Decision-Making Models for Optimal Engineering Design and their Applications

Doktori (PhD) értekezés

AMIRHOSEIN MOSAVI

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DR. NAGY PÉTER TIBOR

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I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person nor material which has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text.

A.Mosavi

*This is to certify that the thesis entitled "**Decision-Making Models for Optimal Engineering Design and their Applications**" submitted by **A. Mosavi** to University of Debrecen for the award of the degree of Doctor of Philosophy is a bona fide record of the research work carried out by him under my (our) supervision and guidance. The content of the thesis, in full or parts have not been submitted to any other Institute or University for the award of any other degree or diploma.*

Dr. Nagy Peter Tibor

Decision-Making Models for Optimal Engineering Design and their Applications

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Abstract

The task of solving optimal engineering design problems is considered as a demanding decision-making process where the real-life industrial problems typically have to be considered from very different perspectives. In this context the most logical approach to achieving the best solution, at the presence of multiple design criteria and numerous design variables, has been the task of performing scientific optimization to produce potential solutions for further decision-making. Accordingly multiple criteria decision-making approaches to optimal engineering design problems, via employing efficient, robust, global and multi-objective optimization algorithms, have brought a significant and competitive advantage to the optimal design. However most of these approaches, due to the characteristics of the real-life problems, often associated with the usage, dimensionality and high computational cost of the objective evaluations, have not been practical and widely acceptable in engineering design community. Here the difficulties and further requirements of utilizing the optimization approaches in optimal engineering design are discussed with a more emphasis on challenges to complex geometries, dimensionality, and multiple criteria nature of the real-life engineering design problems. As a response to the considered challenges, performing the optimizations approaches in the framework of an integrated design environment is proposed as the key success to win industry.

Further this research the metamodels in general approaches to optimal engineering design, are seen as the essential but not sufficient tools to enhance creating the efficient global optimization approaches in dealing with dimensionality. In fact by extension the dimension of multiple criteria decision-making problems which has been mostly due to the increasing number of variables, optimization objectives, and decision criteria, presenting a decision-maker with numerous representative solutions on a multidimensional Pareto-optimal set can not be practical in engineering applications. Accordingly for better dealing with the ever increasing dimensionality a supplementary decision-support system to enhance the metamodels is proposed. As the result an improved decision procedure is formed according to the limited human memory and his data processing capabilities. In this context the research further contributes in shifting from generating the Pareto-optimal solutions, to the reactive and interactive construction of a sequence of solutions, where the decision-maker is the learning component in the decision-making loop. To doing so the conventional evolutionary and interactive optimization and decision-making algorithms are updated by reactive search methodology, empowered with the advanced visualization techniques, in the framework of an integrated design environment.

1 Introduction

In today's increasing global competition, it is very important to design products which are able to optimally satisfy human needs with sustainable use of resources. Consequently in most of the engineering design tasks it is necessary to be able to effectively adjust the product features of quality, cost and performance to meet a certain number of design targets. The design variables highly affect the design targets and the overall expectations. These targets are so called design objectives.

In the process of design, the engineering designer aims to find out what value of design variables can generate an optimal result by satisfying the design objectives. In this context the most logical approach to achieving the best solution, at the presence of many design criteria, has been the task of performing scientific optimization methods and systematic decision-making. Yet in real-life optimal design problems, identification the Pareto-optimal solutions of an engineering problem with the aid of optimization methods and further decision-making task is extremely complicated where the optimal decision has to be taken at the presence of trade-offs between many conflicting objectives. Therefore the whole process of design is rather considered as an improvement process where decision-making task aims to maximize the positive consequences of the choice. The positive consequences in optimal engineering design are basically referred to *criteria* of product's performance where the decision-maker (DM) involves his rational choice. An extended description to the concept of optimal engineering design has been provided for instance in [78].

Considering the traditional means of optimal design, the designer has to create the desired design, for the given tasks, by selecting the values for design variables. In this way, the result is totally based on the expertise of the designer. This kind of design optimization procedure is time consuming and therefore very expensive to be practical for today's needs. Accordingly there have been great desire and efforts in approaching the idea of implementation an automated optimal design environment with the involvement of advanced optimization and decision-making methods [1], [7], [11], [78]. For instance commercial computer aided design (CAD) packages e.g., SolidWorks [79], [80] and CATIA [81], [82] have tried to provide designers with extra optimization and decision-support tools. Although these tools are still able to deal with just simple optimization tasks which definitely would not be enough to deal with real-life optimal design tasks where multiple design criteria are to be simultaneously considered for an optimal decision [5].

Nowadays the engineering analyses have been mathematically well defined and implemented by computer packages providing real-life numerical simulations. Commercial implemented simulation tools, surveyed and well described in [83], cut down the product design time and cost. The computer simulation software packages simulate the behavior of the concept design for quality in virtual environments. These computational simulation packages, also known as computer aided engineering (CAE) tools [84], in an integration with CAD tools, are widely used in different industries allowing the designer to investigate several different design configurations. In this context the finite element analyses (FEA) [85], for structural behavior simulation, and computational fluid dynamics (CFD) analyses [86], for simulating the behavior of fluid dynamics, have been widely utilized e.g., in [87], [88], [89], and [90]. Running the simulator instead of real-life evaluations is often cheaper and faster. Yet in simulation-based design, as it is described in e.g., [91], [145], and [146], a certain number of problems and challenges still remain. For instance the designer has a very large-scale [17] and complicated task to deal with and there are often numerous variables involved to be considered while dealing with the defined constraints. Furthermore it is often difficult to find out the interactions between the design's variables and objectives. Meanwhile the increasing number of involved components i.e., variables, parameters, constraints and objectives in the process, has made the process even more complicated. There are also several conflicting and highly nonlinear objectives that should be simultaneously considered. Therefore it is difficult to gain results just by manually adjusting the design variables' values. That is why the advanced optimization algorithms are quite essential in providing support for generating optimal solutions in the general engineering design processes instead of only relying on expert-based approaches [3], [51], [121], [151], and [249].

1.1 Multiple criteria decision-making (MCDM)

Optimal engineering design is considered as a decision-making process. In this sense the design process would overlap with the other theories and methods in further disciplines, e.g., decision sciences, economics and operations research. This fact would force the process of design into a complex systems context, and demands that design decisions account for a product's integrated development process [6], [28], [373], [374], [394], [395]. In such process the real-life industrial problems typically need to be considered from very different perspectives. This leads to the need for optimizing several conflicting objectives, and decision-making on several conflicting criteria at once. In this context the benefits of utilizing MCDM [5], [44], [53], [70], [92], [93], [167], [189], [197], include that the conflicting design objectives are taken into account simultaneously leading to an overall insight of the problems which would deliver a significant and competitive advantage to the engineering design community. In an optimal engineering design environment solving the MCDM problem is considered as a combined task of multi-objective optimization (MOO) [4], [5], [69], [70], [162], [190], [255] and decision-making. As the process of MCDM is much expanded most MOO problems in different disciplines can be classified on the basis of it. In this sense the benefits of MOO include that the conflicting objectives are taken into account simultaneously, via practically implementing and testing Pareto-optimal solutions. It is very important that before the actual decision about the final solution takes place the DM should gain a good understanding about the trade-offs between the solution alternatives. Then the final decision can be firmly taken. Therefore, MOO approaches for creating Pareto-optimal solutions are considered vital to MCDM community.

Implementing the MCDM task for solving optimal engineering problems is considered as a very important and in the same time complicated approach for engineers to pursue [66]. The problems of this type are mostly nonconvex, nonlinear and computationally expensive, including numerous variables and several conflicting objectives as further explained in e.g., [5]. Solving the optimal engineering design problems as such, which are mostly referred to black-box optimization problems [67], [68], is not a simple task. The black-box optimization problems with multiple objectives can be solved in several different ways. However the characteristics of these problems suggest that efficient, robust and global approaches should be used to tackle the difficulties caused by several local optimums, several conflicting objectives, and high computational cost of the objective evaluations. Meanwhile engineers prefer to utilize the efficient, easy to use approaches in order to solve these problems accurately and effectively.

Even though optimization research community has already developed numerous approaches to global and multi-objective optimization including metamodeling methodologies, interactive, and evolutionary algorithms, mainly surveyed in e.g., [3], [4], [5], [6], [7], [69], [76], [93], [124], [125], [134], and [137], yet most of these approaches, due to the difficulties often associated with the usage and also a number of particular requirements mostly associated with increasing the design space which we have discussed them in details in e.g., [16], [17], [18], [19], haven't been really applicable in real-life engineering optimization problems within industry.

1.2 Practical approaches to optimal engineering design

Due to highly expensive numerical analyses in engineering and process simulations, for an optimal design, DMs have been urged to extract as much information as possible from a limited number of test runs, considering e.g, [1], [2], [67], [68], [69], [77], [83], [84], [91], [145], [146], [185]. The vast number of existing statistical and optimization algorithms are to extract the most relevant qualitative information from a database of experiments in order to support the decisions in real-life engineering optimal design where a number of objectives in multiple design criteria from very different perspectives are to be considered [3]. Besides, the MOO algorithms offer a significant competitive advantage in different fields of engineering optimal design where the conflicting objectives are simultaneously considered leading to an overall insight into the problems. In this context the task of algorithms selection followed by understanding the true nature of a particular problem, is considered vital for an effective approach to the optimal engineering design [4], [5]. For this reason a great amount of efforts by the author, prior to creating this thesis, reflected into a number of surveys e.g., [1], [2], [7], [8], [9], and [10], has been devoted on identification the characteristics of each family of problems and the potential corresponding algorithms. Among all algorithms to MCDM, interactive [70], evolutionary [4] and metamodeling [3], because of their efficiency, have been of our particular interests in solving the optimal engineering design. A classification of the MOO methods including their recently improved algorithms have been well presented in the thesis as a summary to a number of our published state of the art surveys and case studies, e.i., [1], [2], [7], [8], [9], [10]. Although considering shape optimization problems where the aesthetics criterion is a common objective evaluation function in the optimal design tasks the interactive approaches have been found to be more effective as they are capable of supporting the DM actively in finding the preferred Pareto-optimal solutions by continuously involving the preferences in the solution process to better guide the search. Nevertheless prior to selecting a proper algorithm for a particular problem, utilizing a decision-support system with the ability to reduce the design space e.g., the ones proposed in [16], [17], [18], [19], [20] and [65], would help decreasing the complexities as well as providing the ability for understanding the true nature of the problem.

1.3 Contributions

In today's highly competitive market environments, engineering designs must be optimized if they are to succeed in accomplishing design objectives while satisfying the design constraints. Considering further inevitable multiple criteria, e.g., the product development lead-time, cost and performance must be also optimized to ensure affordable and speedy reaction to the changing market needs. Thus, a deep understanding of the computational tools used for MOO [4], MCDM [5], and simulation-based optimal design [77], is critical for supporting the engineering decision-making processes. Drawing on current researches, state of the art surveys, best-practice methodologies and developing tools illustrated by case studies, this thesis contributes to providing an overview to engineering optimal design as well as simulation-based numerical design optimization with a more emphasis on challenges to complex geometries [64], big data [65], decision-making [66] and multiple criteria nature [6] of the real-life engineering design problems.

In today's ever increasing design complexity, by extension the dimension of MCDM problems which is mostly due to increasing the number of variables, optimization objectives, and decision criteria, presenting a human DM with numerous representative solutions on a multidimensional Pareto-optimal frontier is way complicated and not practical indeed. In this context this thesis would contribute in decreasing the dimensionality of MCDM problems by proposing an effective decision-support tool to reduce the design space. Therefore an improved decision procedure is formed according to the limited human memory and his data processing capabilities. The critical survey of Stewart [6] on the status of multiple criteria decision-making along with our state of the art surveys on the existing algorithms, which are included in this thesis [1], [2], [7], [8], [9], [10], report the needs for further improvements in today's ever increasing complexities in order to be able to efficiently deal with real-life applications. As a respond to the reported needs, this thesis preliminary propose a supplementary decision-support system based on classification [11] to identity the most relevant variables in the optimal design problems, in particular, shape optimization for complex geometries, leading to a smaller and manageable design space. Although the examined case studies are proposed in dealing with geometrical and shape optimization problems originally, however the feedback from industries and MCDM research community [12], [13], [14], and [15], indicates that the proposed methodology is also suitable for general applications in optimal engineering design. The citations and revisions of our initial proposed methodology [11] in a number of publications including Elsevier [13] and Springer [14], [15] have motivated the further investigations, researches and publications [16], [17], [18], [19], on this realm.

We should note that the research, development, and successful case studies on MCDM and MOO algorithms suggested to engineering optimal design community are numerous, taking these for instance [4], [5], [6], [26], [43], [66], [69], [70]. However the expansion and progress of applicability and popularity of these algorithms within engineering design communities have been very slow which indicates an obvious gap between academic research and the industrial real-life applications. This gap is further discussed for instance in [25], [28], [66], [69], [78], [94], [108], [109] and [110] where it is concluded that an algorithm can be widely utilized when only it is implemented within an integrated design environment of the optimization packages where its ease of use, and its further integration requirements are well customized. Here the idea behind the design strategy is “the idea of integration”. It is assumed that with an effective integration of the today’s already existing resources of CAD, CAE, and optimization, promising results can be achieved. Yet the improvement on geometrical parameterization techniques, and benefiting from advanced interfaces of commercial optimization packages would be essential. This ideology of design is introduced as the future trend for engineering optimal design. Thus here in the considered case studies instead of getting to the details of the optimization algorithms utilized, the focus would be on the level of integration and the potential advancement we could expect from the novel coupling of CAD, CAE, and optimization for the future designs.

In the framework of an integrated design environment the thesis’s further contributions to shape optimization for complex geometries e.g., [20], [21], and [22], include the development of a design strategy for general engineering optimal design problems on the basis of Non-uniform rational B-spline (NURBS) parameterization [23], [24], [106], [107], which is a standard description method of surfaces in CAD software in industry. Here the existing methodologies e.g., [25], [26], [27] and [28], are improved in terms of integration, optimization algorithms used, complex geometrical modeling methodology and parametrization. The considered applications and case studies utilizing the proposed method can cover a wide range of optimal design problems in hydrodynamics [29], [30], [31], aerodynamics [32], [34], built environments [33], [34], and thermal-fluid structural design [1], [35]. The obtained results, communicated via the above-mentioned publications are promising.

However in the way more challenging real-life applications such as optimal design of composite textiles [36], [49], where the detailed-complex geometry parametrization, big data and increasing the number of criteria in decision-making become the design’s new issues the strategy would demand for the further improvements. For this reason in the improved design strategy the former NURBS-based shape parametrization method is enhanced with a novel methodology called generative algorithms [37], [249]. Additionally the geometrical optimization strategy has been updated with the aid of reactive search methodology [38], in the framework of a novel optimal design strategy described in e.g., [40], [41], [42], [43]. Note that typical MCDM problem in engineering design is considered as a combined task of optimization, and decision-making. Yet in solving real-life MCDM problems often most of attention has been on finding the complete Pareto-optimal set of the associated MOO problem and less on decision-making where the design preferences are not accurately considered. In this context the research contributes in shifting from building a set of Pareto-optimal solutions, to the interactive construction of a sequence of solutions, where the DM is the learning component in the decision-making loop. Thus in order to better deal with big data and the increasing number of design criteria, the optimization and decision-making algorithms are empowered by reactive search methodologies, e.g., [38], [421], and brain-computer optimization [39] in the framework an integrated design environment, described in [44], [48], [51] and [53].

The methodology, case studies, and results have been communicated via a number of publications [40], [41], [42], [43], [44], [45], [46], [47]. Moreover the final workflow integrated with materials selection [49], [50], [51], [52], [53], has been approved and recommended by the Europe's leading CAE design company to the industry [52]. Furthermore the method has been continuously improved to fulfilling the needs of new fields of applications e.g., computer vision [48]. Note that the case studies considered in this thesis are mostly focused on shape optimization for complex geometries. However the proposed methodologies can also be customized and beneficial in other fields and applications of optimal design e.g., [48].

Worth mentioning that in the real-life applications an optimal design strategy receives the contributions of many different departments and multiple criteria, trying to meet conflicting requirements of a design simultaneously. In this context because of the emphasis on human-technology interactions this thesis overlaps with other disciplines, particularly with business intelligence and enterprise decision management in which we should have also considered them as well in a number of research works and publications e.g., [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], which are in fact not included in this thesis.

The contributions of the thesis with the corresponding publications are the following:

1. Section one, two and three including state of art surveys on global optimization, multi-objective optimization, and MCDM [1], [2], [7], [8], [9], [10].
2. Section three including a design strategy for general applications to engineering optimal shape design in the framework of an integrated design environment [1], [29], [30], [31], [32], [34], [34], [35].

3. Section four including a supplementary decision-support system to metamodels based on classification to identity the most relevant variables in the optimal design problems [11], [16], [17], [18], [19].
4. Section five including further improvements on optimal design strategy utilizing reactive search methodology in the framework of an integrated design environment [40], [41], [42], [43], [44], [45], [46], [47], [48].
5. Section five including the concept of design integration with materials selection [49], [50], [51], [52], [53].

1.3 Organization

The rest of the thesis is organized in the further five sections. In *section two* it is aimed to present brief overview on the existing approaches to optimal engineering design. This would include the essential definitions and classification of the methods with respect to a number of our published surveys e.g., [1], [2], [7], [8], [9], [10]. To doing so the basic concepts and definitions of MOO algorithms, MCDM, black-box engineering problems, applied global and MOO algorithms, and the efficient global optimization are described. Furthermore a comparison of applied engineering optimization algorithms with an emphasis on the role of robust design optimization is given. This section follows with a classification of MOO algorithms, and then brief descriptions on genetic algorithms, differential evolution and visualization. Finally the effectiveness of interactive and evolutionary MOO algorithms in the particular application to shape optimization is indicated where the NURBS-based shape parameterization methodology combined with optimization algorithms forms an evolutionary design tool. *Section two* concludes that optimal engineering design community, in order to effectively deal with the multiple local optimums and nonlinear objectives, has been generally urged to utilize efficient global optimization algorithms which are enhanced with metamodels.

In *section three* the difficulties and further requirements associated with utilizing efficient MOO algorithms in real-life applications are described in respect to our articles e.g., [29]-[35]. These difficulties including dimensionality, and the weaknesses in integration, automation, usage, user-friendly visualization tools, post-processing tools, decision-support tools and metamodel supports indicate a gap between optimization approaches and optimal engineering design applications in industry. Consequently it is proposed that a global optimization approach to a MCDM problem can be efficiently conducted only within the framework of an *integrated design environment* where most of the associated difficulties and industrial requirements are well addressed. *Section three* continues with a number of case studies in shape optimization within the framework of an integrated design environment where the importance of employing optimization packages are pointed out as an effective design strategy to fill the gap between academic research and industrial real-life applications. In this section it is concluded that although the optimization packages can deal with most of the difficulties associated with MCDM real-life applications in industry, still the challenges related to dimensionality would remain demanding.

Section four would discuss further difficulties associated with dimensionality in respect to a number of our articles e.g. [11], [16], [17], [18] and [19]. In the previous section metamodels and most importantly DOEs, as the standard means of approximation, have been contributing to reduce the dimensionality to certain levels within integrated design environments for optimal engineering design applications. However they were reported to be not sufficient in dealing with the concept of curse of dimensionality which is the case in most of optimal engineering design problems, in particular in shape optimization. In order to reduce the dimensionality this section propose a methodology based on classification to reduce the number of design variables. The proposed methodology acts as an efficient and reliable decision-support tool which is considered as a supplementary decision-support system to metamodels. A number of case studies concerning shape optimization have been considered to evaluate the effectiveness of the proposed supplementary decision-support system.

Section five presents the main contribution of our research in developing an integrated design environment described in e.g, [42], [48], [49], [50], [51]. Note that evolutionary MOO algorithms along with interactive MOO algorithms enhanced with metamodels, as the most effective approaches to MCDM are indeed among the most used approaches to optimal engineering design problems. Yet there are a number of drawbacks are associated with the usage of these approaches in industry. In this section a number of these drawbacks are discussed. As a response the reactive search strategy of optimization is proposed as a potential replacement to evolutionary and interactive algorithms for today's large-scale optimal engineering design problems where the advanced multidimensional visualization tools can well deal with big data and computational costs. Following this section a number of case studies have been considered for evaluation the performance of the proposed MCDM approach.

Finally *section six* provides a conclusion to the various researches covered in the body of the thesis.

2 Basic concepts and definitions

The materials provided in this section would be a summary to a number of our publications e.g., [2], [7], [9], [21], and [29].

2.1 MOO and MCDM

In real-life problems we often face design optimization problems with several conflicting objectives. Problems of this type are called MOO problems [5]. MOO design problems can be solved using appropriate optimization algorithm. Recently MOO methods have gained wide popularity in optimal engineering design applications as well as other disciplines. Most MOO problems in different disciplines can be classified on the basis of MCDM [92], [93]. In MCDM, solving the related MOO problem assists the DM in finding the right set of solutions. Often the decision-making task in the problems with more than one objective originating in several design criteria, has been a challenge to engineers. They have been asked to solve problems with several conflicting objective functions by generating the solutions which are called Pareto-optimal solutions where the final decision could be one of those.

Traditionally for solving a MOO problem sometimes multiple objectives are summed into one objective utilizing a scalarization approach [191] e.g., weighted-sum method [149] and utility function [150]. The resulting problem is then solved by any of single objective solvers. In addition for many scalarization methods, some information about the range of solutions, identified by the upper and lower bounds of the Pareto-optimal solution set is needed. In this method the DM has not any prior knowledge of the problem. That is why it could be difficult to express preference information at the beginning of the solution. Yet basically using a single objective optimization technology is not sufficient to deal with real-life engineering optimization problems. MOO methods may include the constraint-oriented methods and the minimax formulation strategy [192], where by controlling the upper bounds of the objectives, the Pareto set can be obtained. In addition to the deterministic approaches, evolutionary multi-objective optimization (EMO) approaches have been successfully applied in solving MOO problems in general applications. An extended statement on MOO can be found in the literature of Miettinen [5] and further potential approaches to engineering applications are surveyed in [6] and [69].

2.2 Black-box problems

An optimization algorithm is referred to a routine aiming at reaching the optimal possible values for a number of identified objectives by systematically manipulating design variables [5]. This routine in order to find out the locations of optimums explores the entire design space, by examining a minimum numbers of different combinations of design variables. For evaluation the numerous combinations of design variables with optimization algorithm an objective evaluation function, in the form of any numerical analyses or standard engineering simulation, has to be involved. Although there are lots of different optimization algorithms developed for solving different types of optimization problems [93], [121], [135], [136], yet the implementation of the optimization systems consisting of the optimization algorithms, objective evaluation functions and interfaces is identified as a highly demanding task. Moreover due to the complexity of the engineering simulations, the relationships between design variables and objective functions cannot be available in a unique form. Therefore a series of objective evaluation functions involved in a MOO problem is considered as a black-box function and the whole optimization task is seen as a black-box problem [67], [68], [282], [288]. (See figure 1)

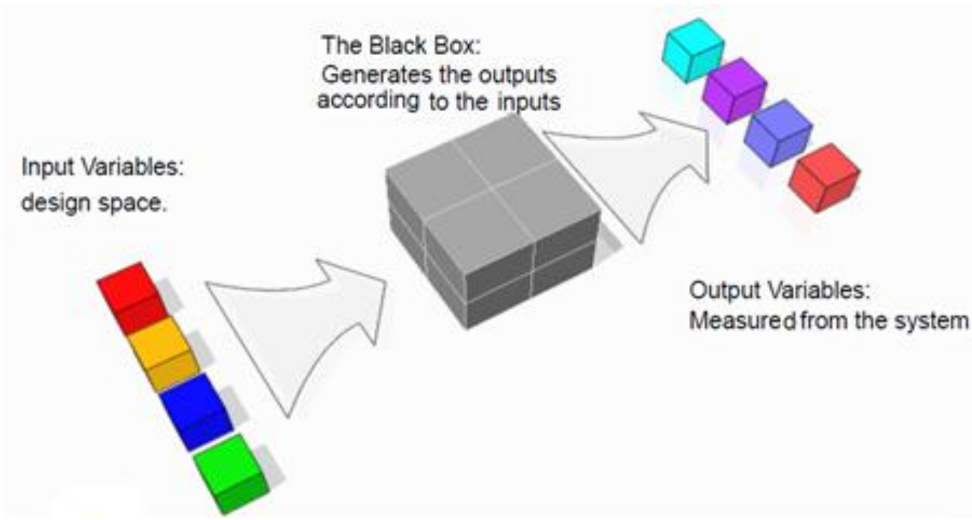


Figure 1: Black-box engineering optimization problem

In order to effectively deal with black-box engineering problems, which may have several local optimums and several conflicting objectives, global [137], [138], MOO

[121], [124] and robust [139], [140], [141], [142], [143], [144], approaches have been widely utilized. However, the computational challenges associated with solving the real-life black-box engineering problems, as we will discuss them in next chapters, will arise numerous issues and difficulties related to utilizing these approaches. In our articles e.g., [1], [2], [29], [30] we discuss on the importance of the black-box optimization and show how a black-box engineering optimization design system can be modeled and solved.

Considering modeling and solving black-box optimization problems, often the solution would have numerous local optimums while the aim is to look for global. Moreover numerous variables are involved and additionally the engineer is not certain which optimization algorithm should be utilized. Furthermore as long as running the FEA and CFD simulations for large-sized models often is time consuming, the computational complexity of objective function evaluations is a major problem. In order to deal with computational complexity it is necessary to carefully select the most efficient algorithms which can produce the best values for objective functions using as few objective function evaluations as possible. Such issues are well studied in the field of simulation based design (SBD) [145].

Considering optimization problems in SBD, generally described by Gosavi [146], the gradient information cannot be accessible at a reasonable computational cost. That is why the gradient-based methods of optimization such as derivatives and automatic differentiation [147] couldn't effectively work in the applications and case studies of optimal engineering design. This is mostly because they are just able to find the local optimal while in engineering optimization problems we are looking for the global solutions which are the best combinations of variables available in the design space. Problems of this type need to be solved using efficient, robust, global and multiobjective approaches to tackle difficulties caused by several local optimums, several conflicting objectives, and expensive objective function evaluations. An optimization method, in dealing with black-box problems, is qualified by its search plan implying the robustness and the accuracy. There are in fact numerous optimization methods available in the literature and different algorithms were developed intending to solve different types of problems.

Most of MOO algorithms for solving a specific black-box optimization problems were developed in research communities supported by huge research grants. The solution workflows may have built from scratch and have their own novel methods and visualization tools. Yet these optimization tools may have not been useful for ordinary engineers in general applications until they become implemented and provided to engineering communities via software packages. In other words, as in our papers [29], [30], [31], [32], [33] it is concluded, a MOO approach could be applicable and effective for industrial applications, only if properly implemented in an easy to use design environment. In this regard we should see the optimization tasks from the engineer's angel whom indeed expects maximum simplification. Design engineer, who is referred to DM, prefers to utilize the efficient optimization algorithms and make most of them without being informed about the details of the functioning.

In a number of surveys such as [78] and [93], the global and MOO algorithms for general applications to black-box problems are well reviewed and permanently described. In the following, according to our publications concerning the applied global and MOO methods for engineering design problems e.g., [2], [34], [35] we explain the methods for dealing with the black-box optimization problems. From this review we aim to get the attentions to the complexity of the optimization procedures, especially for the engineers to implement. Here we briefly review those methods which have more efficiency and popularity in solving real-life problems and are also implemented and accessible for engineers via software packages.

2.3 Global optimization for engineering design problems

An introduction to global optimization problems is given in [152] and the full description on the topic including the popular test problems is available in [153], [154], [159], [160]. Global optimization approaches in optimal engineering design is well surveyed in [151] where the applications and practical approaches of bayesian [155], differential evolution [156], kriging approximations [157], differential evolution [158], stochastic [161] and evolutionary algorithms [162], are introduced as the potential solution techniques according to the number of design variables, objectives and on the properties of the objectives and constraints.

A general global optimization algorithm can be described as; minimize $f(\mathbf{x})$, subjected to $\mathbf{x} \in \mathrm{S}$, where the objective function $f: \mathbf{R}^n \rightarrow \mathbf{R}$ is minimized by altering values of the design variables forming a vector $\mathbf{x} \in \mathbf{R}^n$. The defined points by values of variables lie within the search space, i.e., in a box constrained domain in $\mathbf{R}^n$. An acceptable subset of the search space is called feasible region S. Point $\mathbf{x}^*$ is a globally minimum, if $f(\mathbf{x}^*) \leq f(\mathbf{x})$ with all $\mathbf{x} \in S$. If $\delta > 0$ so that $f(\mathbf{x}^*) \leq f(\mathbf{x})$ with all $\mathbf{x} \in \mathrm{S}$, for which is valid $||\mathbf{x} - \mathbf{x}^*|| \leq \delta$, point $\mathbf{x}^*$ is a local optimum. Yet the problem is convex if the feasible region S and the function f are convex. The convex problems have only one optimal solution and as mentioned can be solved by local optimization methods e.g., [118], [259]. According to [78], [135], [136], [137], and [138], for dealing with the differentiable, convex and single objective optimization problems plenty local optimization algorithms exist for solving the problems efficiently and accurately. However, for dealing with engineering optimization problems which are often non-differentiable with multi-objective functions, utilizing the global optimization algorithms [159], [160] and [161], is essential especially where the solutions are very likely to include numerous local optimums, which is in fact often the case. In the other words nonconvex problems, as we face with them in engineering optimization problems, are in the form of a multimodal function containing several optimums, in which we aim to find the best of them, utilizing global optimization methods.

In order to have an efficient search, global optimization algorithms consist of global and local techniques. However the division between local and global techniques is not necessarily clear, as the ability of local and global of some global optimization method could be adjusted or the algorithm may be in the form of a hybrid method [163]. For instance in evolutionary algorithms [164], parameters of mutation and crossover rates are able to control the local-global search balance in which a larger population leads to a slower convergence with a higher reliability. Moreover adjusting the parameters of the optimization algorithm in order to find the proper values for a problem, for the reason of reaching an efficient and reliable search, is a difficult and complicated optimization task. This is especially the case of most of engineering optimization tasks where objective function evaluations are expensive, and the CAE runs can be executed only for a limited number of times. That is why it is beneficial if the optimization algorithm has only few parameters, and if the algorithm is not sensitive to the parameter values. By adjusting parameters of the algorithms for a particular problem it is possible to get better result. In this way by constructing an algorithm that solves a particular problem most efficiently, it may work poorly in solving other problems [165]. Worth mentioning that there have been also some efforts towards developing automated algorithms, by varying the parameters due to the particular optimization problem [166].

2.4 MOO

Nowadays the importance of globally managing more than one objective at the time is well recognized in engineering design community [121], [124], [133]. MOO is needed where there are several conflicting objective functions to be optimized simultaneously. With MOO we aim to find the best solution for a problem among all possible solutions which are the optimum of multiple objective functions [167]. The optimums are identified by varying the values of design variables with respect to the constraints. Since many engineering optimization problems in numerous disciplines and application areas contain more than one goal which is subjected to optimization, the

MOO has gained attention within the engineering design applications. Accordingly, real-life problems with several objectives have received wide attention due to their unlimited applicability in industries [66], [138].

The general form of a MOO problem can be described as: minimize $\{f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_k(\mathbf{x})\}$, subjected to $\mathbf{x} \in S$, involving k (≥ 2) conflicting objective functions $f_i : \mathbf{R}^n \rightarrow \mathbf{R}$, $i = 1, \ldots, k$. Here, the design variable vector $\mathbf{x} \in \mathbf{R}^n$ and an acceptable subset of the search space is called feasible region S. An objective vector $\mathbf{z} = \mathbf{f}(\mathbf{x}) = (f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_k(\mathbf{x}))^T$ in the objective space $\mathbf{R}^k$ consists of k objective function values calculated in the design variable $\mathbf{x}$. In MOO, the values of several objectives, all together, are optimized. In this case there is not a single point within the search space where all the objectives reach their individual optima. Instead, there would be a set of solutions that we can consider as optimal which is called *Pareto optimal solutions*. In above a design variable vector $\mathbf{x}' \in S$ and the corresponding objective vector $\mathbf{z}$ are called Pareto optimal if there is not another $\mathbf{x} \in S$, in which $f_i(\mathbf{x}) \leq f_i(\mathbf{x}')$, for all $i = 1, \ldots, k$ and $f_j(\mathbf{x}) \leq f_j(\mathbf{x}')$ for at least one index j. In other words the final solution would be a tradeoff between objectives. Moreover the solutions in the Pareto optimal set are ordered with some additional preferences which are provided by engineering designer. With the provided design preferences the most preferred solution is chosen as the final solution. In this context the aim of MOO can be regarded to be supporting a DM in a MCDM problem finding the most preferred solution within the Pareto optimal ones [167], [168].

