SIZING OPTIMIZATION OF A EXOSKELETON STRUCTURE UTILIZING FINITE ELEMENT ANALYSIS AND MULTI-OBJECTIVE SEARCH

João Carlos Pereira Passos*, Carlos Eduardo da Silva Santos†, Renato Coral Sampaio‡, Leandro dos Santos Coelho§, Carlos Humberto Llanos Quintero*

*University of Brasília, Faculty of Technology, Department of Mechanical Engineering
Brasilia, DF, Brazil

†Federal Institute of Education, Science and Technology of Tocantins, Campus Palmas
Palmas, TO, Brazil

‡University of Brasilia, Faculty of Gama, Software Engineering Group
Gama, DF, Brazil

§Federal University of Parana, Electrical Engineering Graduate Program
Curitiba, PR, Brazil

Emails: jpassos92@gmail.com, carlosedu@ifto.edu.br, renatocoral@unb.br, lscoelho2009@gmail.com, llanos@unb.br

Abstract— Nowadays there are many elderly people who need assistance to walk. For that purpose, an exoskeleton is a type of wearable mechanism that can help them in both rehabilitation and locomotion tasks. In its autonomous form, an exoskeleton is required to be both lightweight and sturdy. However, there is a trade-off between these two characteristics. The mechanical design of its parts usually require simulations and stress tests to determine the best shapes that reduce weight and obey a safety factor, which are contradictory criteria. This mechanical design demands highly skilled professionals and is time and cost consuming. In this context, this work proposes the use of multi-objective optimization algorithm to automate mechanical simulations and assist mechanical designers. A case study of the modelling of an exoskeleton part is presented. The multi-objective optimization is performed using finite element analysis by simulating the part under external forces while altering its dimensional parameters. At each iteration, a cost function evaluates the solutions based on the safety factor and the mass of the resulting model. Finally, multiple results in the Pareto Front are presented and discussed.

Keywords— exoskeleton, sizing optimization, multi-objective search, finite element analysis, differential evolution.

Resumo— Atualmente existem muitas pessoas idosas que precisam de assistência para se locomover. Neste contexto, um exoesqueleto é um tipo de mecanismo vestível que pode ajudá-los tanto nas tarefas de reabilitação quanto de deslocamento. Em sua forma autônoma, um exoesqueleto deve ser tanto leve quanto forte para suportar os esforços. No entanto, existe um *trade-off* entre estas características. O projeto mecânico de suas peças requer simulações e testes de esforços para determinar o formato ótimo que seja leve e ao mesmo tempo obedeça a um fator de segurança, critérios que são contraditórios. O desenvolvimento de um projeto mecânico que satisfaça os requisitos de projeto, demanda profissionais qualificados e longo tempo de análise, o que incorre em altos custos. Neste contexto, este trabalho propõe o uso de uma técnica de otimização multi-objetivo bio-inspirada a fim de automatizar o processo de simulações mecânicas e desta forma assistir o projetista. Um estudo de caso do modelo de uma peça para um exoesqueleto é apresentado. O algoritmo de otimização multi-objetivo é empregado juntamente com a técnica de análise de elementos finitos para simular a peça sob esforços externos com várias configurações de dimensões. A cada iteração do algoritmo, uma função custo é utilizada para avaliar as soluções baseado no fator de segurança e na massa total da peça. Finalmente, múltiplas soluções são apresentadas em forma de uma Fronteira de Pareto e os resultados discutidos.

Palavras-chave— exoesqueleto, otimização de dimensionamento, busca multi-objetivo, análise de elementos finitos, evolução diferencial.

1 Introduction

Wearable robots can be defined as those worn by human operators addressed to supplement the function of a limb or to replace it completely. In this context, wearable robots may operate alongside human limbs, as in the case of exoskeletons, or they may substitute missing limbs, for instance following an amputation. Exoskeletons have been defined as a class of robots that extend the strength of the human limb beyond its natural ability while maintaining human control of the robot. A specific and singular aspect of extenders is that the exoskeleton structure maps on to the human anatomy (Rocon and Pons, 2012).

A relevant application of exoskeletons is in the medical rehabilitation area, which develops processes by which human functions (be it physical or cognitive) are restored, at least partially, to their normal conditions. In this sense, the assistance and recovery of elderly people can be greatly benefited by the use of exoskeletons (Kong and Jeon, 2006).

