec{x}) = 0 \text{ (} p \text{ equality constraints)} \\ \text{where } \vec{x} \in \mathbf{R}^n, \vec{f}(\vec{x}) \in \mathbf{R}^l, \vec{g}(\vec{x}) \in \mathbf{R}^m \text{ and } \vec{h}(\vec{x}) \in \mathbf{R}^p \end{array} \right. \quad (1)$$

From where $\vec{f}(\vec{x})$ represents the function to optimize which gathers the set of k objective functions, $\vec{g}(\vec{x})$ represents the set of m inequality constraints of the problem and $\vec{h}(\vec{x})$ represents the set of p equality constraints of the problem, respectively.

The solution of a multi-objective problem is a set of compromised solutions between the different objectives to be optimized. This set of solutions constitutes a balance, in the sense that no improvement can be made on one objective without degradation of at least one other objective.

5. Model formulation

The formulation of the model will be based on a finite element method for the prediction of the lifetime and on a method of estimating the manufacturing cost. The two methods will be expressed in the form of mathematical formulas for use in the modelling of the optimization problem. We present in this section the different methods and tools which contribute to the resolution of the problem treated, as well as the proposed model.

5.1.Lifetime formulation

The method used in our study for the estimation of the lifetime is the method of Darveaux [20], which is a method implemented on the numerical simulation software ABAQUS [21].

The fatigue life at low cycle is characterized by the number of cycles that trigger the initiation of damage and the number of cycles that leads to the total damage of the structure.

The damage initiation based on the hysteresis energy of the first cycle is expressed by Equation (2):

$$N_0 = c_1 \Delta W_0^{c_2}. \quad (2)$$

Where N_0 is the number of damage initiation cycles, ΔW_0 is the hysteresis energy of the first cycle, and c_1 and c_2 are material constants.

As soon as the damage is initiated, the damage state parameter D becomes accessible, and the stiffness of the material is reduced by Equation (3). The damage rate per cycle is expressed by Equation (4).

$$\sigma = (1 - D)\sigma_0 \quad (3)$$

$$\frac{dD}{dN} = \frac{c_3 \Delta W^{c_4}}{L} \quad (4)$$

Where c_3 , and c_4 are material constants, L is the characteristic length, and N is the number of cycle.

By integrating Equation (4), Equation (6) is obtained which shows the number of failure cycles.

$$\int_{N_0}^{N_f} dN = \int_0^1 \frac{L}{c_3 \Delta W^{c_4}} dD \quad (5)$$

$$N_f = N_0 + \int_0^1 \frac{L}{c_3 \Delta W^{c_4}} dD \quad (6)$$

Linked to Equation (3), energy in all material points is:

$$\Delta W = (1 - D)\Delta W_0 \quad (7)$$

Equation (6) then becomes:

$$N_f = c_1 \Delta W_0^{c_2} + \int_0^1 \frac{L}{c_3 ((1-D)\Delta W_0)^{c_4}} dD \quad (8)$$

The formula of the number of failure cycles is therefore summarized by Equation (9):

$$N_f = c_1 \Delta W_0^{c_2} + \frac{L}{c_3 \Delta W_0^{c_4}} \frac{1}{1-c_4}. \quad (9)$$

5.1.1. Abaqus2matlab toolbox coupling tool

The "Abaqus2Matlab" toolbox is a coupling tool that was developed by [22]. This toolbox allows the coupling of the finite element simulation software ABAQUS and the software of computer programming and mathematical analysis MATLAB.

The operation of Abaqus2matlab is based on two main files generated by ABAQUS, the first is a file named *job* (*.inp) or a file named *script* (*.py), and the second is an *output database file* (*.odb). The *job* and *script* files are files that contain the entire scenario for the generation of the simulation model on ABAQUS, and the *output database* file has all the data of the results of the digital simulation performed on the same software.

After obtaining the job and script files generated by the digital simulation of the model on ABAQUS, one of the two files is selected in the Abaqus2Matlab interface, then the choice of variables to be extracted is defined. Based on these data, the toolbox generates the program which allows to run the numerical simulation on ABAQUS from MATLAB and to extract the results of the variables selected beforehand in order to use them on MATLAB according to the objectives of each user.

5.2. Manufacturing cost formulation

The ABC method [23], which is an analytical method of estimating the manufacturing cost, was used in our study.

The philosophy of the ABC method is that the products consume activities, and the activities consume the resources, that is to say, that any result is explained by a chain of activity.

The first step of the method is to identify the resources needed to achieve the product and activities that contribute to its development, and the second step is the quantification of consumption links to bring out the cost.

The approach to implementing the ABC method for estimating manufacturing costs is described as follows [24]:

- The identification of resource centers necessary for the manufacture of products;
- Identification of costs and cost drivers associated with the determined resources;
- Identification of activities that contribute to the manufacture of products;
- The deduction of the costs of each activity according to the resources consumed;
- The determination of the cost drivers of the activities;
- Calculation of the overall manufacturing cost according to the activities.

In this regard, the total cost of industrialization of a product estimated by the ABC method represents the sum of the costs of the different activities that contribute to its manufacture, and it is expressed as follows [25]:

$$C = \sum_{i=1}^N C_{activities}^i \quad (10)$$

Where C represents the total cost of industrializing the product, N represents the number of activities, and $C_{activities}^i$ represents the cost of activity i. The latter is expressed as follows [25]:

$$C_{activité}^i = C_{processing}^i + C_{load-unload}^i + C_{setup}^i + C_{handling}^i + C_{programming-test}^i + C_{overhead}^i \quad (11)$$

Where $C_{processing}^i$ represents the cost of manufacturing activity i, $C_{load-unload}^i$ represents the cost of loading and unloading carried out during activity i, C_{setup}^i represents the cost of installing the activity i, $C_{handling}^i$ represents the cost of handling activity i, $C_{programming-test}^i$ represents the cost of testing and programming activity i, and $C_{overhead}^i$ relates to the overheads of the activity i.