For dealing with global and MOO problems, many different methods have been suggested so far. These methods are classified in different types of deterministic and probabilistic [169]. The accurate solutions to deterministic methods are conducted only at the presents of a priori information. Yet in engineering design optimization problems this condition cannot be met. Therefore these methods have not been useful. While the class of probabilistic [170] methods has been widely utilized in optimal engineering design problems. Here in order to better study this class of global optimization, which has been the main interest of our research, we divide it into two groups of metaheuristics [171] and bayesian [155]. The group of metaheuristics includes methods of scatter search [177], genetic algorithms [202], [340], [174], simulated annealing [178], ant colony [179], particle swarm [180], controlled random search [181], and differential evolution [182] which have found popularity in optimal engineering design mostly because of their effective search tools.

Considering the engineering design optimization problems, which are typically nonlinear and multimodal the consideration is focused on global multi-objective optimization where there are several challenges involved including dimensionality, the multiple optimums, and most importantly costly evaluation functions. Thus in engineering design optimization problems, according to the high cost of computational analyses and simulations, we are urged to minimize the number of objective function evaluations [159]. However there does not exist any general algorithm that can solve a global optimization problem just with limited number of objective function evaluations [160], [161]. Yet in the cases where the evaluations are affordable, infinite number of them can be conducted, and the optimization process can be easier managed. On the other hand even a relatively simple objective function may be demanding to optimize if the evaluation functions are very expensive. This has been the main reason why the approximation methodologies and metamodels have received a great amount of attentions to increase the efficiency of global and MOO approaches.

2.5 Building efficient global optimization with the aid of metamodels

Beside the MOO algorithms the usage of mathematical and statistical tools to approximate, analyze and simulate complex real world systems is widely applied in optimal engineering design domains. In this context interpolation and regression [273], [354], [269], methodologies have been common in contribution to solving complex engineering optimization problems where they are also known as response surface (RS) methods or metamodels [183]. Such models mostly have been developed for dealing with the extremely costly black-box problems where it is not often possible to reduce the complexity of the problem and obtain a function that can be evaluated quickly. In fact in practical engineering design tasks, every single function evaluation may take days or months. That is why utilizing some smart approaches as metamodels are essential. In this case, engineers can turn into a preliminary exploration technique to perform a reduced number of calculations. By this it would be possible to use well-distributed results to create a surface which interpolates these points. This surface represents a surrogate of the original model and can be used to perform the optimization without costly computations.

The approach of using metamodels in global optimization aims at producing algorithms that despite having a rather poor efficiency can be used to solve problems efficiently via replacing the computationally expensive high fidelity objective function with a lower fidelity, and less expensive surrogate model [155]. This model is used for the use of the optimization algorithm instead of the original objective function. The metamodels may be created by kriging [157], artificial neural networks [117], radial basis function networks [185], support vector machines [184], gaussian random field [187] etc.

Building efficient global optimization with the aid of metamodels for solving expensive black-box functions are described in [67] where the original objective function is sampled only in those points where the metamodel could be improved better. In this way, the number of expensive original objective function black-box evaluations can be reduced. This is because only after a few number of evaluations the metamodel should be able to describe the behavior of the original objective function quite accurately in the neighborhood of the global optimum. As the result the efficient global optimization algorithm can utilize an efficient version of the design and analysis of a computer experiments model [188]. This model has a favorable property that it is able to estimate its own uncertainty in predicting objective function values. It begins by generating a number of sampling points within the search space utilizing design of experiment algorithms. Afterward a metamodel is fitted to the sampled points.

2.6 Comparison of approaches; the role of robust design optimization (RDO)

In modern design, where products are developed considering many aspects such as performance, cost, aesthetics, manufacturability, assembly, maintenance, and recycling, the MOO has been an intensively researched topic [93]. Consequently numerus approaches have been implemented so far. According to [135], [136] and [204], for a comparison on existing approaches several issues related to the performance of methods should be considered. In today's ever-increasing engineering design problems' dimension the main issues would be solution quality, computational effort, and most importantly robustness. Solution quality can be measured as the difference between the actual value of optimal and the value reached by the algorithm. Computational effort arises from running the optimization algorithm and the computational cost of evaluating the objective functions. The required computational effort to solve a certain problem could be measured by the number of essential objective function evaluations e.g., [175], [171], [204].

The robustness on the other hand is defined as the ability of an algorithm to perform well over a wide range of problems. Yet robust optimization [139], [140], [141], as the vital requirement of any engineering design has been looking for the optimum values of objective functions that are not sensitive to the variation of design variables. RDO [142], [143], [144], can be in fact formulated as a single objective robust design problem by minimizing simultaneously the mean and variance of the objective functions with respect to design variables. Therefore the RDO can be considered as an special case of the MOO problems.

2.6 Classification the MOO algorithms

It is very important that at the time of the selecting an approach to a MOO problem its pros and cons are well understood. Otherwise, the optimal results may not deliver the right impression about the problem. In this regard the classification of the existing algorithms would help to give an overview to the problems and their suitable algorithms. Yet because of the conflicting nature of the multiple objectives, the dimension of existing MOO methods is a major challenge to the classification methods. Examples of classification methods to MOO approaches are available in Miettinen's literature [5]. In fact there are different methods of classification for MOO available and we can review the optimization algorithms from different perspectives e.g., [6], [69], [124] and [190]. As here we see the problems from the engineers point of view our classification is done according to the role of the DM, engineer, in the solution process, just as our earlier surveys [2], [8], [9]. This approach of classification could also be conducted in different ways. Here the approach is based on whether the Pareto-optimal solutions are generated or not, and the further role of the DM in solving the MCDM problem. Following figure describes this classification of MOO approaches.

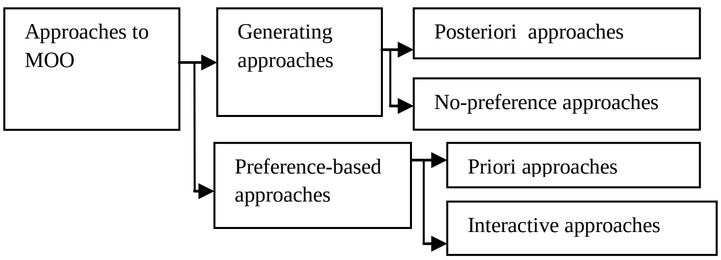


Figure 2: Classification of the MOO approaches

Based on this classification method the MOO approaches are divided into two main groups; *Generating* methods and *Preference-based* approaches. The *Generating* methods generate the Pareto-optimal solutions without any preferences from the DM. On the other hand, preference-based approaches use the preferences provided by the DM in solving the MOO problem.

The group of Generating approaches is also divided into two groups of *no-preference* approaches and *Posteriori* approaches. If there is no DM involved but the preference information available, it is possible to use *No-preference* approaches which find some neutral compromise solution without any additional preference information. In this type of approaches there are no preference information is used. In the other words the opinions of the DM are not taken into account. Therefore these methods are suitable only for situations where there is not any DM available. On the other hand in the *Posteriori* approaches e.g. EMO algorithms, a representative set of Pareto-optimal solutions is generated and then the DM select the preferred one via an overview on objectives' visualization. Yet generating the computationally expensive Pareto-optimal solutions is a drawback to this class. In this kind of approaches a posteriori articulation of preference information is used where the Pareto-optimal set is generated and presented to the DM in order to select the final solution. Methods of this type are also called approximation methods [193].

The preference-based approaches are also divided into two main groups of the *Priori* approaches and the i*nteractive* approaches. In the *Priori* approaches, the DM first gives preference information and then the Pareto-optimal solutions are identified satisfying the objectives. In this type of approaches a priori articulation of preference information is used. In a priori methods, the DM specifies expected preferences before process. The lexicographic ordering [194], value function method [195] and goal programming [196] are some examples of this class of methods.

There are numerous interactive approaches [206], [207] available yet they are not still widely known among engineers in real-life applications [234]. In interactive approaches, a solution pattern is created and the DM can specify the preference of each interaction. Interactive approaches in general allow the DM to learn about the problem considered and the interrelationships in it. As the result, deeper understanding of the problem is achieved. In this class of methods the progressive articulation of preference information is used. For this reason a solution pattern is formed and repeated iteratively for overcoming drawbacks of the other methods. In this method small part of the Pareto-optimal set is generated, and based on the information the DM can adjust the preferences. Due to the interactive solution process the nature of the problem is identified and the problem is solved with more confidence and acceptable cognitive load. Because the DM can manage the search for the most preferred solution, only interesting solutions are generated which means savings in computation time which is a significant advantage comparing to *Posteriori* approaches. Yet when the problem has more than two objectives, the visualization is no longer simple. In this situation the interactive approaches offer a viable alternative to solve the problem without artificial simplifications. The main specification of this interactive approaches is its ability to deal with more than three objectives [388]. In this context the true nature of the problem can come into account. In fact by including the environmental and economical design criteria into the process the interactive methods better design are easier achieved. Worth mentioning that interactive methods rely heavily on the preference information specified by the DM, it is important to select such a user-friendly method where the style of specifying preferences is convenient for the DM. The presented applications in our article [2] have shown how interactive MOO can be utilized in optimal engineering process design by demonstrating the benefits of interactive decision-support systems. More details about interactive approaches and their applications to optimal engineering design have been provided e.g., in [183], [205], [206], [284].

2.7 Genetic algorithm (GA) and differential evolution approaches

GAs [202] along with differential evolution approaches [182] belong to the family of evolutionary algorithms (EA) [198] and also known as population based algorithms. These methods very effectively have been utilized in the optimization of the popular nonlinear, non-differentiable and nonconvex engineering design problems. The population based algorithms use different variety of terminologies, mostly inspired by the nature, e.g., evolution, swarm [179], [180]. GAs and differential evolution optimization approaches have both similarities and differences.

In order to produce a good approximation set, most of the current EA approaches work based on the dominance approach [199]. With this approach, the population is usually ranked based on dominance, and naturally non-dominated solutions are considered better, and favored in reproduction. EA approaches to MOO are categorized in three different groups of e.g., EMO Pareto achieved [200], EMO Pareto Strength [201], and non-dominated sorting genetic algorithm (NSGA-II) [174]. The NSGA-II has been one of the most useful method within the engineering community in particular in applications of shape optimization e.g., [94], [109]. According to Laumans et al. [203] this has been mainly because it can maintain the best found solution during the process, and the achieved solutions located near the Pareto-optimal set are replaced by non-dominated solutions which improve diversity. Yet there are many ways to evaluate the performance of the GAs via a number of test problems e.g., problems described in [175], [201], [204]. By utilizing such test problems the algorithm selection is done in an informed manner.

2.8 Visualization and selection of the final solution

After the MOO problem solved the approximation of the Pareto-optimal set is generated. Then the DM should select the final solution among all solutions. This task is usually done with the aid of visualization tools as it would be easy to view all possible solutions visually. Yet in problems with more than three objectives this could be a complicated task. In fact with a higher number of objectives it gets more difficult to represent the information of many non-dominated solutions to the DM, and it gets harder to explore the solutions.

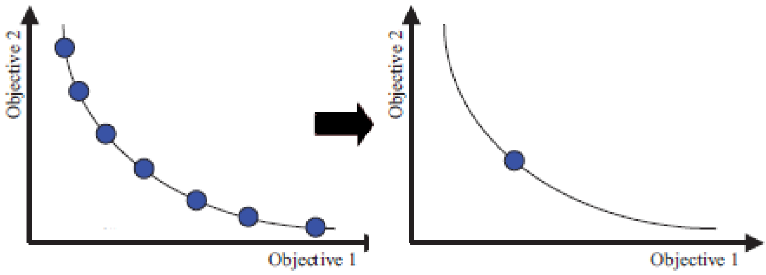


Figure 3: Pareto-optimal solutions and the process of decision-making.

There are different Pareto visualization techniques available to deal with dimensionality of Pareto-optimal solutions. Visualization of Pareto-frontier for MOO in n-dimensional performance space is discuss in [211], [212].

2.9 Interactive vs. evolutionary MOO

From the mentioned classes of MOO which we well reviewed in [2], the *Interactive* and *EMO* methods have been reported, for instance in [121], to be more effective in solving optimal engineering design problems, and in particular, in shape optimization. The applications of EMO in shape optimization have been surveyed and practically used in some articles of ours e.g., [20] and [21], and the applications of interactive methods, in particular in engineering problems with more than three objectives, have been surveyed in [2]. A comparison on applicability of interactive and evolutionary approaches to MOO is given in [205]. However most importantly the interactive treatment can complement scalarization methods, including EMO approaches, in the decision-making process [183], [205], [390], [393], and [398]. Interactive approaches in many points, differs from the EMO methods and it is still possible that the DM in an interactive approach misses some region of the Pareto-optimal set, which may be important to the solution. Furthermore, every time the preference information is adjusted, the scalarized problem must be solved once again, which might be very time consuming if the problem is computationally demanding. On the other hand utilizing interactive methods would let DM to deal with the problem with the reasonable number of objective evaluation functions. This is mostly because only those regions of the Pareto-optimal which are important are explored even though the DM has to wait for the generation of a new Pareto-optimal solution set.

Considering EMO approaches, the DM is involved in the solution process only after the whole computation is over. Afterwards an exploration through the Pareto-optimal set would be conducted. In other words the approach of EMO algorithms is to produce a full discrete approximation of the Pareto-optimal set. In this way the approximation is well distributed covering the entire Pareto optimal.

Both methods of EMO and interactive for engineering optimization are considered as the active research fields of work and naturally numerous approaches and techniques have been developed based on their idea of functioning. In this thesis and in our contributions we mostly utilized GA from the class of EMO methods and NIMBUS method [234] from the class of interactive methods.

2.9.1 Interactive and evolutionary MOO for shape optimization

Shape optimal design, as a complex task, is seen as an MOO problem in which the parameters describing the best quality design are searched. Evolutionary algorithms [125], [126] constitute a class of search algorithms especially suited for solving complex shape optimization problems e.g., [94], [109], [110], [122], [123], [126], [163], [176]. The use of evolutionary tools for shapes optimizing by Splining [94] has been the most effective design optimization technique to be widely used in different industries such as automotive, aerospace and architectures. The surveys by Renner and Ekart [71] and the candidate's [20] and [21], have been devoted to this subject. The Splined shapes and evolutionary tools form the basis of an evolutionary designed process. Lampinen [27] overviews this approach as a dynamic mechanism. Albers et al. [28], [94], Hilbert et al. [109], Nobile et al. [110] and Pinto et al. [11] utilized similar strategy. However there are many drawbacks associated with utilizing this design strategy in industry, mostly related to computational costs, and also the absence of the important role of designers' skills and experiences in design improvement workflow, in both terms of performance and aesthetics. Therefore in order to make the shape optimization more practical in industrial applications and also more applicable, several researchers [129], [130], [205], [206], [207] have addressed this problem by involving DMs through an interactive design optimization process where designers can qualitatively judge the shape by giving preferences. With interactive evolutionary design systems it is possible to explore solution spaces for design solutions which never have been considered using former traditional means. Note that the interactive design optimization process would remain useful just for simple geometries, unless, as we assume, utilizing NURBS-based CAD software packages integrated with the process [209]. Integration of an *interactive evolutionary design tool* with a NURBS-based CAD software package has been well described in [208], dealing with development and exploration of a range of visual aesthetic design spaces related to complex geometries. However this method hasn't been yet properly utilized in industrial design which has been due to the limitation of the utilized NURBS-based CAD software package in handling the engineering related tasks e.g., integration with optimization and CAE tools. This integration has been further improved in [129] and [130] by delivering promising results. On the other hand the research of Boris et al. [209] has made the interactive evolutionary shape design easier and much more accessible for designers in modeling and optimizing the large-size geometries of the entire concept. This approach, proposed for solving mostly aesthetic shape design in a creative way, can be classified as a *generative evolutionary design system* [210]. A generative evolutionary design system provides guidance and inspiration for creativity in design process by exploring the search space for novel designs. However, as we will mention in next section, during the process of utilizing MOO algorithms, whether interactive, or evolutionary, and also during further integration with NURBS-based CAD software packages a number of difficulties arises and consequently designers would have various requirements in dealing with complexity. As a response to these difficulties and requirements a general form of implemented MOO algorithms integrated with NURBS-based CAD packages in a convenient design environment would be essential for supporting the engineer's creativity and freedom to design.

2.10 Final remarks

Considering problems in the particular field of optimal engineering design, at the presence of CAE simulations, which are known as black-box optimization tasks, when the computation of the numerical analysis of the evaluation functions are highly expensive employing the metamodels are inevitable. Yet in dealing with more manageable objective evaluation functions utilizing EMO algorithms have been widespread in industry, even though there are numerous drawbacks identified associated with utilizing the EMO algorithms. As in fact a human DM would be way more intelligent comparing with genetic and swarm operators say e.g., bees, ants and immune operators in EMO, involving the human intelligence into the decision process have become indeed preferable and more effective in some applications recently. This has been the motivation of further development and research on the application of the interactive [284], hybrid [163] and very importantly reactive approaches [400] in industry where the intelligence of human is directly involved in the design process.

From section two lets conclude that optimal engineering design community, in order to effectively deal with the multiple local optimums and nonlinear objectives, has been often urged to utilize efficient global optimization algorithms which are enhanced with metamodels. Furthermore a classification of MOO has been given where among all the global optimization approaches to optimal engineering design the EMO and interactive algorithms have found to be more effective and widely used within industry. In fact the most successful shape optimization solutions for industry often have been conducted either with the aid of EMO or interactive algorithms. However the complexity involved demand for a shift to integrating the NURBS-based CAD packages to the process of shape optimization in order to better handle the complex geometries.

3 Difficulties and further requirements in MCDM

In dealing with MCDM problems in engineering design, the main emphasis has been on two issues: firstly dealing with the difficulties caused by implementation of optimization model, which is the complicated task of coupling CAD/CAE tools, optimizers, decision-supports tools and visualization, and secondly dimensionality due to the large number of input variables and objectives. As a response to these issues in this section utilizing the integrated optimization software packages, for the reason of simplification the process and automating the workflow is proposed. Yet the convenient usage of metamodels provided by optimization packages can also deal with dimensionality in some level. In the next section the problem of dimensionality in MCDM problems will be effectively addressed where a general strategy on the basis of data mining tools for the reason of reducing the number of input variables and design space is proposed.

In this section the importance of optimization packages are pointed out that how they, as today's novel integrated design environments, can actively fill the gap between optimization research and the industrial real-life application. In this section it was assumed that considering the optimal engineering design in the framework of an integrated design environment can decrease the complexity and further make the dimensionality of the design process more manageable for engineers. The materials of this section would be a summary to a number of our publications e.g., [1], [8], [10], [20], [21], [29], [31], [33], [34] and [35].

For pursuing a MCDM in engineering design creating an integrated model of CAD/CAE and optimization is essential. As in CAE objective evaluations there is no clear relationship between variables and objectives, modeling the engineering optimal design is considered as a black-box optimization problem. Building an integrated model including CAD and CAE tools, creating efficient global optimization algorithms with the aid of metamodels and further integration, graphical interfaces and further dealing with multiple criteria and numerous variables in decision-making tasks, present a high-dimensional problem which is considered as a large-scale system [17]. In fact dimensionality has been one of the main reason of creating a gap between optimization research community and optimal engineering design in industry.

In this section it is assumed that considering the optimal engineering design in the framework of an integrated design environment can decrease the complexity and further make the dimensionality of the design process more manageable. Consequently utilizing the optimization packages as today's novel integrated design environments is proposed where the usage of optimization algorithms, and further integration requirements are well customized aiming at simplification the process and automating the workflow. Here it is shown that optimization software packages contribute in "the idea of integration" by providing a user-friendly environment for examining a wide range of optimization algorithms, CAD, CAE, and decision-making tools. This in fact would lead to identify the ideal configurations for producing the specialized optimal design environments for particular design applications. It has been further proven that with an effective integration of the today's already existing resources of CAD, CAE, and optimization algorithms, promising results can be achieved.

3.1 The gap between optimization approaches and optimal engineering design in industry

The operations research (OR) [338] community during past few decades has been contributing to optimal design decision-making and complex problem-solving by developing efficient mathematical optimization models for MOO, and adequate decision-support techniques. In fact adopting even the simple optimization approaches, which OR can today offer to engineering design community, would bring tremendous amount of excitement and satisfaction for optimal engineering design processes.

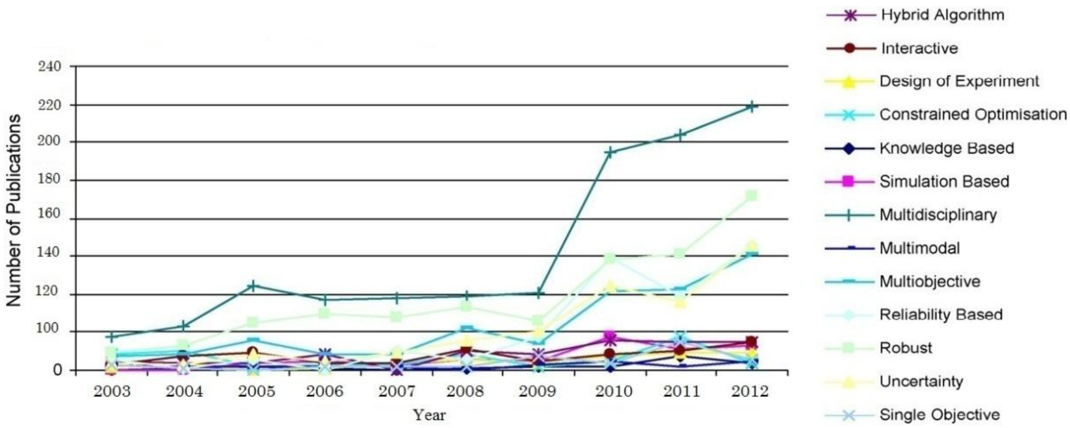


Figure 4: Different optimization approaches produced over past 10 years.

OR with the adequate and already existing approaches for multicriteria decision-making, evolutionary multi-objective optimization, metamodels, interactive multi-objective optimization, reactive and brain-computer multi-objective optimization, multidimensional visualization and hybrid algorithms to multi-objective optimization problems, would have a great potential to effectively address the future challenges to optimal engineering design associated with increasing the decision criteria, aesthetics evaluation, and dimensionality in general applications to industry.

In this context we should however note that due to the lack of awareness in engineering design community about the benefits and applicabilities of the recently produced MOO and decision-support algorithms, the research in OR has been always way ahead of optimal design approaches used in industry. Following figure very well shows the extending gap between potential optimization approaches proposed to optimal engineering design community and the optimal design approaches which have been practically used by industry.

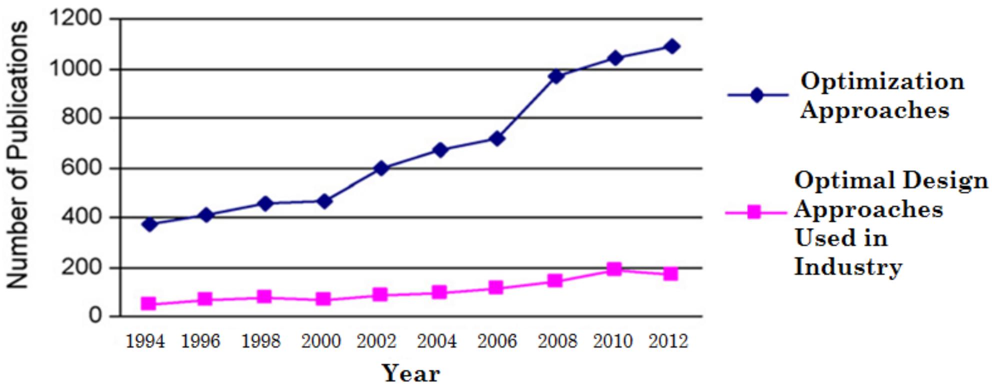


Figure 5: Monitoring the growth of optimization research vs. optimal engineering design progress in industry since 1994

In fact the theory of modern MOO and its dependent algorithms [372], [373] and [374], developed in late seventies and early eighties, took years to be practically recognized and widely used in optimal engineering design applications. Thus filling the gap between OR and optimal engineering design would be absolutely vital and influential in today's ever increasing design complexity where a design has to be considered simultaneously from multiple criteria and perspectives. To doing so a number of difficulties and further requirements in utilizing MOO algorithms and decision-making tools should come to consideration. In this context in order to make the most of optimization algorithms, here, it is assumed that by conducting respective responses and further efforts from industry's side, via software engineering community, to better transform and formulate the problems into the OR's acceptable forms and standards, the problems can be in fact easier considered by the existing approaches and novel algorithms.

As it was mentioned above there have been numerous MOO algorithms developed which are theoretically able to deal even with the most demanding engineering problems. However a typical engineer can not be necessarily an expert in mathematically formulating of the optimal design problem at hand [25], [31], [11]. Additionally the optimal design problems are dynamic, and computationally demanding which may change time to time. Moreover due to a number of challenging difficulties e.g., absence of a user-friendly environment, lack of proper visualization tools, complexity of algorithms, absence of decision-support tools, weakness of the existing algorithms in dealing with a wide range of problems, and the lack of proper integration with the simulators, these algorithms haven't been very effective and popular in engineering design community yet.

In fact an algorithm can be widely utilized in industry when only it is implemented as a package suitable for engineers where its ease of use, and its further integration requirements are well customized. For instance IOSO [220], and reactive search [400] approaches developed in nineties recently gained popularity in industry only after they became implemented as software packages providing an integrated design environment. Consequently here the idea behind the design strategy is "the idea of integration". It is assumed that with an effective integration of the today's already existing resources of CAD, CAE, and optimization, promising results can be achieved. Although the improvement on geometrical parameterization techniques, and benefiting from advanced interfaces of commercial optimization packages would be essential. This ideology of design is introduced as the future trend for engineering optimal design. Consequently here in the considered case studies instead of getting to the details of the optimization algorithms utilized, the focus would be on the quality, quantity and the level of integration and the potential advancement we could expect from the novel coupling of CAD, CAE, optimization algorithms, post-processing and decision-support tools for the future designs.

Optimization software packages contribute in "the idea of integration" by providing a user-friendly environment for examining a wide range of optimization algorithms, CAD, CAE, CAM and decision-making tools. This in fact would lead to identify the ideal configurations of CAD, CAE, CAM and optimizations algorithm, for producing the specialized optimal design environments for the particular design applications.

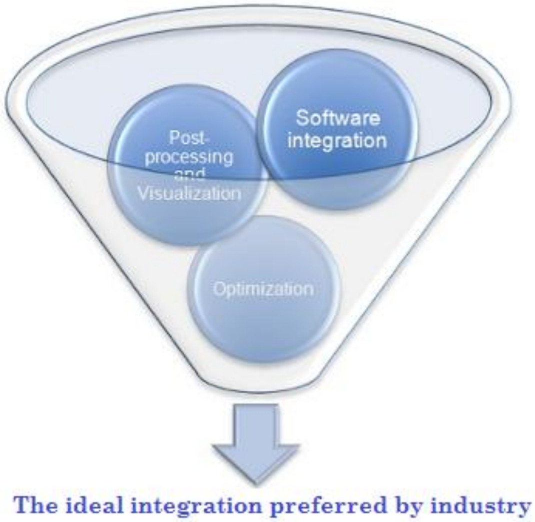


Figure 6: Description of the ideal optimal engineering design environment.

Very relatively in an article [21], which will be described in the following of this section, we researched the issues related to the possible different design modeling configurations for an optimal design problem. In this work our case study in optimal hydrodynamic design was modeled in two different ways with utilizing two different groups of modeling tools. It was simply proven that the quality of the optimization modeling, utilizing different modeling configurations, has indeed direct effect on computation cost and the quality of optimal design achieved. As the result it would be quite logical and natural to invest on research and development of optimization software packages in order to further research and to achieve advancement in optimal design. In figure 6 the description of an ideal optimal engineering design environment is provided which could be accessible via integrated software packages.

In the following we provide, in more details, the difficulties and requirements that solving engineering optimization problem poses to optimization systems. We then discuss some respective responses that optimization software packages can offer to these difficulties and requirements. Once these difficulties, which are in fact the obstacles to proceeding forward on the proposed design ideology in achieving ideal optimization packages, eliminated the ideal configurations of CAD, CAE, CAM and optimizations algorithm, for producing the specialized optimal design environments could be easier researched. Further recommendation of specialized optimal design tools built on the basis of the ideal configurations for particular applications to industry will be a strong motivation to fill the gap between optimization approaches and optimal engineering design in industry.

3.2 Difficulties in utilizing MOO algorithms

An engineering MOO system consists of three main parts i.e., the optimization algorithm, decision-making and the part which computes values of the objective function via engineering analyses and simulations [398]. Furthermore interfaces between optimizers and the simulators along with visualization tools are essential. During the modeling and creating the structure of such system, which is the process of identification of objectives, variables, simulators, CAD/CAE package, and interfaces, some challenging issues arise. These issues include difficulties caused by computational complexity of the objective evaluation functions, dimensionality, difficulties of implementation the algorithm, implementing interfaces between optimizer and engineering analyses, and also difficulties of choosing the final solution among a large set of Pareto-optimal or non-dominated solutions in the absence of a reliable decision-support tool. Concerning dealing with difficulties of modeling the optimization problems we need to mention that just by means of optimization it is not possible to cure the weaknesses of either the design model or the simulators. As if the design model was incomplete containing unnecessary high number of design variables, or if the simulator was very inaccurate, even the best of optimization algorithms cannot overcome these difficulties and produce acceptable solutions. For this reason, for getting sufficient accuracy, it is essential to utilize special strategy of modeling that design models and simulators are selected and implemented correctly with extra attention and informed decisions [51], [53].

In the following a number of challenges and difficulties associated with the application of MOO in MCDM tasks in industry i.e., integration, automation, algorithms selection, hybridization and parallelization, dimensionality, usage, lack of user-friendly visualization and post-processing tools, decision-support tools and metamodel supports are briefly described.

3.2.1 Algorithms selection

As mentioned earlier solving real-life black-box optimization problems is a complicated task. These problems have to be solved using global and multi-objective algorithms to tackle difficulties caused by several conflicting objectives, and computational costly objective function evaluations. As there are numerous approaches and algorithms to be utilized throughout the solution process, it definitely requires some experiences or an intelligent system in order to select the appropriate ones. The task of *algorithm selection* is an issue for engineers as they often have no knowledge on the type of tools can suit a particular problem. In this regard the aim of the engineering community is to make this important task as simple as possible [42], [69], [70], [123].

After the simulators are chosen and the design model of the engineering problem is created, based on the characteristics of the problem and the design model, it is necessary to select a proper optimization algorithm. Often in engineering optimization problems the computational complexity in evaluating the objectives effects the selection of the algorithm. However utilizing the efficient algorithms is always beneficial to manage and somehow reduce the computational efforts of the simulations.

3.2.2 Hybridization and parallelization

As most of the engineering optimization problems are complicated involving different level of solution expectations it is not likely to solve a problem with an acceptable accuracy and speed while benefiting from the robustness of the method. In this regards combining the algorithms and therefore obtaining some hybrid approaches [163] according to the expectations are required. In this context combining metamodels with other algorithms e.g., EMO and interactive, in order to increase the quality of the algorithms, has been reported effective [183], [213]. Furthermore the ability of utilizing a number of algorithms parallely, i.e., running more than one evaluation via queuing systems, could be valuable and in some cases essential [213]. The above mentioned abilities of parallelization and hybridization theoretically are quite effective in engineering design optimization. However providing a user-friendly way of implementation those abilities, in a practical and simple manner suitable for engineers, has been an issue.

3.2.3 Dimensionality

In modeling the optimization problems engineers would be facing two conflicting desires. It is often tried to minimize the size of the design model by decreasing the design space, for instance via reducing the number of variables as much as possible. On the other hand the number of variables should be flexible enough to be able to represent all possible and necessary design configurations. Dealing with dimensionality has been permanently discussed in our articles [16], [17], [18]. It was proven that optimization algorithms should be supported with a dimension reduction system to perform effective.

Dimensionality, which mostly associates with the numerous design variables, increases the problem complexity. In general, higher dimensional problems are more difficult to solve. Numerous variables create higher dimensional space which increases exponentially accordingly and add to complexity. Moreover higher dimensionality can increase the number of local minima. In this case, relative sizes of basins of attractions may be reduced, leading to a more difficult detection of the global minimum. In most engineering optimization problems increasing number of variables is a major and serious problem, as the existing algorithms could not handle it alone. This would need extra tools and software implementation which we will explain them more in the following section.

3.2.4 Usage

Implementation the optimization method for each individual problem accommodates individual difficulties as we described in [29] and [30]. Additionally working with optimization algorithms needs a relatively strong mathematical background and expertise in utilizing a specific algorithm. Moreover dealing with visualization tasks of an optimization tool has its own complexity. Thus the usage factors of an approach, in engineering design optimization tasks, are very much related to the simplicity of it, as the engineers would prefer to pick up and utilize the simple techniques [111], [133]. Yet either interactive or EMO-based algorithms are very demanding to effectively work in the industrial problems operated via engineers. The manual configuring the optimization parameters in a complex workflow, monitoring the functioning, visualization a massive amount of solutions and decision-making on the end results would be just a few examples of the source of complications. Although the proposed MOO algorithms for engineering optimal design applications, potentially and theoretically, reported to be useful, however cannot be practically and widely utilized in the real-life problems unless the issues related to usage solved.