In robotic exoskeletons, the kinematic compatibility has paramount importance specially when working on the principle of internal forces. The typical misalignment between exoskeleton and anatomical joints results in uncomfortable interaction forces where both systems are attached to each other. Given the complex kinematics of most human anatomical joints, this problem is hard to avoid. The issue of compliant kinematics claims for bioinspired design of wearable robots and imposes a strong need for control of the human-robot physical interaction (Panich, 2012).

In the context of mechanical design of exoskeletons (specially for elderly people) the balance between weight and safety factor is a very important issue because the elderly can not carry heavy weight. For many years, design dimensioning was closely related to the experience of its designers. A classic example of this is the robustness of ancient buildings, where high safety factors are found far beyond today's standards. This characteristic can be justified by the rudimentariness of the techniques used to develop these projects, as well as the severe penalties applied in the occurrence of failures, which could be the death penalty (Pollio, 1914).

Therefore, projects in some mechanical engineering areas are mainly verified through computational simulations, where critical failure tests are not even performed either because of the cost of their execution or the scale of the project. In this case, the simulation procedures tries to express the physical behaviour of the mechanical structure through mathematical equation systems.

In the case of an exoskeleton mechanical project, for instance, the system that models the features of a solid design has fifteen equations in which nine of them are partial differential equations (Cook et al., 1989). As such, solving this kind of mathematical system is the bottleneck of the simulation process, and the exact solution cannot be found for most geometries.

In this way, the discretization technique called Finite Element Analysis (FEA) is used to solve this problem. It consists of sectioning the model part into a set of pieces, named elements. This procedure aims to approximate the solution of the original system of equations by solving a set of linear equations describing the displacements and stresses in each of these elements.

The accuracy of this approximation is directly related to the mesh elements created by the discretization of the model part. The appropriated procedure for the creation of the representation mesh is one of the main subjects of study in the finite element analysis. However, for the most rudimentary mesh creation techniques, these are described by the number of elements used in their construction as well as the size of these elements.

The mechanical design of an exoskeleton is complex and full of challenges. The first difficulty is to identify the project's requirements. The second is the selection of transmission and drive components, respectively the pulleys, belts, motors, gearboxes and transmissions. The latter being the construction of a frame that is capable of housing off-the-shelf components and meeting the requirements of the project.

In this context, off-the-shelf components are chosen from catalogs, since the manufacturing of customized items to the requirements of this project is economically infeasible. Therefore, the models contained in these catalogs of each component are then classified according to criteria of cost, ergonomics, weight, resistance and even availability in the market. Based on this process, the designers perform the selection of the set of components to be used in the project.

The next step consists of the suitability of the frame to the shape and fixture characteristics of the commercial components. Thus, despite the imposition of different restrictions on the shape of the frame, this is the only element of the exoskeleton in which designers have the freedom to show their potential. Therefore, it is of utmost importance to apply an appropriate methodology for this purpose.

This work aims to demonstrate a methodology to tune the design parameters of one part of an exoskeleton design by using the Multi-objective Differential Evolution (MODE) technique in conjunction with finite element analysis, in order to evaluate both weigh and safety factor as objective functions (Robic and Filipc, 2005; Deb et al., 2001).

2 Model Part Simulation

The model part to be optimized was previously built in *SolidWorks 2017*, as shown in Fig. 1. This is similar in shape to a circular head wrench, disregarding the characteristic contact grooves, as well as the presence of the two fixation points at the end of its handle.

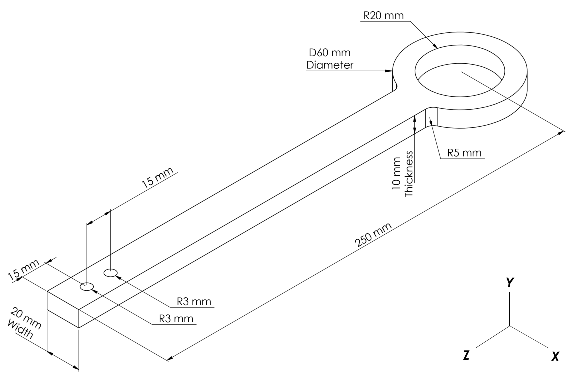

Figure 1: **Shape of the Exoskeleton Frame.**

During the simulations, it was considered that the material used to manufacture the model part was an aluminum alloy 7075-O (SS), of which mechanical properties were obtained from *SolidWorks 2017* materials library, as shown in Table 1.