The prevision of the costs of the activities of different manufacturing processes using the ABC method is available in the literature, namely for machining [25] , casting [26], forging [27], etc.

5.3. Multi-objective optimization formulation

Multi-objective problem solving approaches are divided into three classes: meta-heuristics, Pareto approaches and non-Pareto approaches.

Our optimization problem can be solved by different methods, we used the NSGA-II method (non-dominated sorting genetic algorithm) belonging to the class of Pareto approaches. This method is a multi-objective optimization method that has been widely used in solving different types of industrial problems. It has proven its relevance in solving problems of optimization of failure [25,26], problems of optimization of manufacturing costs [30], problems of optimization of safety and maintenance of equipment [31], design optimization issues [31-33], and various other types of industrial problems.

The Non-Dominated Elite Genetic Sorting Algorithm II (NSGA-II) is one of the most popular multiple-objective optimization algorithms that was introduced by [34]. It represents an improved version of the Elite Non-Dominated Genetic Sorting Algorithm (NSGA). The NSGA-II differs from the NSGA version in three main features; it is a method of fast non-dominated sorting, fast estimation of congested distance, and simple congested comparison.

The steps of the NSGA-II procedure are presented as follows (Figure 1):

- Step 1: Generation of the initial population;
- Step 2: Sorting of individuals based on the criteria of non-domination of the initial population;
- Step 3: Sorting the individuals according to the encumbrance distance;
- Step 4: Selection of individuals;
- Step 5: Crossing and mutation of individuals;
- Step 6: Assessment of individuals;
- Step 7: Obtaining a new population combining the individuals of the initial population and the population of the current generation. The NSGA-II loop repeats from step 2 to the stop criterion.

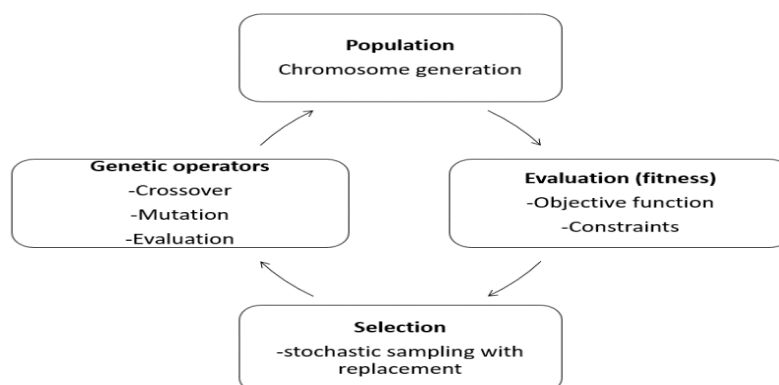


Figure 1: The basic concept of Genetic Algorithms.

5.3.1. Genetic algorithms on Matlab (Optimization toolbox)

MATLAB computer programming software has an optimization toolbox that contains predefined optimization algorithms, including the Multiobjective Optimization Problem Solving Algorithm [35]. Genetic algorithms are predefined on MATLAB under a function called ‘gamultiobj’ (Multiobjective optimization using Genetic Algorithm), the objective of which is to find the set of Pareto solutions that

minimize several objective functions. The mathematical formulation of the optimization problem solved by ‘gamultiobj’ is as follows:

$$\left\{ \begin{array}{l} \text{minimize } f(x) \\ \text{Subject to:} \\ C(x) \leq 0 \\ Ceq(x) = 0 \\ A \cdot x \leq b \\ Aeq \cdot x = beq \\ lb \leq x \leq ub \end{array} \right. \quad (12)$$

In addition, the general syntax of the ‘gamultiobj’ function is presented as follows:

$$[x, fval] = \text{gamultiobj}(\text{fun}, \text{nvars}, A, b, Aeq, beq, lb, ub, \text{nonlcon}, \text{options}) \quad (13)$$

Where:

- x: indicate the vector of the variables of the problem;
- fval: represents the values of the objective functions appropriate to the values of the variables of the problem;
- fun: uses the set of objective functions f (x) to be minimized;
- nvars: indicate the number of variables of the problem;
- A & B: indicate a matrix and a vector of linear inequalities, respectively;
- Aeq & Beq: represent respectively a matrix and a linear stress vector of equality;
- lb & ub: indicate respectively the lower and upper bounds of the variables of the problem;
- Nonlcon: uses the function defined externally on MATLAB which defines the non-linear constraints of equality C (x) and the non-linear constraints of inequality Ceq (x);
- Options: allows to control the parameters of the operators of the genetic algorithms.

5.3.2. Taguchi's experimental design for the calibration of the parameters of genetic algorithms

The quality of the solution to an optimization problem is influenced by the parameters of the optimization algorithm used. Therefore, we use the Taguchi method to optimally choose the parameters of NSGA-II that influence the quality of the results. The Taguchi method is a statistical analysis technique developed by [36] that allows the influence of parameters to be quantified and calibrated by ensuring that all levels of each of its parameters are taken into account in the same way.

Taguchi's method uses a signal to noise ratio S / N (Signal / Noise) to improve the robust design of objective functions and to mitigate loss of quality. Various S / N ratios are proposed in the literature, three of which are the most widely used: 'Bigger - better', 'Nominal - better' and 'smaller - better'.