3.2.5 Lack of user-friendly visualization and post-processing tools

Visualization for MOO described for instance in [211], [212], [215], [216], [217] and [361], including statistical charts and multidimensional graphs, has been used as post-processing operations to visualize results in optimal engineering design as well as monitoring the results of engineering simulations, optimizations and decision-support systems. Based on visualization on Pareto-optimal solutions the engineer can choose preferred solution. After a MOO performed, we typically wish to visualize the entire set of results, rather than simply analyzing each single result. Understanding the results of a multi-objective process can be quite hard, particularly in higher dimensional visualization spaces. Visualizing the objective space and the Pareto points is quite a demanding task for the higher number of objectives. Therefore further complex techniques should be implemented in an integrated manner with optimization algorithms in an user-friendly environment.

3.2.6 Decision-support tools

In the absence of a preference information analyzing system, all Pareto-optimal solutions, produced by the optimizers, can be regarded as equally important in the mathematical pint of view. Ranking a long list of Pareto-optimal solutions and alternatives is a difficult task, in particular in engineering design cases, where several conflicting goals and numerous solutions are involved. In this regards finding the final solution among all the possible choices, i.e., decision-making task, would be a demanding task in the absence of a reliable decision-support tool with the characteristics provided in e.g., [127], [128], [134], [168]. Once an optimization algorithm integrated with a decision-support tool the promising results from the whole created MCDM system could be expected.

3.2.7 Metamodel supports

In many practical engineering design problems, every single function evaluation can take hours and days. In such cases where running a single step of an optimization algorithm for even a few evaluations are time consuming, getting support from metamodels before running the actual optimizer is inevitable [183], [219], [220]. Utilizing preliminary exploration techniques of metamodels allows a faster analysis in order to perform a reduced number of calculations. This technique makes it possible to use these well-distributed results to create a surface which interpolates these points. This surface represents a metamodel of the original problem and can be used to perform the optimization without costly computations. The use of mathematical and statistical tools to approximate, analyze and simulate complex real world systems is widely applied in many scientific domains. These kinds of interpolation and regression methodologies are now becoming common, in particular for solving complex optimization problems. However constructing a useful metamodel starting from a reduced number of real evaluations is not a trivial task and in fact demanding for optimization algorithms' users. Mathematical complexities in implementation, computational costs and prediction errors are just a few points to take into account when developing metamodels. Moreover when the metamodel is created there is no certify available for the accuracy. In this case engineers would need an environment to enable them to utilize the beneficial metamodels in a simplified manner.

3.2.8 Integration and automation

An effective engineering optimization method must provide the ability of integration the optimal design tools of CAD, CAE, simulators, optimization, decision-support and visualizations tools in an automated and easy to use manner. In this case the provided integration and automation could be considered as a unique solution for general engineering optimization problems. Yet most of the current existing algorithms, due to the complications party considered in [214], have not this ability by their own. With the ability of integration an engineer can consider, for instance, a wide range of different CAD tools to see which one can better satisfy his model's needs and further which CAD tool can work better with his preferred CAE tool and the optimization algorithm used. Here the ability of an automated integration would let the user to find the preferred combination of optimization modeling tools for a particular application. A number of case studies conducted in a convenient integration and automated workflow are available in e.g., [111], [220], [221] and [222].

3.2.9 Response to the above challenges

As a response to the above briefly mentioned challenges, difficulties and requirements, arisen during modeling the design optimization models, utilizing an integrated environment of MOO algorithms such as the ones initiated in e.g., [220], [221], [222], [223], is suggested. Optimization packages accommodate improved version of the optimization algorithms where the above discussed difficulties are well addressed. In this case, demanding engineering design problems can be modeled by the implemented algorithms that contain only minor mathematical programming-based methods. This strategy would be extremely practical, as the engineers or analysts do not necessarily trained for the mathematical formulation of the problem at hand and the dynamic problems may change time to time. This is the main reasons why the multipurpose MCDM software packages represent a practicable solution for industry.

MOO and decision-making packages in the position of an integrated design environment can satisfy most of the requirements and difficulties of the optimization methods. However the difficulties, associated with dimensionality, which are caused by increasing the number of variables, may need further tools. In the next section we explain how data mining tools can be effective in this realm.

3.3 MCDM software packages

MCDM software packages for optimal engineering design can be classified in the more complex and integrated environments of process integration and design optimization (PIDO) [224] as well as in the problem solving environments (PSE) [225]. Representing the optimization algorithms in such environments to industry has increased the popularity of the optimization approaches in industry during the past few years [220], [400]. It is evident that the both research and industry are increasingly becoming interested in MCDM software packages. Additionally engineering design companies are eager to support developing these packages to achieve advancement in design.

A MCDM software package as an integrated environment provides the engineers with all the necessary tools, via an easy-to-use graphical user interface for solving MOO problems and visualization for supporting the informed decision. These packages provide numerous valuable advantages to the engineering optimization community. In this sense utilizing an optimization software package is more convenient comparing to open source algorithms. For instance the usage of NSGA-II [174], after being implemented and proposed to industry via MCDM software package of modeFRONTIER [223], has been dramatically increased [20].

However setting up, troubleshooting, installing and testing the software packages on a number of different platforms have been a quite demanding job which permanently have been reflected in our literature [29], [30], [31]. These packages have been surveyed in a number of our articles [2], [8], [9], [10], and evaluated in our case studies [32], [34], [35], [36], [37], aiming for further improvements, via informing the engineering communities of the advantages and also potential applications of these tools. For example in [22], [31] design variables are converted into a NURBS curve defining the desired shapes. With a proper input file, the simulator run is executed as an external stand-alone program, producing an output file, which tries to evaluate objective function values. The output file of the simulator contained all the necessary information.

3.4 Improved features in MCDM software packages

In creating MCDM software packages main concern is devoted to developing the software on the basis of the existing algorithms, supported by metamodeling and validation of models when dealing with time-consuming function evaluations. Software developers have been trying to develop and improve the optimization software packages by paying attention to the important features and requirements of an effective engineering optimization software package in the frameworks of PIDO and PSE that mentioned above. In the following these improvements which are the essential properties of an engineering optimization tool are briefly described. In today's development era these features have been carefully identified, improved and included to the software packages e.g., [220], [221], [222], [223], [226], [227], [228], [229], [230], [231], [232], [234] according to the requirements and difficulties of utilizing MCDM tools in engineering community for industrial applications.

• In this context the inclusion of the *metamodeling capability* is of particular importance. In order to reduce the number of calculations, in engineering design optimization cases, engineers have turned to a preliminary exploration technique, metamodeling and validation of models, in order to perform a reduced number of calculations. As mentioned above constructing a useful metamodel is a serious challenge in engineering optimization. In this regard the optimization software implementation was a logical response to this challenge especially when the ergonomics of the implemented software are considered in a wide range of applications. In this way the users of metamodels can grasp the general trends in the phenomena and try the nonlinear behavior of the problems. Furthermore engineers would be able to reuse the experience accumulated, in order to spread the possible advantages to different projects. Different metamodeling tools have been developed and added to MCDM packages to provide inexpensive simulation models to substitute computationally expensive modules e.g., in [220] and [222]. However there is not a unique metamodel that is valid for any kind of situations. For this reason MCDM software would deal with this problem by containing several different interpolation techniques e.g., neural networks [185], radial basis functions [186], kriging [251] and gaussian processes [187]. Furthermore software packages include the tools for exploring and measuring the quality of metamodels in terms of statistical and approximation strategies.

- Beside the metamodels the task of *robustness and reliability check* of approaches would be other important matter which has been well considered in developing optimization packages. In fact the robustness, reliability, absence of bugs, extensibility and maintainability of solutions are of the primary importance which has been implemented in today's MCDM software packages. When dealing with uncertainty, former optimization techniques produce solutions that may perform well at the optimal point but have poor characteristics against the dispersion of design variables or environmental variables. In this case it is possible that the optimal solution was not a stable solution, in which a small change in the input values can cause drastic performance degradation Therefore the robustness and reliability are other important factors beside the performance of solutions which need to be checked. For this reason, inclusion the tools that allow the user to perform a robust design analysis along with the actual optimizer is vital in the MCDM packages.

- *Parallel computing* the evaluation functions by evaluating a single function on several processors, for the reason of reducing the computational time, is a challenging task in most engineering optimization cases which have time consuming evaluation functions. In this regards an optimization software package provides the option of parallelization. The parallelization process is managed by the package based on the fact that the optimization process usually can be divided into smaller steps. These smaller steps can be carried out simultaneously on parallel computers with some special coordination. When the parallel computing ability is included to the process of optimal design the whole optimization, or a part of it, can even be submitted to a queuing system and executed, taking advantages of several different remote processors [213].

- Furthermore MCDM packages benefit from *hybridization* for the reason of improving the quality of MOO algorithms. These packages provide an easy way of combining MOO algorithms together. There are in fact a number of drawbacks associated with utilizing certain optimization algorithms which could be eliminated by combining them with other algorithms. Today's optimization packages for instance made it possible to use a hybrid form of scalarization methods with EMO for the reason of producing very effective tools in solving certain problems.

- As mentioned earlier the *visualization* [211], [212] including the statistical charts and graphs and further post-processing tools is the key in understanding the results coming out from the large optimization systems, particularly in higher dimensional spaces. Moreover a proper visualization tool which is user-friendly and speedy is essential for an optimization technique. For this reason some more advanced techniques have been implemented in optimization packages in order to enhance the process of decision-making. There are now plenty of generic and effective visualization tools now available via software packages of MCDM, such as parallel coordinate's charts [215], self organizing maps [361], heatmaps [216] and multidimensional [253]. The advantages of an effective visualization in the integrated design environment of an optimization package speeds up the decision-making tasks as it is described in [42], [48], [49], [51], [53], [60], [158], and [361], and proved in [216].

• The developed *decision-support tools* surveyed for instance in [127], [128] and [134], implemented in MCDM software packages are effective and useful tools which perfectly assist the engineers in finding the best solution among a set of reasonable alternatives. Moreover, an implemented decision-support tool can even allow the correct grouping of objectives into a single utility function by identifying possible relations between the objectives.

3.5 Description and list of software packages

A description on recently developed MCDM software packages with a general overview on the algorithms used, and their applicability in industry is available in [78], [123], [124], [128], [133] and [134]. Additionally the recent existing nonlinear MOO algorithms and software packages have been reviewed and further explained in a number of our articles e.g., [2], [10], [29]. Although the description of an ideal software package is similar to the integrated environments in the frameworks of PIDO and PSE with the improved features mentioned above [133], yet each of the developed software packages clearly has its own associated advantages and drawbacks. Overall a few number of general purpose MCDM software packages available today, e.g., modeFRONTIER [133], OPTIMUS [227], iSIGHT [228], NIMBUS [234], PROMOIN [229], MKO-2 [230], IOSO [143], pareto front viewer (PFV) [133], Reasonable Goals Method [231], ParadisEO and GUIMOO [232], are to cover the essential properties of an engineering optimization tool. These packages may include one or several MOO algorithms, decision-supports tools and graphical user interfaces (GUI) [233], [234]. As each package may better solve a specific kind of problem it is obviously difficult to identify the best package. In fact many issues e.g., ease of use, completeness, configurability, robustness, efficiency and user support should be taken into account for evaluating software packages. In the following we briefly describe three of today's most popular integrated design environments for optimal design in engineering applications i.e., IOSO, NIMBUS and modeFRONTIER.

• Indirect optimization on the basis of self-organization (IOSO) [143], [144], designed for solving complex problems faster, has been successfully applied in searching for optimal decisions in a number of cases [220], [221]. It is based on the metamodeling methodology approach and on universal mathematical algorithms that can easily be applied to deal with MOO problems. If a problem could be represented by a mathematical model, IOSO optimization technology is able to approximate it into certain degrees. In this sense it works as an efficient metamodel. During operation, the information about the system behavior is stored for the points in the neighborhood of the extremum, therefore the RS model of design space will be more accurate providing wider range of capabilities, and would be practically insensitive with respect to the types of objective function and constraints. Recent approaches utilizing IOSO are classified based on design evaluation effort and degrees of freedom viewpoints. An overview on the applications of the IOSO is surveyed in a number of our articles [8], [9], [10]. Furthermore in [22] one case study in shape optimization, utilizing IOSO, is successfully conducted where the demanding and highly nonlinear MOO problem of curves and surfaces is considered, and further the computation time, ability of CAD/CAE integration and the efficiency of its GUI, along with the other major challenges to IOSO strategy are studied in the framework of PIDO.

- Despite of the effectiveness and efficient computation of interactive optimization approaches [206], [207], vs EMO approaches, the applicability and the usage of them, due to the lack of a reliable GUI and further complexity involved in mathematical representation of the method, has not been popular within industry yet. In this regard an implementation of interactive optimization methods with advanced visualization tools, e.g., NIMBUS [388], could be considered as a gift to the optimal engineering design community. NIMBUS stands for *nondifferentiable interactive multi-objective bundle-based optimization system* [234]. It is an implementation of interactive MOO method created especially for efficient handling of nonlinear industrial related functions. The NIMBUS implementation provides user-friendly tools and lots of visualization techniques tackling industrial problems with numerous objective functions. The interaction phase is comparatively simple and easy to understand for the engineers. At the each iteration the NIMBUS method offers flexible ways to direct the search according to the designer's expectation with the aid of classification.

The classification of the objectives means that the DM indicates what kinds of improvements are desirable and what kinds of impairments are acceptable. The classification information obtained from an engineer is used to generate one to four Pareto optimal solutions that best reflect the preferences. As long as the preferences are provided by engineer, according to the desirable objective values, the preference information would have an understandable meaning. After the DM has classified the objectives, the initial MOO problem is changed into a single objective optimization problem to be easier solved. Furthermore in NIMBUS package there are a number of hybrid solvers [163], [213], available including a proximal bundle method and a global genetic algorithms with different constraint handling techniques. In this case the engineering optimization problems can be effectively modeled and solved. The application of NIMBUS in optimal engineering design has been surveyed in a number of our publications e.g. in [2], followed by a classification on the existing MOO methods emphasizing on the interactive methods. Additionally the effectiveness of NIMBUS in shape optimization has been discussed in [26]. NIMBUS has been successfully applied for optimal shape design of a paper machine headbox [130] and nonsmooth structural design problems [129].

• MCDM design environment of modeFRONTIER is written to allow easy coupling to almost any CAE tool. Its integrated environment allows engineers to integrate their various configurations of CAD/CAE tools in order to choose the ideal one. Its GUI also included direct interfaces for Excel, Matlab and Simulink as we described them in e.g., [32]. modeFRONTIER includes a variety of optimization algorithms e.g., multi-objective genetic algorithm (MOGA), adaptive range MOGA, multi-objective simulated annealing (MOSA), multi-objective game theory, NSGA-II [174], evolutionary strategies methodologies and normal boundary intersection (NBI). Moreover, different algorithms can even be combined by the user in order to obtain some hybrid approaches according to their applications. Beside algorithms can be easily used in parallel forms, to run more than one evaluation at once via the queuing systems. Furthermore the extensive post-processing toolkits consisting of statistical and graphical methods can be utilized to gain understanding out of the obtained results from the optimizers for further decision-making. In this context the post-processing toolkits of modeFRONTIER including DOE, scatter chart of parameter values, correlation matrix of inputs vs objectives, student charts for providing interaction effects, response surface and cluster distribution play an important role. Examples of case studies on increasing the applicability of modeFRONTIER in industry are available in e.g., [110], [111], [133], [222], [223], [245] and [248].

In a number of publications e.g. [20], [21], [22], [29], [31], [33] along with presenting a number of case studies we surveyed the effectiveness of modeFRONTIER in general applications to engineering design, in particular in shape optimization. In the following a number of these case studies is briefly described. From considering the case studies in shape optimization, along with pursuing the goal of getting to optimal designs, we also aim at identifying the ideal configurations of CAD/CAE/Optimizers for a particular application.

3.6 Case study

This study concerns the design development of an evaporator cooling systems within an integrated design environment conducted in our article [1]. Due to the maximum amount of required heat transfer, a very efficient cooling system is required. Yet the refrigerant efficiency is mostly dependent on the geometry and materials of evaporator coil. In this regard the arrangement and the shape of the fins are important for the reason of the heat transfer. On the other hand the position of the fins on the tubes as well as the shape of the fins are generally the most important determination of the flowed air around the coil, and therefore the cooling performance of the system. There are many different types of the fins' configurations possible that could be modeled into finned tube heat exchanger coils. These varied fin types have their own features and advantages and when properly applied for the particular cooling/heating application, are able to provide an economical coil with a long service life [235], [236]. Meanwhile in an attempt to achieve the optimal shape of coil, besides of the coil surrounding air, other simulation variables such as pressure and temperature of refrigerant flow in the tubes must be simulated and analyzed.

In this case study the optimal design in heat transfer is discussed where the shape of an evaporator coil is subjected to optimization. The detailed description of this case study is available in our literature [1]. The methodology used is implemented through a complete integrated CAD/CAE approach, which is executed many times for the thermal-fluid exploration of several designs' configurations within the integrated design environment of modeFRONTIER. Hence the design is carried out automatically by parallel computations, with an optimization package contributing in making informed decision. The engineer instead takes the decision on the physical settings and initializing the computational models to employ, the number and the extension of the geometrical parameters of the coil fins and the optimization tools to be employed. Recently a number of similar shape optimization cases in heat transfer e.g., [108], [109], [110], [111] have been considered in the framework of integrated design environment of modeFRONTIER.

3.6.1 Introduction to the case

The recent use of advanced structural optimization is rapidly growing in heat transfer [238]. A thermal system which can transfer maximum amount of heat by minimum thermal devices will be required for today's new refrigerant systems. Influences of heat flux, coolant flow rate, and inlet temperature need to be simulated and optimized within a number conflicting design objectives. Applying computational methods of simulation have widely utilized and have popularity along with other experimental methods in the design loop [239]. Simulation the heat transfer is a general method of studying the heat behavior in a system. As the system of an evaporator coil is a multidisciplinary engineering problem, it may need more than one simulation including many optimization criteria to be run in order to consider the real condition of the problem. In this context identifying the optimums needs a robust, powerful, and automatic MCDM approach. Yet the main scientific challenges of optimal shape design in heat transfer problems have been concerned with the development of an efficient numerical technique and with the computational procedures required for the necessary couplings to create a multidisciplinary design system. Also, the applications related to real problems such as parameter identification have been reported to be very difficult due to the existing gap between the industrial requirements and academic research [240].

In this realm the design strategy often has been based on computational simulation and modeling in order to deliver information about the heat transfer behavior in different structures modeled by CAD tools. For informing the designer the simulations deliver valuable experiments and offer insight on system's functions delivering an understanding of the heat behavior in different geometries. These traditional ways of the optimization processes are mostly based on the expert decision e.g. [241], [239]. In such cases according to the results of simulations the expert's decision is set to satisfy the objectives. Yet expert-based design strategies for the MCDM design problems reported to be not efficient [242], [243].

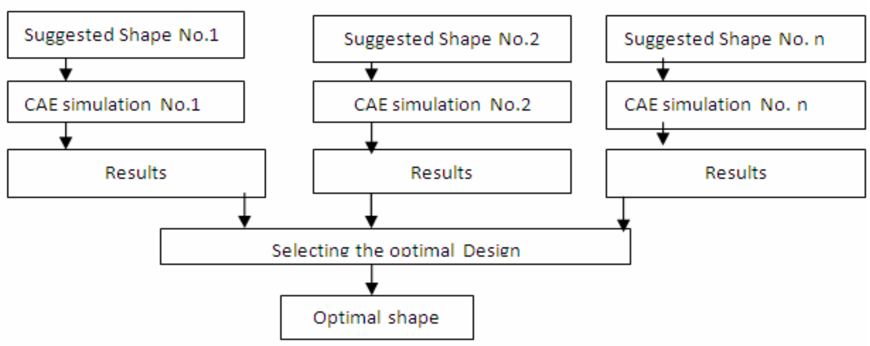


Figure 7: The workflow of a traditional expert-based optimal design strategy in heat transfer; the optimal geometry is identified via an expert-based decision taken after considering the simulations results of a number of random design

The optimal design of the heat transfer geometry of horizontal tubes of an evaporator in [239] is an example of typical expert-based design strategy. In this work a three-dimensional heat transfer simulation is carried out. The structure of tube is modeled and a FEA tool simulated the heat condition effects. In other related work [238] a heat transfer problem is simulated, utilizing a CFD code in a two dimensional domain. Based on the result of the simulations the optimal shape between all suggested shapes is selected by designer following an expert-based strategy.

3.6.2 MOO approaches to heat transfer problems

Optimal shape design of the coil is a MOO task involving a number of highly expensive CAE simulations. EMO algorithms have been utilized to deal MOO of heat transfer problems in a number of cases e.g., in [111], where a large number of variables, constraints and objectives are involved. In [25],[109] and [244] genetic algorithms for MOO have been utilized for solving a problem of heat transfer related to longitudinal wavy geometries. In these works the geometry of 2D profiles is optimized by means of multi-objective genetic algorithm which aims to find geometries that maximize the heat transfer and minimize the hydraulic resistance. The geometry here is parameterized by means of a complicated polynomial function. The considered objectives were the maximization of the heat transfer rate and the minimization of friction factor, with the additional objective of minimization the heat transfer surface for the recuperator module. This research present a theoretical evolutionary MOO method which is proved to be quite effective in solving the problem, yet due to the implementation complexity involved it couldn't be properly utilized by a typical engineer.

3.6.3 Considering the problems in the framework of an integrated design environment

In order to employ the EMO in an efficient and easy-to-use framework we reconsidered the problem within an integrated design environment where the CAD, CAE and optimization algorithms are well integrated. In such design environment the EMO search algorithms can be further supported and empowered with the aid of metamodels, and the optimization results could be better communicated to the DM via an effective GUI. Following figure shows a schematic view an integrated design environment.

Here the modeFRONTIER is utilized for providing an integrated design environment. In modeling the problem identifying the variables, variables bounds, constraints, and objectives is considered as the initial step. Later on, identifying an ideal combination of CAD, CAE and optimizer would be essential. Here modeFRONTIER as an advanced integrated design environment provides the opportunity to find and implement an ideal combination of the modeling tools.

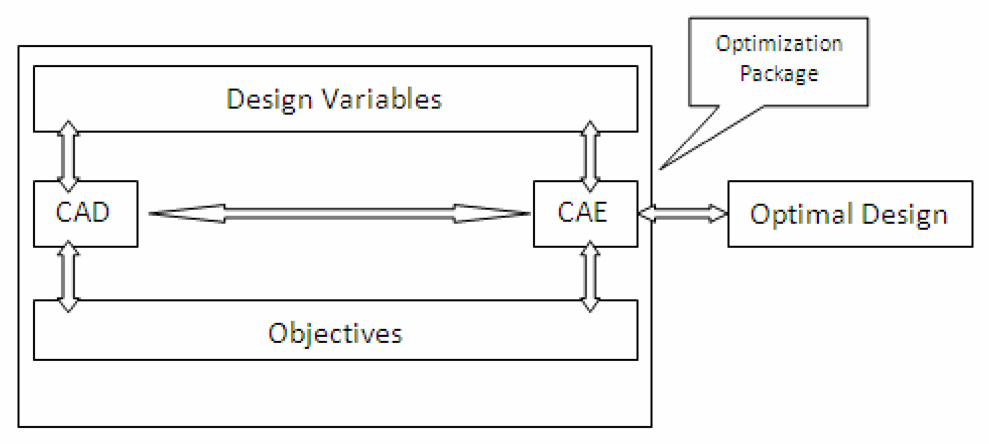


Figure 8: The workflow of the multi-objective design optimization process, in the framework of an integrated design environment

• *Variables*; in this case some input variables are linear dependent and some variables are not. The plate fin is a continued metal strip has holes for tubes punched for a particular tube, in a pattern and established distance. Fin enhancers are available in different shapes. Besides the shape, the fin spacing also has an important effect on heat transfer of an evaporator. Therefore a group of variables deal with the geometry of the coil which is modeled by CAD tools. Variables of the geometry and the dimensions of the evaporator coil is subjected to the physical space in which it can be located within the other components. The fins dimensions and the place of the holes are the first series of the variables. The graphical description of the geometrical variables in the form of a parametric geometry is shown in the result figure. Further simulation variables are associated with the surrounding flow which may include the direction, moisture, temperature and speed of the flow. These variables must be accurately initialized in the simulation. The incorrect initializing the air flow and compromising the system temperature setting in the simulation workflow can lead to coil-system failure. A proper involvement of variables in simulation of the coil can help minimizing the error issues. Here the constraints and design variables have been initialized according to the original description available in [237], [238].

• *Objectives*; The shape optimization model is represented as an optimal design problem with four conflicting objectives including; maximizing the resulting flash temperature, minimizing air friction, maximizing thermal conductivity and finally, maximizing the overall heat transfer. The ejected air must cover all the surfaces in order to create a cold film between the hot fin and the surroundings. As the coil region is characterized by a 3D flow field, it is very difficult and time consuming to optimize the cooling system using standard design methodologies also considering the other fin tip requirements such as minimizing the hot leakage air from pressure to suction side, which has a negative impact on the evaporator coil aerodynamic efficiency. For these reasons, the condition of the coil is simulated within a parametric CAD-CFD approach coupled with optimization algorithm.

• *Workflow*; for the geometrical modeling and simulation, the potential software packages of CAD and CAE can be integrated in the workflow via interfaces. Yet performing each of the FEA and/or CFD codes may take hours or days. Therefore limited number of simulations could be run in a reasonable period of time. In this context utilizing the DOE and metamodels for getting maximum information from minimum number of simulations is inevitable. DOE explores the design space and automatically chooses the minimum set of designs which contains the maximum amount of information. DOE starts from values of governing parameters. Parameters' variations and properties identify the governing parameters. Varying the governing parameters from their initial values to the maximum possible limitation gives the different designs with a variety of characteristics. Furthermore, through the large number of experiences gained the several simulations run by the optimizer generate virtual database of fins configurations, allowing the designer to find laws, functions and correlations between input parameters and output performance, with a further and deeper insight into this specific design coil cooling problem. A parametric batch procedure allows the creation of different geometrical models, the mesh generation and the CFD analyses of the coil in an automatic way. A series of preliminary CFD simulations is planned and a screening is performed in order to build an input-output database. The error of the expert system is a known value and is the parameter which yields the accuracy of the interpolator relative to the database of real experiments so far acquired. It is up to us to choose the final value of the expert system. Basically, the more CFD analysis makes the expert system more trained and the more accurate, but with an increased CPU efforts. NSGA-II algorithm investigates runs with further CFD virtual analysis, exploring the space of possible solutions on the coil. Basically a virtual optimization of the cooling system is carried out without further CPU expensive CFD analysis. The best virtual solutions are selected and the virtual solutions are validated by a real CFD analysis. The virtual optimization can be executed again and new and more performing designs can be found. This procedure is repeated till the desired convergence to the set of optimal solutions is achieved. Finally, a layout of cooling fins is found by the optimizer and validated by a CFD analysis. The final chosen design proved to yield the same heat transfer performance with a reduction of approximately 10% of the cooling air required. Following figure shows the utilized workflow for the optimal design.

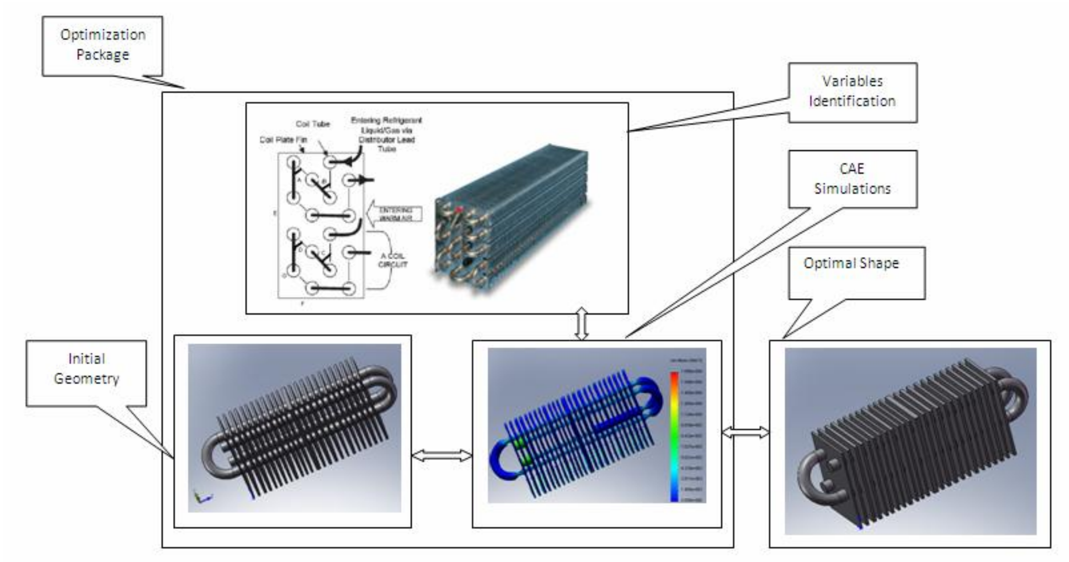


Figure 9: Workflow of the automatic MOO design process, utilizing the integrated design environment of modeFRONTIER

3.6.5 Final remarks

A general strategy for developing the geometry of an evaporator coil using an integrated design environment has been presented. This work has demonstrated the effectiveness of MOO techniques in improving thermal-fluid problems. A remarkable increase of performance of 10% is obtained by an innovative complete CAE design process with CFD parametric models. The use and integrating of optimization tools and innovation capabilities are intended to provide a means for automatically varying the shapes reached from the evaluation made by CAE systems without any needs of high-level understanding of mathematical equations involved in CAD/CAE and optimization procedure. This is a step closer to building a CAE innovation system that goes much further into the evolution of technical systems, as an automatic evolution.

The proposed methodology, which relies on optimization packages capabilities can be easily generalized and applied to any thermal-fluid system whose behavior is reproducible through CAE simulation. Further details are available in our paper [1].

3.7 Shape optimization for complex geometries

Here with the aid of convenient optimization tools provided via integrated design environments we focus on a branch of engineering optimal design called *shape optimization for complex geometries*. We contribute to the ongoing researches on approaching to the framework of a general strategy for developing complex shapes in the optimal engineering design process e.g. [28]. For this reason it has been tried to bring together techniques that have their origins in the field of optimization and new tools of geometrical innovation.

Shape optimization consists of changing the external borders of the mechanical components [94] where the geometry is defined in terms of surface and curve parameters [95], [96], [97], [98] allowing more freedom to manipulate. Principals, approximations, and computation of shape optimization have been provided in reference books of Haslinger and Mäkinen [26], Sokolowski and Zolesio [99], and Mohammadi [100]. Moreover the surveys on the methods are available in [101], [102]. Shape optimization can be conducted using standard optimization appraoches including indirect or direct algorithms whether gradient-based or global search methods if a parameterization [103], [104], [105] of the geometry is well defined. Such parameterization is very important in CAE simulation-based design where goal functions are usually complex functions, evaluated using numerical models e.g. CFD and FEA. According to [26] it is assumed that with a powerful parameterization technique over geometrical models we would be able to consider optimization the complex geometries of big-sized models. In this regard the NURBS-based methods [106], [107], [108], [109] of parameterization have found to be beneficial comparing with the other traditional means e.g. linear piecewise parameterization approach [110]. However in the literature mostly the simple geometries have been examined so far [111].

Computer aided geometric design (CAGD) [96], [112] as a branch of computational geometry [113] deals with the modeling, representation, and parameterization of curve and surface. The most important instruments of CAGD are parametric curves and parametric surfaces. The major achievement in parameterization has been the theory of Bezier curves and surfaces [114], [115], [116] which later was combined with Splines [117] as an earlier version of NURBS. The parameterization of simple shapes by Bezier curves has been described by Haslinger and Mäkinen [27]. Yet the parameterization of geometries using NURBS is beneficial because of its efficient computational implementation with numerical stability, providing smooth shape changes which are highly suited for the parameterization of a design. According to Toivanen et al. [116] the use of NURBS parameterizations allows obtaining versatile new shapes maintaining good control over admissible geometries. In [21] and [22] we reviewed the shape parameterization and optimization process with the aid of NURBS, where it has been shown as an effective parameterization tool, yet relatively new. Manzan et al. [108] utilized NURBS in optimization of the profile of a connective wavy channel of a heat exchanger. During the process of parameterization they face difficulties in handing the geometry thought they considered a simple 2D profile in hand. Relatively we widely used NURBS for parameterization and shape presentation e.g. in [11], [16], [20]. However in our approaches, for the reason of simplification the parameterization process and also handling the whole concept of complex geometries, our innovative idea was to utilize the NURBS, facilitated via the NURBS-based CAD packages e.g., [79], [80], [81], [82], [199], integrated to the optimal design process, instead of manual implementations [94], [106], [108], [109], [110],[111].