Table 1: **Mechanical Properties.**

Tensile Yield Strength	94.99E6	N/m^2
Young's Module	7.20E10	N/m^2
Poisson's Ratio	0.33	
Density	2810	kg/m^3

To evaluate the optimization procedure, a test scenario was created to simulate the reaction force caused by the midstance of a person's gait (see Fig. 2). In this stance, the gross weight, including the exoskeleton, is supported by a single leg. Therefore, during in the simulations, the entire weight is supported by the exoskeleton structure, due to its user's leg deficient.

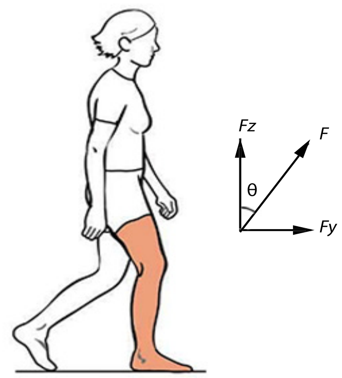

Figure 2: **Gait Midstance** (Barton et al., 2017)**.**

In this situation, most of the load is in the opposite direction to the Z-axis shown in Fig. 1. The force in the Y-axis direction is caused by a misalignment in the structure or an incorrect step, described as the angle Θ. Regarding the X-axis, there was no reaction force for the simulated scenario. Thus, an angle of five degrees was assumed in the misalignment of the reaction force the coordinate system of the model part, and the user and exoskeleton weighted together 100 kg.

The point of application of the resulting forces were the two attachment points present in the handle, equally distributed between the contact surfaces. In addition, the effect of gravity and the restriction of the displacement of the inner face of the circular head of the model part were also considered.

Therefore, the dimensional parameters selected for optimization of the model part were the model part thickness (T), the width (W) of the handle and the outer diameter (D) of the circular part, as marked in Fig. 1. Their respective search spaces are found in Table 2.

Table 2: **Search Space.**

Parameters	Minimum	Maximum
Thickness (mm)	5	25
Width (mm)	10	50
Diameter (mm)	55	75

Due to the non-standard geometry of the model part, techniques of discretization were used to simulate the stress applied to its structure. Section 3 addresses the adoption and implementation of the Finite Element Analysis technique.

3 Finite Element Analysis

In this work, the problem of structural analysis of the model part is solved by a numerical method called "Finite Element Analysis" (FEA). This method seeks to approximate the solution of a complex problem by integrating a set of discrete solutions of the evaluated domain. The applications of this technique are not restricted to solving structural problems. In fact, it is widely used to solve boundary value problems for partial differential equations.

The *Matlab R2017b*'s Partial Differential Equation Toolbox was used to perform stress and displacement analysis on the model part structure. In this FEA software, the main adjustment parameter for creating the mesh is the maximum edge length of the elements H_{max}, which directly influences the size of the mesh. The smaller the size of the element used, the greater the number of elements in the resulting mesh.

The H_{max} parameter has no physical unit. However, only positive real numbers can be assigned. Internally, the FEA algorithm relates the overall dimensions of the geometry analysed to this parameter and define the sizes of the elements mesh.

One of the main metrics used to evaluate the complexity of these meshes is its number of degrees of freedom (DOF). The DOF is related to the amount of nodes used in the construction of the mesh, that is, the vertices of each finite element. It can also be used to estimate the computational cost in solving FEA's system of equations and the procedure for creating the mesh itself.

Given the iterative characteristic of the shape optimization procedure, simulations are performed to evaluate new configurations. In this way, the adjustment parameter must be chosen so as to allow the execution of the experiment with a reasonable accuracy and in a timely manner.

For the definition of the mesh adjustment parameter, five configurations of the model part were considered for the external stress scenario, constructed from the regular variation of the dimensions described in the search space, as described in Table 3.

Table 3: **Simulations.**

Parameters	P_1	P_2	P_3	P_4	P_5
Thickness (mm)	5	10	15	20	25
Width (mm)	10	20	30	40	50
Diameter (mm)	55	60	65	70	75

During this procedure, the values for H_{max} were evaluated in the range $3 - 10$, considering an increment of 1.0 between experiments. This procedure aims to carry out the weighting between the accuracy of the results and their respective processing time.