As we use in the present study the function 'gamultiobj' which deals with the minimization of objective functions, the signal-to-noise ratio should be determined by the ratio 'smaller - better' formulated as follows:

$$\frac{S}{N} = -10 \log_{10} \left(\frac{1}{n} \sum_{i=1}^n \frac{1}{y_i^2} \right) \quad (14)$$

Where, n denotes the number of observations and y the response variable.

5.4. Proposed model

The main objective of our approach is to achieve maximum lifetime at a reduced cost. The first objective function $f_1(x)$, to be maximized, is therefore the number of failure cycles that is expressed by Equation (15). The second objective function $f_2(x)$, to be minimized, is the total manufacturing cost, expressed by Equation (16):

$$f_1(x) = N_f \quad (15)$$

$$f_2(x) = C \quad (16)$$

When N_f is giving by Equation (9) and C is giving by Equation (11).

We apply multi-objective optimization by the method of genetic algorithms (NSGA II), predefined in Matlab, at the dimensioning problem of the part to deduce the two optimal objectives.

As indicated in figure 2, the proposed model consists of three main phases: a) a phase of modeling the numerical simulation on ABAQUS with a view to extracting the first objective function which expresses the number of failure cycles, b) a phase of modeling the second objective function which represents the cost of industrialization, and c) a phase of modeling the process of optimizing the two objective functions:

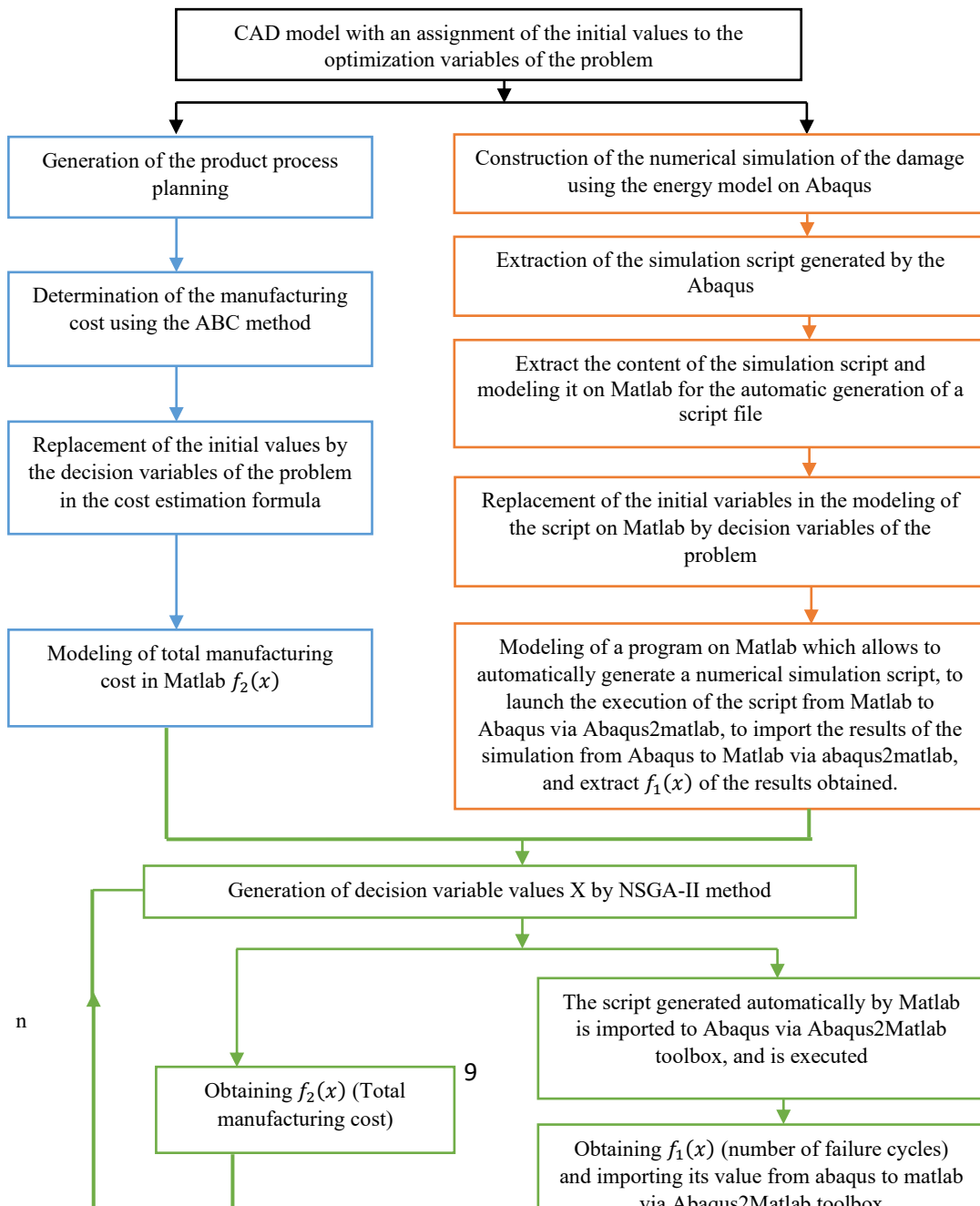


Figure 2: Diagram of proposed approach.