Generally the process of optimization the parameterized shapes with NURBS, the tuning parameters' values, is a MOO problem in a heavily constrained environment [120]. This leads to the need of optimizing several conflicting objectives simultaneously [5]. A series of MOO tools which can address this problem has been reviewed in [51], [71], [80] [101] and [102]. An ideal MOO approach to optimal shape design should be able to handle the multiple objectives while also could work interactively with designer. However a reliable interface between parametric models and optimization models that ensure automatic bidirectional conversion does not exist at present [121]. Although several researches have got close to this idea by identifying deficiency of the process [122]. According to [121] the lack of feature information prevents the application of meaningful constraints. Addressing this issue requires high level geometric reasoning to be more integrated into the optimization/analysis models. It is assumed that the application of NURBS-based CAD packages for parameterization, capable of providing more automation in generating and reasoning, allows optimization/analysis and parametric systems to be perfectly integrated. This means an integrated infrastructure, i.e., a developed version of earlier studies [102], [105], [106], [107], [122], which is capable of supporting optimal changes into geometry. In this case we would expect a great deal of improvement in the process of an automated shape optimization. This improvement means delivering more performance, efficiency, robustness, application in industry, ease of use and less computational efforts while dealing with complex geometries of the entire concept. An automated/integrated shape optimization tool could deliver numerous advantages to the optimal shape design in the different disciplines of engineering design e.g. marine, appliance, magnetism, multibody, crash, structural, vibro-acoustics, turbomachinery, civil engineering and aerospace. For this reason we have tried to improve the earlier approaches [94], [111] by putting the NURBS parameterization in the hands of CAD packages instead of self manual complicated calculations e.g., [25]. In this case a general optimal design environment is created.

We should note that the research and development on producing suitable MCDM and MOO algorithms for engineering optimal design and in particular shape optimization are numerous e.g., [78], [93], [123], 124], [125], [53], [126], [128]. However the expansion and progress of applicability and popularity of these algorithms within shape optimization have been very slow [221]. In fact a design strategy can be widely utilized only when it is implemented within an integrated design environment where its ease of use, and its further integration requirements are well customized. Here the idea behind the design strategy is "the idea of integration". It is assumed that with an effective integration of the today's already existing resources of CAD, CAE, and optimization, promising results can be achieved. Consequently the improvement on geometrical parameterization techniques, and benefiting from advanced interfaces of commercial optimization packages would be essential. This ideology of design, in our case studies, is introduced as the future trend for engineering optimal design. In the considered case studies instead of getting to the details of the optimization algorithms utilized, the focus would be on the level of integration and the potential advancement that we could expect from the novel coupling of CAD, CAE, and optimization for the future designs.

By involving a general engineering design tool into the process of optimal shape design, several advantages will make the process more attractive to engineers in industry who are not experts in optimization and parameterization techniques. Furthermore it would be easier to interactively generate intuitive visualization which has been identified earlier in [129], [130] as a key need for designers in industry to be comfortable with the use of optimization techniques.

The result of our research and contributions in improving a general strategy for optimal design, by conducting the shape optimization in the framework of an integrated design environment, beside of application in shape optimization, it could be also utilized in other engineering design means for further industrial applications. Furthermore it can compete with the other approaches e.g., [131], [132] which are currently going on, and in some points it can be combined with the other researches

[94], [109] fulfilling their possible lacks and shortages. Moreover:

• The robustness and effectiveness of the integrated interactive MCDM in dealing with multiple objective problems will be learned.

• Practical usage of the method in industries is proved.

• Accelerating the development of knowledge in the field of interactive MCDM applicable in shape optimization

• Opening new research possibilities in the field.

• Providing a better understanding of facts that will allow a more appropriate course of actions.

3.8 Optimal design of profiles

Design of profiles [20], [21], is important as by applying further surface design tools of CAD such as extrude, lofting and/or sweeping almost any shape can be reached. Profile design is the foundation of shape design and has wide application in different disciplines of engineering. As long as the NURBS have found to be the best choice for modeling the fine, smooth and accurate profiles and furthermore can easily substitute the original profiles of the initial shape, the optimization the NURBS has got importance. In order to invent a general strategy for getting the optimal geometry of the profiles there have been many research on this real which is a multiobjetive and highly non-linear problem [94], [110], [111], but we haven't reached the goals of an automatic and high performance design process yet. In this case study we aimed to widen the awareness of the readers about the effective application of utilizing an integrated design environment in optimization the NURBS. Here the combination of modeFRONTIER and NURBS is introduced for developing the profile design procedure which uses CAD and CAE tools as an interface to the designer and NURBS for geometrical construction.

3.8.1 Introduction to the case

The standard approach to *surface design* has been focused on designing a network of curves and build a surface to cover the network utilizing computer tools [107]. Currently many CAD software systems exist for this purpose, employing standard techniques of surface design on the basis of the profiles [79], [82], [119]. As far as the geometry of profiles is concerned, one of the major issues of CAGD applications is how to automatically reach to *optimal curvature shape* using nonstandard data which is not ordered in a convenient order. Yet it depends critically on designer, aesthetic stylists and manufacturing engineers.

When a profile design cannot be based on features defined, *optimization* system provides a tool for automatically achieving a desired geometry using limited design information. The essence of the method is to choose a single or multiple functions, called an *objective function,* whose value is determined by the control points of a NURBS. Then each objective function must attain a minimum or maximum value when the shape variables assume values that correspond to the desired shape. In order to find the optimal value for an objective function, a CAE system must solve simultaneous equations. Solving equations generally requires too much computation time, often hours of runtime, and sometimes no suitable solution is actually found [33]. In this regard efficient EMO algorithms have been seen as a solution for dealing with such complexity in CAGD in managing the process [25], [108], [120], [140]. Although still there is not any straight solution for the MOO problems of curves and surfaces. However because of the complexity of MOO problems, mainly nonlinearity, caused by multiple conflicting objectives, CAGD optimization has generally focused on simpler application problems with fewer objectives which can be solved by available tools e.g., [25]. Yet an integrated design environment tries to push designs to reach the optimal solutions for more complex geometries with the aid of evolutionary design and informed decision-making.

An integrated engineering design environment uses integrated CAD/CAE tools for providing support to the process in generating variants, simulations and decision-making. This support, can improve the performance of the concepts by generating alternative solutions to optimization problems. In this case *shape parameterization, evolutionary design process* and *optimization system* can be considered as the foundations of creating an integrated engineering design environment. Yet an automated NURBS-based engineering design environment can guarantee the design efficiency of the different disciplines of engineering e.g., marine, appliance, multibody, crash, structural, vibro-acoustics, turbomachinery, civil engineering and aerospace.

Worth mentioning that the application of advanced computation methods in generating the optimal design is around for the last three decades [123]. However a new area of development called evolutionary design [37], [249] has recently become a topic of intensive research. According to Bentley [210] evolutionary design process is capable of generating designs by optimizing the geometry. The ability of combining CAD and CAE which has been empowered by the advanced computation tools, geometric parameterization and evolutionary biology is well utilized in this application. Additionally the integrated CAD/CAE design method presents characteristics that adds value to the product by creating the novel shapes which deliver higher performance.

Yet in optimal shape design the experience and judgment leads to better profile design. In its most reviewed applications [94], [108], [208], judgment has been done by evolutionary algorithms, which are mostly genetic algorithms, when evaluating a fitness function and comparison against certain criteria.

The NURBS parameterization approach [109], [110] has the potential to be classified as creative where the shape optimization task is converted to a parameter value optimization task by using NURBS-based curves for profile representation. Furthermore its parameterization is beneficial because its computational implementation is efficient and free of problems with numerical stability and smooth shape changes via the coordinates of their control points. Yet it is advantageous that the degree of the curve and the number of control points can be selected independently in order to satisfy curve smoothness and continuity for curve shape modifications.

3.8.2 Profile design in the framework of an integrated design environment

It is assumed that NURBS can deliver extraordinary results in an automated optimization environment such as modeFRONTIER. There have been reported a number of successful attempt in this regard e.g., [25], [133],. Although according to author's knowledge there is not enough description available regarding the details of coupling NURBS and modeFRONTIER. However automatic shape optimization on the basis of the solid modeling tools is one of the well-known applications of modeFRONTIER where the shapes have been often modeled and parameterized by solid modeling tools. Lung design, MEMS design [396] and ball grid array design [245] are just few examples.

Yet the research on the applied strategy of modeFRONTIER in optimizing the NURBS for profile design is relatively young. For instance Nobile et al. [110] in optimization the profile of connective wavy channel of a heat exchanger utilize similar strategy for modeling, parameterization and MOO. In fact with the aid of NURBS, lots of different possibilities were generated and the optimal geometry of profile applying modeFRONTIER was achieved. In the other case [247] the geometry profile of a transonic airfoil with uncertainties has been optimized. For parameterization the upper and lower sides of the profile a NURBS curve has been utilized. The role of NURBS in this context is found to be closely integrated with modeFRONTIER in enabling this development on a CAD/CAE software interface, and in enabling automation of the development. The optimization procedure utilizing modeFRONTIER freely explores a wide range of possible geometries. Thevenin, and

Janiga [25] developed a flexible NURBS-based reconstruction technique utilizing mofeFRONTIER to reconstruct a distribution. The modeFRONTIER easily was coupled with Matlab and the NSGA-II algorithm was applied to adjust the control points. It is concluded that optimization may support the development of an even more efficient procedures.

3.8.3 Workflow

The NURBS control points during optimization process are called floating-points which are actually variables for optimization. The NURBS profile is defined with a number of floating-points valued as parameters (see Figure 10). The idea is to convert a NURBS profile optimization task into a parameter value optimization task. Same as the presented general workflow in [20], parametric CAD software is manipulated by the efficient EMO algorithm within the modeFRONTIER environment via interface software. This interface allows the CAD software to run continually and get saved in the computer memory, therefore every time a solution is generated the geometry automatically adapts to the set of parameters.

The process starts with an existing design, substitutes the current construction with NURBS and adds control points. The NURBS is modeled inside the tolerances of the original shape's profile and later changes during the development process. The *floating points* of the NURBS which are subjected to improvement are parameterized. A single coordinate of the curve *floating points* (for instance *Y* coordinate as in [25]) are encoded as genes. In other worlds each gene represents one floating point of the NURBS curve. Three main genetic operators act on the genes of the geometry are selection, crossover, and mutation. Crossover allows the geometrical characteristics of selected NURBS to be merged in pairs and their properties to be extended to following generations. The crossover and mutation are responsible for generating new alternative shapes by altering the organization of floating-points.

Each individual of the population describes one complete concept shape with constant number of floating-point values in a parametric form. So, a chromosome, composed of many *floating points* valued genes, represents each individual shape. The GAs-based optimization process attempts to find a series of shapes which satisfy the design objectives and meets all constraints. The objectives of the analysis are to develop the geometry in order to obtain the optimal results of emphasized CAE simulations.

The objectives are introduced into the CAD and automatically provide the value of the fitness function. Individual shapes, represented by a vector of constant number of control points, will be evaluated with this fitness-function which is automatically updated every time the geometry is modified. When evaluating a fitness function, GA relies on judgment, based on evaluation and comparison against certain criteria. Yet it is supposed that with experience and judgment the new shapes created by floating-point sets can lead to an optimal design.

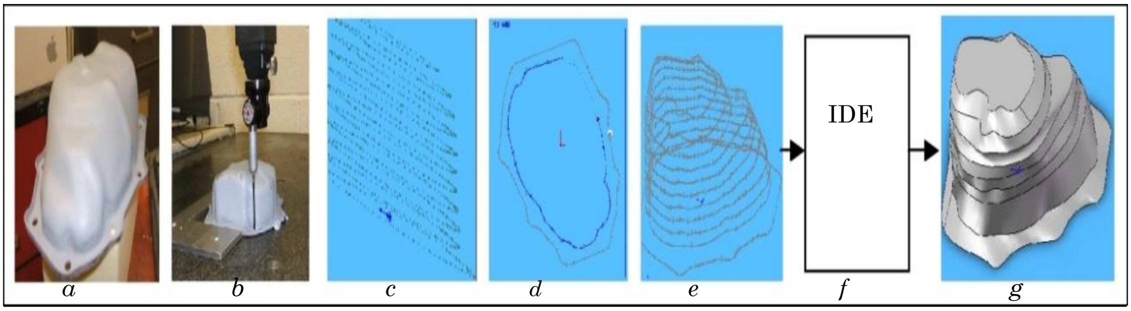


Figure 10: *a*. Initial geometry (existing design) subjected to optimization *b*. Digitizing process *c*: point cloud *d*: substituting the actual geometry with NURBS, inserting control points and parameterization the spline *e*: NURBS shape and parameterization the surfaces *f*: integrated design environment (IDE) for profiles *g*: optimal shape

3.9 An ideal CAD/CFD/optimizer combination for optimal design

Here we present a case study in the particular field of hydrodynamic/aerodynamic design by summarizing our research in CFD-based optimal design utilizing modeFRONTIER as an integrated design environment, where the NURBS-based CAD package of SOLIDWORKS is coupled with optimization algorithms and CAE tools, according to the above described technique [29], [30], [31]. Here in order to identify an ideal CAD/CFD/optimizer combination an evaluation case study in optimal design is set to reduce the drag and noise in a hydrodynamic geometry. To doing so a common MOO method is applied in two different setups' combinations in order to find the ideal one in terms of ease of use and computation costs. The utilized MOO algorithms in both cases are NSGA-II supported with a metamodel.

3.9.1 Proposed methodology

The proposed method is managed in the way to be accurate, cheap and speedy. Presented method is based on utilizing all necessary packages including CFD, NURBS-based CAD, meshing tools and reporting tools under control of optimization package of modeFRONTIER. In order to reach the maximum accuracy and minimizing the human faults, the role of CFD engineer in the design process is limited. Therefore the results of each CFD simulation interaction are sampled and analyzed by computer instead of engineer. Design method is fully automatic and user friendly. Besides initializing the parameters of design in parametric CAD and CFD packages and also running the whole optimization process including all involved engineering packages have been simplified according to [247], [248]. Consequently here the designer doesn't have to benefit from a strong knowledge of mathematics or fluid dynamics.

Overall here the presented SBD methodology is not a novel way of engineering design yet implementing the workflow in the user-friendly and automatic framework of an integrated design environment could be considered as a revolutionary method for aerodynamics and hydrodynamics applications. In this context the case studies as such can further contribute in improving the performance and efficiency of workflow by investigating the right combinations of CAD, CAE tools and optimization algorithms.

- Objectives; the optimal geometry must deliver minimum drag at the direct movement, minimum drag at the diving movement and minimum turbulent noise at the direct movement. Consequently a number of simulations are essential i.e., three drag simulations in different directions of movement into a virtual duct, three of them for turbulent noise simulation and three of them for pressure simulation in different movement directions. Needless to mentioning that according to numerous simulations, obviously analyzing the results would be totally a confusing task for human mind without involvement of an integarted design environment. First requirement for optimizing is a parametric CAD model on the basis of NURBS. In this case the parametric model is created by SOLIDWORKS. The MOO is powered by modeFRONTIER which in this case firstly couples CAD with CFD package of ANSYS CFX and in the second case with COSMOS SOLIDWORKS in order to find best packages for utilizing in the workflow. The idea is to run optimization process with two different tools of meshing and CFD. After the optimization is done the results of both processes are compared to find the better combination of tools fluid dynamics design. The first combination of tools which are involved in the first workflow of optimal design are listed as follow;

- modeFRONTIER as automatic optimizer; running the NSGA-II and GUI,
- SOLIDWORKS as the NURBS-based CAD tool,
- ANSA for meshing applications,

• ANSYS CFX as the CFD simulator and

• Microsoft Office Excel as a reporting host,

The idea behind proposing the second arrangement is to present a new arrangement of tools which is much simpler to integrate. In other words it is tried to utilize minimum tools as possible and ask for more than one application from a single package. In this case we tried to do the modeling, meshing, CFD simulation and reporting with SOLIDWORKS. The tools which are involved in second optimization and design are listed as follow;

• modeFRONTIER as automatic optimizer; in charge of running the NSGA-II and GUI

• SOLIDWORKS as a common tool for the NURBS-based CAD, CFD, Meshing and reporting host.

The initial geometry is modeled in SOLIDWORKS applying Loft techniques utilizing thirteen NURBS-based curves positioned in profiles with constant distances. Model is parametric-based designs which means distance between the curves and also shapes of curves has relation with each other and are changeable according to defined equations [247], [248]. It gives the ability to create new models in short time with just changing a single dimension of the model.

3.9.2 Discussion and results

It is managed to run the process for eighty shapes of different geometries which are created and selected automatically by system. The optimization algorithm is NSGA-II supported with a metamodel. Besides the post-processing tools including scatter chart of parameter values, correlation matrix of inputs vs objectives, student charts for providing interaction effects, response surface and cluster distribution could contribute. The process is totally automated. The process continues till getting a full Pareto-optimal solution. In the next step by utilizing a decision tool available in modeFRONTIER the final geometry is selected within the Pareto optimal solutions.

Our utilized graphical result charts, presented in the papers [29] and [31], include scatter chart of parameters, response surface, cluster distribution and optimization results. According to the results, many optimal design configurations have been introduced. Choosing the best design is completely up to the designer. Based on the selected optimal design the characteristics' information of that design could be loaded into CAD parametric model in order to model the optimal final geometry. Information of design contains the equation of each curve and distance between them. By using the presented method of design and optimization in conjunction with the CFD code of ANSYS CFX and SOLIDWORKS, as the first tools' combination, in order to reach the final design geometry was achieved in nine days on a Pentium IV 2.4 MHZ. Yet two thousands CFD evaluations have been done without operator intervention.

The second tools' combination took twelve days to be done. Which means reducing the number of involved tool packages and doing more than one job with a single package, in order to reduce the optimization time, couldn't be effective and beneficial terms of computation time. In other words applying an individual CAE tool for doing a single task could be a efficient way of reducing the time of optimization process. Therefore the combination of SOLIDWORKS, ANSYS CFX and ANSA with modeFRONTIER found out to be a great company for fluid dynamics design.

3.10 Case study; aerodynamic optimal design

In the last case study an ideal configuration for fluid dynamic optimal design has been suggested that here is used in an other application to aerodynamic optimal design. Here we summarize the results of our research and case studies in CFD shape optimization [33], [34]. In this work a MCDM problem in computational fluid dynamic is modeled and solved within the integrated design environment of modeFRONTIER. This case study presents a SBD workflow to approach safer built forest planting patterns against the wind. Planting the trees based on the suggested patterns which are modeled and simulated according to the topological map of the site, trees' shading, number of trees/planting space, kind of trees and finally wind behavior is assumed to make the future forests much safer against the wind's attack. For the reason of modelling and simulation the forest environment the recent technological advances in CAD and CAE are applied in the integrated design environment of modeFRONTIER according to the last study case's confuguration. The result of this research shows how the planting pattern could be effective in order to reduce the speed of wind at the position of each tree. For this reason the process of simulation and optimization continues till finding the optimal pattern.

3.10.1 Methodology

Based on the area of the site and planting space the maximum number of trees in site is calculated. Then the topographic map of the site is converted into a parametric CAD model with the aid of NURBS surfaces. According to the number of trees in the site and initial pattern, a complete parametric model of trees is created with the aid of NURBS, (see Figure 11). Parametric model of forest is completely manipulated with the optimization operators. In this case creating the parametric geometrical model of the forest plays the vital role.

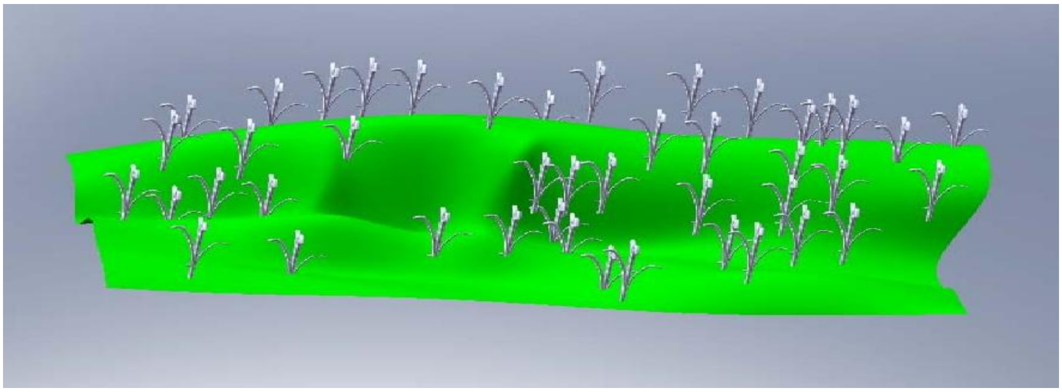


Figure 11: The initial parametric modeling of forest holding a random planting patter.

The optimization objective evaluations aiming at the speed of wind at the position of trees are calculated in the integrated CAD/CAE environment for twenty different patterns' arrangement. Finally with the aid of decision-support tools the final planting pattern is identified. (see Figure 12).

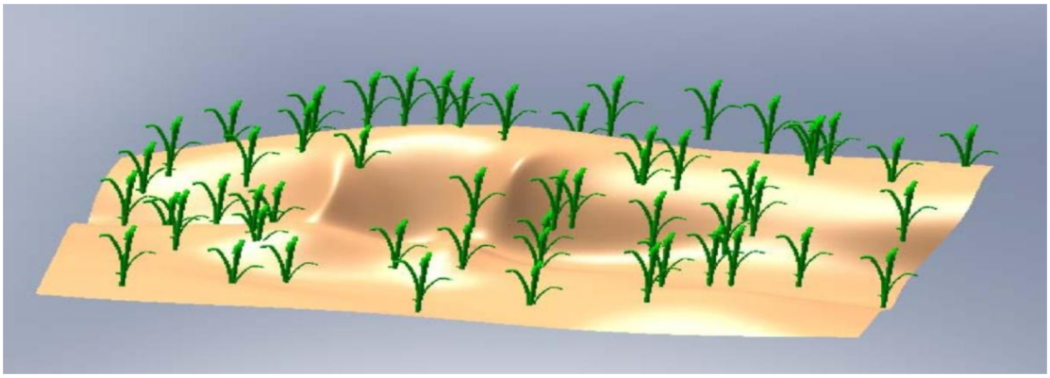


Figure 12: The optimal planting pattern of forest after optimization which delivers up to seven percent lower wind speed at the positions of trees.

Optimization package automatically simulated and optimized the objectives. The presented workflow of simulations and design process is an example of environmental simulation and design which could be useful in simulation of further built environment tasks. Approaching the optimal planting pattern is the result of successful coupling CAD and CFD in an integrated design environment. The results show that the planting pattern has effect on reducing the speed of the wind at the positions of trees up to seven percent. More details on this case study are available in [33] and [34].

3.10.2 Final remarks

For an optimal solution to the engineering design problems, the optimization process of design must consider multiple criteria simultaneously. The problems of this type are mostly nonconvex, nonlinear and computationally expensive, including numerous variables, constraints and several conflicting objectives. In this context for pursuing the optimization task and decision-making on the optimal solution, an integrated model of CAD/CAE and optimization is essential. As in CAE objective evaluations there is no clear relationship between variables and objectives, modeling the engineering optimal design is considered as a black-box optimization problem. Black-box optimization problems with multiple objectives can be solved in several different ways. However the characteristics of these types of problems suggest that we need to use efficient global optimization approaches to tackle the difficulties caused by several local optimums, several conflicting objectives, and high computational cost of objective evaluations.

Building an integrated model including CAD and CAE tools, creating efficient global optimization algorithms with the aid of metamodels and further integration, graphical interfaces and further dealing with multiple criteria and numerous variables in decision-making tasks, present a high-dimensional problem which should be consider as a large-scale system [17]. In fact dimensionality has been the main reason of creating a gap between optimization research community and optimal engineering design in industry. In this regard worth mentioning that although optimization research community developed numerous global and MOO approaches so far, however most of these approaches, due to some difficulties and requirements mostly associated with dimensionality which we have discussed them in details, haven't been really applicable in real-life engineering optimization problems within the industrial communities. In fact the expansion and progress of applicability and popularity of these algorithms within engineering design communities due to dimensionality have been very slow.

In this section it was assumed that considering the optimal engineering design in the framework of an integrated design environment can decrease the complexity and further make the dimensionality of the design process more manageable. Consequently utilizing the optimization packages as today's novel integrated design environments is proposed where the usage of optimization algorithms, and further integration requirements are well customized aiming at simplification the process and automating the workflow. It has been shown that optimization software packages contribute in “the idea of integration” by providing a user-friendly environment for examining a wide range of optimization algorithms, CAD, CAE, CAM and decision-making tools. This in fact would lead to identify the ideal configurations for producing the specialized optimal design environments for particular design applications. It has been further proven that with an effective integration of the today’s already existing resources of CAD, CAE, and optimization algorithms, promising results can be achieved, and potential advancement could be expected from the coupling of CAD, CAE, and optimization for the future novel designs.

4 Dimension reduction

In the previous section the importance of utilizing optimization packages in reducing the complexity from the process of optimal engineering design was discussed. The CAD/CAE/optimizers coupling capability of optimization packages, as well as reducing the complexity of the design process, can also manage the dimensionality in some levels. In fact the integrated design environment of optimization packages provides the possibility of creating efficient global optimization approaches via facilitating the usage of metamodels. Although the effective usage of the metamodels can in fact reduce the design space of the optimal engineering design, yet in dealing with high-dimensional (large-scale) problems of complex geometries [17], where there are numerous geometrical variables included, utilizing more effective tools would be required. The innovative part of this section has been the utilizing of the data mining tools [331] in dealing with the dimensionality mostly associated with the high number of variables. The materials of this section would be a summary to a number of our publications e.g., [8], [9], [10], [16], [17], [18], [19], [22].

4.1 Motivation

OR with the adequate and already existing approaches for multicriteria decision-making, evolutionary multi-objective optimization, metamodels, interactive multi-objective optimization, multidimensional visualization and hybrid algorithms to multi-objective optimization problems, would have a great potential to effectively address the future challenges to optimal engineering design associated to increasing the decision criteria and aesthetics evaluation.

For instance in dealing with optimal engineering design problems at the presence of CAE simulations, i.e., black-box optimization tasks, when the computation of the numerical analysis of the evaluation functions are highly expensive employing the metamodels are inevitable. Yet in dealing with more manageable objective evaluation functions utilizing EMO algorithms have been widespread in industry, even though there are numerous drawbacks identified associated with utilizing the EMO algorithms. As in fact a human DM would be way more intelligent compairing with genetic operators e.g., bees, ants and immune operators, in aesthetics evaluation, involving the human intelligence into the decision process would indeed be preferable and more effective. This has been the motivation of further development and research on the application of the interactive, hybrid and very importantly reactive approaches in industry where the intelligence of human is directly involved in design process.

In order to make the most of optimization algorithms, here, it is assumed that further efforts should be conducted from industry side, via software engineering community, to better transform and formulate the problems into the OR acceptable forms and standards to be in fact easier considered by the existing approaches and novel algorithms.

Considering optimal shape design, in today's ever increasing complexity, the dimensionality of the problems has been a real challenge posing to the optimization approaches. Increasing the number of variables, multiple design criteria and traditional means of shape parameterization have been the main source of increasing dimensionality. In this context dimension reduction finds its importance in optimal design. In fact reducing the design variables will decreas the computation cost. It will also reduce the budget required for developing optimization tools. Reducing the number of variables associated with the geometry criterion would reduce the cost of optimization. This would only happen via advanced paratemetrization tools. Although the NURBS are the ideal tools for representing the complex geometries yet they would generate way more variables.

Reducing the variables from the geometry criterion in shape optimization can be done in two ways. Firstly, by identifying the most relevant variables to objective functions while maintaining the efficiency of the process. Secondly, utilizing novel shape parameterization e.g., [37], [249], which can eliminate extra variables while maintaining a high quality shape representation. Once the geometrical variables are reduced, the consideration of new variables from other criteria e.g. materials selection, aesthetics and product performance can be easier facilitated.

4.2 Introduction

Computational analysis and simulations for real-life design problems are becoming increasingly common in *optimal engineering design* [78]. Yet the complexity of *design computation* [250] has been continuously increased due to the expensive evaluation analyses required to reach a comparable level of accuracy as physical testing data. Although the use of simulation models for optimal design employs a high demand on the computational expenses, the recent computing advances [121] have tended to reduce the complexities of design problems associated with non-linearity, complex solvers and dimensionality. Consequently this has demanded for faster and more reliable computation tools. To address such a challenge, approximation techniques of metamodeling [251] i.e., surrogates to the expensive simulation process, have found to be effective in order to improve the overall computation efficiency by reducing the dimensionality. This has accelerated the need for advanced metamodels in design optimization e.g., the metamodels developed and used in [252], [253]. Metamodels are indeed valuable tool to support a wide scope of activities in solving various types of MOO problems in modern engineering design by conducting problem formulation, model approximation and design space exploration [254]. The benefits of metamodels versus the actual MOO models, besides the delivering smaller design space, include the capability of easier connection of the expensive simulation codes and also better filtering the numerical analysis noises.

In this section the dimensionality of the MOO models [255] is being discussed as the main challenge to the future of engineering optimal design. Moreover it is discussed that even though utilizing DOE techniques [256] and metamodeling methodologies and approximations to MOO have been reported as the efficient tools for reducing the design space, the optimal design community would still need more effective tools to deal with *Curse of dimensionality* [257], [267], [291] which is a well-known challenge for optimization approaches in optimal engineering design including metamodel-assisted strategies. In this section after a brief overview on DOE techniques and metamodeling approaches to optimal engineering design, as the classical methods to deal with dimensionality, a novel tool is proposed to reduce the design space. The proposed method can systematically identify valuable variables and regions from the original design space of multiple objectives, where it is very likely to satisfy multiple objectives for a robust design.

4.3 Dimension reduction in optimal engineering design

Considering engineering design problems where CAE tools e.g. FEA and CFD are extensively used for design evaluation and simulation, e.g. [258], the involved process reported to be often computationally expensive. Yet optimization approaches can provide engineers with very accurate and systematic search strategies that can contribute in considering optimal design problems [251]. However, there are several limitations to classical optimization methods in dealing with real-life applications that prevent the effectiveness of these methods in modern engineering design applications. In fact classical optimization methods e.g. gradient-based optimization methods [259], can only work on the basis of well formulated and low cost computational models, while engineering design, as also mentioned above, involves expensive models such as FEA, CFD. Moreover classic methods only provide a single solution, while engineers would prefer multiple solution alternatives achieved, requiring minimum expertise and optimization skills from the DM's side. Therefore, there is a gap between the capability of classic optimization and the demand for modern engineering design strategies. In fact an ideal decision-support tool should be able to give the engineers more insights into the design problem for approaching to a series of simple, robust, reliable, and globally optimal solutions.

Today's engineering optimal design problems involve computationally demanding numerical analysis and simulation processes with involvement of the numerous variables and ever increasing multiple objectives. In order to promptly deal with the complexity, engineers prefer to utilize efficient decision-support tools that can provide them insight into the problems for an optimal design. In this context dimension reduction in engineering design optimization [260] has been always an extensively researched area. The need for the dimensions reduction tools arises in large-scale real-life optimal design problems with very high dimensions [261], [262], which can increase the computational complexity of the optimal design process. This has been due to the required large sampled design space for the optimal search that is increased exponentially with the problem's dimensions. Consequently the engineering design community continuously demanded for the techniques that can systematically identify smaller design space, where it is very likely to satisfy multiple objectives for a robust design. To address the need for multiple solutions while maintaining the solution's robustness and the efficiency of optimization, such techniques aimed to reduce the design spaces of the global and MOO problems in optimal design.

4.4 DOE techniques; the essential dimension reduction tools

In order to get the most relevant qualitative information from a database of experiments in optimal engineering design, to identify the most important design variables and also to reduce the design space to a reasonable number of variables, objectives and constraints, traditionally the methodologies of DOE [263], [264], have been helping in maximizing the knowledge gained from the experimental data. Since in fact it is not practical in a multi-variable problem to test all combinations of input parameters, DOE techniques have been utilized to extract as much information from a limited number of test runs. In this context exploration tools of DOEs [265] have been useful for getting information about the problem and its design space. DOE analyzes experiments, and eliminates redundant observations and reduces the time and resources to make experiments. Therefore DOE techniques allow the user to try to extract information from the available test runs. In fact DOEs as the major classical experimental design methodologies are extremely important in identifying which input variables most affect the experiment being run.

The result of a DOE run and the initial population of designs could be fed either into the optimization algorithms or MOO metamodels where the DOE is used to provide the initial data points. In other words they can serve as the starting point for a subsequent optimization process, or as a database for metamodels, or for checking the response sensitivity of a candidate solution. (See figure 13).