After its execution, for each of the dimension configurations, as performed by Liu and Glass (Liu and Glass, 2013), the results of the experiment with the lowest value for H_{max} was used as the reference value making it possible to evaluate the error related to the use of a mesh with bigger elements.

According to the von Mises's theory, plastic distortions occur when the density of the distortion energy reaches the critical value of the material. That is, when the von Mises equivalent stress is higher than the material's yield stress, the model part can no longer return to its initial shape without external actuation.

Given that the focus of the study is related to the safety factor of the resulting model part, a criterion that describes how much the model part is stronger than its intended load was used. The error related to the von Misses stress together with the time required to execute the simulations was used to determine the maximum edge size of the elements.

However, tuning the parameters T, W and D to optimize the mass and safety factor has conflicting objectives. Therefore a multi-objective optimization approach had to be applied in order to solve this problem.

4 Sizing Optimization by Multi-objective Differential Evolution

Figure 3 depicts the data flow of the overall method proposed in this work, where different tools are integrated, such as Multiobjective Optimization based in Differential Evolution (MODE) algorithm, SolidWorks, and Matlab's FEA toolbox. SolidWorks and FEA are used for the purpose of evaluating the cost function (fitness) in order to guide the optimization process.

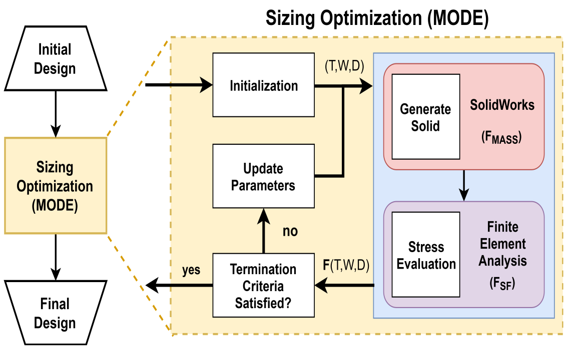

Figure 3: **Sizing Optimization Process.**

In the context of optimization tasks, multi-objective optimization problem (MOOP) algorithms are used in problems with two or more conflicting criteria. The sizing optimization (used in this work) was modeled as a MOOP because both safety factor and mass are conflicting objectives. In this context, the notion of the dominance concept is important to measure which solutions are better, because both objective functions in MOOP can have equivalent importance to a decision maker (Coello et al., 2007).

Equation 1 represents the sizing problem modeled as a MOOP.

$$\begin{aligned} &\text{Min } \mathbf{F}(T, W, D) = (F_{SF}, F_{MASS}) \\ &\text{s.t.} \\ &T \in [5,\ 25]\,, W \in [10,\ 50]\,, D \in [55,\ 75] \end{aligned} \tag{1}$$

where $\mathbf{F}$ is a vector of objective functions, F_{SF} is the safety factor, F_{MASS} is the mass of the part and T, W and D boundaries were defined as explained in Table 2.

The dominance concept is defined as: A vector $\mathbf{u} = (u_1, u_2, ..., u_k)$ is said to dominate another vector $\mathbf{v} = (v_1, v_2, ..., v_k)$ (denoted by $\mathbf{u} \preceq \mathbf{v}$) if and only if $\mathbf{u}$ is partially less than $\mathbf{v}$, i.e. $\forall i \in \{1, ..., k\}, u_i \leq v_i \wedge \exists i \in \{1, ..., k\} : u_i < v_i$.

The solutions which do not dominate each other are called non-dominated solutions. The set of optimal non-dominated solutions is the Pareto Set (PS) and the image of the PS over the function space is called the Pareto Front (Coello et al., 2007).

Achieving the Pareto Set of Multi-objective problems is usually a complex problem and needs an exhaustive exploration over the search space. Therefore, evolutionary algorithms have good performance over MOOP and often produce a non-dominated set close the Pareto Set. Like other evolutionary algorithms, Differential Evolution repeats mutation, crossover, and selection operators generation by generation to evolve its solution toward the good solutions (Tvrdík, 2009; Storn and Price, 1997). In this work, the DE was adapted to solve the sizing problem that was modelled as a MOOP.

The MODE algorithm (like most metaheuristic search algorithm) consists of an initialization procedure and an iterative procedure, as described in the Algorithm 1. During the execution of the first, the initial values of the individuals are generated from the boundaries of their search spaces, and the second consists of the optimization procedure itself.