From the CAD model of the product, and replacing the problem variables with initial values:

- a. Modeling of numerical simulation on ABAQUS:
 - We build a numerical simulation by the finite element method on Abaqus to extract the number of failure cycles corresponding to the initial values. The simulation is done using the energy method;
 - Once the numerical simulation is finished, we extract the script generated by the simulation on Abaqus;
 - We then extract the content of the simulation script. It will be used to model the generation of an automatic script file on Matlab;
 - We replace the initial variables of the modelling of the script on Matlab by the decision variables of the problem;
 - Modelling of a program on Matlab which allows to automatically generate a digital simulation script, to launch the execution of the script from Matlab to Abaqus via Abaqus2matlab [22], to import the results of the simulation from Abaqus to Matlab via abaqus2matlab, and extract $f_1(x)$ (which corresponds to the number of failure cycles) of the results obtained.
- b. Modeling the cost of industrialization:
 - We generate the process-planning necessary for production of the product;
 - From the data provided by the process-planning (chosen manufacturing process, number of operations, machine tools, tools, manufacturing time, etc.), we determine the manufacturing cost of the product using the ABC method;
 - The extraction of the parameters influenced by the variation of the variables of the problem. We then model the manufacturing cost that corresponds to the second objective function $f_2(x)$ on Matlab as a function of these parameters.
- c. Modeling of the optimization process:
 - Genetic algorithms generate values for decision variables X;
 - The script of the numerical simulation by the finite element method is generated automatically. It is imported from Matlab to Abaqus via the Abaqus2matlab toolbox, and it is subsequently executed;
 - Once the simulation is completed, its results are imported from Abaqus to Matlab using the Abaqus2Matlab toolbox. The value of $f_1(x)$ is extracted from the results of the simulation;
 - Obtaining $f_2(x)$;
 - NSGA-II iterations are repeated n times until the best X in the product is obtained.

In order to perform the optimization process, we have built two files on MATLAB, the first is dedicated to the definition of the two objective functions (Algorithm 1), and the second is the main file that uses the function of genetic algorithms of the optimization toolbox (Algorithm 2).

Algorithm 1: The pseudo code of the declaration of objective functions

Files 1 :**Start:**

Define objective functions: $f(x)$

Generate the numerical simulation script file

Run the Numerical Simulation Script from MATLAB:

```
!abaqus cae noGui=script.py
```

Call the function for extracting the SDEG output variable: readElementFieldOdb:

```
[odbOut_SDEG,odbDat_SDEG,rpyOut_SDEG]=readElementFieldOdb(odb_name,stepName,'None','None',outputVar,indOut);
```

End

Algorithm 2: The pseudo code of the main file

File 2 :**Start:**

Declare the number of decision variables:

```
nvars = [nvars] ;
```

Declare the vector of the upper values of decision variables:

```
ub = [ub1 ub2 ...] ;
```

Declare the vector of the lower values of decision variables:

```
lb = [lb1 lb2 ...] ;
```

Declare the constraints of linear inequality:

```
A = [ A1, A2, ...] ;
```

```
b = [ b1 b2 ...] ;
```

Define the main program

```
objectif = @objfonction ;
```

Call the gamultiobj function

```
[x, fval] = gamultiobj (objectif, nvars, A, b, lb, ub);
```

Display the end objectif

Display the Optimum

End

6. Numerical example

The case study is carried out on the optimization of the dimensions of a hollow disc whose shape is illustrated in figure 3. The dimensions to be optimized are the outside diameter $x(1)$ and inside $x(2)$ of the disc. The size constraints imposed by the location of the room are as follows:

$$30 \leq x(1) \leq 36 \quad (17)$$

$$23 \leq x(2) \leq 29 \quad (18)$$

$$x(1) - x(2) < 5 \quad (19)$$

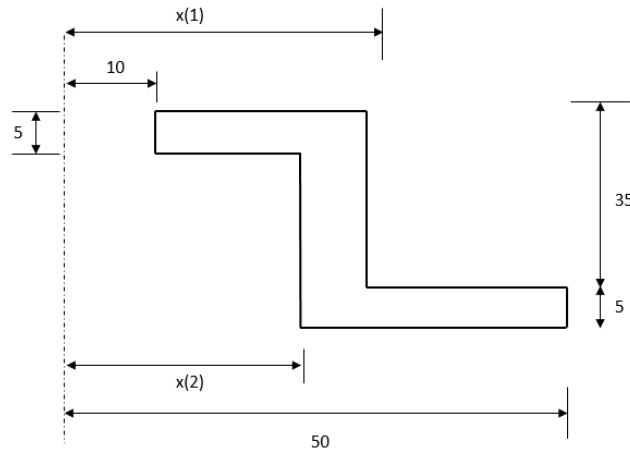


Figure 3: Axisymmetric drawing of the disk.

The disk material is S550 high strength steel. Its chemical composition, mechanical properties, and the damage parameters are shown, respectively, in Table 2, 3 and 4 [37]. The characteristic length L is 0.5 mm. Constants c_1 , c_2 , c_3 , c_4 and L are constants from an experimental profound analysis. Many experimental tests have been carried out under charging under controlled deformation [37].

Table 2: Chemical compositions of S550 high strength steel.

S550	Fe	C	Si	Mn	P	S	Cu	Cr	Ni	Mo
Weight (%)	96.19	0.106	0.327	1.41	0.010	0.0015	0.121	0.454	0.918	0.462

Table 3: Mechanical properties of S550 high strength steel.

Material	Young's modulus (Gpa)	Yield strength (Mpa)	Ultimate strength (Mpa)
S550	209	640	734

Table 4: Parameters of the damage of s550 high strength steel.

$c_1 \left(\frac{\text{Cycle}}{N^{c_2} \text{ mm}^{-2c_2}} \right)$	c_2	$c_3 \left(\frac{\text{mm}}{\text{Cycle}(N^{c_4} \text{ mm}^{-2c_4})} \right)$	c_4
22961	-1.7696	1E-3	0.15

6.1.Lifetime modelling

As described in figure 4, the disk is subjected to a pressure of 500 MPa, and to both embedding at its two ends.