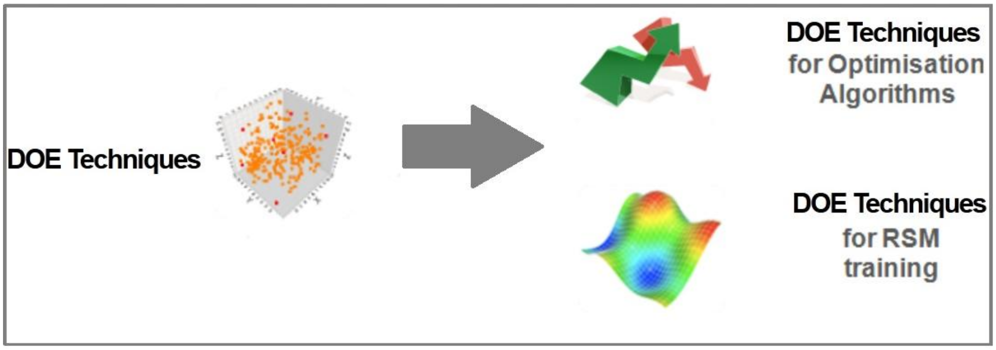


Figure 13: Demonstrating the applicability of DOE in both supporting optimization algorithms and metamodels.

The relation between experiments and optimization, i.e., the use of optimization to design experiments, and the use of experiments to support optimization is discussed in [266]. As we will later in this section study, in real-life optimal engineering design problems where a large number of design variables are existed, building useful DOE requires vast quantities of data points to sample the search space which in fact makes a DOE model a very expensive task. This has been referred to as *curse of dimensionality* [257], [267], [291] which would be demanding for further research.

4.5 Metamodels

As we mentioned above the classic experimental designs were originated from the theory of DOE where physical experiments are conducted. Yet due to the complexity of today' analysis codes, such as FEA and CFD, the approximation-based optimization methodologies, e.g., metamodeling, evolves from classical DOE theory, where polynomial and radial basis functions are used as metamodels [268]. Metamodels approximate computational functions with simple analytical models. These simple models are called metamodels and the process of constructing a metamodel is called metamodeling. With a metamodel, optimization methods can then be applied to search for the optimum, which is therefore referred as metamodel-based design optimization where metamodeling provides an efficient decision-support methodology for design engineers where an accurate global model at a reasonable cost is approximated. In this sense the metamodels can act as the computationally cheap alternatives to the original model and reduce the computational complexity [251]. In fact the idea behind metamodeling is to analyze a set of initial designs to generate data points, to build an approximate model to fit the objective function, variables and constraints. The optimization and decision-making task is then conducted using the approximated model.

In the metamodel-based design methodologies in engineering a global metamodel is fitted and then it is used as a surrogate to the actual expensive function, considering e.g., [269], [270], [283]. Radial basis functions [271], [282], multivariate adaptive regression splines [272], least interpolating polynomials [273], inductive learning [274] neural networks [275], guassian processes [276] and stochastic models [313] e.g., kriging [251], [254], [277], have been all used for building metamodels. The applications of metamodels in optimal design have been reviewed in [278]. In addition a detailed revision on associated fitting and validation methods to each metamodel type are relatively available in [3] and [279]. In fact the validation and optimization could be also involved in the loop of sampling and modeling strategy in which samples are generated iteratively to update the approximation in order to maintain the model accuracy [280], [281]. More on metamodels-based optimal design, popular sampling methods, approximation models, strategies, and applications are available in [3].

4.6 Supporting MOO with metamodels; building efficient algorithms

Considering the general form of MOO optimization problems which is basically formulated as;

$$\min F(\mathbf{x}) = \{F_1(\mathbf{x}), \dots, F_r(\mathbf{x})\}$$
$$S.T\,.\ \mathrm{g}_k(\mathbf{x}) \leq 0, \ \ (k = 1, \dots, K)$$
$$\mathbf{x} \in [\mathbf{x}_L\,,\ \mathbf{x}_U\,]$$

where $\mathbf{x} = [x_1 \ \ , \ x_2 \dots \ , \ x_n]^{\boldsymbol{T}}$, is a vector of design variables, *r,* number of objective functions to be optimized and $\mathbf{x}_L\,, \mathbf{x}_U$ are the lower and upper bound vectors. $\mathbf{x}_L$ defines the search range and $\mathbf{x}_U$ defines design space, the solution would be to select the best of alternative design variables from a candidate design space subjected to certain constraints. Yet, an optimal design problem needs to evaluate nonlinear objective functions in a high-dimensional design space. Nonlinear programming methods, such as sequential quadratic programming [338] and simplex search [339], have been used to find the optimal solution, and they usually converge to a solution in a relatively short time. However the quality of the final solution depends highly on the selection of an initial design. These methods are known as "local" optimization methods. In order to escape local optimums, utilizing random search-based method of EMO e.g., GA [340] or the simulated annealing algorithm (SA) [341] are preferable. Evidence from e.g., [342] shows that GA and SA are indeed quite effective in escaping local optimums but at a considerably slower convergence, and thus are not practical when the computation cost of evaluating an objective function is high. Therefore we have to use metalodels or considering data mining-based optimal design methods [331], [337], as we will discuss later in this chapter.

Here we should briefly note that in a general workflow of MOO process the variables are identified and initialized at the first step, whether the utilized MOO approach is DOE, GA, SA, and/or hybrid optimization systems. Then the identified variables are passed directly to the next steps of numerical analysis and MOO. Therefore, there won't be any control and monitoring on the quality of input variables. Compressor blade optimization [365] is an example of this workflow. Figure 14 describes this workflow better.

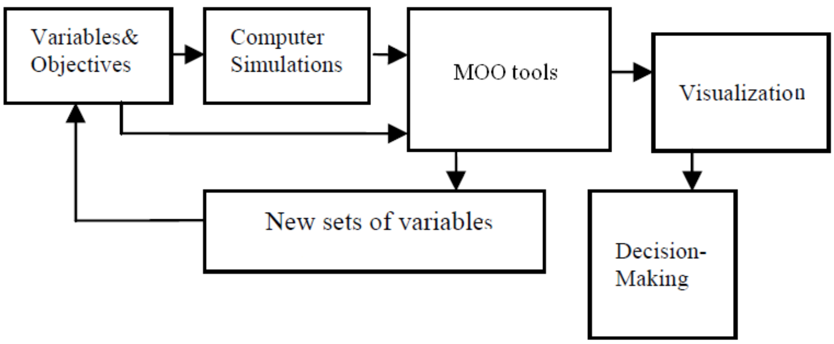


Figure 14: The general workflow of the MCDM process including MOO and decision-making

In a typical global and MOO, the relationship between design variables and design objectives is usually embedded in complex equations and models in FEA or CFD codes which would only deliver a vague idea about the problem [282]. With an accurate approximation, the design space can be explored to obtain deeper insight into the design problem and better formulate the optimization problem. In this context the metamodeling approach can well assist the engineer to gain insight to the design problem [270], [283]. In the other words metamodeling can be applied to solve various types of optimization problems that involve computational analysis processes. Yet the global approximation across the entire design space is used to reduce computation costs. Then the design space is explored to enhance the understanding of the design problem by running the approximated metamodel. Furthermore based on the enhanced understanding of a design optimization problem, the number and search range of design variables will be reduced. This would indeed assist the formulation of the optimization problem.

Recent approaches to solve MOO problems with black-box functions were to either approximate each objective function or a direct approximation to the Pareto-front [275]. Metamodeling has been also used to improve the efficiency and performance of the other global and multi-objective optimization algorithms e.g. EMO [292]. A number of approaches have been used for creating metamodel-based global optimization e.g. Kriging [285], bayesian method [281], [155], Voronoi method [289], multipoint approximation and intervals [290], constrained global optimization [286], and further stochastic systems [**313**]. However the efficient usage in utilizing these algorithms have been limited to problems with a small design space with only a single design objective and a maximum number of three design variables. A typical metamodel to the above formulated global optimization problem with a single design objective function could be defined as the following, where a local optimizer is applied to the following equation to search for the optimum.

$$\min \tilde{F}(\mathbf{x})$$
$$S.T.\ \tilde{g}_k(\mathbf{x}) \leq 0, \ \ (k = 1, \dots, K)$$
$$\mathbf{x} \in [\mathbf{x}_L, \mathbf{x}_U]$$

Metamodel approximations have been widely used instead of the computationally expensive analyses to explore the entire design space to identify the Pareto-front [287]. However due to the presence of conflicting objectives in multi-objective engineering design problems [291] the dimensionality was found difficult to reduce, yet it could be approximated to simple models. In this context metamodeling has been intensively used in approximation and supporting the global and multi-objective optimization problems.

A metamodel-based global optimization problem for more than one objective function can be defined just like the MOO equation described above,where r number of objective functions are to be optimized.

$$\min \tilde{F}(\mathbf{x}) = \{\tilde{F}_1(\mathbf{x}), \dots, \tilde{F}_r(\mathbf{x})\}$$
$$S.T.\ \tilde{g}_k(\mathbf{x}) \leq 0, \quad (k = 1, \dots, K)$$
$$\mathbf{x} \in [\mathbf{x}_L, \mathbf{x}_U],$$

Currently metamodeling techniques are widely used for approximating the design variables of the global and MOO and their performances, which are often used in black-box optimization functions.

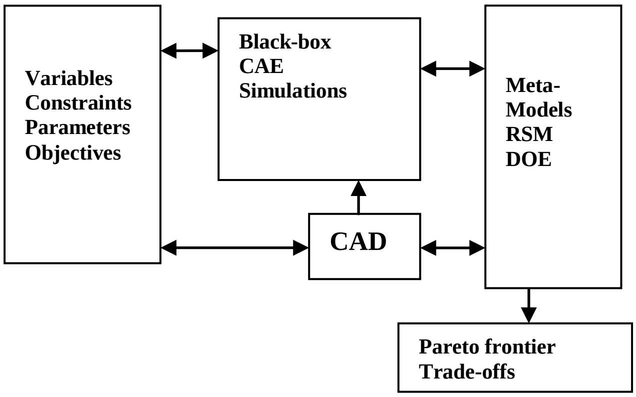


Figure 15: A general description of the role of metamodeling tools in MOO processes.

Today's metamodeling-based optimization approaches aim to address the challenges associated with dimensionality, by approximating the computational analysis processes with providing simpler models. This has been greatly improving the efficiency of global and MOO tools. In fact engineering optimal design would need metamodels to support global and MOO in dealing with real-life optimal design problems even though each type of optimization would face its own challenges. Yet the strategy of metamodeling-based optimal design in problem modeling, model approximation, and design space exploration forms a reliable supportive tool for almost all types of optimization problems. As the approximation process would support the study of sensitivity of either continuous and discrete design variables, and thus would give engineers insights to a wide variety of problems.

A review on methods and managing the approximation and the recent approaches to solve MOO problems with black-box functions could be find in [280], [287], [288],

[293]. Among them hyper ellipse-based metamodels [294] have been found quite handy to approximate the Pareto-front for engineering optimization problems. Furthermore metamodels have been widely used in approximation tasks where EMO methods had difficulty in producing accurate Pareto-front near extreme points [287].

4.7 Curse of dimensionality in metamodels; the urge for design space reduction;

The advantages of applying metamodeling in optimization are numerous. Metamodeling and design space exploration can help the engineers to decide on a reasonable goal for objectives and limits on constraints. In this way some of the objective functions and constraints can be combined, or modified. More importantly, metamodeling helps significantly in reducing the number of design variables and their range of search. Yet in real-life problems where we will be dealing with large-scale problems [17], despite of the metamodel's methodology utilized, the major difficulty in the usage of the most tools, is identified as *Curse of dimensionality* [257], [267], [291] which is associated with exponential increasing of the number of design variables and the number of sample points needed to construct an approximation model [285]. In the other words if the density samples are n-locations for a single dimension, then for k-dimensions, n^k observations are required which makes a metamodel sample a very demanding task. In fact when the number of design variables is large, the total computation expense for metamodel-based approaches makes them less attractive or even infeasible [291]. Even though metamodels can be accurately constructed from high-dimensional data, it is still highly desirable to reduce dimensionality and to find ways of expressing the objective function with fewer dimensions. There have been developed a number methods to reduce the dimensionality of the the engineering design problems [295], where the trends have been aiming at reducing the size of the search space by searching for attractive regions [270], [296]. Yet there seems to be a lack of research on large-scale engineering optimal design problems. In fact many methods have been proposed in the past towards this goal e.g., [296], however none stands as being suitable for the high level of dimensionality involved in today's problems.

4.7.1 Curse of dimensionality; variables reduction

Building a design optimization model is the critical step for an optimal design, as the quality of the optimization model directly affects the feasibility, cost, and effectiveness of optimization. The model is created on the basis of the objective functions, the constraint functions and more importantly design variables. Yet in real-life optimal design problems where a large number of design variables are existed, building useful MOO or metamodels may require the consideration of vast quantities of variables and data points to sample the search space. In fact often, in high-dimensional problems, not all the variables are relevant to the objective functions [18]. Yet building a model on the basis of less important variables may effect the quality of the model. Therefore there have been an urge for a technique which takes into account the effect of the important variables, while reducing dimensionality.

The reduction of variables and search space is important for metamodeling because the sampling cost is directly influenced by the number of variables and their search range [297]. Latent variable reduction models [298] e.g., Gibbs sampling [299], principal component analysis [300], factor analysis [301], probabilistic PCA [302], elastic nets [303], self organizing map [304] and generative topographic mapping [305], [316], [317], [318], which represent the probability distribution of high-dimensional data in a low-dimensional space of latent variables with considering all variable information, have been found to be highly beneficial. Box and Draper [306] and later Welch et al. [307] introduced some screening methods for reducing the number of design variables to communicate less important variables. Reducing the design space to the region of interested variables is further presented in [308], [309]. Chen et al. [310] developed heuristic approaches to lead the models into the smaller design spaces and Wujek and Renaud [311], [312] applied function approximation to find manageable design space. In this context the sequential metamodeling approaches [313], [314], [315] have also been used.

4.8 Data mining for dimension reduction and decision-support systems

MCDM consists of two parts, MOO and decision-making. The involved dataset in both parts are likely to be huge and complex. Thus the large-scale data of MCDM problems can only be handled with the aid of computer applications. Yet the field of knowledge discovery, or data mining [13], has evolved very rapidly in the recent past addressing the problem of automatic analysis the big data. However, processing commands may need to be entered manually by data analysts, and data mining results can be fully used by DMs only when the results are understood explicitly. Within the large quantities of approaches have been developed for solving nonlinear MOO problems [189], the data mining applications have been applied in a number of these approaches in order to make the process less complicated and minimize the computational cost. For instance Zitzler et al. [350] in an integrated MOO technique applied a clustering task of data mining called average linkage method [360] to maintain the diversity. Moreover while graphs and plots are usually applied for understanding up to only three-dimensional relationships among MOO objectives, visualization the multiple objective problems with the aid of data mining tasks have been reported beneficial. In this regard classifications and clustering [361], [362] are the most popular tasks. Common data mining methods utilized for classification are the k-nearest neighbor decision tree [344], and neural network [363]. Obayashi et al. [362] utilizes the clustering technique of data mining for visualizing the four objectives of optimization in a self-organizing map. Without the aid of data mining the visualization of the huge amounts of data in MOO is extremely difficult. For instance dealing with the computational complexity of heatmap-based MOO visualization in [216] is completely dependent on the clustering methods.

Dimension reduction in MCDM processes has been involved in a number of researches, e.g. [364], [365], [36], to fulfill objectives such as improving the accuracy of models, scaling the models, reducing computational cost, and providing a better understanding of data where the aim of data reduction is to find a subset of attributes which represent the concept of data without losing important information. The surveys on dimension reduction with the involvement of data mining techniques are available in [332], [336], [345], [346]. Additionally in [333] geometric methods for feature extraction and dimensional reduction, dimension reduction and feature selection, *curse of dimensionality*, classification, visualization and data mining for high dimensional datasets, mining high-dimensional data with the aid of frequent pattern, clustering and classification are well defined. Among the potential data mining tools considered for dimension reduction, the association [334] and clustering rules [335], [347], have found to be more popular.

In dealing with MCDM problems, the final obtained solution must be as close to the true optimal solution as possible and that solution must satisfy the supplied preference information. In dealing with such a task, input data to MCDM such as initial value of variables is extremely important. An additional difficulty is the fact that the DM is not necessarily an expert in the field of the decision-making process so as to be able to correctly identify effective and valuable variables. Hence, getting support for analyzing the input variables and decision-making variables from an intelligent computational system seems to be necessary. For instance Morik et al. [367] utilize a data-mining applications for supporting the process of decision-making. Furthermore satisfying trade-off method (STOM) [364] has been seen as a reliable tool in this realm. Nakayama, [368] in some multi-objective STOM problems utilizes the classification task of data-mining for the reason of supporting the decision-making procedure. Different tasks of data-mining, including description, estimation, prediction, classification, clustering and association, were utilized in different applications of MCDM e.g., [325], [326], [327], [328], [329], [330] as the novel decision-support systems. In these works the importance of knowledge discovery in databases, data mining and visualization in developing advanced decision-support systems for solving business problems are emphasized.

The difficulties in optimal engineering design include the complicated interactions between large numbers of objective functions, design variables, and constraints. This difficulty often leads to an unsuitable formulation of design problems. Yet data-mining applications are highly recommended to address these challenges as it is described for instance in [323], [337] where data mining provides insight into the design of complicated systems. The information obtained from data mining can further be utilized to support the decisions, formulation of design problems and visualization. A review of recent developments and applications of data mining techniques in the engineering design field, and real-life examples of state-of-the-art data mining techniques is available in [323]. Additionally a survey and case study on optimal engineering system design guided by data-mining methods is available in [337] where the data mining-aided optimal design methods, would deliver the ability to find a competitive design solution with a relatively low computational cost. In this survey the benefits of the data-mining–aided optimal design are clearly demonstrated by comparison with both local optimization methods e.g., simplex search, and random search-based optimizations including GA and SA. As a result the clustering rule of data mining has been seen as a reliable tool that can generate a design library based on the evaluation of feature functions instead of an objective function while the classification tasks by creating the design selection rules would lead to the competitive designs.

4.8.1 Contributions

Optimal engineering design plays a significant role in today's design cycle and decision-making. Yet the involved optimization process is essentially seen as a system improvement which identifies and arranges the effective variables and tunes the design parameters [324] where approaches to nonlinear MOO e.g., metamodels, deliver an extensive, self-contained solution [255]. In this sense nonlinear MOO approaches to optimal engineering design could be interpreted as MCDM tasks dealing with nonlinear functions of decision variables. However, as it was also discussed earlier, identification of the optimum solution of a nonlinear multi-objective problem and decision-making, in the black-box optimization tasks, is often not possible because of the size of the problem and lack of knowledge about effective variables [316], [317]. As it was mentioned the different tasks of MOO and decision-making in engineering optimization applications mostly utilizing metamodeling tools have the common difficulty of dealing with the large amounts of design variables, decision variables and objectives. And in fact the DM often has no idea about the importance of the variables. Thus it is difficult to organize the number of variables based on expert knowledge. Additionally variables ranking is also a difficult task, especially when several computer simulations, objectives and decision makers are involved [320], [321], [322]. In the other words the involved datasets in MCDM problems, in particular in solving the MOO problem, are often very likely to be huge and complex. Large-scale data of MOO problems [17], which is mostly due to the high number of variables, can only be handled with the aid of computer tools. Here with data-mining applications we aim to deal with this problem. Earlier, different tools for data mining e.g., neural network, decision tree and regression analysis [354] had been effectively utilized in optimization systems involving various modeling techniques. These tasks are well reviewed in [324] where data mining for multi-disciplinary design optimization applications is surveyed. Further it was suggested that the classification and prediction tasks of data mining can effectively be applied in this regard. Case studies of utilizing the data mining applications especially classification tasks, for handling the complexity of a huge amount of data associated with huge number of variables, for improving the accuracy of meta-models, scaling the data mining models, reducing computational cost, and providing a better understanding of data are available in our research works communicated in [18]. In [16] we proposed data mining techniques in dealing with the dataset of MOO problems, as a pre-processing sequence reducing the complexity of systems in terms of input variables. For this reason data reduction aims to select a subset of attributes which represents the concept of data without loosing important information. In our other works e.g. [11] and [19] same strategy has been evaluated in different case studies utilizing different classification algorithms and different geometries.

4.9 Proposed methodology

While the new generation of commercial MOO packages e.g., [133], via providing an integrated design environment, has made the optimization process more automated, initializing the process and setting the initial value of simulation tools and also identifying the effective input variables and objectives in order to reach the smaller design space are highly desirable in order to reduce the computations costs and dimensionality. In this situation adding a pre-processing step into the MCDM procedure could make a huge difference in terms of organizing the input variables according to their effects on the optimization objectives of the system. In this case before any optimization can be done, identifying all dimensions of the problem such as formulation of the optimization problem with specifying input variables, decision variables, objectives, constraints, and variable bounds is an important task [369]. Here however in the considered case studies in shape optimization the problems are not clear in terms of input variables. In these cases our proposed method tries to identify the variables which have greater effects on the design's objective functions. The approach would support the MCDM processes, either metamodel-based or other MOO algorithms, in uncertain sampled records in order to estimate the whole design space. The approach is based on mining the problem's dataset including input variables and their effects on objectives. The result would deliver a better understanding of the design space prior to actually modeling and solving the problem.

The engineers in creating a real-life optimal design project often face a high amount of variables and objectives which makes the process very complex. Ranking and identifying the less important variables and objectives, and following it, reducing the number of variables and even, in some cases, objectives which have minimum effects on product design's performance, could make the process less complicated and faster. In the field of optimal engineering design there haven't been adequate research on the applicability of data mining tools yet [323], even though it was approved that analyzing the inputs and outputs of engineering numerical analysis for even a few records could deliver enough information for estimating the whole system's behavior [323], [337]. In this context the most relevant works have been done by Obayashi et al. in [361], [362]. They utilized the analysis of variance (ANOVA) approach, i.e., studying the effects of each design variable on the objectives and the constraint functions in a quantitative way. The ANOVA approach uses the variance of the model due to the design variables on an approximation function. By utilizing their proposed method, applying the data mining task of clustering, the effect of each design variable on the objective functions can be calculated and visualized. They showed how data mining applications could be applied for data processing of the numerical analysis systems. Following figure describes the position of an expected data pre-processing step in the general workflow of a MCDM process.

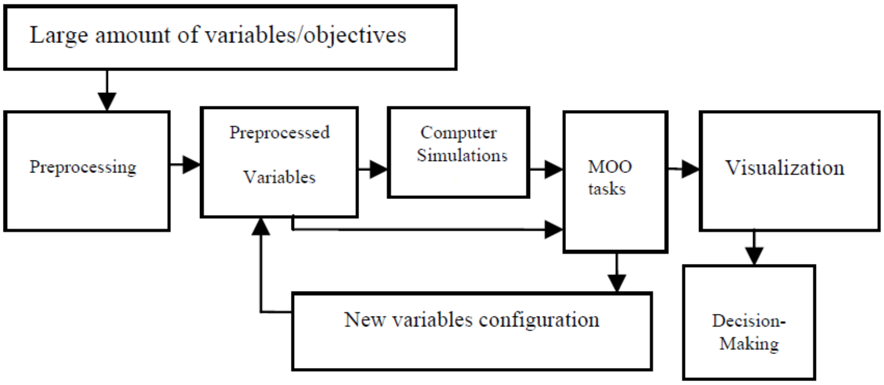


Figure 16: Description of the proposed data pre-processing approach in MCDM processes, unlike the description in figure 14 the variables are to be mined before handed.

In this case before the MOO process takes place, in the pre-processing step, the dataset of problems including the numerical analysis records of engineering simulations is analyzed utilizing data mining tasks e.g. clustering and classification where the design space is reduced and well refined/prepared for the rest of the process.

4.9.1 Classification approach

In order to reduce the number of variables a data mining classification-based method for effectively and efficiently processing the massive dataset in shape optimization cases is proposed. Classification is the learning of a function that classifies a data item into one of several predefined classes [355]. The importance of classification applications in both business and engineering communities are well recognized in today's advancement in knowledge discovery and data mining [357]. Adequate examples on classification approaches used as part of knowledge discovery applications are available in [356]. For instance in [337] a classification approach was utilized to create the design selection rules, leading to the competitive optimal designs.

Our proposed methodology is developed on the basis of classification task to rank the importance of the design variables on the design objectives. The methodology is well customized to deal with shape optimization cases with geometrical variables while design objectives are evaluated with the aid of CAE expensive analyses and simulations. In such cases due to the computation costs, metamodels are widely involved. Yet building the metamodels on the basis of the most effective variables would dramatically reduce the overall costs of the optimization and decision-making. On the other hand the cost of the commercial MCDM packages is proportional to the number of variables in which they are capable to handle. In this regard the proposed methodology can complement the metamodels in an optimal design for an affordable cost.

Further advantages of utilizing a data classification as a pre-processing step include that if the product design goals are not achievable, this method can efficiently identify this situation without wasting time running expensive metamodels and other optimization methods. Moreover in a reduced space, it is very likely that all the design solutions satisfy the design goals and further optimization may not be necessary. Additionally this method supports simultaneous computation because it samples several points simultaneously.

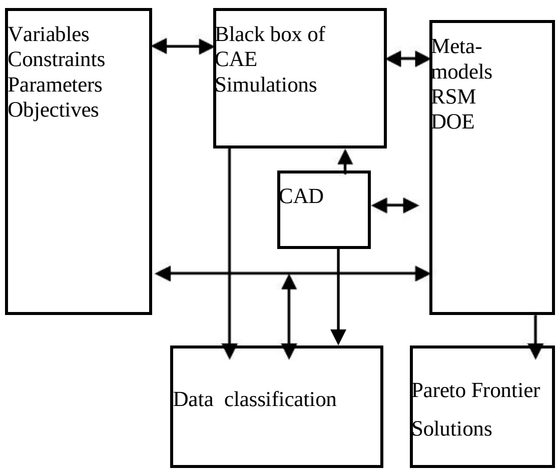


Figure 17: Supporting the metamodeling process by mining the dataset; classification in the loop.

In this method first of all the target categorical variables according to their values and expected accuracy are partitioned into different classes. Then the classification algorithm examines the dataset which contains both the input variables and the classified target variables. Afterwards the algorithm would learn which combinations of input variables are associated with which class of target categorical variable. The achieved knowledge will deliver the training set. As the numerical simulations by most of the engineering packages are very expensive, the dataset of most metamodelling-based MCDM problems does not include the information of the whole design space. In this context classification can work efficiently on estimating the entire design space. The workflow of proposed methodology is described in Figure 18 where the classification method is utilized in order to create several classifiers or decision trees.

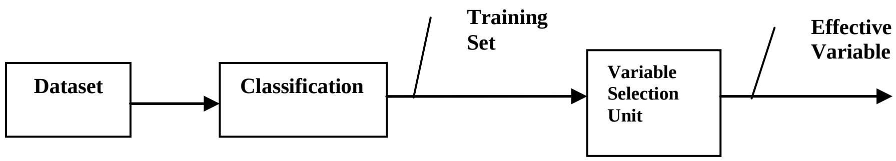


Figure 18: Description of the proposed classification-based methodology.

In the next steps the most important variables which have more effects on the objectives are selected. Regressions and model trees are constructed by a decision tree in order to build an initial tree. The splitting criterion is used to determine which variable is the better to split the portion T of the training set. Based on the treating of the standard deviation of the objective values in T, as a measure of the error, the expected reduction in error as a result of testing each variable is calculated. Those variables which maximize the expected error reduction are chosen for splitting. The splitting process terminates when the objective values of the instances vary very slightly, that is, when their standard deviation has only a small fraction of the standard deviation of the original instance set. The mean absolute error (MAE) and root mean squared error (RMSE) of the class probability are estimated and reported by the algorithm. The RMSE is the square root of the average quadratic loss and the MAE is calculated in a similar way using the absolute differences.

Here in order to simplify the data mining process the classification algorithms have been used via a data-mining software package named WEKA [113], [343]. The acceptance of WEKA is widespread in academic research and industry. An introduction to the WEKA workbench, and a review on the history of the project is provided in [358]. The data mining classifier package of Weka provides implementations of learning algorithms for datasets which could be pre-processed and feed into a learning scheme, analyzing the classifier results and its performance. Note that the Weka includes most of the standard data-mining algorithms such as regression and classification which are necessary for the proposed approach. Weka also includes many data visualization facilities and data pre-processing tools. Classification algorithms in WEKA 3.6 include; best-first decision tree (BFTree) [349]: builds a decision tree using a best-first search strategy, LADTree [351]: classifiers trees, J48 [358]: classifiers trees, simple CART [354]: a decision tree learner that implements minimal cost-complexity pruning, variants of AODE [348]: averaged one-dependence estimators with subsumption resolution (AODEsr), Gaussian processes [108]: implements the well-known gaussian process method for regression, , and functional trees [353]: decision trees with oblique splits and linear functions at the leaves. Either of the above mentioned classification algorithms may be chosen for the pre-processing task to search the whole design space for the input variables where there are no records of target categorical variables. Based on the classifications in the training set, the algorithms would be able to classify these records as well.

This method has been first introduced in [11] to address the variable reduction in general MOO problems. Later the similar approach [16] was successfully utilized in pre-processing of an airfoil shape optimization. In this method the same prepared dataset for metamodelling is mined right before modelling the MCDM problem. Pre-processing the dataset of MCDM makes understanding the problem easier, because it becomes possible to focus on the most important parts of design space. Applied data mining in pre-processing tries to bring together all the variables available and examine them. The proposed classification-based method studies the effect value of each design variable on the objectives.

4.10 Case studies in aerospace structures

The optimal design case studies in aerospace engineering where the structural simulation is tightly integrated into more than one discipline and criterion the trend has been to utilize independent computational codes for each discipline. In this situation, the aim of MCDM tools is to develop methods in order to guarantee that effective physical variables are accurately considered. In order to approach the optimal shape in aerospace engineering optimization problems, the MOO techniques are urged to deal with all the important objectives and variables efficiently. MOO in aerospace structures have to face the huge number of variables and objectives. Yet increasing the number of variables causes high computation cost to optimization process. In this regard a variable reduction tool which could remove the less effective variables and prioritize them appeared to be vital. To evaluate the effectiveness of the proposed classification method a number of case studies have been considered for a 3D airfoil structure modeled by a NURBS-based CAD package.

4.10.1 Case study 1; considering forty two variables, two objectives and nine simulation runs [16]

The case study has been given in shape optimization of a 3D airfoil with defined objectives in *displacements distribution*. The geometry of airfoil is subjected to optimization in order to deliver minimum displacement distribution in terms of applied pressure on the surface. In the similar cases [370], [371], [372] there is an attempt to utilize the MCDM approaches where the shape's geometrical parameters are actually input variables. However all possible variables have been involved in the optimization process ignoring the value of their effects on objectives. Yet the MCDM models could be more effective, accurate and less complicated if they were just created upon effective variables. In shape optimization problems input variables are naturally in high quantity, with many of them possibly not even having any effect on the system's behavior, yet still being included in the workflow. This fact has dramatically increased the size of metamodels.

a) b)

Figure 19: a) airfoil geometry modeled by NURBS, the shape is subjected to optimization in order to deliver minimum displacement in terms of applied pressure on the surface according to a number of objectives. b) shows the forty two basic points of the surface created by a number of NURBS curves.

For modeling the 3D airfoil with NURBS four profiles have been utilized including a total of forty two points. The coordinates of the points have been supplied by a digitizer. Each point includes three dimensions of *x, y*, and *z*. Consequently there are 126 columns plus two objectives. An optimal configuration of forty two variables is supposed to satisfy the two described objectives. The associated *z* coordinates of the points is identified as input variables. An optimal configuration of forty two variables is supposed to satisfy the two described design objectives. In the described pre-processing the number of variables is subjected to minimization before further MCDM process takes place.