The initialization procedure has a deterministic and a stochastic component. In that, $NumSearch$ individuals are generated from the interspersed sweep of the search space, being the other individuals generated from a procedure of randomizing the particle values within their search space boundaries.

The iterative part of the MODE algorithm consists of three distinct stages of operation: *mutation*, *crossover* and *selection* as described in Algorithm 1. In this work, new candidate solutions are generated by mutation and crossover. Follow-

Algorithm 1: MODE

```
Result: Pareto Front and its Solutions's Set
Input  : SearchSpace, NumSearch, NumPop, ScalingFactor, CrossoverP
Output: PFront, PSet
Src = Initialization(SearchSpace, NumSearch, NumPop)
FxSrc = CostFunction(Src, NumPop)
for n = 1:IterLimit do
    Mutant = Mutation(Src, ScalingFactor)
    New = Crossover(CrossoverP, Mutant, Src)
    JxNew = CostFunction(Src, NumPop)
    [Pop, FxPop] = Minimization(New, FxNew, Scr, FxSrc)
    [Src, FxSrc] = Selection(Pop, FxPop, NumPop)
end
[PFront, PSet] = ParetoFront(Src, FxSrc)
```

ing the selective process is performed on this solutions set. And in the final stage, after the execution of *IterLimit* iterations the Pareto Set is identified.

During *mutation*, three pre-existing solutions are randomly selected to create a solution called *mutant*, taking *ScallingFactor* as a weighting mechanism. After completing the crossover, the validity of this solution is verified. That is if the search space constraints for each particle are respected. If not, it is replaced by the initial value of the individual. Finally, the individuals of the solution are analysed individually. In order to evaluate the substitution of the pre-existing value for an offspring one, this procedure is handled by the probability *CrossOverP*.

The selection operator defines which are the best individuals. In a MOOP context, both objective functions have the same weight, so the complete dominance is used to evaluate it. The concept of complete domination defines that one solution is only said better than the other if all the results of the objective functions are lower than their counterpart, otherwise, these solutions are then called non-dominant. If the solution is found to be complete dominant it is added to the solution's database, if not, both of them are included in the database.

The *Truncate function* was then used to reduce the number of items in the solution database to *NumPop* (Zitzler et al., 2001).

In short, the Pareto Set is a set of non-dominated solutions, being chosen as optimal, if no objective function can be improved without sacrificing at least one other (Manne, 2018). In an optimization context, these objectives represent the results obtained after the evaluation of the *cost function*, quantified by the objective functions.

The objective functions chosen to evaluate the new configurations of the model part during optimization were Mass and the critical value of the Safety Factor (SF). However, due to the minimizing character of the MODE algorithm, the negative value of the second objective function was evaluated during the iterative process, since it is aimed to achieve its maximization.

Algorithm 2 describes the evaluation of the *cost function*, which is performed in three stages. In the first stage, the CAD representations (which have not yet been previously processed) are generated in *SolidWorks 2017* using the values assigned to the individuals of the evaluated solutions, and an integration is carried out by *Matlab R2017b*'s CADLab Toolbox. In this same stage, the acquisition of the geometrical characteristics of these model parts is performed, such as the mass, the position of the center of mass and the moments of inertia. In the second stage (as in the first) the finite element analysis is only performed in unseen solutions. The final stage consists of processing the information generated in the previous stages to assign the objective functions.

Algorithm 2: CostFunction

```
Result: Objectives functions evaluation
Input  : Pop, Database
Output: Objectives
Pop(k) = round(Pop(k))
Experiment = Load(Database)
Open(SolidWorksApp)
for k = 1:NumPop do
    if !exist(Experiment(Pop(k)).Solid) then
        Experiment(Pop(k)).Solid = SolidWorks(Pop(k))
end
Close(SolidWorksApp)
for k = 1:NumPop do
    if !exist(Experiment(Pop(k)).FEA) then
        Experiment(Pop(k)).FEA = FEA(Pop(k))
end
Save(Database, Experiment)
Objectives(Experiment)
```

Given the methodology adopted by the search algorithm, it is expected that the solution found is not necessarily the optimal solution to the problem. Thus, the execution of a single experiment is insufficient to produce satisfactory conclusions for the study. In order to provide an analysis based on a normal distribution, 51 independent experiments are performed for each of the simulation scenarios. The information pertinent to the geometry and analysis of finite elements of the model parts were stored in a database. Thus, given a previously held request, only the third stage is actually performed, in this case accelerating considerably the time required to execute the simulations.