(a)

(b)

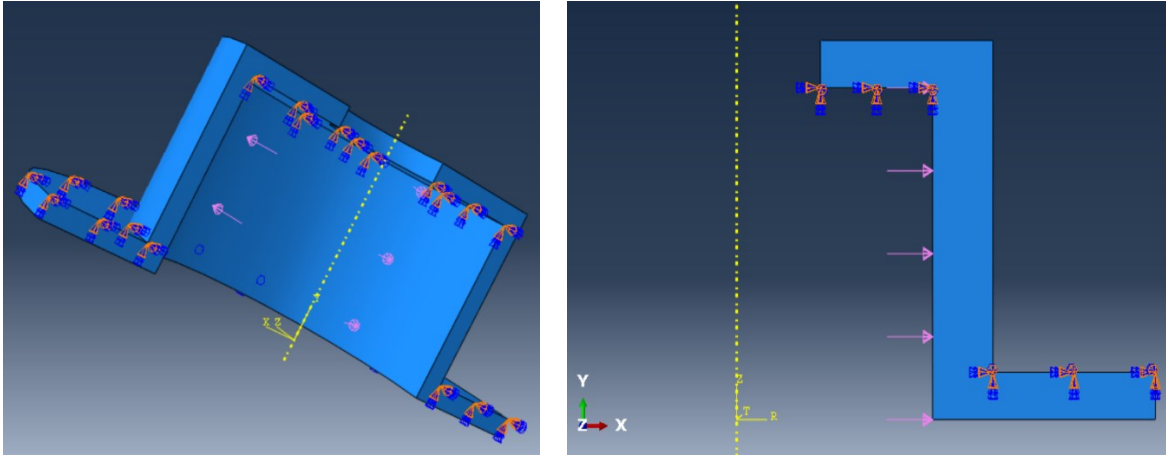


Figure 4: The boundary conditions and applied loading represented on (a) the half-disc and the symmetry along the Y and Z axes and on (b) the axisymmetric of the disc.

The number of fatigue cycle applied is 10000 cycles. Each cycle represents one hour of charging (figure 5).

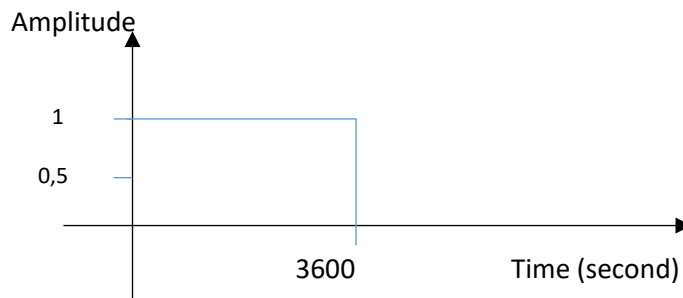


Figure 5: Magnitude of pressure applied in once cycle.

In order to simplify the numerical model, we use an axisymmetric representation of the part. The mesh imposed by the failure model is a rectangular mesh of type CAX4RH, and of a size of 0.5 mm (figure 6).

For an initial value of 24 for $x(1)$ and 30 for $x(2)$, we obtain the results of the numerical simulation (Figure 6). We use the SDEG output variable that describes the damage state D of the part. The first cycle corresponding to a $SDEG = 1$ is the number of failure cycles, which corresponds to 4083 cycles (Figure 7).

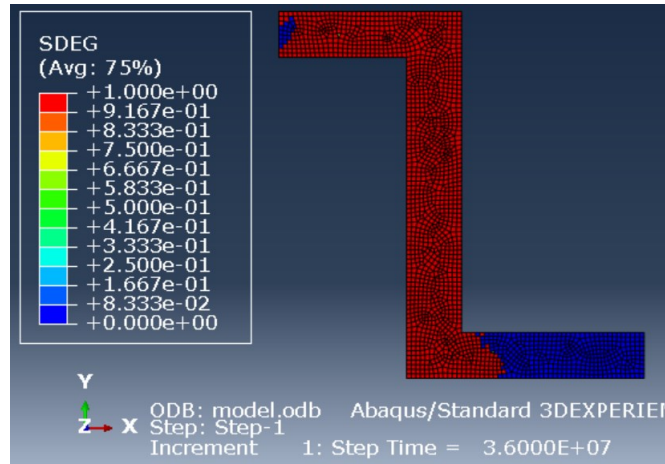


Figure 6: Representation of the model mesh and the simulation results.

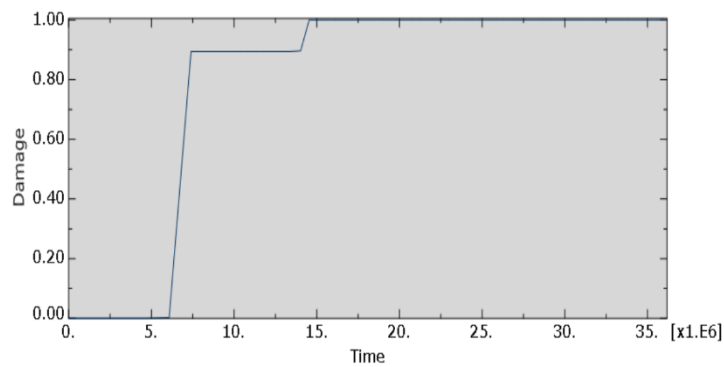


Figure 7: Variation of the damage state as a function of number of charge cycles.