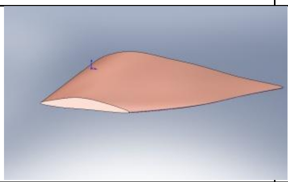
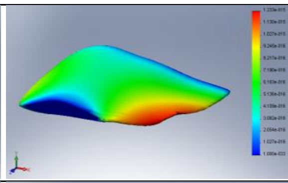
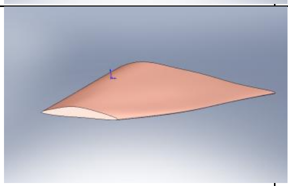
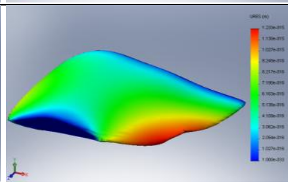
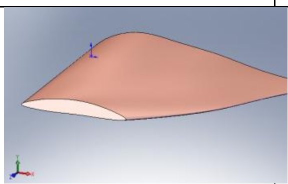
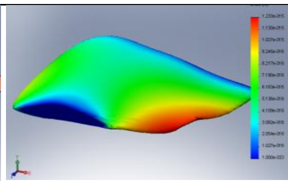
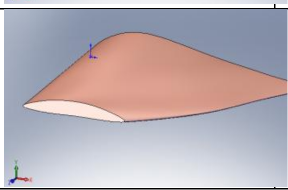
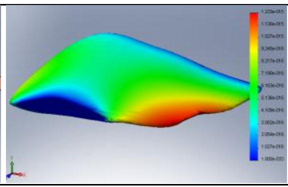
Design objectives are listed as follow:

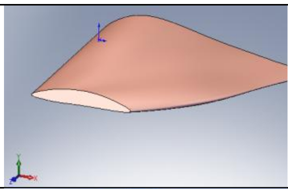
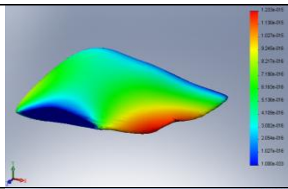
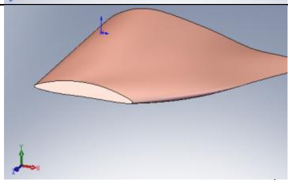
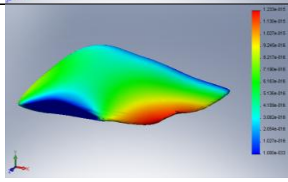
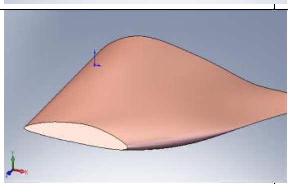
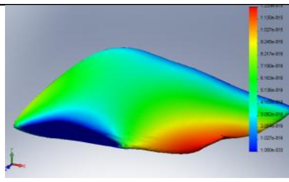
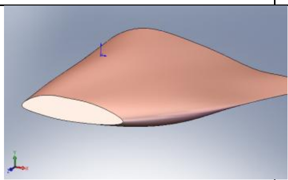
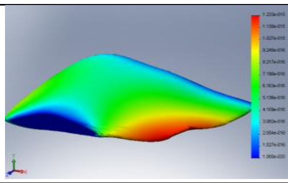
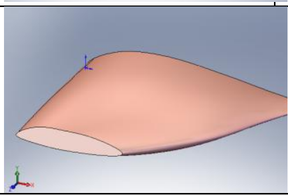
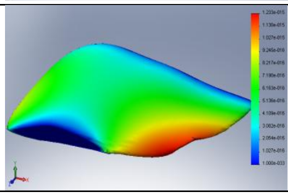
Objective1 (O_1): Minimizing the displacements distribution in the airfoil for constant pressure value of α.

Objective2 (O_2): Minimizing the displacements distribution in the airfoil for constant pressure value of 2α.

The target categorical variables are the value of displacements distribution calculated by numerical simulations in ANSYS, and their values are classified in four classes of *a, b, c* and *d*. In the datasets of geometrical and numerical analysis the objective values taken for analysis are given in table 1. This table has gathered initial datasets including the geometry of shapes and numerical simulations from nine evaluations, based on random configuration of variables. For the first case study the BFTree classification algorithm has been chosen.

Table 1: Dataset including nine sets of simulation result samples.

	Variables Configuration : V1-V42	**CAD Model**	**Simulation results/ Displacement Distribution**	**Objective Results**
No. 1	0,1,1.2,1,0.8,0.4,0.2,0,-0.4,-0.48, 0.6,-0.8,-0.72, 0,0.84,0.99,0.84,0.62,0.26,0,-0.20,-0.40,-0.36,-0.70,-0.58, 0,0.59,0.78,0.56,0.30,0,-0.21,-0.24,-0.38,-0.38 0,0.26,0.50,0.39,-0.03,-0.10,-0.12,			Objective 1=c Objective 2=c
No. 2	0,1.1,1.21,.9,0.82,0.42,0.18,.1,-0.41,-0.46,-0.62,-0.81,-0.70, 0,0.86,0.1,0.82,0.60,0.25,0.01,-0.20,-0.39,-0.39,-0.70,-0.58, 0,0.58,0.76,0.57,0.32,0,-0.21,-0.23,-0.37,-0.39 0,0.26,0.54,0.40,-0.03,-0.1,-0.1,			Objective 1=b Objective 2=c
No. 3	0,1,1.2,1,0.8,0.4,0.2,0,-0.4,-0.48,-0.6,-0.8,-0.72, 0,.88,0.99,0.84,0.62,0.26,0,-0.23,-0.35,-0.37,-0.70,-0.54, 0,0.58,0.76,0.58,0.31,0,-0.23,-0.23,-0.37,-0.37 0,0.24,0.50,0.40,-0.03,-0.13,-0.10,			Objective 1=b Objective 2=c
No. 4	0,1.3,1.23,1.06,0.83,0.41,0.28,0.07,-0.41,-0.48,-0.6,-0.8,-0.78,0,0.84,.92,0.84,0.62,0.26,0,-0.23,-0.39,-0.37,-0.70,-0.54,0,0.58,0.76,0.58,0.31,0,-0.24,-0.22,-0.36,-0.38, 0,0.24,0.52,0.38,-0.02,-0.12,-0.12,			Objective 1=d Objective 2=c

No. 5	0,1.01,1.21,1,0.8,0.4,0.21,0,-0.41,-0.47,-0.59,-0.79,-0.69, 0,0.80,1.01,0.86,0.64,0.26,-0.01,-0.20,-0.40,-0.40,-0.72,-0.56, 0,0.58,0.76,0.58,0.31,0,-0.23,-0.23,-0.37,-0.37 0,0.24,0.52,0.38,-0.06,-0.10,-0.10,			Objective 1=c Objective 2=d
No. 6	0,1,1.2,1,0.8,0.4,0.2,0,-0.39,-0.50,-0.61,-0.78,-0.70, 0,0.86,1.02,0.84,0.59,0.26,0,-0.21,-0.39,-0.39,-0.68,-0.58, 0,0.58,0.76,0.58,0.31,0,-0.23,-0.23,-0.37,-0.37 0,0.20,0.52,0.40,-0.02,-0.15,-0.15,			Objective 1= b Objective 2= c
No. 7	0,1,1.2,1,0.8,0.4,0.2,0,-0.4,-0.48,-0.6,-0.8,-0.72, 0,0.84,0.95,0.83,0.63,0.25,0,-0.20,-0.35,-0.39,-0.72,-0.56, 0,0.58,0.76,0.58,0.31,0,-0.23,-0.23,-0.37,-0.37 0,0.20,0.52,0.38,-0.04,-0.13,-0.13,			Objective 1=a Objective 2=c
No. 8	0,1,1.2,1,0.8,0.4,0.2,0,-0.4,-0.48,-0.6,-0.8,-0.72, 0,0.84,1.03,0.86,0.62,0.27,0,-0.19,-0.41,-0.41,-0.66,-0.50, 0,0.58,0.76,0.58,0.31,0,-0.23,-0.23,-0.37,-0.37 0,0.24,0.52,0.38,-0.02,-0.08,-0.09,			Objective 1= b Objective 2= b
No. 9	0,1.1,1.4,1.2,0.9,0.4,0.2,0.01,-0.39,-0.49,-0.63,-0.81,-0.68, 0,0.80,0.91,0.84,0.62,0.24,0,-0.25,-0.34,-0.39,-0.72,-0.56, 0,0.58,0.76,0.57,0.31,0,-0.23,-0.23,-0.37,-0.37 0,0.24,0.52,0.38,-0.18,-0.1,-0.1,			Objective 1= c Objective 2= b

• Results

The obtained results from pre-processing, utilizing BFTree classification algorithm, are available in the following table. Eight variables out of forty two have been selected having more effects on O_1 and, seven variables that have more effects on O_2. Two types of classification error (MAE, RMSE) are calculated for the utilized algorithm corresponding to different classes of objectives. Experiments show that the obtained results are not very sensitive to the exact choice of these thresholds.

Table 2: Variables importance ranking for BFTree classification algorithm.

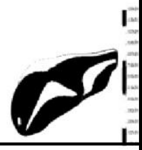
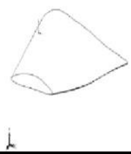
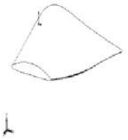
Classification Algorithm	MAE	RMSE	Effective Variables	Objectives
BFTree	0.370	0.517	38,15,24,2,32,41,39,3	O_1
	0.412	0.519	41,35,9,17,11,38,37	O_2

The whole pre-processing was done within 6.3 minutes on a Pentium IV 2.4 MHZ Processor. The variables were reduced by more than 50%. The dataset of the given MOO problem was pre-processed and the most effective variables have been identified.

4.10.2 Case study 2; considering forty two variables, three objectives and five simulation runs [11] & [17]

In the first pre-processing approach, utilizing the proposed method presented above, the database is created by nine computational simulation runs, forty two variables, two objectives and the data mining classification algorithm of BFTree was utilized. In our other literature [11], [17], following the proposed strategy, we have tried to evaluate our proposed method via further case studies utilizing other classification algorithms. However the rest of the workflow's parts still remain unchanged e.g. the geometry is created by NURBS. In engineering optimization problems due to costly computational simulations, as it is always the case, the intention is to run minimum number of simulations as possible. Thus in the further case studies there was an attempt to decrease the number of simulations from nine to five calculations while the number of objectives has been increased to three and number of geometrical variables has been remained forty two. Following table from our paper [17] shows these changes.

Table 3: Dataset including the results of five CAE calculations' run

	Variables Configuration : V1-V42	CAD Model	Displacement Distribution	Objective Results
1	0,1,1.2,1,0.8,0.4,0.2,0,-0.4,-0.48, 0.6,-0.8,-0.72, 0,0.84,0.99,0.84,0.62,0.26,0,-0.20,-0.40,-0.36,-0.70,-0.58, 0,0.59,0.78,0.56,0.30,0,-0.21,-0.24,-0.38,-0.38 0,0.26,0.50,0.39,-0.03,-0.10,-0.12,			O1=c O2=c O3=c
2	0,1.1,1.21,.9,0.82,0.42,0.18,.1,-0.41,-0.46,-0.62,-0.81,-0.70, 0,0.86,0.1,0.82,0.60,0.25,0.01,-0.20,-0.39,-0.39,-0.70,-0.58, 0,0.58,0.76,0.57,0.32,0,-0.21,-0.23,-0.37,-0.39 0,0.26,0.54,0.40,-0.03,-0.1,-0.1,			O1=b O2=c O3=d
3	0,1,1.2,1,0.8,0.4,0.2,0,-0.4,-0.48,-0.6,-0.8,-0.72, 0,.88,0.99,0.84,0.62,0.26,0,-0.23,-0.35,-0.37,-0.70,-0.54, 0,0.58,0.76,0.58,0.31,0,-0.23,-0.23,-0.37,-0.37 0,0.24,0.50,0.40,-0.03,-0.13,-0.10,			O1=b O2=c O3=b
4	0,1.3,1.23,1.06,0.83,0.41,0.28,0.07,-0.41,-0.48,-0.6,-0.8,-0.78,0,0.84,.92,0.84,0.62,0.26,0,-0.23,-0.39,-0.37,-0.70,-0.54,0,0.58,0.76,0.58,0.31,0,-0.24,-0.22,-0.36,-0.38, 0,0.24,0.52,0.38,-0.02,-0.12,-0.12,			O1=d O2=c O3=b
5	0,1.01,1.21,1,0.8,0.4,0.21,0-0.41,-0.47,-0.59,-0.79,-0.69, 0,0.80,1.01,0.86,0.64,0.26,-0.01,-0.20,-0.40,-0.40,-0.72,-0.56, 0,0.58,0.76,0.58,0.31,0,-0.23,-0.23,-0.37,-0.37 0,0.24,0.52,0.38,-0.06,-0.10,-0.10,			O1=c O2=d O3=e

In this case study, as it is reflected in the following table, alternatively we try to include other classification algorithms i.e., J48, BFTree, LADTree, in order to better evaluate the method. Following table from our paper [17] includes the results of the performed pre-processing, utilizing three different data mining classification algorithms. According to the table the selected variables of all algorithms don't completely match. However for some particular objectives the results are very satisfying and meet our assumptions.

Table 4: Variable importance ranking of three classification algorithms for three objectives

Classification Method	MAE	RMSE	Variables Importance	Objective
BFTree	0.370	0.517	15,24	O_1
	0.412	0.519	13,23	O_2
	0.418	0.555	41,32,35	O_3
J48	0.309	0.514	15,24	O_1
	0.482	0.642	13	O_2
	0.378	0.590	35,41	O_3
LADTree	0.277	0.500	15,24,2,32,41,39,3	O_1
	0.604	0.769	23,22,18,15,42,2,17,20	O_2
	0.365	0.584	41,35,9,17,11,38,37,16	O_3

- **Results**

The dataset of the given MOO problem was pre-processed and the most effective variables have been identified. The variables were reduced by more than 50%. The obtained results from pre-processing are available in the above table. Important variables out of forty two have been selected having more effects on O_1, O_2 and O_3. Two types of classification error (MAE, RMSE) are calculated for the utilized algorithm corresponding to different classes of objectives. Experiments show that the obtained results are not very sensitive to the exact choice of these thresholds. The whole preprocessing was done within 6.0 minutes on a Pentium IV 2.4 MHZ Processor for each algorithm's run. It is evident that decreasing the CAE runs in dataset challenges the pre-processing tasks as the results of all the algorithms doesn't completely match.

4.10.3 Case study 3; considering thirty variables, three objectives and five simulation runs [18] & [19]

For third study case, the strategy is to consider the case with including further classification algorithms e.g., J48, BFTree, LADTree, functional trees, simple CART, Gaussian processes. The new geometry is represented with thirty geometrical variables. The associated z coordinates of the points are identified as input variables. An optimal configuration of thirty variables is supposed to satisfy the three described design objectives.

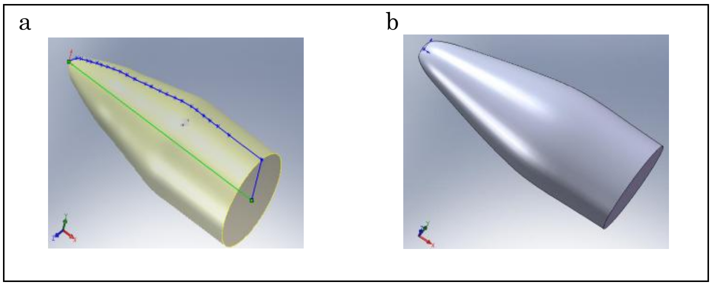


Figure 20: Description of geometry of case study 3, modeled by thirty points.

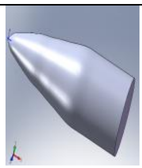
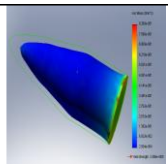
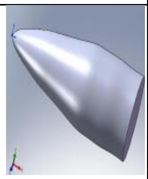
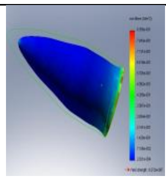
Design objectives are listed as follow;

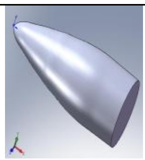
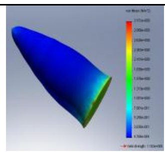
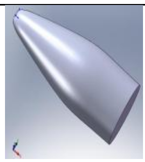
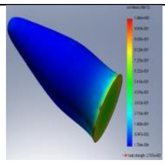
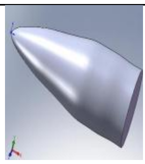
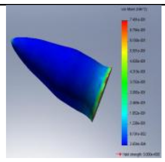
Objective1 (O_1): Minimizing the displacements distribution in the airfoil for constant pressure value of α

Objective2 (O_2): Minimizing the displacements distribution in the airfoil for constant pressure value of 2α

Objective3 (O_3): Minimizing the displacements distribution in the airfoil for constant pressure value of 3α

Table 5: Dataset including the results of five simulations

	Variables Configuration : V1-V30	**CAD Model**	**Displacement Distribution**	**Objective / target variable**
1	0,0.84,0.99,0.84,0.62,0.26,0,-0.20,-0.40,-0.36,-0.70,-0.58, 0,0.59,0.78,0.56,0.30,0,-0.21,-0.24,-0.38, 0,1,1.2,1,0.8,0.4,0.2,0,-0.4,-0.48, 0.6,-0.8,-0.72,			O1=c O2=c O3=b
2	0.62,-0.81,-0.70, 0,0.86,0.1,0.82,0.60,0.25,0.01,-0.20, -0.39,-0.39,-0.70, -0.58, 0,0.58,0.76,0.57,0.32,0,-0.21,-0.23,-0.37, 0,1.1,1.21,.9,0.82, 0.42,0.18,.1,-0.41,-0.46,			O1=b O2=c O3=a

3	0.72, 0,.88,0.99,0.84,0.62 ,0.26,0,-0.23,-0.35,- 0.37,-0.70,-0.54, 0,0.58,0.76,0.58,0.3 1,0,-0.23,-0.23,- 0.37, 0,1,1.2,1,0.8,0.4,0.2 ,0,-0.4,-0.48,-0.6,- 0.8,			O1=b O2=c O3=c
4	0.6,-0.8,- 0.78,0,0.84,.92,0.84 ,0.62,0.26,0,-0.23,- 0.39,-0.37,-0.70,- 0.54,0,0.58,0.76,0.5 8,0.31,0,-0.24,- 0.22,-0.36, 0,1.3,1.23,1.06,0.83 ,0.41,0.28,0.07,- 0.41, 0.48,			O1= c O2= d O3=a
5	0.59,-0.79,-0.69, 0,0.80,1.01,0.86,0.6 4,0.26,-0.01,-0.20,- 0.40,-0.40,-0.72,- 0.56, 0,0.58,0.76,0.58,0.3 1,0,-0.23,-0.23,- 0.37, 0,1.01,1.21,1,0.8,0. 4,0.21,0-0.41,-0.47,			O1=c O2=a O3=c

• **Results**

The obtained results from pre-processing are available in the following table. A number of variables out of thirty have been selected having more effects on O_1, O_2, and O_3. Two types of classification error (MAE, RMSE) are calculated for the utilized algorithm corresponding to different classes of objectives. The whole pre-processing was done within 3.00 minutes on a Pentium IV 2.4 MHZ Processor for each algorithm. The variables were reduced by more than 70%. The dataset of the given MOO problem was pre-processed and the most effective variables have been identified.

Table 6: Variable importance ranking of seven classification algorithms for three objectives

Classification algorithm	MAE	RMSE	Variables Importance	Objectives
BFTree	0.307 0.312 0.302	0.319 0.376 0.312	7, 12 4, 7, 12, 22 3, 7, 22, 25	O_1 O_2 O_3
J48	0.290 0.312 0.356	0.325 0.334 0.390	7, 12, 21 4, 7, 12, 21 3, 7, 21, 22, 25	O_1 O_2 O_3
LADTree	0.325 0.231 0.334	0.422 0.340 0.388	7, 12, 21 4, 7, 11, 22 3, 7, 21, 22, 25	O_1 O_2 O_3
AODE	0.340 0.266 0.308	0.423 0.299 0.346	7, 12, 22 4, 7, 12, 22 3, 7, 22, 25	O_1 O_2 O_3

functional trees	0.238 0.376 0.296	0.387 0.390 0.385	7, 12, 21, 22 4, 7, 12, 21 3, 7, 21, 22, 25	O_1 O_2 O_3
simple CART	0.239 0.329 0.330	0.329 0.426 0.376	7, 11, 21 4, 7, 12, 22 3, 7, 21, 22, 25	O_1 O_2 O_3
Gaussian processes	0.278 0.308 0.374	0.283 0.346 0.425	7, 12, 22 4, 7, 22 3, 7, 21, 22, 25	O_1 O_2 O_3

4.11 Discussion and final remarks

Case studies show that the smaller regions can be efficiently identified. The work presents a new method that can help reduce the design search space for MCDM problems and robust design optimization problems, if they are formulated as a special case of MOO. In this context the classification task of data mining has been introduced as an effective option for identifying the most effective variables of the MOO in MCDM systems. The number of the optimization variables has been managed very effectively and reduced in the considered case studies. The modified methodology is demonstrated successfully in the framework. From the test problems, one can see that the original design space for multi-objective optimization problems can be reduced with a limited number of function evaluations by using the proposed method. Moreover, the reduced space can then better capture all of the Pareto points, i.e., the space reduction can be adequate without the risk of loosing the important Pareto design points. It is also found that if goals are too tough, it might be hard to sample points satisfying the goals. Often more sample points are required to reach a reasonably accurate subspace. Otherwise, the probability of missing attractive spaces is high. However if goals are too easy to satisfy, the space reduction effect is not significant.

With the results of the pre-processing the optimization problem has been much clear in terms of variable and objective interactions. The new created design space based on the new sets of variables is much smaller which would make the further MOO processes much easier. By adjusting the MAE and RMSE in each classification the expected number of variables could be arranged. For the cases we were expecting more than a 50% reduction in design space for the mentioned errors. The achieved pre-processing results as reduced variables will speed up the process of optimization due to delivered smaller design space and minimum requested computational cost for MOO process. Data mining tools have been found to be effective in this regard. It is evident that the growing complexity of MCDM systems could be handled by a pre-processing step utilizing data mining classification algorithms.

As the future work to this research work, studying the effectiveness of the introduced data reduction process in different applications is suggested. Also trying to use other tasks of data mining such as clustering, association rules, and comparison could produce beneficial results. More detail of this research is available in our recently published research article [18].

5 Reactive search for MCDM

In the last two sections the vital role of the metamodels and data mining in creating and supporting the efficient global optimization algorithms for dealing with MCDM problems and dimensionality involved has been discussed where the EMO and conventional interactive algorithms have been mainly the principal MOO solvers. In this section the drawbacks to EMO-based approaches are briefly discussed, and alternatively utilizing the methodology of reactive search optimization (RSO) [38] procedure and its recently implemented visualization software [253] is proposed as an integrated environment for optimization, analytics and decision-support in general engineering design problems. Here the new set of powerful integrated data mining, modeling, visualization and learning tools via a handy procedure stretches beyond a decision-making task and attempts to discover new optimal designs relating to decision variables and objectives, so that a deeper understanding of the underlying problem can be obtained. In an integrated design environment as such solving the MCDM problem is considered as a combined task of optimization and decision-making, unlike the former conventional approaches considered in the last sections where in solving real-life MCDM problems most of attention has been on finding the complete Pareto-optimal set of the associated MOO problems and less on decision-making. In this section, along with presenting three case studies, the proposed interactive procedure which involves the DM in the process addresses this issue effectively. Moreover the methodology delivers the capability of handling the dimensionality (big data) often associated with shape optimization as well as materials selection tasks in engineering design problems.

The material of this section would be a summary to a number of our recently published articles e.g., [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [51], [52] and [53].

5.1 Introduction

The MCDM design environments e.g., [28], [47], [48], [52], [53], [133], [222], build their bases on software tools used for a large number of applications from modeling, optimization and decision-making tasks, to performance's simulation. Further addition of new tools is intended to extend the support to the creative part of the design process and also the capability to deal with big data [17]. This support empower the designers to improve the performance of their concepts, allowing computers to take part on the generation of variants, and on the judgment, by true modeling of these variants. Integration of data mining, modeling, learning, and interactive decision-making are all parts of a reliable software tool that can nurture the knowledge of designers to generate new solutions, based on many separate ideas leading to the novel design concepts [398], [401].

The methods for structural and topological optimal design, based on evolutionary design, currently are widely used to obtain optimal geometric solutions [28], [71], [205], [392], [396], [399]. The methods and design strategy as such are evolving into configurations that minimize the cost of trial and error and perform far beyond the abilities of the most skilled designers. Although in developing a multicriteria decision making environment relying only on evolutionary design components, in today's ever-increasing complexity when often numerous design objectives involved, is not sufficient [39], [390], [398], [393]. Moreover most studies in the past concentrated in finding the optimum corresponding to a single goal, say designing for minimum cost or maximum quality. The single-objective optimization procedure searches through possible feasible solutions and at the end identifies the best solution [78], [89], [101], [151], [176], [191]. Often, such solution lacks the consideration of other important design objectives. Fortunately applied optimization over the years have been dramatically changed, particularly with the availability of interactive MCDM algorithms which facilitates a DM to consider more than one conflicting goals simultaneously e.g., [129], [130], [206], [207].

The task of MCDM is divided into two parts: (1) a MOO procedure to discover conflicting design trad-offs and (2) a decision-making process to choose a single preferred solution among them. Although both processes of optimization and decision-making are considered as two joint tasks, yet they are often treated as a couple of independent activities. For instance EMO algorithms [4], [126], have mostly concentrated on the optimization aspects i.e. developing efficient methodologies of finding a set of Pareto-optimal solutions. However finding a set of trade-off optimal solutions is just half the process of optimal design in a MCDM environment. This has been the reason why EMO researchers were looking to find ways to efficiently integrate both optimization and decision making tasks in a convenient way [398], where the efficient MOO algorithms facilitate the DMs to consider multiple and conflicting goals of a MCDM problem simultaneously. Some examples of such algorithms and potential applications could be found in e.g., [406], [407], [408] [409]. Nevertheless within the known approaches to solving complicated MCDM problems there are different ideologies and considerations in which any decision-making task would find a fine balance among them.

In traditional applications to MCDM e.g., [372], [373], [374], [397], often the single optimal solution is chosen by collecting the DM's preferences where MOO and decision-making tasks are combined for obtaining a point by point search approach. In addition in MOO and decision-making, the final obtained solutions must be as close to the true optimal solution as possible and the solution must satisfy the preference information. Towards such a task, an interactive DM tool to consider decision preferences is essential. This fact has motivated novel researches to properly figure out the important task of integration between MOO and decision-making in MCDM [393], [398]. Naturally in MCDM, interactions with the DM can come either during the optimization process, e.g., in the interactive EMO optimization including; [39], [205], [398], or during the decision-making process e.g., [69], [70], [110], [156], [137], [172], [173]. Interactive MOO methods in the MCDM literature concerning optimal engineering deign reviewed for instance in [192], [284] [253], [420].

5.2 Motivation

The usage of EMO in real-life optimal engineering design has been always an important interest to MCDM community concerning e.g., [4], [70], [82], [123], [125], [126], [162], [172], [219]. For an optimal decision in EMO-based optimal design there are two different ways identified by which EMO and MCDM methodologies can be combined together. [390]. Either EMO followed by MCDM or, MCDM integrated in an EMO. In the first way, an EMO algorithm is applied to find the Pareto-front solutions. Afterward, a single preferred solution is chosen from the obtained set by using a MCDM procedure. In this way EMO application helps a DM to analyze different trade-off solutions to choose the final one. However the DM has to go through analyzing many different solutions to be able to make the final decision. Therefore the DM has to consider too many possible solutions. Yet as the typical DM cannot deal with more than a very limited number of information items at a time, according to [72], the methods as such are reported inefficient considering e.g., [39], [398], [400] and [406].

Alternatively a MCDM procedure could be integrated within an EMO approach to find the preferred Pareto-front solutions where the search is concentrated on the important region of the Pareto-front [390]. This would let the optimization task to evaluate the preferences of the DM interactively. Such approaches of interactive evolutionary algorithms to MCDM are reviewed in [129], [205], [207], [209], [393], [396]. Additionally a survey can be found in the literature of Miettinen [5], [70]. Other popular approaches as such include interactive surrogate worth trade-off method [394], the reference point method [395] and the NIMBUS approach [388].

All above interactive procedures require a DM to provide the design preferences. A search workflow is then used to find the optimum of the objective evaluation. This procedure is repeated many times until the DM is satisfied with the obtained final solution. For instance in [390], an EMO procedure is applied to a complicated design problem and then an interactive methodology is employed to choose a single solution. In [397], EMO is combined with MCDM procedures, and an interactive procedure is suggested where the EMO methodologies are combined with a certain and efficient MCDM technique. The work later in [398] was extended by involving more objective evaluation tools and integrations with further software packages such as MATLAB, for providing better working on more real-life case studies e.g., [396]. In [398] unlike the classical interactive methods presented for instance in [205], a good estimation of the Pareto-optimal frontier is created, in which helps to concentrate on a particular region. The authors in [398] conclude that when an approach is best suited for one problem it may be inadequate in another problem. As the result worth mentioning that in developing MCDM tools with the EMO novel integrations, a successful procedure could include more than one optimization and decision-making tool in it so that any number of optimization and decision-making tool may be combined to build an effective problem solving procedure. The researches reviewed above, have motivated other EMO, MCDM and optimal design researches, including our research, to improve such integration schemes further by considering other potential interactive optimization and decision-making tools.

5.3 Drawbacks to solving MOO problems with EMO algorithms

Lets rephrase the general form of a MOO problem according to [421], stating that; minimize $\mathbf{f}(\boldsymbol{x}) = \{f_1(\boldsymbol{x}), \dots, f_m(\boldsymbol{x})\}$, Subjected to $\boldsymbol{x} \in \Omega$, where $\mathbf{x} \in \mathbb{R}^n$ is a vector of n decision variables; $\mathbf{x} \subset \mathbb{R}^n$ is the feasible region and is specified as a set of constraints on the decision variables; $\mathbf{f} : \Omega \to \mathbb{R}^m$ is made of m objective functions subjected to be minimization. Objective vectors are images of decision vectors written as $\mathbf{z} = \mathbf{f}(\boldsymbol{x}) = \{f_1(\boldsymbol{x}), \dots, f_m(\boldsymbol{x})\}$. Yet an objective vector is considered optimal if none of its components can be improved without worsening at least one of the others. An objective vector $\mathbf{z}$ is said to dominate $\mathbf{z}'$, denoted as $\mathbf{z} \prec \mathbf{z}'$, if $z_k \leq z'_k$ for all k and there exist at least one h that $z_h \leq z'_h$. A point $\hat{\boldsymbol{x}}$ is Pareto optimal if there is no other $\boldsymbol{x} \in \Omega$ such that $\mathbf{f}(\boldsymbol{x})$ dominates $\mathbf{f}(\hat{\boldsymbol{x}})$. The set of Pareto optimal points is called Pareto set (PS). And the corresponding set of Pareto optimal objective vectors is called Pareto front (PF).

The EMO tools e.g., [392], [174], for solving the above described MOO problem have been around for up to two decades now, and are well suited to search for a set of PS to be forwarded to the DM. Considering solving MCDM problems, EMO algorithms are among the most popular *a posteriori* methods for generating PS of a MOO problem aiming at building a set of points near the PF. However they become inefficient for increasing number of objectives. MOO problem of curve and surfaces, described e.g., in [20], [21], [22], [389], would be a good example for such an ineffective attempt due to increasing complexity. Because the proportion of PF in a set grows very rapidly with the dimension $\boldsymbol{m}$, therefore the former approaches for solving the MOO of the curve and surfaces whether a *priori* or *a posteriori*, and in particular EMO, would involve plenty of various complications. In fact the reality of applied optimal design has to consider plenty of priorities and drawbacks to both interactive and non-interactive approaches. Although the mathematical representative set of the MCDM model is often created however presenting a human DM with numerous representative solutions on a multi-dimensional PF is way complicated. This is because the typical DM cannot deal with more than a very limited number of information items at a time [72]. Therefore an improved decision procedures should be developed according to human memory and his data processing capabilities. In addition often DMs cannot formulate their objectives and preferences at the beginning. Instead they would rather learn on the job. This is already recognized in the optimal design formulation, where a combination of the individual objectives into a single preference function is not executed. Considering the problems in [21], [120], [423], the DM is not clear about the preference function. This uncertainty is even increased when the objectives such as beauty involved. This fact would employ lots of uncertainty and inconsistency.

Consequently interactive approaches try to overcome some of these difficulties by keeping the user in the loop of the optimization process and progressively focusing on the most relevant areas of the PF directed by DM. This is done when the fitness function is replaced by a human user. However most DMs are typically more confident in judging and comparing than in explaining. They would rather answer simple questions and qualitative judgments to quantitative evaluations. In fact the identified number of questions that has to be asked from the DM a crucial performance indicator of interactive methods. This would demand for selecting appropriate questions, for building approximated models which could reduce bothering the DM [38], [39], [42], [401], [420].

The above facts, as also mentioned in [39], and later in [42] demand a shift from building a set of PF, to the interactive construction of a sequence of solutions, so called brain-computer optimization [39], where the DM is the learning component in the optimization loop, a component characterized by limited rationality and advanced question-answering capabilities. This has been the reason for the systematic use of machine learning techniques for online learning schemes [45], [274], in optimization processes available in the software architectures of RSO [253].