It is worth pointing out that the sharing of results through the database does not violate the independence of the experiments since this practice does not directly influence the internal behaviour of the multi-objective optimization algorithm.

However, this procedure was only feasible due to the physical meaning attributed to the individuals. This feature results in restrictions on the manufacturing process. In this way, the values of the individuals were rounded, imposing a precision in the millimetres. This problem then is restricted to a finite number of solutions, 16 thousand possible configurations.

Evaluating the results of an optimization problem is a complex task (Fonseca et al., 2006). Therefore, in this work, two performance metrics are used to help identify the best solution set: Hypervolume (HV) and Spacing.

In the Hypervolume metric, the space described by the objective functions of the problem is evaluated, more precisely the relative volume between the Pareto Front of the solution is determined in relation to a reference point (Auger et al., 2009; Bradstreet, 2011). Thus, for this metric, it can be inferred that solution sets with a higher hypervolume describe better trade-offs than those with a lower hypervolume.

In turn, the Spacing metric evaluates the distribution of non-dominated solutions in the objective space, determined by the relative distance among such solutions (Manne, 2016). Smaller results indicate a better delineated Pareto Front.

For the compatibilization of the results of these metrics, the complement of 1 of the Hypervolume metric was adopted during the determination of the best solution set. These results were then normalized. So the best set of solutions was the one that presented the lowest value after the sum of these two normalized metrics. In this way, evaluating both aspects related to the diversity and convergence of the Pareto Front (Riquelme et al., 2015).

The configuration parameters of the MODE algorithm previously listed are listed in Table 4.

Table 4: **Settings.**

ScalingFactor	0.5
CrossOverP	0.2
NumSearch	5
NumPop	30
IterLimit	100

5 Results and Discussion

The use of FEA in iterative procedures demands a weighting between computational cost and fidelity of the generated data. Given that decreases in estimated error result in an exponential growth in mesh complexity, directly reflecting in the amount of memory and time required to process the solutions.

This work takes into account that one of the criteria adopted to define the adjustment parameter for the creation of the mesh in the finite element analysis has a direct correlation with the computational power of the machine used. As a benchmark, the experiments in this work were performed on a notebook using the Windows 10 operating system, consisting of an i7-6700HQ processor and 100 GB of memory, of which 16 GB of them was physical memory.

From a practical point of view, the use of virtual memory (SWAP) should be avoided if possible due to a high increase in the processing time of the simulations, as well as eventual peaks of instability in the system.

To that end, three design criteria were adopted to choose the mesh adjustment parameter, respectively related to memory usage, processing time and estimated error. The first restriction states that throughout the experiment the memory used should not exceed the amount of physical memory available. The second, a maximum time of 60 seconds to perform the finite element analysis. And the latter, an error less than 15% over the highest fidelity setting.

It can be seen in Figure 4 that the processing time has a logarithmic decrement in relation to the variation of $Hmax$.

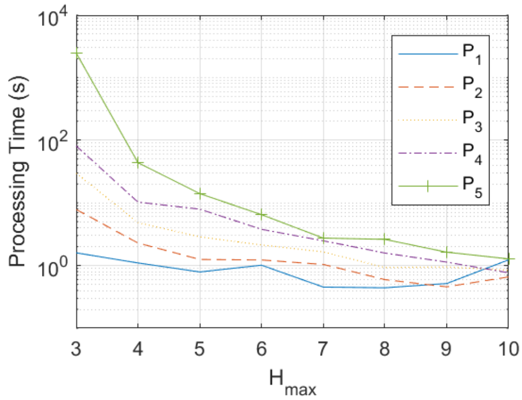

Figure 4: **FEA - Processing Time.**

In contrast, in Figure 5, an approximately linear growth is observed in the of the relative error of the finite element analysis.