The content of the script of this simulation is used to create a program that automatically generates a script file (*.py) on MATLAB. Once the script file is automatically generated by MATLAB, the Abaqus2Matlab toolbox is then used to extract the program that allows you to run the script from MATLAB and import the results of the digital simulation from ABAQUS to be able to extract $f_1(x)$. The initial values (24 and 30) are then replaced by x (1) and x (2) in the program for the automatic generation of the script on MATLAB.

6.2. Cost of manufacturing modelling

Based on the product data, the forming process chosen is automatic casting, and the machining process is three CNC turning operations.

Given the availability of machining machines within the company and the unavailability of casting machines, all the turning processes of the part will be operated by the company, and the casting process will be outsourced by another foundry specialist company. The forming process corresponding to the part studied is automatic shell casting.

In order to simplify the expression of the industrialization cost, we keep only the costs influenced by the variation in the dimensions of the part. In this case, the cost estimation equation (Equation (20)) becomes:

$$C = \sum_{i=1}^N C_{activité}^i = \sum_{i=1}^N C_{processing}^i \quad (20)$$

The cost of industrialization of the part is therefore made up of the costs of the three turning activities and the cost of the subcontracted molding:

$$C = C_f + \sum_{i=1}^3 C_{ma}^i \quad (21)$$

Where C_f is the cost of contract molding and C_{ma}^i is the cost of machining for machining activity i .

❖ Foundry cost modeling

The company subcontracting the foundry process proposes a casting cost of 4 USD / Kg. The cost of the foundry process depends on the weight of the raw part, this parameter that is influenced by the variation of the geometric dimensions. The modeling of the foundry cost will therefore be modeled based on the weight of the raw part.

According to ISO 8062 [38], the roughing tolerance is 3.2 mm, the corresponding machining allowance for roughing and finishing is 0.5 and 0.2 respectively. Figure 8 shows the geometric dimensions and the geometrical coordinates of the rough piece.

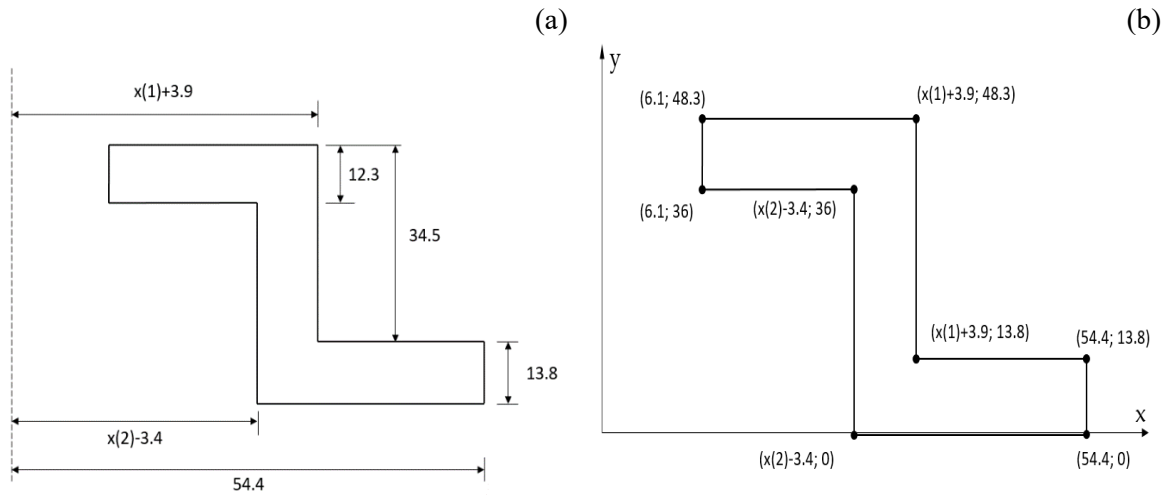


Figure 8: (a) Geometric dimensions and (b) geometric coordinates along the x and y axes of the brute.

The volume of the raw part can be calculated based on Figure 8.b and expressed by Equation (22):

$$V = 132.822x(1)^2 - 136.59x(2)^2 + 1036.011x(1) + 3972.753x(2) + 124913 \quad (22)$$

for a subtracting cost of 4 USD / Kg and a density of S550 steel of $7.23E-6$ g / m³, the cost of casting per part is therefore:

$$C_f = 4 * 7,23 - 6 * [132.822x(1)^2 - 136.59x(2)^2 + 1036.011x(1) + 3972.753x(2) + 124913] \quad (23)$$

❖ Machining cost modeling

The variation in geometric dimensions influences the path of the machining tool. The latter will be used to model the machining cost. The formula that reveals the total cost of a machining process is established by [25], and is expressed by Equation (24).

$$C_{ma} = \sum(h_{cm} * t_j) + \sum(c_{ti} * \frac{t_i}{L_{fi}}) \quad (24)$$

Where, C_{ma} is the total machining cost, h_{cm} is the hourly cost of the machining machine, t_j is the machining process time, c_{ti} is the cost of the machining tool i , t_i is the time manufacturing tool i on the machine, and L_{fi} is the lifetime of the tool i .

The time of a machining process t_j is composed of the machining time by the machining tool t_i , the tool change time, and the rapid movement time of the tool to the piece. The last two times are not influenced by the variation of the geometry of the part, so we can replace, in our case, the time t_j by the time t_i .

The machining time by a machining tool is expressed by Equation (25) [39]:

$$t_i = \frac{P_i}{S_i} \quad (25)$$

Where, P_i is the path traversed by tool i , and S_i is the feed rate of tool i .