5.4 Brain-computer optimization (BCO) approach to stochastic local search

As Battiti et al. [39], [420], [421] clearly state, the aim of brain-computer stochastic local search is to find the minimum of the combinatorial optimization function f, on a set of discrete possible input values X. To effectively and interactively doing so the focus in [39], [42] and [43], is devoted to a local search, hinting at RSO with internal self-tuning mechanisms, and BCO which is referred to the interactive role of DM in the problem-solving loop. Accordingly in this context the basic problem-solving strategy would start from an initial tentative solution modifying the optimization function. According to [421] the local search starts from a configuration of $X(0)$ and builds a search trajectory $X^{(0)}, \ldots, X^{(t+1)}$. where X is the search space and $X^{(t)}$ is the current solution at iteration t, time. Then $N(X^{(t)})$ would be the neighborhood of point $X^{(t)}$,obtained by applying a set of basic moves $\mu_0, \mu_1, \ldots, \mu_M$ to the configuration of $N\big(X^{(t)}\big) = \{ X \in x \text{ such that } X = \mu_i\big(X^{(t)}\big), i = 0, \ldots, M\}$. If the search space is given by binary strings with a given length L: $X = \{0{,}1\}^L$, the moves can be those changing the individual bits, and therefore L is equal to the string length M. The accuracy of the achieved point is a point in the neighborhood with a lower value of f to be minimized. The search then would stop if the configuration reaches a local minimum [420].

Y ← IMPROVING-NEIGHBOR $(N\big(X^{(t)}\big))$

$$X^{(t+1)} = \begin{cases} Y & \text{if } f(Y) < X^{(t)} \\ X^{(t)} & \text{otherwise (search stops)} \end{cases}$$

Yet in above statement adapted from [421] and [39], the local search works very effectively and the improving-neighbor returns an improving element in the neighborhood. This is manily because most combinatorial optimization problems have a very rich internal structure relating the configuration X and the f value [421]. In the neighborhood the vector containing the partial derivatives is the gradient, and the change of f after a small displacement is approximated by the scalar product between the gradient and the displacement [400].

5.4.1 Learning component; DM in the loop

In problem-solving methods of brain-computer stochastic local search, proposed in [39], where the free parameters are tuned through a feedback loop, the user is considered as a crucial learning component in which different options are developed and tested until acceptable results are obtained. As explained in [420] by inserting the machine learning the human intervention is decreased by transferring intelligent expertise into the algorithm itself. Yet in order to optimize the outcome setting the parameters and observing the outcome, a simple loop is performed where the parameters in an intelligent manner changed until a suitable solution is identified. Additionally to operate efficiently, RSO uses memory and intelligence, to recognize ways to improve solutions in a directed and focused manner.

In RSO approach of problem solving the brain-computer interaction is simplified. This is done via learning-optimizing process which is basically the insertion of the machine learning component into the solution algorithm, as it is permanently described in [42], [45] and [51]. In fact the strengths of RSO are associated to the brain characteristics which is learning from the past experience, learning on the job, rapid analysis of alternatives, ability to cope with incomplete information, quick adaptation to new situations and events [401]. Moreover the term of intelligent optimization in RSO refers to the online and offline schemes based on the use of memory, adaptation, incremental development of models, experimental algorithmics applied to optimization, intelligent tuning and design of heuristics. In this context with the aid of advanced visualization tools implemented within the software architecture packages of RSO e.g., [253] the novel integration of visualization, automated problem solving and decision-making would provide an inteligent interactive design environment for future designs.

5.5 RSO and visualization tools; an effective approach to MCDM

Visualization is an effective approach in the OR and mathematical programming applications to explore optimal solutions, and to summarize the results into an insight, instead of numbers [379], [380]. Fortunately during past few years, it has been a huge development in combinatorial optimization, machine learning, intelligent optimization, and RSO, which have moved the advanced visualization methods even further. Previous works in the area of visualization for MCDM [41], [60], [211], [212], [216], [226], [318], [361], [379], allow the DM to better formulate the multiple objective functions for large optimization runs. Alternatively in our research utilizing RSO and visualization [253], which advocates learning for optimizing, the algorithm selection, adaptation and integration, are done in an automated way and the desgin engineer is kept in the loop for subsequent refinements. Here one of the crucial issue in MCDM is to critically analyzing a mass of tentative solutions associated with big data, which is visually mined to extract useful information. In developing RSO in terms of learning capabilities there has been a progressive shift from the DM to the algorithm itself, through machine learning techniques [400], [401]. Consequently in solving the MCDM problems utilizing RSO, the design engineer is not distracted by technical details, instead concentrates on using his expertise and informed decision among the large number of possibilities. Algorithms with self-tuning capabilities like RSO make optimal design tasks simpler for the final user. To doing so the novel approach of RSO is to integrate the machine learning techniques, artificial intelligence, reinforcement learning and active learning into search heuristics. According to the original literature [401] during a solving process the alternative solutions are tested through an online feedback loop for the optimal parameters' tuning. Therefor the DM would deal with the diversity of the problems, stochasticity, and dynamicity more efficiently. Worth mentioning that RSO approach of learning on the job is contrasted with off-line accurate parameter tuning which automatically tunes the parameter values of a stochastic local search algorithm. The very promising case studies in optimal engineering design treated by RSO would include e.g., [40], [41], [42], [42], [44], [48], [253], [405].

5.6 Characteristics of the proposed approach

During the process of solving the real-life problems exploring the search space, utilizing RSO, many alternative solutions are tested and as the result adequate patterns and regularities appear. While exploring, the design engineer quickly learns and drives future decisions based on the previous observations and searching alternatives. For the reason of rapidly exploiting the most promising solutions the online machine learning techniques are inserted into the optimization engine of RSO [421]. Furthermore with the aid of inserted machine learning a set of diverse, accurate and crucial alternatives are offered to the DM. The complete series of solutions are generated. After the exploration of the design space, making the crucial decisions, within the multiple existing criteria, totally depends on several factors and priorities which are not always easy to describe before starting the solution process. In this context the feedback from the DM in the preliminary exploration phase can be considered so that a better arrangement of the parameters takes the preferences into account. Further relevant characteristics of RSO, according to [38], could be summarized as; learning on the job, rapid generation, and analysis of many alternatives, flexible decision support, diversity of solutions and anytime solutions.

5.7 Applications

A number of complex optimization problems arising in widely different contexts and applications which has been effectively treated by the general framework of RSO are reviewed in [42], [44], and [53] where the real-life applications in computer science, OR community combinatorial tasks, applications in the area of neural networks related to machine learning and continuous optimization tasks have been emphasized. Furthe real-life applications would particularly include risk management, managing the big data of social networks, transportation, healthcare, marketing and e-commerce. Additionally in the following we briefly review some applications in industry which are the main interests of this research.

In the area of electric power distribution there have been reported a series of real-life applications [403]. An open vehicle routing problem [404], as well as the pickup and delivery problem [405] both with the time and zoning constraints is modeled where the RSO methodology is applied to the distribution problem in a major metropolitan area. Alternatively to solve the vehicle routing problem with backhauls a heuristic approach based on a hybrid operation of reactive tabu search is proposed in [406]. By utilizing the RSO the flexible job-shop scheduling [407], the plant location problem [408], the continuous flow-shop scheduling problem [409], adaptive self-tuning neurocontrol [410] and the real-time dispatch of trams [411] were effectively solved. Moreover various applications of RSO focused on problems arising in telecommunication networks, internet and wireless in terms of optimal design, management and reliability improvements are reviewed in [412]. The multiple-choice multi-dimensional knapsack problem with applications to service level agreements and multimedia distribution is studied in [413]. In the military related applications, in optimal designing of an unmanned aerial vehicle routing system [414] and in finding the underwater vehicle trajectories [415], RSO worked wonder. The problem of active structural acoustic control [416] and visual representation of data through clustering [417] are also well treated. Additionally the solution of the engineering roof truss design problem is discussed in [418]. An application of RSO for designing barrelled cylinders and domes of generalized elliptical profile is studied in [419]. Further applications of RSO are listed in [60] and [401], and also in the book of stochastic local search [402].

5.8 Integrated design environment for the proposed reactive and interactive MCDM approach

The software package implementations of RSO [253] provide a strong interface between a generic optimization algorithm and DM. While optimizing the systems produce different solutions, the DM is pursuing conflicting goals, and tradeoff policies represented on the multi-dimensional graphs [38], [39]. During multi-dimensional graphs visualization in these software packages, it is possible to call user-specific routines associated with visualized items. This is intended as the starting point for interactive optimization or problem solving attempts, where the user specifies a routine to be called to get information about a specific solution. These implementations of RSO are based on a three-tier model, independent from the optimization algorithm, effective and flexible software architecture for integrating problem-solving and optimization schemes into the integrated engineering design processes and optimal design, modeling, and decision-making.

For solving problems with a high level of complexity, modeling the true nature of the problem is of importance and essential. For this reason a considerable amount of efforts is made in modeling the MOO problems in Scilab [430] which later are integrated into optimizer package. Here, as an alternative to the previous approaches [397], [398], [399], the robust and interactive MOO algorithm of RSO is proposed in order to efficiently optimize all the design objectives at once in which couldn't be completely considered in the previous attempts. In this framework the quality of the design, similar to the previous research workflows, is measured using a set of certain functions. Then an optimization algorithm is applied in order to optimize the function to improve the quality of the solution. Once the problem is modeled in Scilab it is integrated to the optimizer via advanced interfaces to the RSO algorithm and its brain-computer implementations and visualizations. In this framework the application of learning and intelligent optimization and reactive business intelligence approaches in improving the process of such complex optimization problems is accomplished. Furthermore the problem could be further treated by reducing the dimensionality and the dataset size, multi-dimensional scaling, clustering and visualization tools.

5.9 Case study 1; welded beam design [42]

The problem of welded beam design is a well-known case study in structural engineering, dealing with optimal designing the form of steel beams and with connecting them to form complex structures [399]. This case study has been used by many experts as a benchmark problem of single and also multi-objective design optimization. The problem of optimal designing a welded beam consists of dimensioning a welded steel beam and the welding length in order to minimize the cost subjected to bending stress, constraints on shear stress, the buckling load on the bar, the end the deflection of the beam, and side constraints. There are four design variables i.e., *h, l, t, b* shown in figure 21. Structural analysis of the welded beam leads to two nonlinear objective functions subjected to five nonlinear and two linear inequality constraints. The objectives include the minimizing the fabrication cost and the minimizing the end deflection of the beam. In our case, the aim is to reduce fabrication cost without causing a higher deflection. Decision-making on the preferred solution among the Pareto-optimal set requires the intelligent participation of the designer, to identify the trade-offs between cost and deflection.

As it is shown in the figure 21 the beam is welded on another beam carrying a certain load P. The problem is well studied as a single objective optimization problem e.g., in [399], but we have transformed the original single objective problem into a two-objective problem for a more flexible design. In the original study the fabrication cost (f_1(x)) of the joint is minimized with four nonlinear constraints related to normal stress, shear stress, buckling limitations and a geometry constraint.

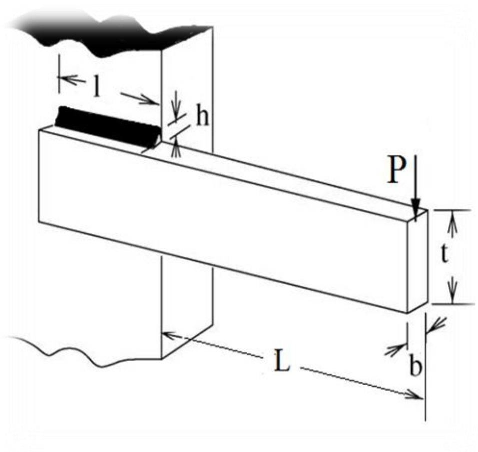


Figure 21: Ilustracion of the welded beam optimal design problem.

With the following formulation we have introduced one more objective i.e. minimization of the end deflection ($\delta(x)$) of the structure. The problem has four decision variables presented in the optimization formulation, i.e. thickness of the beam b, width of the beam t, length of weld l, and weld thickness h. The overhang portion of the beam has a length of 14 in and F ¼ 6; 000 lb force is applied at the end of the beam. The mathematical formulation of the problem is given as;

Minimize $f_1(\mathrm{x}) = 1.104711h^2\,l + 0.04811tb(14.0 + l)$,

Minimize $f_2(\mathrm{x}) = \delta(x) = \frac{2.1952}{t^3\,b}$

Subjected to $g_1(\mathrm{x}) \equiv 13{,}600 - \tau(\mathrm{x}) \geq 0$,

$g_2(\mathrm{x}) \equiv 30{,}000 - \sigma(\mathrm{x}) \geq 0$,

$g_3(\mathrm{x}) \equiv b - h \geq 0$,

$g_4(\mathrm{x}) \equiv P_c(\mathrm{x}) - 6{,}000 \geq 0$

$0.125 \leq h,\ \ b \leq 5.0, \quad 0. \leq l,\ \ t \leq 10.0$

The described problem has recently been modeled and solved utilizing a novel optimal design strategy so called interactive multi-objective optimization and decision-making using evolutionary methods (I-MODE) [398]. However I-MODE approach and its software implementation due to limitation of visual representation of the Pareto-optimal solutions would have difficulties in handling the increasing of objectives.

5.9.1 Creating the model in Scilab

Scilab [430] is now a robust, flexible and low-cost alternative to MATLAB which makes it an ideal modeling tool to be integrated to the MCDM. The success story presented in this paper in a short time and on a limited budget is the evidence of this statement. In fact he ongoing global crisis started in 2008 has forced the design companies to focus on efficiency and costs reduction by exploring open source software tools as a possible alternative to closed source. Moreover the final integrated optimal design tool has a fast and efficient computational capabilities in addition to the possibilities to automatically call parallel instances of the Scilab routine in background batch mode.

Here in this case study Scilab file contains a string definition, i.e. g_name, inluding a short, mnemonic name for the model as well as two 8-bit integers, i.e. g_dimension and g_range, defining the number of input and output variables of the model. Additionally the file has two real-valued arrays; i.e. g_min and g_max, containing the minimum and maximum values allowed for each of the input and output variables.

The following description is a simple definition of a function that is integrated to RSO so it can be understood and utilized by software implementation [253], [421].

The extensive implementation of the model in Scilab is available in [42].

```
g_name = "ZDT1";
g_dimension = int8(2);
g_range = int8(2);
g_min = [0, 0, 0, 0];
g_max = [1, 1, 1, 1];
g_names = ["x1", "x2", "f1", "f2"];
function f = g_function(x)
f1_x1 = x(1)
g_x2 = 1 + 9 * x(2)
h = 1 - sqrt(f1_x1 / g_x2)
f = [ 1 - f1_x1, 1 - g_x2 * h ]
end function;
```

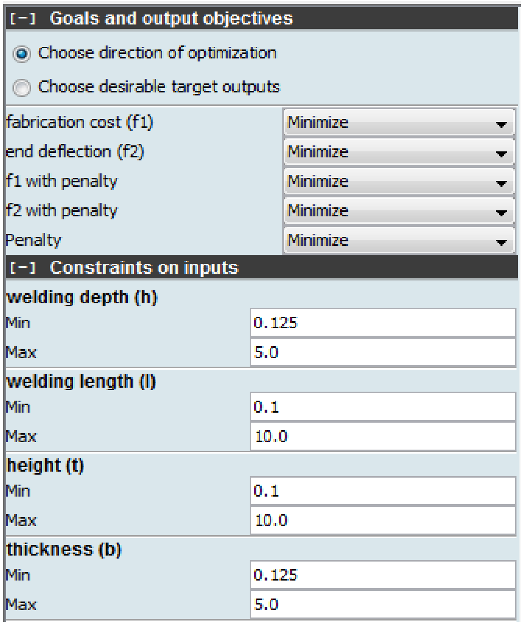


Figure 22: Description of the welded beam design problem in the software architecture of RSO multi-objective optimization; tuning the objectives and constraints.

Among the four constraints, $g_1$deals with the shear stress developed at the support location of the beam which is meant to be smaller than the allowable shear strength of the material (13,600 psi). The g_2 guarantees that normal stress developed at the support location of the beam is smaller than the allowable yield strength of the material (30,000 psi). The g_3 makes certain that thickness of the beam is not smaller than the weld thickness from the standpoint. The g_4 keeps the allowable buckling load of the beam more than the applied load P for safe design. A violation of any of the above four constraints will make the design unacceptable. More on adjusting the constraints would be available in [397], [398]. Additionally considering the stress and buckling terms calculated in [399], needless mentioning that they are highly non-linear to design variables.

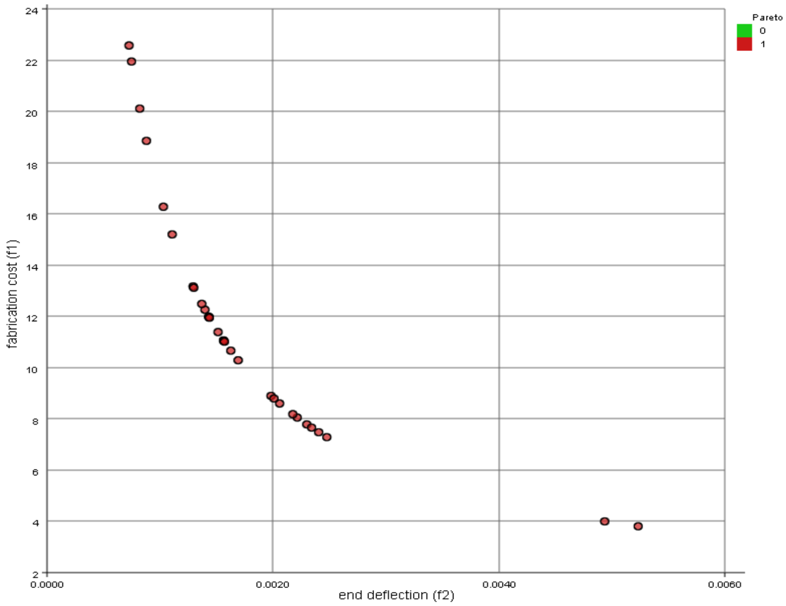


Figure 23: Pareto-optimal solutions, fabrication cost vs. end deflection of the beam.

5.9.2 Setting up the RSO Software

Here the implemented software architecture of RSO [253] as an integrated design environment helps the designer to become aware of the different posibilities and focus on his preferred solutions, within the boundary of constraints. Consequently the constraints are transformed into a penalty function which sums the absolute values of the violations of the constraints plus a large constant. Unless the two functions are scaled, the effect of deflection in the weighted sum will tend to be negligible, and most Pareto-optimal points will be in the area corresponding to the lowest cost. Therefore each function is devided by the estimated maximum value of each function in the input range [399]. The Pareto-optimal solutions of the multi-objective optimization corresponding to fabrication cost vs. end deflection of the beam are visualy presented in the graph of figure 22.

By associating a multidimentional graph for an advanced visualization, available in Figure 23, and a paralell chart, available in Figure 24, to the results table, the MCDM problem very clearly comes to the consideartion and the final decision is very confidently made. Here as the result, quite similar to the results abtained from the other approach in [398] it is observed that the welding length l and depth h are inversely proportional, the shorter the welding length, the larger the depth has to be, and that height t tends to be close to its maximum allowed value.

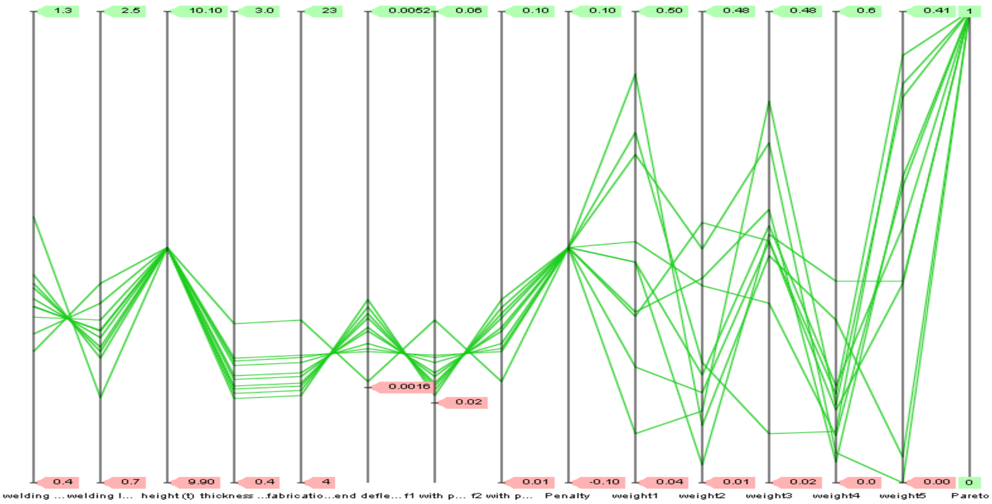


Figure 24: Parallel chart including design variables, constraints and optimization objectives.

The final visualization and observations can inspire many problem simplifications e.g., it is observed that by fixing the height to its maximum value and by expressing the length as a function of depth, therefore eliminating two variables from consideration in the future explorations, the optimal design problem would be simpler.

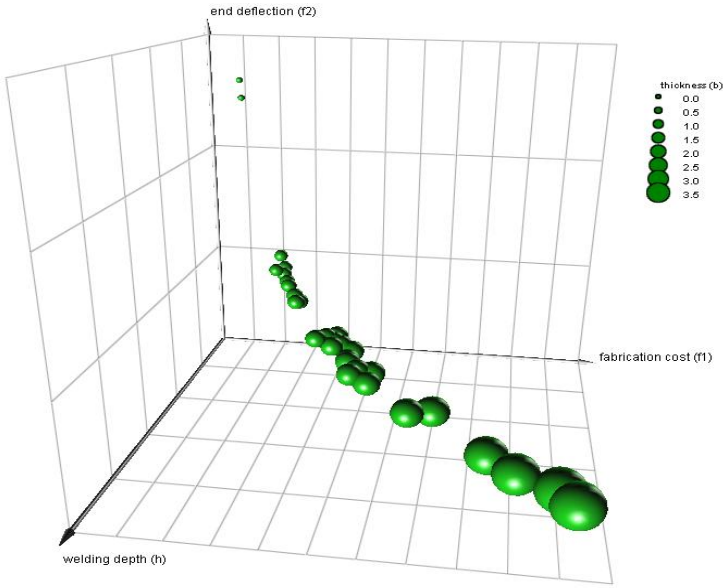


Figure 25: Multidimentional graph for an advanced visualization; the fabrication cost vs. end deflection of the beam.

5.9.3 Final remarks

In this case study the novel integrated design environment of reactive search optimization procedure and its recently implemented software packages are utilized. The new set of powerful integrated data mining-assisted visualization, modeling and learning tools via a handy procedure stretches beyond a decision-making task and attempts to discover new optimal designs relating to decision variables and objectives, so that a deeper understanding of the underlying problem can be obtained. In this case study the interactive procedure involve the DM in the optimization process helping to choose a single solution at the end. The method is well capable of handling the big data often associated with MCDM problems.

The preliminary tests of the software environment in the concrete context of optimal designing the welded beam design problem have shown the effectiveness of the approach in rapidly reaching a design preferred by the DM via advanced visualization tools and brain-computer novel interactions.

5.10 Case study 2; Optimal design of textile composites including materials selection [49], [50] & [52]

The second case study would be dealing with optimal design of textile composites, a more challenging task where the number of design criteria are increased and the geometry becomes way complicated. Textile composite materials [36], [49], consist of a polymer matrix combined with textile reinforcement. Typical applications range from high performance aerospace components to structural parts of transportation industry. In fact because of the numerous advantages of composites in comparison to traditional materials there has been an increasing trend in the usage of composite materials in different industries.

For the optimal design of composites, with the aid of advancement of interdisciplinary and data analysis tools, a series of criteria including mechanical, electrical, chemical, cost, life cycle assessment and environmental aspects are now able to be simultaneously considered. As one of the most efficient approach, the MCDM applications can provide the ability to formulate and systematically compare different alternatives against the large sets of design criteria. However, the mechanical behavior of woven textiles during the draping process has not been yet fully integrated to the optimal design approaches of MCDM algorithms. In this case the criteria of mechanical behavior of the woven textile during the draping and the further involved simulations and analysis are included in the process of the optimal design and decision making.

5.10.1 Introduction to the research

The integrated and multi-disciplinary design process of composites is very complicated as it is divided into several criteria and sub-criteria, while receiving the contributions of many different departments trying to meet conflicting requirements of the design simultaneously. Each department may direct its efforts towards improvements of objectives relating to criteria of that particular department. Hence, unexpected conflicting effects may rise from each department that the other departments need to take into account. Consequently, an optimal design process within such complex systems is required through advanced decision-support tools that can account for interactions and conflicts between several criteria. This leads to the need of optimizing several conflicting objectives simultaneously via reliable MCDM models which are the most known decision-support tools. In the process of selection and design of the textile reinforced polymer composite materials the desire is to choose the most reliable, comprehensive and innovative tools to solve the complex related engineering and business problems and arriving at target improvements. In the light of this the proposed research is planed to automaticaly choosing and adapting advanced MCDM models in improving the selection and design precesses.

Often modeling the MCDM problems of design or manufacturing processes is dependent on professionals and advanced skills which typical decision-makers are not usually trained for. Furthermore, due to poor visualization techniques, the nature of decision conflicts are not seen by the decision-makers and thus the final decision is not made confidently. In this case study, the first objective is to adapt RSO techniques along with fast regenerative design tools [37], [249] to perform the material selection/design of textile composites. Although today there are a number of commercial computer-aided textile design systems used in the composite industry, they may still be limited to the design and simulation of flat-shaped textiles. Accordingly, the modeling and parametrization of the free-form textile composites is desirable for fast optimization routines. Once a parameterized model is linked to the MCDM models, as the second objective of the work, it is intended to simplify the final selection process by adapting powerful visualization techniques to assist a company staff to make a final material choice without requiring a detailed knowledge of optimization. In this context, the expectation of decision-makers in composite sectors from a research in the field may be to assist managers and engineers to quickly and efficiently investigate several textile composite options for a given product under a multitude of criteria. It is worth adding that there have been numerous MCDM models introduced by the research communities to deal with complexities in engineering design processes. However, for every given problem, the choice of model needs to be very carefully examined as each model may adapt a particular aspect of given application; such as compensation or non-compensation between design criteria, incorporating the managers' criteria weights in different ways, etc. The strategy for empowering the MCDM process in selecting optimum, in this case textile composites, is to employ a parametric design approach known as Parametricism. This particular approach is adapted because of its novel capabilities in working effectively with the free-form geometries of textiles. More precisely, in order to generate the complex hierarchical systems of reinforced parts, we aim to develop a generative algorithm that virtually weaves fiber yarns and drapes the multi-layer textile reinforcements on to 3D geometries such as shells, tubes, and cones. The final geometry of the textile-reinforced part (the shell) is defined as a NURBS surface.

5.10.2 Review

Former researches on optimal design of textile composites e.g., [377], [385], highlighted that the ability to test preliminary designs is not economically workable and the assesment of preliminary materials systems urges the use of simulation tools. Such a strategy would improve the process of multi-criteria materials selection [386], and also can empower designers in considering the role of materials selection in design of materials and products. Jahan and Edwards believe [76] that there appears to be a simulation-based materials design revolution underway in which materials selection could be improved in order to more rapidly qualify new material designs. This would happen by shift from costly and time-consuming physical experimentation to less costly computational modeling and design [387].

The integrated and multi-disciplinary design process of composites has been very challenging. The design process is divided into several criteria and sub-criteria, while receiving the contributions of many different departments trying to meet conflicting requirements of the design simultaneously. Consequently, an optimal design process within such complex systems is required through advanced decision-support tools that can account for interactions and conflicts between several criteria. This leads to the need of optimizing several conflicting objectives simultaneously via reliable multicriteria decision-making models.

For the optimal design of composites, with the aid of advancement of interdisciplinary and data analysis tools, a series of criteria including mechanical, electrical, chemical, cost, life cycle assessment and environmental aspects are now able to be simultaneously considered. As one of the most efficient approach, the MCDM applications can provide the ability to formulate and systematically compare different alternatives against the large sets of design criteria. However, the mechanical behavior of woven textiles during the draping process has not been yet fully integrated to the optimal design approaches of MCDM algorithms. In this case study the criteria of mechanical behavior of the woven textile during the draping and the further involved simulations and analysis are included in the process of the optimal design and decision-making. For this reason the proposed optimal design strategy has been upgraded in terms of complex geometry modeling, and integration to materials selection. Comparing material properties and selecting the most appropriate materials, help to enhance the performance of products. Therefore it is important to consider and rank all the available materials.

A key objective of mechanical modeling of textiles is to define the dimensions and characteristics of a product and the materials from which it is made so that it can perform an acceptable function [384]. The area of the design decision-making for simultaneous consideration of the structural solution and materials selection, which is generally needed at the early design stage is relatively weak. Although the importance of integrating materials selection and product design has been often emphasized [73].

The designer in engineering of the optimal textile structures assume a material before optimizing the geometry or select the best material for an existing geometry of a structure, but clearly either approach does not guarantee the optimal combination of geometry and material [74]. Alternatively here the materials properties are directly transmitted to the design software package so that the effect of changing materials properties on the geometry and dimentions of a component design can be directly evaluated and ranked. At the same time the engineering designer can evaluate the effect of changing geometry and dimentions on product performance.

Worth mentioning that the process of meterials selction is highly dependent on data related to material properties. In fact with a large number of materials, clearly there is a need for an information-management system [375]. Therefore in the initial proposed optimal design strategy for interactive optimization and MCDM the existing drawbacks to utilizing MCDM are improved by connecting the data mining, visualization and optimization through the user interaction and decision-making. Besides the materials databases are used as materials selection systems, which are essentially developed for data storage searching. Morover the electronic materials databases and data search software packages would help designer in this regard [76].

5.10.3 Draping

The manufacturing of woven reinforced composites requires a forming stage so called draping [36], in which the preforms take the required shapes. The main deformation mechanisms during forming of woven reinforced composites are compression, bend, stretch, and shear which cause changes in orientation of the fibers. Since fiber reorientation influences the overall performance it would be an important factor that in the process of material selection to consider the draping along with the other criteria.

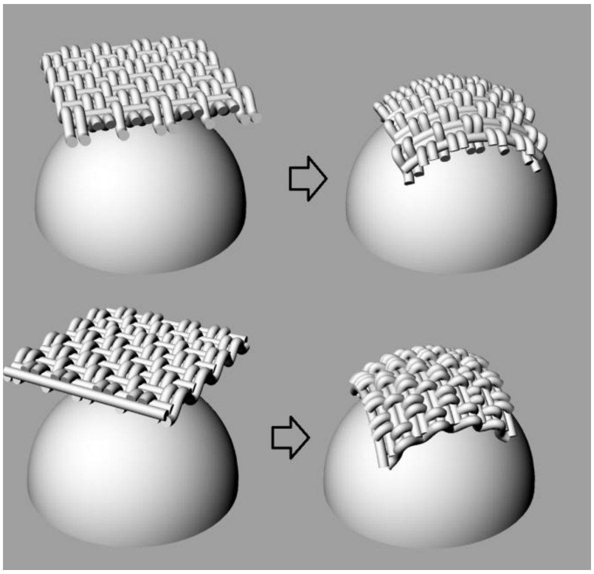


Figure 26: Simulation of draping process including a combined mechanical modeling of compression, bend, stretch, and shear shown from two different draping angles.

In an optimal engineering design process for the textile composites, the materials selection integrated with draping can well determine the durability, cost, and manufacturability of final products [49]. The process would naturally involve the identification of multiple criteria properties of mechanical, electrical, chemical, thermal, environmental and life cycle costs of candidate materials [385]. In fact multiple criteria from different disciplines which are to be satisfied in a materials selection problem, often because of the criteria conflicts the complexities are even increased. Moreover the mechanical behavior of woven textiles during the draping process has not been yet fully integrated to the MCDM algorithms. Although many applications and algorithms of MCDM [385] have been previously presented to deal with decision conflicts often seen among design criteria in materials selection. However many drawbacks and challenges are identified associated with their applicability [377].

5.10.4 Geometrical-mechanical modeling and simulation of draping

The mechanical models of draping with a much higher computation cost, comparing to the kinematic models, offer the benefit of representing the non-linear materials behavior. Moreover the mechanical simulation, as the most promising technique, gives a real-life prediction of the fiber reorientation. Beside of all presented approaches to the geometrical modeling of woven textiles so far [381], the NURBS-based methods have been the most effective technique. In fact, the NURBS-based geometrical representation of a real-life model of any type of the flat-shaped woven textile, are done with implementing the related CAGD code. However the mathematical representation of a multiple-dome shaped woven, which is essential for draping simulation, in the practical scale, could not be computationally efficient. Threfore in order to handle the computational complexity of geometrical modeling the multiple-dome woven shapes, utilizing the NURBS-based CAGD *packages* are proposed. Khabazi [37] and Krish [249] introduced generative algorithms for creating such complex geometries. Their improved algorithm is capable of producing the whole mechanism of deformation with combining all details of compressed, bended stretched and sheared properties.