Unfortunately, it was not possible to plot the memory usage during the creation of the mesh and solution of its system of equations given that the Partial Differential Equation Toolbox does not provide this information, making necessary the

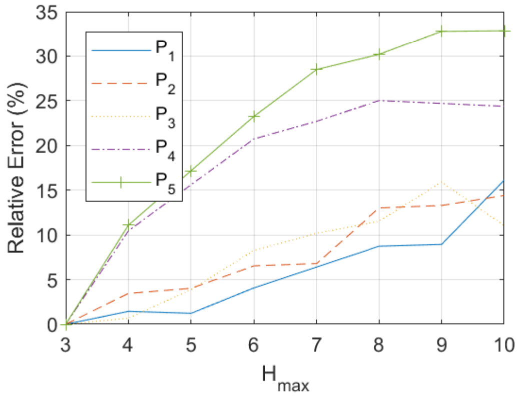

Figure 5: **FEA - Relative Error.**

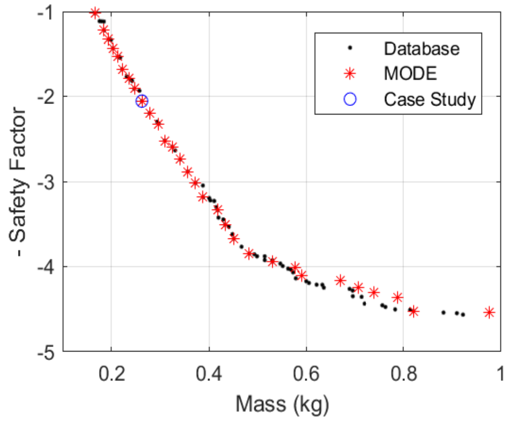

Figure 6: **Pareto Front.**

use of some external tool.

Based on these restrictions (and also the time constrains), a value equal to 4.0 was adopted for the parameter $Hmax$. Therefore, a configuration that provides (for most of the analysed model parts) a processing time within 20 seconds, with a relative maximum error of less than 12%, and an economical use of memory was achieved.

Then the optimization of the model part was carried out, in which the effective processing time of these experiments was considerably reduced, due to the sharing of results through the solution database.

The performance metrics Spacing and Hypervolume were then calculated for each of these independent experiments. Table 5 lists the mean, median, minimum, maximum and standard deviation of the results of these metrics.

Table 5: **Metrics.**

Spacing

Mean	Median	Min.	Max.	Std.
0.047	0.047	0.031	0.061	7.18e-03

Hypervolume

Mean	Median	Min.	Max.	Std.
0.713	0.716	0.676	0.727	1.14e-02

The results of the Spacing metric show practically identical mean, median and minimum values, but they are also small. Which means that the identified Pareto Frontiers have a good spatial distribution of its solutions. In turn, in the Hypervolume, the closeness of its mean and median, as well as a small value in its standard deviation indicate the convergence capacity of the MODE algorithm in all realized experiments.

Adopting the procedure previously described, the best solution group has been identified, as depicted in Figure 6. Note that in the Pareto Front (identified by the multi-objective optimization procedure) the axis of the Factor of Safety is negative, due to the minimizing characteristic of the MODE algorithm. Additionally, the solutions that resulted in Safety Factor lower than 1 (configurations that would break given the conditions of the simulated scenario) were excluded. This process of exclusion automatically via the process of identification of the Pareto Front was accomplished through an application of penalty for such solutions.

The results for the safety factor criterion are only regarding the behaviour of the structure of the model part for a given set of mechanical proprieties and to the scenario of external stresses. The engineer (in charge of the project) must take into consideration that mechanical proprieties of the material (of the final product) may differ from the values used in the simulations; as well as the influence of the process utilized to manufacture the model part in these proprieties. In that context, a margin of safety criteria is usually applied to prevent these problems.

Given the human-related application of an exoskeleton, a safety factor of at least 2 was chosen as the bare minimum standard. Table 6 lists the parameters of a model part that results in a safety factor that respects such restrictions, marked in Figure 6 as "Case Study".

Table 6: **Case Study.**

Thickness	25 mm
Width	12 mm
Diameter	55 mm
Mass	262.76 g
SF	2.06

Figure 7 demonstrates the influence that the purpose model part has in its design process, which is evidenced by the distribution of the safety factor in the body of the model part. That is, due to the design of the part, external stresses in the direction of the Y-axis more easily affect the integrity of the model part.