The trajectory (from position 1 to position 3) and the coordinates of the path traversed by the machining tool of the first sub-operation of the machining operation 1 are shown schematically in figure 9.

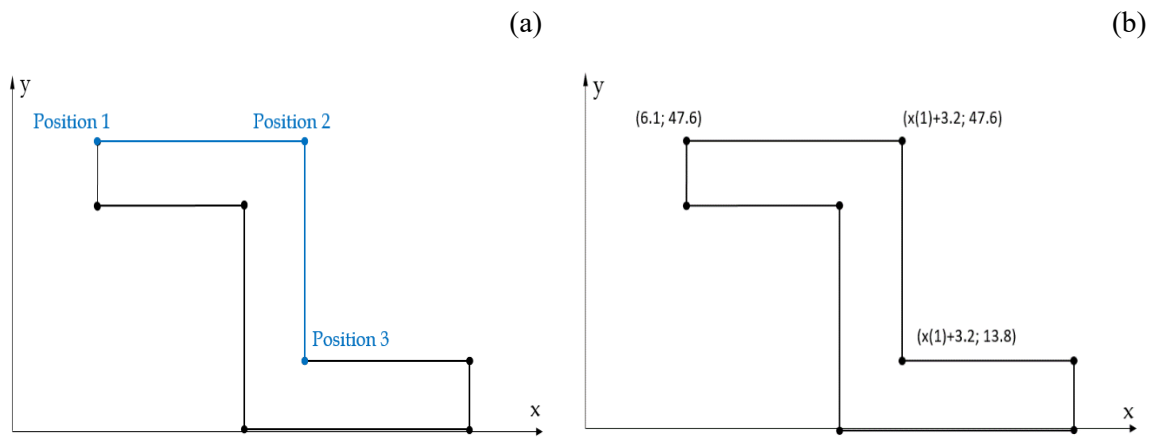


Figure 9: (a) The path and (b) the coordinates of the path traversed by the machining tool of the sub-operation 1 of the machining operation 1.

The equation of the trajectory of this sub-operation is:

$$p_{1,1} = 6.1 - (x(1) + 3.2) + 47.6 - 13.8 = \mathbf{36.7 - x(1)} \quad (26)$$

The feed rate of the machining tool is 700 m / min, its cost is 30 USD, and its service life is 3 hours. The hourly cost of the machine is USD 50 per hour.

The cost of this sub-operation is:

$$C_{ma_{1,1}} = (36.7 - x(1))/1.78 \quad (27)$$

The same is done for the remaining operations to calculate the total machining cost. The following total machining cost is obtained:

$$C_{ma} = 6.13 - 0.01 * (x(2) + x(1)) \quad (28)$$

❖ Total cost

The total cost of the product, to be minimized, will therefore be:

$$f_2(x) = C_f + C_{ma} \quad (29)$$

$$f_2(x) = 4 * 7.2E - 6 * [132.822x(1)^2 - 136.59x(2)^2 + 1036.0116x(1) + 3972.75312x(2) + 124913] + 6.13 - 0.01 * (x(2) + x(1)) \quad (30)$$

6.3. The optimization process Modeling

After having modeled the two objective functions, we model the optimization problem which will be solved by the NSGA-II method predefined on MATLAB. We multiply the first objective function by (-1) since it is a function to be maximized and the NSGA-II predefined on MATLAB minimizes the objective functions. The formulation of the optimization problem solved by the MATLAB optimization toolbox is as follows:

$$\begin{cases} \text{minimiz } \vec{f}(\vec{x}) \begin{pmatrix} f_1(x) = -N_f \\ f_2(x) = C \end{pmatrix} \\ \text{subject to:} \\ 30 \leq x(1) \leq 36 \\ 23 \leq x(2) \leq 29 \\ x(1) - x(2) < 5 \end{cases} \quad (31)$$

6.4. Results

In accordance with the optimization algorithm used in our model, four parameters must be calibrated to obtain optimal solutions: The size of the population, the maximum number of iterations, the probability of crossing and the probability of mutation. The calibration process is performed on the MINITAB software. 27 sets of experiments were performed and three levels were assigned to each parameter as shown in Table 5.

Table 5: The range of parameter levels of genetic algorithms.

Levels	Pop_size	Max iteration	Pc	Pm
Level 1	50	100	0.4	0.1
Level 2	100	200	0.6	0.4
Level 3	200	300	0.9	0.8

Figure 10 and Table 6 reveal the best values of the parameters of the genetic algorithms to be used to optimize the lifetime and the manufacturing cost of the studied disc. For this, the four parameters must be adjusted so that: the population size = 100, the maximum number of iterations = 300, the probability of crossing = 0.4 and the probability of mutation = 0.4.

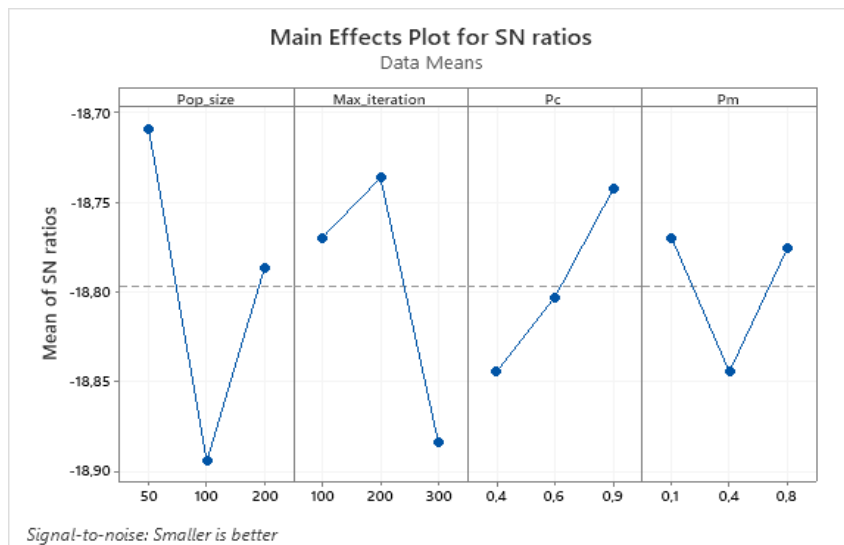


Figure 10: Graph of the effects of the S / N ratio of the parameters of the genetic algorithms.