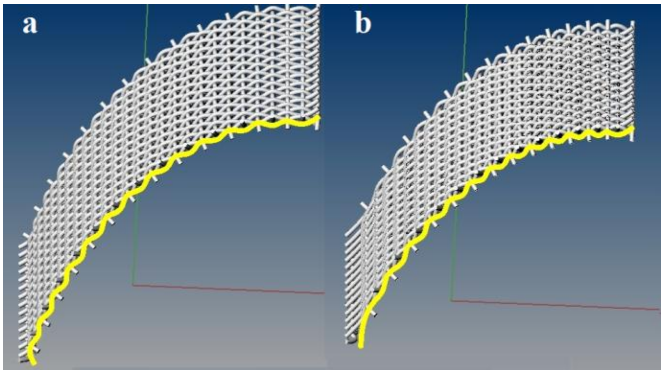


Figure 27: A combination of four different simulation criteria including the compression, bend, stretch, and shear form the draping a) Geometrical modeling and simulation of the woven textiles b) Mechanical modeling of the bending; the behavior of textile under its weight is simulated by manipulating the related geometrical model within the CAGD package.

It is assumed that if the mechanical behavior of a particular woven fabric of a particular type and material is identified then the final geometrical model of the draping could be very accurately approximated. In this technique the defined mechanical mechanisms of a particular material, in this case glass fiber [381], are translated into a geometrical logic form integrated with the NURBS-based CAGD package through the process of scripting [37].

Worh mentioning that traditionally in order to include the materials property into the mechanical models of textile the outputs from FEA are utilized as inputes to MCDM in material selection. FEA allows materials property data to be transmitted directly to a design software package so that the effect of changing materials properties on the geometry and dimentions of a component design can be directly evaluated. At the same time the DM can evaluate the effect of changing geometry and dimentions on product performance [382].

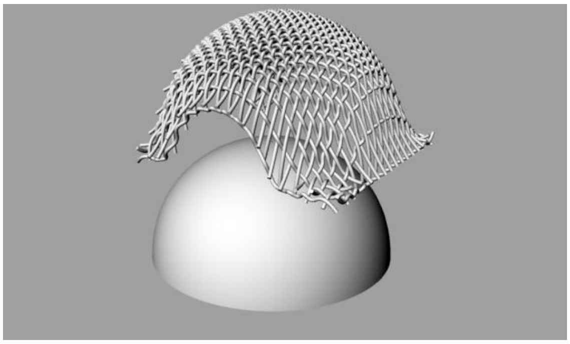


Figure 28: Geometrical modeling of a double dome.

5.10.5 Integration the MCDM-assisted materials selection with draping simulation

Recently a combined FEA-MCDM approach as a framework that links the capabilities of FEA tools to the MCDM approaches for composite structural materials selection problem [385] proposed. However due do the geometricaly challenging modeling of the composite product the draping simulation has not been considered in their work.

In order to select the best material of a woven textile as well as the right angel of draping, the draping simulation needs to be carried out for a number of draping degrees for a particular material. The results of all the draping simulations of different drape angles are gathered as a data-set for consideration, in addition to already existed data-sets from the earlier case studies [383], including the other criteria e.g., mechanical, electrical, chemical, cost, life cycle assessment and environmental.

5.10.6 Visualization; an effective approach to MCDM and materials selection

Visualization is an effective approach in the OR and mathematical programming applications to explore optimal solutions, and to summarize the results into an insight, instead of numbers [378], [379]. Fortunately during past few years, it has been a huge development in combinatorial optimization, machine learning, intelligent optimization, and RSO, which have moved the research in advanced visualization methods forward [380].

The previous work in the area of visualization for MCDM [380] allows the user to better formulate the multiple objective functions for large optimization runs. Alternatively in our research utilizing integrated design environment of RSO which advocates learning for optimizing, the algorithm selection, adaptation and integration, are done in an automated way and the user is kept in the loop for subsequent refinements and final decision-making. Here one of the crucial issue in MCDM is to critically analyzing a mass of tentative solutions related to materials and draping simulation, which is visually mined to extract useful information. Concerning solving the MCDM problems the DM is not distracted by technical details instead concentrates on using his expertise and informed choice among the large number of possibilities. As the whole process may be carried out in different design and design-making departments worth mentioning that the workflow may overlaps with a number of other fields of research such as enterprise decision management [61].

5.10.7 Software architecture of the reactive and interactive MCDM visualization environment

The proposed software is based on a three-tier model, independent from the optimization which is an effective and flexible software architecture for integrating problem-solving and optimization schemes into the integrated engineering design processes and optimal design, modeling, and decision-making. The software is implemented a strong interface between the generic optimization algorithm and DM. While optimization systems produce different solutions, the DM is pursuing conflicting goals and tradeoff policies represented on the multi-dimensional graphs (see figures 29 and 30).

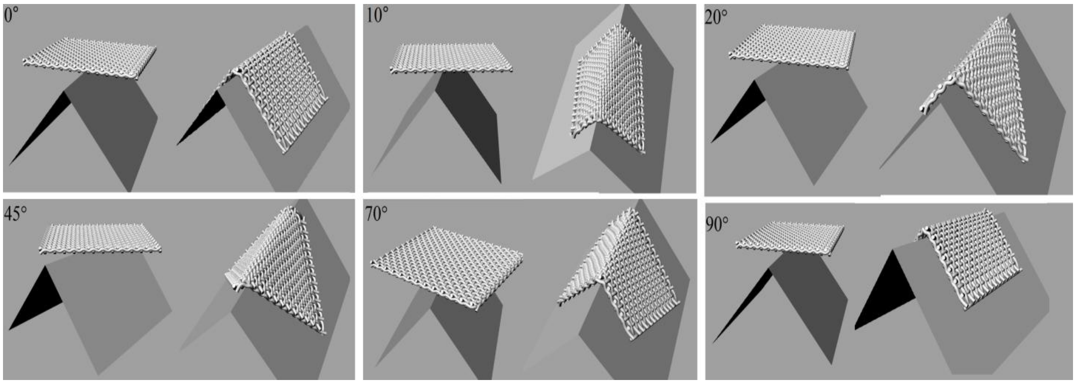


Figure 29: Mechanical modeling of draping process for a number of draping degrees.

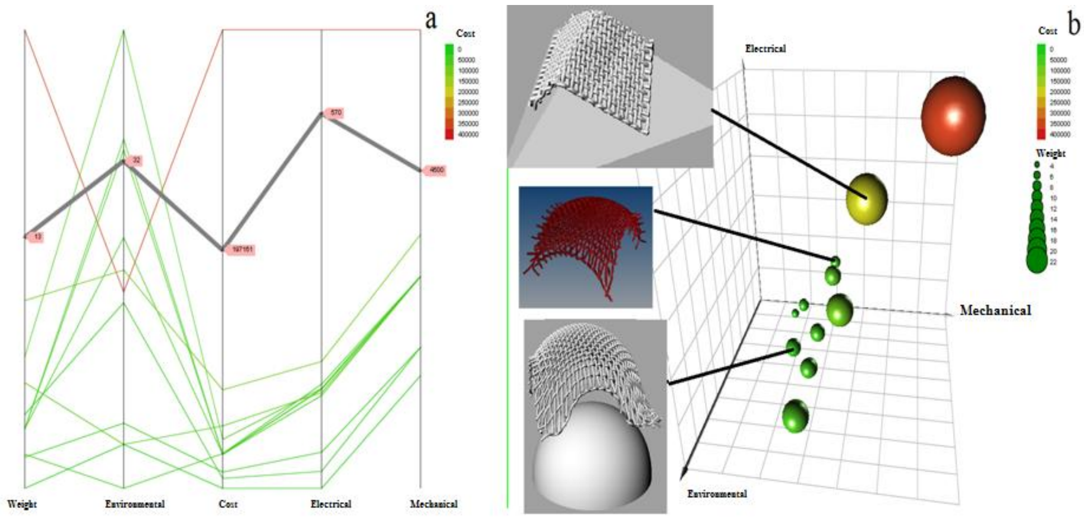


Figure 30: a) Paralel chart considering five optimization objectives simultaneously b) The 7D visualization graph used for considering different prodcuts, materials and draping characteristics simultaneously.

5.10.8 Final remarks

Along with presenting this case study the aspects of data mining, modeling, and visualization the data related to materials selection are considered. Further the utilization of the proposed software architectures for MOO and decision-making, with a particular emphasis on supporting flexible visualization is discussed. The applicability of the software can be easily customized for different problems and usage contexts.

The advanced visual analytical interfaces are involved to support the DM interactively. With utilizing the features such as parallel filters and clustering tasks, in the materials selection study case the engineering designer can solve MOO problems as it amends previous approaches. The preliminary tests of the software environment in the concrete context of designing a multiple dome shape have shown the effectiveness of the approach in rapidly reaching a design preferred by the decision-maker.

5.11 Case study 3; developing a decision-making tool for general applications to computer vision [40], [41], [42], [43]&[48]

The general applications to computer vision are full of problems expressed in terms of mathematical energy optimization. Within this context developing a reliable optimal design process for the NURBS curves and surfaces which in fact has a wide and foundational application in image processing, CAGD, CAD and computer animation, is the focus of this work. Yet the optimal design and parameter tuning of the NURBS is a highly non-linear and complicated MOO problem. The complexity of the problem is even increased when the criteria of product beauty is included to the design process. In this case study for an optimal configuration, the operating design parameters are tuned within the proposed interactive MCDM design environment where the DM is included into the process. Along with presenting the NURBS's optimal design problem the drawbacks to the former approaches are reviewed, and the applicability of the proposed decision-making tool in the general applications to computer vision is described.

5.11.1 Introduction

The general applications to computer vision are full of problems expressed in terms of mathematical energy optimization [319]. Problems as such are often complicated, highly non-linear and multi-objective in nature. In this context the optimal design of the NURBS curves and surfaces [389], is considered as an interesting case study as it has a wide application in computer vision e.g., [427], [428], as well as other fileds of industry e.g., [16], [20], [21], [22]. The applications include a wide range of problems from medical image processing [426], [391], CAGD [97] and CAD [103] to computer animation [429]. Yet the optimal design and parameters tuning of the NURBS is a highly non-linear and complicated MOO problem as earlier described e.g., [120], [389], [22], [40]. In fact the mathematical modeling of the NURBS optimal design problem results in a MOO problem which cannot be handled as such by traditional single objective optimization algorithms [389]. Furthermore the complexity of the problem is even increased when the criteria of product beauty is included to the design process. In this article the optimization process of NURBS including four conflicting and highly non-liner design objectives is of the particular interest.

Applied optimization over the past few years have dramatically advanced, particularly with the availability of efficient MOO algorithms e.g. [39], [401] which facilitates a DM to consider more than one conflicting goals at the time. In a MCDM problem for the reason of decision-making on the optimality and further selecting the preferred solution with the aid of the MOO algorithms many conflicting objectives are traded off simultaneously. To doing so numerous biology-inspired metaphors e.g. GA with in fact a very limited learning capabilities, have been widely utilized so far. Yet in this case study for an optimal configuration, alternatively the operating design parameters are tuned in the interactive MCDM environment of RSO, which in fact is inpired by [400] and [415], where the DM is included into the process. By involving the DM interactively in the loop intelligent expertise is loaded to the algorithm leading to increasing the learning capabilities. Here it is assumed that integration of machine learning techniques into the search heuristics along with utilizing the advanced visualization tools would automate the algorithem selection, adaptation and integration for approaching a robust solution [45], [421].

5.11.2 Statement of the problem

A tensor product NURBS is defined as; $S(u,v) = \sum_{i=0}^{n-1} \sum_{j=0}^{m-1} \mathbf{P}_{\mathbf{i,j}}\, R_{\boldsymbol{i,j}}(s,t)$, where $\boldsymbol{P_{i,j}}$ are control points of the surface with the orders and the numbers of $n \; and \; m$. $R_{\boldsymbol{i,j}}(s,t)$ are the NURBS basis function, depended on the design variables including weights, $\boldsymbol{w}$, the knot vectors, $\boldsymbol{u}$ & $\boldsymbol{v}$, the d_u & d_v orders of the surface and the parameterization, s & t. Handling the parameterization, knot vectors, interpolation and NURBS weights is further described in e.g., [23], [120], [389], [423], [424], [218]. Tuning NURBS weights and knot vector all together dramatically increases the number of DOF which is proportional to $n * m$.

According to the input points, $\boldsymbol{Q}_{i,j}$, and the design variables, the control points, $\boldsymbol{P_{i,j}}$, via utilizing the linear least squares fitting, are calculated and the surface is created [425].

Let $\boldsymbol{M}$ be the collocation matrix used for surface fitting; $\boldsymbol{Q}_x$, $\boldsymbol{Q}_y$, $\boldsymbol{Q}_z$ are the coordinates of Q, the data to be fitted; $diag(x)$ a diagonal matrix whose entries are the vector x.

$t = M * w,$

$X = diag(Q_x) \quad Y = diag(Q_y) \qquad Z = diag(Q_z)$

$v_x = X * t \qquad v_y = Y * t \qquad v_z = Z * t$

The position of the surface's control points $\boldsymbol{p}_x, \boldsymbol{p}_y, \boldsymbol{p}_z$ are given by least solution of the following equations: $d_x = M * v_x \qquad d_y = M * v_y \qquad d_z = M * v_z$

5.11.3 Optimization objectives

The goal of the optimization process is to produce a set of NURBS surfaces which approximates a set of input points, $\boldsymbol{Q} = \boldsymbol{Q}_{0,0}, \dots, \boldsymbol{Q}_{N-1,M-1} \in \mathbb{R}^d$, $d = 2, 3$, and are optimal with respect to the specified design objectives. Once the surface is created the quality of it could be considered by evaluating a set of specified design objectives, i.e. $O_1(S(s,t))$, . . ., $O_k(S(s,t)$. The optimization process includes four conflicting and highly non-liner design objectives described in the following.

Approximation Error, O_1, the distance between the surface and the points $\boldsymbol{Q}$ measured at the parametrization points $\boldsymbol{s_i}, \boldsymbol{t_i}$, is often subjected to minimization;

$O_1 = \min\left(\sum_{i=0}^{n-1}\sum_{j=0}^{m-1}\left\|\boldsymbol{S}(s_i,t_i) - \boldsymbol{Q}_{i,j}\right\|^2\right)$,

under L_2 norm,

$O_1 = \max(\left\| \boldsymbol{S}(s_i,t_i) - \boldsymbol{Q}_{i,j}\right\|)$, $i = 0, \dots, n-1; j = 0, \dots, m-1$, under L_∞ norm.

Surface Area, O_2, in conflict with approximation error, controls artifacts due to over-fitting; $O_2 = \int_0^1\int_0^1 \left\|\frac{dS}{ds} \times \frac{dS}{dt}\right\| dsdt.$

Surface Elastic Energy, O_3, as an other conflicting objective is a highly non-linear term;

$O_3 = \int_0^1\int_0^1 \|k_{min}^2 + k_{max}^2\| dA$, where A is the surface area.

5.11.4 Review

As mentioned above the mathematical modeling of the NURBS curves and surfaces design problem results in a MOO problem which cannot be effectively handled as such by traditional single objective optimization algorithms. Considering the problem with conjugate gradient and Newton-based approaches, the optimization process is divided into several phases and each functional is optimized separately [422], [423], [424].

In the approaches as such the MOO problem is solved via a single objective optimization algorithm. However the results obtained reported to be not promising [120], [389], [40]. The detailed description of the problem, applications and previous approaches where the use of MOO algorithms enhances the design process by enabling optimization of several design objectives at once are available in [20], [21], [48].

EMOs are natural choices for MOO since at each step the algorithm keeps a population, which is a set of solutions instead of a single, optimal, solution. Because of the robustness and efficient handling of highly non-linear objective functions and constrains the use of EMOs in geometrical problem has proved to be a powerful technique [22], [40], [71], [389]. In fact EMO is well suited to search for a set of PS to be forwarded to the DM while aiming at building a set of points near the PF. Afterward, a single preferred solution is chosen from the obtained set by using a MCDM procedure. In this way EMO application helps a DM to analyze different trade-offs before choosing the final one. However the DM has to go through analyzing many different solutions to be able to confidently make the final decision. This is done by considering too many possible solutions within the multi-objective and multicriteria trade-offs as experienced in e.g. [389]. It has been seen that the EMO may employ plenty of complications in usage, efficiency, robustness, and decision-making on the final solution when the number of objectives increases. In fact in a number of case studies including our case of MOO of NURBS by increasing the number of objectives, EMO algorithms have been reported ineffective [39], [70], [163], [401]. The problem of MOO of curves and surfaces [21] would be indeed a good example for such ineffective attempt within the increasing complexity. Previously an EMO algorithm [20], [389] was used to handle this case. In this approach due to the robustness and efficiency of the evolutionary algorithms the problem was well modeled. Nevertheless such approaches to solving the MOO problem of NURBS curves and surfaces whether *a priori* or *a posteriori*, due to high number of objectives, would involve plenty of various complications. The reason is that the proportion of PF in a set grows very rapidly with the dimension $\boldsymbol{m}$.

Yet for an ideal and seamless approach to solving the MOO problems of NURBS the integrated design environment of RSO builds its bases on software tools used for a large number of applications in computer vision from modeling activities, optimization and decision-making tasks, to performance's simulation and beauty evaluations. Furthermore the addition of new tools is intended to extend the support to the creative part of the design process and also the capability to deal with big data. This support allows the DM to improve the performance of their concepts, allowing computers to take part on the generation of variants, and on the judgment, by true modeling of these variants. Integration of data mining, modeling, learning, and interactive decision-making are all parts of a reliable software tool that can nurture the knowledge of designers to generate new solutions, based on many separate ideas leading to the new design concepts.

5.11.5 Methodology

The task of MCDM in the proposed integrated design and decision-making environment, unlike the former MOO approaches [395], [397], where the workflow is divided into two different parts of optimization and decision-making, is seen as a single task. Although both processes of optimization, to discover conflicting design trad-offs, and decision-making, to choose a single preferred solution among them, are considered as two joint tasks, yet they have been previously treated as a couple of independent activities. For instance EMO have mostly concentrated on the optimization aspects, developing efficient methodologies of finding a PS. However finding a set of trade-off optimal solutions is just half the process of optimal design in the multicriteria decision making environments. This has been the reason why EMO researchers were looking to find ways to efficiently integrate both optimization and decision making tasks in a convenient way. Within the known approaches to solving complicated MCDM problems there are different ideologies and considerations in which any decision-making task would find a fine balance among them.

Although the mathematical representative set of the decision-making model is often created however presenting a human DM with numerous representative solutions on a multi-dimensional PF is way complicated. This is because the typical DM cannot deal with more than a very limited number of information items at a time [72]. Yet in this case study DM in addition to decision-making duty would be involved in aesthetic evaluation as well.

In problem-solving methods of stochastic local search, proposed in [39], [43], where the free parameters are tuned through a feedback loop, the user is considered as a crucial learning component in which different options are developed and tested until acceptable results are obtained. As explained in [420], [421], by inserting the machine learning the human intervention is decreased by transferring intelligent expertise into the algorithm itself. Yet in order to optimize the outcome setting the parameters and observing the outcome, a simple loop is performed where the parameters in an intelligent manner changed until a suitable solution is identified. Additionally to operate efficiently, RSO uses memory and intelligence, to recognize ways to improve solutions in a directed and focused manner.

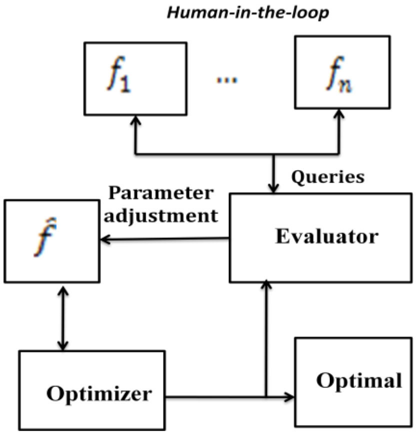


Figure 31: Schematic flowchart of the optimal design process; human-in-the-loop [401] for aesthetic evaluation and decision-making.

In the RSO approach of problem solving the brain-computer interaction is simplified. This is done via learning-optimizing process which is basically the insertion of the machine learning component into the solution algorithm. In fact the strengths of RSO integrated design environment are associated to the brain characteristics i.e. learning from the past experience, learning on the job, rapid analysis of alternatives, ability to cope with incomplete information, quick adaptation to new situations and. Moreover the term of intelligent optimization in RSO refers to the online and offline schemes based on the use of memory, adaptation, incremental development of models, experimental algorithmics applied to optimization, intelligent tuning and design of heuristics. In this context with the aid of advanced visualization tools implemented within the software architecture packages [253] the integration of visualization and automated problem solving and optimization would be the center of attention.

Here in contrast to the EMO, the DM guides the optimization in the desirable search locations and the final desirable surface. In this case the computation cost is minimized and the preferences of the DM are effectively considered.

During the process of solving the real-life problems exploring the search space, utilizing RSO, many alternative solutions are tested and as the result adequate patterns and regularities appear. While exploring, the human brain quickly learns and drives future decisions based on the previous observations and searching alternatives. For the reason of rapidly exploiting the most promising solutions the online machine learning techniques are inserted into the optimization engine of RSO. Furthermore with the aid of inserted machine learning a set of diverse, accurate and crucial alternatives are offered to the DM. In this context the feedback from the DM in the preliminary exploration phase can be incorporated so that a better tuning of the parameters takes the preferences into account.

5.11.6 Communicating the results of the case study via multi-dimensional graphs

For solving problems as such, with a high level of complexity, modeling the true nature of the problem is of importance and essential. Here, as an alternative to the previous approaches, the robust and interactive MOO algorithm of RSO efficiently optimizes all the objectives at once including the criteria of beauty in which couldn't be completely considered in the previous attempts [389]. In this framework the quality of the surface, similar to the previous research workflows, is measured using a set of certain functions, then an optimization algorithm is applied in order to optimize the function to improve the quality of the surface.

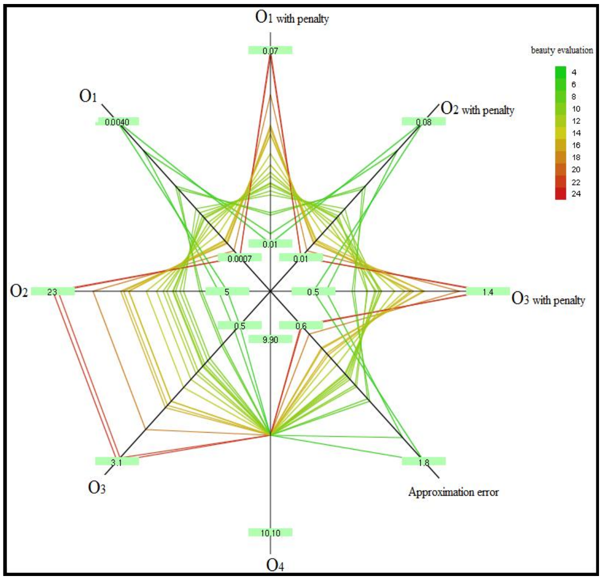


Figure 32: Considering four objectives of the case study in a multi-dimensional graph, including beauty criteria.

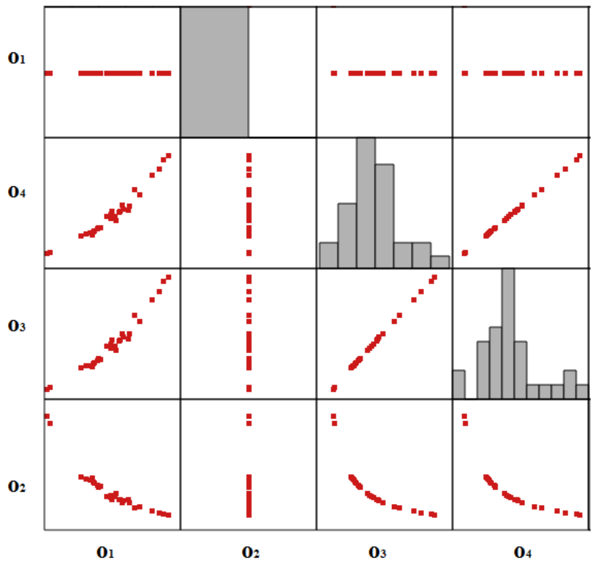


Figure 33: Considering four objectives of the case study in a multi-dimensional graph.

The problem is modeled in Scilab and the model is integrated to the optimizer via advanced interfaces to the RSO algorithm and its brain-computer evolutionary multi-objective optimization implementations and visualization. In this framework the application of learning and intelligent optimization and reactive business intelligence approaches in improving the process of such complex optimization problems are described. Furthermore the problem is further reconsidered by reducing the dimensionality and the dataset size, multi-dimensional scaling, clustering and visualization tools. Figure 32 and 33 present the multi-dimensional graphs to the case study.

5.11.7 Final remarks

In this case study along with presenting a highly nonlinear and multi-objective case study the aspects of data mining-assisted visualization, modeling, and the data related to computer vision, geometry and image processing are considered. A novel environment for optimization, analytics and decision-support in general computer vision design problems is proposed. The new set of powerful integrated data mining, modeling, visualization and learning tools via a handy procedure stretches beyond a decision-making task and attempts to discover new optimal designs relating to decision variables and objectives, so that a deeper understanding of the underlying problem can be obtained. Here along with presenting the study case of NURBS optimal design, the interactive procedure is introduced which involves the DM in the optimization process helping to choose a single solution at the end. The method is well capable of handling the big data often associated with MCDM problems in computer vision and image processing.

The methodology implements a strong interface between a generic optimization algorithm and DM. While optimizing the systems produce different solutions, the DM is pursuing conflicting goals, and trade-off policies represented on the multi-dimensional graphs. Moreover the preliminary results of the proposed optimal design environment in the concrete context of optimal designing the NURBS have shown the effectiveness of the approach in rapidly reaching a design preferred by the DM via advanced visualization tools and the brain-computer novel interactions.

In addition the future research is set out to investigate the role that the proposed optimization strategy can play in the optimal design of skinning of circles and spheres [246], and isoptics of Bézier curves [148] which are considered as interesting subjects in CAGD. Moreover customizing the proposed methodology for decision-making tasks e.g., in [359], and in further optimal engineering designs, would be a part of our future research.

6 Conclusions

Performing the process of optimal engineering design within the integrated design environment of an optimization package where the ease of use, and the further coupling and integration requirements are well customized can effectively fill the gap between optimization approaches and optimal engineering design in industry. The benefits further include that the optimization algorithms whether evolutionary or interactive's can easier be enhanced by metamodels, and the optimization results can be better communicated to the decision-maker via effective graphical user interfaces, and finally the decision-support tools can make the decision-making task more convenient for engineers. In fact with an ideal integration of the today's already existing resources of CAD, CAE, and optimization tools achieving the promising results can be more convenient for engineers. Pursuing the proposed design strategy in this thesis has shown promising results in shape optimization applications. Furthermore consideration of the different combinations of CAD, CAE and optimizer in order to find the ideal combination of tools for a particular engineering design application, in this case; fluid dynamics optimal design, has been easier facilitated.

Concerning the dimensionality which is often the case in optimal engineering design; it is discussed that in today's ever increasing design complexity, by extension the dimension of MCDM problems which is mostly due to increasing the number of variables, optimization objectives, and decision criteria, presenting a decision-maker with numerous representative solutions on a multidimensional Pareto-optimal frontier is way complicated and not practical indeed. In this thesis in order to deal with the dimensionality firstly a supplementary decision-support system on the basis of classification task of data mining is proposed. This technique has been shown to be effective in reducing the design space by ranking the importance of the design variables according to the objectives. The considered case studies in shape optimization have proved the simplicity and the effectiveness of the proposed technique in the real-life industrial application. Secondly, as a potential replacement to evolutionary and interactive algorithms, for today's large-scale optimal engineering design problems, the reactive search optimization strategy in the framework of an integrated design environment is proposed where the brain-computer interactions and advanced multidimensional visualization tools can well deal with dimensionality and computational costs in tough decision-making tasks. Consequently the promising achieved results from solving a number of demanding case studies have shown the effectiveness of the approach in dealing with dimensionality.

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A Summary

- For finding optimal solutions to the engineering design problems, these problems which are indeed demanding decision-making tasks need to be typically considered simultaneously from very different perspectives. In this context the most logical approach to achieving the best solution, at the presence of many design criteria and numerous design variables, has been the task of performing scientific optimization to produce potential solutions for further decision-making. Solving the optimal engineering design problems as such, which are mostly referred to black-box optimization problems, is not a simple task. The black-box optimization problems with multiple objectives can be solved in several different approaches. However the characteristics of these problems suggest that efficient and robust global approaches should be utilized to tackle the difficulties caused by several local optimums, several conflicting objectives, and high computational cost of the engineering evaluations functions. Accordingly multiple criteria decision-making strategies to optimal engineering design problems, as the combined tasks of optimization and decision-making, via employing efficient, robust, global and multi-objective optimization algorithms along with decision-support tools, have brought a significant and competitive advantage to the optimal design. However most of these approaches, due to a number of challenges often associated with the usage, poor visualization techniques, lack of proper decision-support tools, weak integration and also dimensionality have not been practical and widely acceptable within engineering design community. Moreover modeling multiple criteria decision-making problems has been very dependent on professionals and advanced skills which typical decision-makers in engineering community are not usually trained for. This has been the main reason why engineers prefer to utilize the efficient and easy to use approaches in order to solve the problems effectively.

Despite of the all optimization algorithms suggested to engineering optimal design community the expansion and progress of applicability and popularity of these algorithms within engineering design communities have been very slow which indicates an obvious gap between academic research and the industrial real-life applications. It has been proven that an algorithm can be widely utilized only when it is implemented within an integrated design environments of the optimization packages where its ease of use, and its further integration requirements are well customized. In fact with an an ideal integration of the today's already existing resources of CAD, CAE, and optimization tools achieving the promising results can be more convenient for engineers; leading to filling the gap between optimization approaches and optimal engineering design in industry. The further benefits include

that the optimization algorithms whether evolutionary or interactive can easier be enhanced by metamodels, and the optimization results can be better communicated to the decision-maker via effective graphical user interfaces, and finally the decision-support tools can make the decision-making tasks more convenient for engineers. The pursuit of the proposed design strategy in this thesis has shown promising results in shape optimization applications. Furthermore the consideration of the different combinations of CAD, CAE and optimizer in order to find the ideal combination of tools for the particular engineering design applications, in this case fluid dynamics design, has been easier facilitated.

- Due to highly expensive numerical analyses in engineering for an optimal design, engineers have been urged to extract as much information as possible from a limited number of test runs in order to increase the efficiency and also reduce the effects of dimensionality. A vast number of statistical and optimization algorithms exist to extract the most relevant qualitative information from a database of experiments in order to support the decisions in real-life engineering optimal design where a number of objectives in multiple design criteria from very different perspectives are to be considered simultaneously. However by extension the dimension of multiple criteria decision-making problems which is mostly due to the increasing number of variables, dimensionality of the decision-making models is being discussed as the main challenge to the future of engineering optimal design. Moreover it is discussed that even though metamodeling methodologies have been reported as the efficient tools for reducing the design space, the optimal design community would still need more effective tools to deal with Curse of dimensionality. Accordingly the proposed supplementary decision-support system on the basis of classification has shown promising results in effectively dealing with the ever increasing dimensionality. The technique used, has been shown to be effective in reducing the design space by ranking the importance of the design variables to the objectives. Furthermore considered case studies in shape optimization have proved the simplicity and the effectiveness of the proposed technique in the real-life industrial application.

- In dealing with optimal engineering design problems at the presence of CAE simulations, when the computation of the numerical analysis of the evaluation functions are highly expensive employing the metamodels are inevitable to compete other multi-objective optimization algorithms either evolutionary' or interactive', even though there are numerous drawbacks identified associated with these algorithms' usage. As a potential replacement to evolutionary and interactive algorithms, for today's large-scale optimal engineering design problems, the reactive search strategy in the framework of an integrated design environment is proposed where the brain-computer interactions and advanced multidimensional visualization tools can well deal with dimensionality and computational costs in tough decision-making tasks. In this design strategy a set of powerful integrated data mining, modeling, visualization and learning tools via a handy procedure stretches beyond the decision-making task and attempts to discover new optimal designs relating to decision variables and objectives, so that a deeper understanding of the underlying problem can be obtained. In an optimal engineering design environment as such solving the MCDM problems is considered as a combined task of optimization and decision-making. Yet in solving real-life MCDM problems often most of attention has been on finding the complete Pareto-optimal set of the associated MOO problem and less on decision-making. Consequently the promising achieved results from solving a number of demanding case studies have shown the effectiveness of the approach in dealing with dimensionality. For instance in case study of optimal design of composite textiles where the detailed-complex geometry parametrization, big data and increasing the number of criteria in decision-making become the design's new issues the reactive search strategy delivers promising results. Moreover in the other case study the preliminary results of the proposed optimal design environment in the concrete context of optimal designing the NURBS have shown the effectiveness of the approach in rapidly reaching a design preferred by the DM via advanced visualization tools and the brain-computer novel interactions. In this case study the methodology implements a strong interface between a generic optimization algorithm and DM; while optimizing the systems produce different solutions, the DM is pursuing conflicting goals, and trade-off policies represented on the multi-dimensional graphs aiming at final decision.

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