6 Conclusion

In this work, the multi-objective optimization technique MODE was applied to automate the sizing procedure of a mechanical design for a given

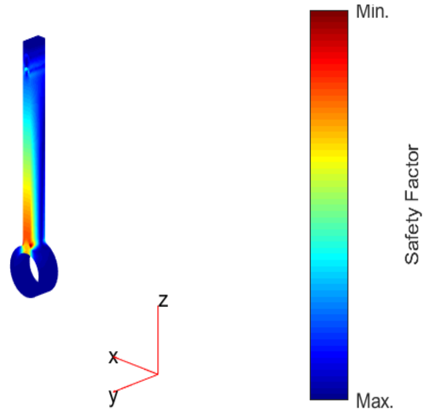

Figure 7: **Optimized Model Part.**

set of external stress and material mechanical proprieties. Thus allowing the fulfilment of the requirements for the mechanical structure safety factor while utilizing a sub-optimum set of dimensional parameters that results in a lighter model part.

In future works, the use of a better FEA tool that allows the creation of more effective meshes as well as the application of more complex meshing refinement techniques is desired.

References

Auger, A., Bader, J., Brockhoff, D. and Zitzler, E. (2009). Theory of the hypervolume indicator: optimal μ-distributions and the choice of the reference point, *Proceedings of the tenth ACM SIGEVO workshop on Foundations of genetic algorithms*, ACM, pp. 87–102.

Barton, J., Tedesco, S., Healy, T. and OFlynn, B. (2017). Potential for new smart knee device to cut down on knee surgery recovery time, Engineers Journal - Ireland's Engineering News Source.

Bradstreet, L. (2011). *The hypervolume indicator for multi-objective optimisation: calculation and use*, PhD thesis, University of Western Australia.

Coello, C. A. C., Lamont, G. B. and Veldhuizen, D. A. V. (2007). *Evolutionary Algorithms for Solving Multi-Objective Problems*, Springer Science, USA.

Cook, R. D., Malkus, D. S. and Plesha, M. E. (1989). *Concepts and Applications of Finite Element Analysis*, 3 edn, John Wiley & Sons.

Deb, K., Thiele, L., Laumanns, M. and Zitzler, E. (2001). Scalable test problems for evolutionary multiobjective optimization, *Technical Report 112*, ETH, Zurich, Switzerland.

Fonseca, C. M., Paquete, L. and Lopez-Ibanez, M. (2006). Effects of mesh density on finite element analysis, *IEEE Congress on Evolutionary Computation* .

Kong, K. and Jeon, D. (2006). Design and control of an exoskeleton for the elderly and patients, *IEEE/ASME Transactions on Mechatronics* **11**(4): 428–432.

Liu, Y. and Glass, G. (2013). Effects of mesh density on finite element analysis, *SAE International* .

Manne, J. R. (2016). Multiobjective optimization in water and environmental systems management- mode approach, *Handbook of Research on Advanced Computational Techniques for Simulation-Based Engineering*, 1 edn, IGI Global.

Manne, J. R. (2018). Swarm intelligence for multi-objective optimization in engineering design, *Encyclopedia of Information Science and Technology*, 4 edn, IGI Global, pp. 239–250.

Panich, S. (2012). *Design and Simulation of Leg-Exoskeleton Suit for Rehabilitation*, 1 edn, Global Journal of Medical Research (USA.

Pollio, M. V. (1914). *The Ten Books on Architecture*, Harvard University Press. tr. by Morgan, M. H.

Riquelme, N., Von Lucken, C. and BarÃ¡n, B. (2015). Performance metrics in multi-objective optimization, *XLI Latin American Computing Conference* .

Robic, T. and Filipc, B. (2005). Demo: differential evolution for multiobjective optimization, *EMO - International Conference on Evolutionary Multi-Criterion Optimization* pp. 520–533.

Rocon, E. and Pons, J. L. (2012). *Exoskeletons in Rehabilitation Robotics*, 1 edn, Global Journal of Medical Research (USA.

Storn, R. and Price, K. (1997). Differential evolution–a simple and efficient heuristic for global optimization over continuous spaces, *Journal of global optimization* **11**(4): 341–359.

Tvrdík, J. (2009). Adaptation in differential evolution: A numerical comparison, *Applied Soft Computing* **9**(3): 1149–1155.

Zitzler, E., Laumanns, M. and Thiele, L. (2001). Spea2: Improving the strength pareto evolutionary algorithm, *TIK-report* **103**.