Table 6: Results of optimized parameters of genetic algorithms.

Population size	Maximum number of iterations	Crossing probability	Probability of mutation
100	300	0.4	0.4

The Multiobjective optimization process using the genetic algorithm method, applied to a hollow disc, allowed us to obtain the results presented in figure 11 and Table 7.

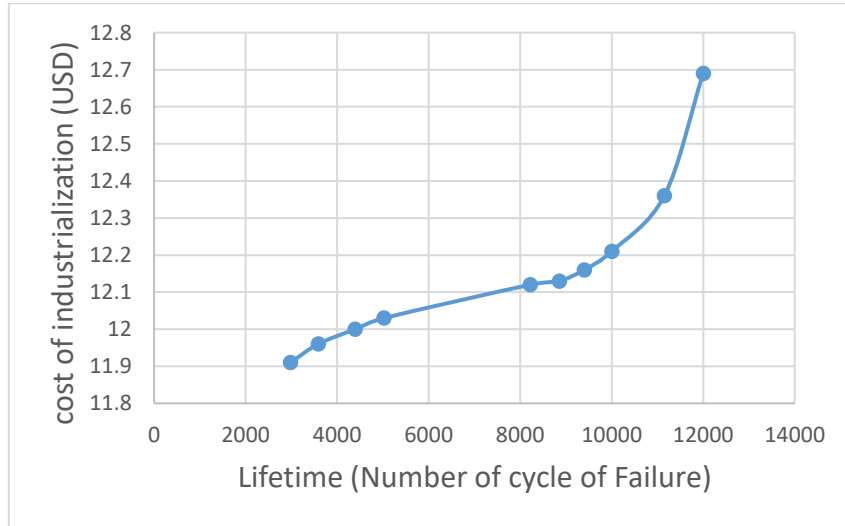


Figure 11: Graph of optimization results.

Table 7: Points forming the graph of optimization results.

Lifetime $f_1(x)$	Industrialization cost $f_2(x)$	Outside diameter $x(1)$	Internal diameter $x(2)$
> 12000	12.69	33.2	24.3
11152	12.36	31.7	23.9
10000	12.21	30.6	23.1
9399	12.16	30.5	23.4
8855	12.13	30.7	23.7
8220	12.12	30.3	23.2
5025	12.03	30.3	23.7
4393	12	30.3	23.9
3586	11.96	30.4	24.3
2981	11.91	30.3	24.4

It emerges from the results of figure 10 and table 4 that the minimum cost of the industrialization of the part corresponds to a minimum lifetime: the lifetime of the part falls by a value of more than 12000 cycles which corresponds at a cost of 12.69 USD, and it drops below 8220 cycle starting at a cost of 12.12 USD. Beyond this value, the lifetime of the part decreases considerably without gaining as much in terms of its industrialization cost. The company can opt for a decision according to different situations:

- Opt for the solution for which the service lifetime is greater than or equal to the requested lifetime (10,000 cycles) and with a low industrialization cost and this in the situation where the customer requires a short delivery time (the cost industrialization is conditioned by manufacturing time);
- Select the solution for which the lifetime and the cost are maximum in the case where the lifetime is 2 to 3 times greater than the lifetime requested. This allows the customer to make gains in terms of the lifetime of the part, which implies gains in the expense of buying it back.

Conclusion

Throughout this article, a new model was proposed to jointly optimize the reliability and cost of manufacturing for a new product during the design phase. The lifetime of the product is expressed by the number of failure cycles while an energy model was simulated using the finite element method under ABAQUS. The lifetime modeling was performed on MATLAB and numerical simulation results were extracted from ABAQUS to MATLAB using the Abaqus2Matlab toolbox. Regarding the manufacturing cost target, it was predicted by the ABC cost estimation method and programmed on MATLAB. The solution of the Multiobjective optimization problem was carried out by the NSGA-II method using the Optimization toolbox implemented on MATLAB in order to deduce the optimal geometric dimensions. Calibration of operator parameters for NSGA-II is performed by Taguchi's method to improve the quality of optimization results. And finally, a case study is presented at the end of the article to illustrate the usefulness of the proposed model.

The main outcomes from this research are:

- The proposed model shows an improvement of the lifetime almost 2 to 3 times greater than the lifetime requested;
- The service lifetime is greater than or equal to the requested lifetime (10,000 cycles) and with a much lower industrialization cost.

The numerical test performed to obtain the results of the case study took a total run time of 120 hours. This time is due to the time required to run the numerical simulations on ABAQUS to generate the values of the individuals of the genetic algorithms. Therefore, solving such a problem applied to multi-component parts becomes difficult or even impossible due to the run times that can last a long time.

In this context, and in order to improve the results obtained, our future research will focus on:

- The use of artificial intelligence methods for prediction the lifetime of new products to minimize optimization time. These methods can generate a lifetime prediction function. The function can be directly used by the optimization toolbox without having to run ABAQUS each time to generate the values of the individuals of the genetic algorithms.

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